Planning Energy Communities with Flexibility Provision and Energy and Cross-Sector Flexible Assets

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***Abstract* — Planning Energy communities (ECs) requires engaging members, designing business models and governance rules, and sizing distributed energy resources (DERs) for a cost-effective investment. Meanwhile, the growing share of non-dispatchable renewable generation demands more flexible energy systems. Local flexibility markets (LFMs) are emerging as effective mechanisms to procure this flexibility, granting ECs a new revenue stream. Since sizing with flexibility becomes a highly complex problem, we propose a 2-stage methodology for estimating DERs size in an EC with collective self-consumption, flexibility provision and cross-sector (CS) assets such as thermal loads and electric vehicles (EVs). The first stage computes the optimal DER capacities to be installed for each member without flexibility provision. The second stage departs from the first stage capacities to assess how to modify the initial capacities to profit from providing flexibility. The impact of data clustering and flexibility provision are assessed through a case study.**

***Index Terms*— distributed energy resources, energy communities, flexibility markets, flexibility provision, investment optimization**

I. Introduction

The transition toward a decentralized renewable-based power systems is boosting the development of energy communities (ECs) as a key strategy to promote local energy generation and consumption [1]. ECs enable consumers to collectively invest in distributed energy resources (DERs) such as photovoltaic (PV) panels and battery energy storage systems (BESS) [2]. However, the integration of non-dispatchable energy sources, introduces challenges in balancing supply and demand, needing additional flexibility [3].

To address this, local flexibility markets (LFMs) are emerging as mechanisms to procure flexibility at distribution level, where ECs could participate by adjusting consumption and generation patterns in response to flexibility market signals [4]. ECs can then monetize their flexible potential, creating additional revenues [5]. However, incorporating flexibility into EC planning requires careful DER sizing. In this context, this work builds upon the methodology introduced in [6] to operate ECs while providing flexibility, but further extends it by including DER sizing with a focus on investment optimization. In addition, to reflect the electrification of mobility and heating, cross-sector (CS) assets such as electric vehicles (EVs) and electric water heaters (EWHs) are integrated in the model. Thus, the main contributions of this work include:

- A two-stage linear optimization model to size PVs and BESS in ECs pre-equipped with energy and CS assets, such as EVs and EWHs, considering both capital expenditure (CAPEX) and operational expenditure (OPEX)
- Evaluation of the impact of input data clustering on computational efficiency by analysing its effects on DER sizing accuracy and optimization runtime.
- Insights into the trade-offs between accuracy and computational effort, offering a practical overview on how clustering input data to reduce the computational burden influences EC planning.
- Integration of LFM participation into DERs planning process by estimating flexibility needs and prices, helping ECs to monetize flexibility while optimizing investments.

Next Section describes the optimization problem, section III the case study for an EC with energy and CS flexible assets and the results analysis, and section IV concludes.

II. Optimization Model

The optimization model proposed determines the optimal capacity of both BESS and PV panels to be installed by each member of an EC. To account for uncertainty and seasonality, a full year data would be advisable, but since this can lead to computational issues, data clustering was used to reduce computational times and memory requirements [7]. In this paper, the K-medoids algorithm is applied, a more robust variation of K-means [8]. The model proposed has 2 stages, as shown in Figure 1. Stage S1 computes the optimal DER investment by considering the structure of the EC and its business model, consumption and generation forecasts, the existing energy and CS assets, members' opportunity costs (the prices at which they buy and sell energy), and the DERs investment costs. From these initial PV and BESS capacities, stage S2, divided in sub-stages S2.1 and S2.2, is applied. S2.1 calculates the optimal schedule of the EC flexible assets without flexibility provision, providing the baseline from which the flexibility to be offered is computed in S2.2. Then, S2.2 re-schedules the flexible EC's assets considering the

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expected incomes from participating in an LFM. Therefore, the flexibility to be offered is the difference between the EC's net consumption in S2.2 and the baseline obtained in S2.1. In periods where no flexibility is required, the EC is allowed to deviate from the baseline within a predefined tolerance [6].

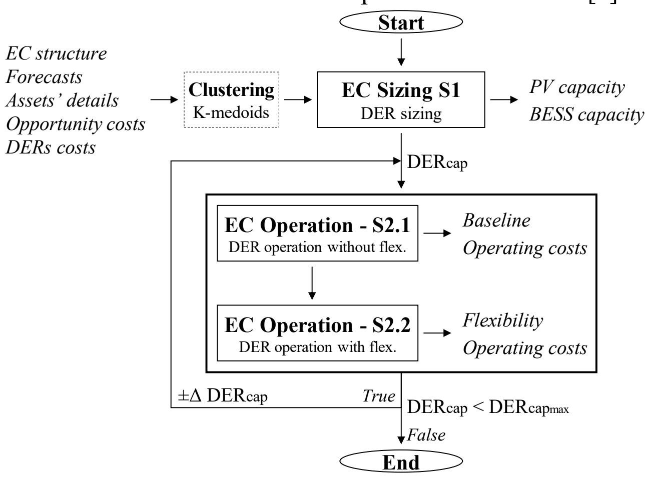

Figure 1. DERs sizing algorithm

This approach was selected since DER sizing with flexibility involves computing the optimal capacities given a baseline that depends on these optimal capacities, leading to a complex bilevel problem. To avoid this, this approach uses capacities from S1 to test alternative values in S2. A metaheuristic algorithm to evolve from the S1 capacities in S2 is also being designed. The mathematical formulation for S1, S2.1, and S2.2 is presented in the next sections.

A. Stage S1: EC sizing (without flexibility)

In S1 the EC's CAPEX and OPEX are minimized with a Mixed-Integer Linear Programming (MILP) with objective (1):

$$min \sum_{t\in T}\Big(\sum_{n\in N}\big[E_{n,t}^{SUP}\cdot\hat{\lambda}_{n,t}^{buy} - E_{n,t}^{SUR}\cdot\hat{\lambda}_{n,t}^{sell} + E_{n,t}^{SLC}\cdot\hat{\lambda}_{t}^{grid} + E_{n,t}^{B,D}\cdot\hat{\lambda}_{n}^{deg} + cost_{n,e,t}^{use}\cdot\hat{\lambda}_{n,e,t}^{comf}\big]\cdot\hat{w}_{t}^{cluster}\Big) + \sum_{n\in N}\big(P_{n}^{CONT}\cdot\hat{\lambda}_{n}^{cont}\cdot\hat{D} + P_{n}^{GN}\cdot\hat{\lambda}_{n}^{G}\cdot\hat{D} + E_{n}^{BN}\cdot\hat{\lambda}_{n}^{B}\cdot\hat{D}\big) \tag{1}$$

where, for each member $n \in N$, $E_{n,t}^{SUP}$ is the energy supplied by its retailer at price $\hat{\lambda}_{n,t}^{buy}$, $E_{n,t}^{SUR}$ is the surplus sold to its aggregator at feed-in price $\hat{\lambda}_{n,t}^{sell}$ and $E_{n,t}^{SLC}$ is the self-consumed energy which pays a grid access tariff $\hat{\lambda}_{t}^{grid}$. To avoid unprofitable BESS cycles, a degradation cost $\hat{\lambda}_{n}^{deg}$ is applied to each discharge $E_{n,t}^{B,D}$, and, for the EWHs, a comfort parameter $\hat{\lambda}_{n,e,t}^{comf}$ is applied to $cost_{n,e,t}^{use}$ as a penalty incurred when water temperature falls below a user-defined level. Clustering is used to reduce input data with $\hat{w}_{t}^{cluster}$ being the number of days represented by each cluster. P_{n}^{CONT} is the contracted power, $\hat{\lambda}_{n}^{cont}$ is the daily contracted power tariff, $\hat{D}$ is the number of days in the optimization horizon, P_{n}^{GN} is the newly installed PV capacity, $\hat{\lambda}_{n}^{G}$ is the unitary cost of PV installation per capacity, adjusted to one day, E_{n}^{BN} is the newly installed BESS capacity, and $\hat{\lambda}_{n}^{B}$ is the unitary cost of BESS installation per capacity, also adjusted to one day. Energy is traded internally in the EC in a pool-like market, as in (2):

$$\sum_{n}\big(E_{n,t}^{PUR}\big) - \sum_{n}\big(E_{n,t}^{SALE}\big) = 0 \tag{2}$$

where $E_{n,t}^{PUR}$ and $E_{n,t}^{SALE}$ are the energy bought and sold in the LEM. The energy traded balance is given by (3):

$$E_{n,t}^{CMET_1} = E_{n,t}^{SUP} - E_{n,t}^{SUR} + E_{n,t}^{PUR} - E_{n,t}^{SALE} \tag{3}$$

where $E_{n,t}^{CMET_1}$ is the metered net consumption of member *n* in S1. Equation (4) balances energy considering all assets:

$$E_{n,t}^{CMET_1} = \hat{E}_{n,t}^{C} - E_{n,t}^{G} + \big(E_{n,t}^{B,C} - E_{n,t}^{B,D}\big) + \sum_{ev\,\in\,EV}\big(E_{n,e,t}^{EV,C} - E_{n,ev,t}^{EV,D}\big) + \sum_{e\in E}\big(E_{n,e,t}^{EWH}\big) \tag{4}$$

where $\hat{E}_{n,t}^{C}$ is the load profile, $E_{n,t}^{G}$ is the PV generation, $E_{n,s,t}^{B,C}$ is the energy charged by member *n* BESS, $E_{n,ev,t}^{EV,C}$ and $E_{n,ev,t}^{EV,D}$ are, respectively, the energy charged and discharged by the EV, and $E_{n,e,t}^{EWH}$ is the energy consumed by the EWH. The newly installed PV capacity is given by (5):

$$P_{n}^{GN} = P_{n}^{GN,total} - \hat{P}_{n}^{GN,init} \tag{5}$$

where $P_{n}^{GN,total}$ and $\hat{P}_{n}^{GN,init}$ are the total and initial installed PV capacity, respectively. The PV generation is given by (6):

$$E_{n,t}^{G} = \hat{f}_{n,t}^{G}\cdot P_{n}^{GN,total} \tag{6}$$

where $\hat{f}_{n,t}^{G}$ is the PV generation profile. Equation (7) limits minimum and maximum PV installed capacity to $\hat{P}_{n}^{GN,min}$ and $\hat{P}_{n}^{GN,max}$.

$$\hat{P}_{n}^{GN,min} \le P_{n}^{GN} \le \hat{P}_{n}^{GN,max} \tag{7}$$

The newly installed BESS capacity is given by (8):

$$E_{n}^{BN} = E_{n}^{BN,total} - \hat{E}_{n}^{BN,init} \tag{8}$$

where $E_{n}^{BN,total}$ and $\hat{E}_{n}^{BN,init}$ are the total and initial installed BESS capacity, respectively. BESS charging and discharging powers are limited by (9) and (10) respectively:

$$E_{n,t}^{B,C} \le E_{n}^{BN,total}\cdot\frac{\hat{P}^{B,ref}}{\hat{E}^{B,ref}} \tag{9}$$

$$E_{n,t}^{B,D} \le E_{n}^{BN,total}\cdot\frac{\hat{P}^{B,ref}}{\hat{E}^{B,ref}} \tag{10}$$

where $\frac{\hat{P}^{B,ref}}{\hat{E}^{B,ref}}$ is the ratio between a pre-defined maximum input/output power and the storage nominal capacity. Equation (11) limits the minimum and the maximum BESS capacity to $\hat{E}_{n}^{BN,min}$ and $\hat{E}_{n}^{BN,max}$.

$$\hat{E}_{n}^{BN,min} \le E_{n}^{BN} \le \hat{E}_{n}^{BN,max} \tag{11}$$

The energy stored in the BESS is tracked with (12):

$$E_{n,t}^{B} = E_{n,t-1}^{B} + \left(E_{n,t}^{B,C}\cdot\hat{\eta}_{n}^{B,C} - \frac{E_{n,t}^{B,D}}{\hat{\eta}_{n}^{B,D}}\right) \tag{12}$$

where $E_{n,t}^{B}$ is the energy stored by the BESS, $\hat{\eta}_{n,s}^{B,C}$ and $\hat{\eta}_{n,s}^{B,D}$ are the charging and discharging efficiencies. Their state of charge (SOC) is limited by (13):

$$\widehat{SOC}_{n}^{B,min}\cdot E_{n}^{BN,total} \le E_{n,t}^{B} \le \widehat{SOC}_{n}^{B,max}\cdot E_{n}^{BN,total} \tag{13}$$

where $\widehat{SOC}_{n}^{B,min}$ and $\widehat{SOC}_{n}^{B,max}$ the minimum and maximum SOC. Equation (14) limits the grid energy exchanges to contracted powers $P_{n}^{CONT_1}$:

$$-P_{n}^{CONT_1} \le E_{n,t}^{CMET} \le P_{n}^{CONT_1} \tag{14}$$

Equation (15) limits the contracted power to $\hat{P}_{n}^{max}$, the maximum allowable power flow through the meter:

$$P_{n}^{CONT_1} \le \hat{P}_{n}^{max} \tag{15}$$

Regarding EVs, their energy is tracked by (16):

$$E_{n,ev,t}^{EV,Stored} = E_{n,ev,t-1}^{EV,Stored} + \hat{\eta}_{n,ev}^{EV,C}\cdot E_{n,ev,t}^{EV,C} - \frac{E_{n,ev,t}^{EV,D}}{\hat{\eta}_{n,ev}^{EV,D}} - \hat{E}_{n,ev,t}^{Trip} \tag{16}$$

where $E_{n,ev,t}^{EV,Stored}$ is the energy stored by the EV, $\hat{\eta}_{n,ev}^{EV,C}$ and $\hat{\eta}_{n,ev}^{EV,D}$ are its charging/discharging efficiencies, and $\hat{E}_{n,ev,t}^{Trip}$ is the energy consumed for mobility. EV charging/discharging rates are limited by (17) and (18):

$$\frac{1}{\hat{\eta}_{n,ev}^{EV,D}} \cdot E_{n,ev,t}^{EV,D} \leq \hat{P}_{n,ev}^{EV,D\ Limit} \cdot \hat{X}_{n,ev,t}^{EV} \quad (17)$$

$$\hat{\eta}_{n,ev}^{EV,C} \cdot E_{n,ev,t}^{EV,C} \leq \hat{P}_{n,ev}^{EV,C\ Limit} \cdot \hat{X}_{n,ev,t}^{EV} \quad (18)$$

where $\hat{P}_{n,ev}^{EV,D\ Limit}$ and $\hat{P}_{n,ev}^{EV,C\ Limit}$ are the maximum discharge and charge power of the EV, and $\hat{X}_{n,ev,t}^{EV}$ is a binary parameter equal to 1 when it is plugged-in, and 0 otherwise. Equation (19) limits the minimum and maximum energy stored in the EVs:

$$\hat{E}_{n,ev}^{EV,MinCharge} \leq E_{n,ev,t}^{EV,Stored} \leq \hat{E}_{n,ev}^{EV,BatCap} \quad (19)$$

where $\hat{E}_{n,ev}^{EV,MinCharge}$ is the minimum energy level of the EV battery and $\hat{E}_{n,ev}^{EV,BatCap}$ its total capacity. EWH constraints are summarized next, see [9] for a more complete description with thermodynamic considerations. Equation (20) represents the thermal energy dynamics in the EWH over time, accounting for energy usage, input, and losses:

$$W_{n,e,t}^{tot} = W_{n,e,t-1}^{water} + W_{n,e,t-1}^{in} + W_{n,e,t-1}^{loss} \quad (20)$$

where $W_{n,e,t}^{tot}$ is the total thermal energy stored in the EWH, $W_{n,e,t-1}^{water}$ is the remaining energy after accounting for water usage and mixing with the inlet water, $W_{n,e,t-1}^{in}$ is the energy input from the heating element, and $W_{n,e,t-1}^{loss}$ are the thermal losses due to heat dissipation. Next, (21) describes energy input by the EWH's heating element:

$$W_{n,e,t}^{in} = \widehat{EWH}_{n,e}^{power} \cdot \delta_{n,e,t}^{in} \quad (21)$$

where $\widehat{EWH}_{n,e}^{power}$ is the rated power of the EWH and $\delta_{n,e,t}^{in}$ is a binary variable equal to 1 when the EWH is on, and 0 otherwise. Next, (22) wields the electrical energy consumed by the EWH.

$$E_{n,e,t}^{EWH} = \widehat{EWH}_{n,e}^{power} \cdot \delta_{n,e,t}^{in} \quad (22)$$

Equation (23) determines the EWH's water temperature, which depends on the energy balance from (20):

$$temp_{n,e,t}^{EWH} = \frac{W_{n,e,t}^{tot}}{\widehat{EWH}_{n,e}^{cap} \cdot \hat{c}} \quad (23)$$

where $temp_{n,e,t}^{EWH}$ is the water temperature at the EWH's outlet, $\widehat{EWH}_{n,e}^{StartTemp}$ is its initial water temperature, $\widehat{EWH}_{n,e}^{cap}$ is its volume, $\hat{c}$ is the specific heat capacity of water. Equation (24) quantifies the thermal losses through the EWH's surface:

$$W_{n,e,t}^{loss} = \widehat{HC}_{n,e} \cdot \widehat{EWH}_{n,e}^{area} \cdot \left(temp_{n,e,t}^{EWH} - \widehat{temp}_{n,e}^{amb}\right) \quad (24)$$

where HC is the overall heat transfer coefficient of the EWH, $\widehat{EWH}^{area}$ is its surface area, and $\widehat{temp}_{n,e}^{amb}$ is the ambient temperature of the room where the EWH is placed. Next, (25) and (26) enforce upper and lower bounds on the energy and water temperature of the EWH:

$$\widehat{W}_{n,e,t}^{min} \leq W_{n,e,t}^{tot} \leq \widehat{W}_{n,e,t}^{max} \quad (25)$$

$$\widehat{EWH}_{n,e,t}^{min} \leq temp_t^{EWH} \leq \widehat{EWH}_{n,e,t}^{max} \quad (26)$$

where $W_{n,e,t}^{min}$, $W_{n,e,t}^{max}$ are the minimum/maximum energy balance limit, $\widehat{EWH}^{min}$, $\widehat{EWH}^{\max}$ are the minimum/maximum temperature limits. Equation (27) ensures that the water temperature after use meets or exceeds the user-defined comfort level. A penalty cost is applied when the temperature falls below that level, which in turn is added to (1) as a positive term:

$$W_{n,e,t}^{tot} \geq \widehat{temp}_{n,e}^{set} \cdot \widehat{EWH}_{n,e}^{cap} \cdot \hat{c} - cost_{n,e,t}^{use} \quad (27)$$

where $\widehat{temp}_{n,e}^{set}$ is a user-defined comfort temperature for water.

B. *Stage S2.1: EC operation without flexibility*

S2.1 computes the optimal operation of the EC by minimizing its OPEX according to (28), given the PV and BESS capacities as inputs:

$$min \sum_{t\in T}\left(\sum_{n\in N}\left[E_{n,t}^{SUP} \cdot \hat{\lambda}_{n,t}^{buy} - E_{n,t}^{SUR} \cdot \hat{\lambda}_{n,t}^{sell} + E_{n,t}^{SLC} \cdot \hat{\lambda}_{t}^{grid} + E_{n,t}^{B,D} \cdot \hat{\lambda}_{n}^{deg} + cost_{n,e,t}^{use} \cdot \hat{\lambda}_{n,e,t}^{comf}\right]\right) \quad (28)$$

The energy balance constraint, (4), is replace by (29):

$$E_{n,t}^{CMET_{2.1}} = \hat{E}_{n,t}^{C} - \hat{E}_{n,t}^{G} + \left(E_{n,t}^{B,C} - E_{n,t}^{B,D}\right) + \sum_{ev\in EV}\left(E_{n,e,t}^{EV,C} - E_{n,ev,t}^{EV,D}\right) + \sum_{e\in E}\left(E_{n,e,t}^{EWH}\right) \quad (29)$$

where $E_{n,t}^{CMET_{2.1}}$ is individual metered net consumption in S2.1, and $\hat{E}_{n,t}^{G}$ is the load profile resulting from the PV capacity defined in S1, $\hat{P}_{n}^{GN_1}$, and calculated using (30):

$$\hat{E}_{n,t}^{G} = \hat{f}_{n,t}^{G} \cdot \hat{P}_{n}^{GN_1} \quad (30)$$

Similarly, BESS capacity is set to $\hat{E}_{n}^{BN_1}$ obtained in S1:

$$\hat{E}_{n}^{BN} = \hat{E}_{n}^{BN_1} \quad (31)$$

The remaining BESS constraints apply as in S1. Contracted power is defined in S1, so (14) is replaced by (32):

$$-\hat{P}_{n}^{CONT_1} \leq E_{n,t}^{CMET} \leq \hat{P}_{n}^{CONT_1} \quad (32)$$

where $\hat{P}_{n}^{CONT}$ is the contracted power computed in S1, and thus (15) is no longer necessary. All EV and EWH constrains apply.

C. *Stage S2.2: EC operation with flexibility*

S2.2 computes the optimal EC operation minimizing its OPEX according to (28) given the PV and BESS capacities as inputs and accounting for the income from flexibility provision:

$$min \sum_{t\in T}\left(\sum_{n\in N}\left[E_{n,t}^{SUP} \cdot \hat{\lambda}_{n,t}^{buy} - E_{n,t}^{SUR} \cdot \hat{\lambda}_{n,t}^{sell} - E_{n,t}^{FLEX} \cdot \hat{\lambda}_{t}^{flex} + E_{n,t}^{SLC} \cdot \hat{\lambda}_{t}^{grid} + E_{n,t}^{B,D} \cdot \hat{\lambda}_{n}^{deg} + cost_{n,e,t}^{use} \cdot \hat{\lambda}_{n,e,t}^{comf}\right]\right) \quad (33)$$

where $E_{n,t}^{FLEX}$ is the offered flexibility for flexibility price $\hat{\lambda}_{t}^{flex}$. The energy balance constraint is:

$$E_{n,t}^{CMET_{2.2}} = \hat{E}_{n,t}^{C} - E_{n,t}^{G} + \left(E_{n,t}^{B,C} - E_{n,t}^{B,D}\right) + \sum_{ev\in EV}\left(E_{n,e,t}^{EV,C} - E_{n,ev,t}^{EV,D}\right) + \sum_{e\in E}\left(E_{n,e,t}^{EWH}\right) \quad (34)$$

where $E_{n,t}^{CMET_{2.2}}$ is individual metered net consumption in S2.2. and $E_{n,t}^{G}$ is the behind-the meter generation given by (35):

$$E_{n,t}^{G} = \hat{E}_{n,t}^{G} - E_{n,t}^{CURT} \quad (35)$$

where $E_{n,t}^{CURT}$ is generation curtailment. The flexibility provided for the periods when it is requested ($t \in T_{wf}$) is:

$$E_{n,t}^{FLEX} = E_{n,t}^{CMET_{2.2}} - \hat{E}_{n,t}^{CMET_{2.1}} \quad (36)$$

In the periods when flexibility is not requested ($t \in T_{nf}$), a tolerance from the baselines $E_{n,t}^{CMET_{2.1}}$ from S2.1 is allowed in (37), increasing the flexibility when it is needed:

$$\sum_N \hat{E}_{n,t}^{CMET_1} - \rho_t \leq \sum_N E_{n,t}^{CMET_2} \leq \sum_N \hat{E}_{n,t}^{CMET_1} + \rho_t \quad (37)$$

where ρ_t is an hourly tolerance pre-defined by the DSO. All other constraints described in S1 and S2.1 apply to S2.2.

III. Case Study

A. *Case description*

An EC with 4 members is simulated. Their maximum contracted power (limited by grid connection), maximum PV and BESS capacity, and main characteristics of their assets are given in TABLE I.

TABLE I. CHARACTERIZATION OF EC MEMBERS AND ASSETS SPECIFICATIONS

ID	Max. contracted power	Max. PV power	BESS			EV				EWH		
			Max. Capacity	SOC^{min}	SOC^{max}	Capacity	Charger power	SOC^{min}	SOC^{max}	Capacity	Power	Temp. setpoint
M1	6.9 kVA	—	—	—	—	—	—	—	—	—	—	—
M2	10.35 kVA	6.8 kW	—	—	—	40 kWh	3.7 kW	20%[1]	80%[1]	—	—	—
M3	10.35 kVA	—	8.0 kWh	5%	95%	—	—	—	—	—	—	—
M4	17.25 kVA	12.0 kW	16.0 kWh	5%	95%	—	—	—	—	100 L	1500 W	60 ºC

[1]maintained within the specified range to decrease EV battery degradation [10]

The prices at which EC members buy [11] and sell [12] energy from retailers and aggregators (opportunity costs), and grid access tariffs [13] are provided in TABLE II.

TABLE II. EC ENERGY PRICES AND TARIFFS

λ^{cont}	λ^{buy}	λ^{sell}	λ^{grid}
0.35 €/day	0.16 €/kWh	0.05 €/kWh	0.0106 €/kWh

The economic parameters for PV and BESS, namely their CAPEX and operational lifespans are given in TABLE III.

TABLE III. ECONOMIC CHARACTERISTICS OF SOLAR PV AND BESS

DER	CAPEX	Lifespan
PV panels	1200 €/kWh [14]	20 years [15]
BESS	400 €/kWh [16]	10 years [16]

S1 provides the base case (BC) where the EC is sized without flexibility. The S2 scenarios with flexibility provision are in TABLE IV. where NF refers to noon downwards flexibility (DwFlex) DSO request, and EF to evening upwards flexibility (UpFlex) request. DwFlex is defined as an increase in consumption and/or a reduction in generation, and UpFlex as a reduction in consumption and/or an increase in generation [17]. Given limited access to real-world LFM data, flexibility needs and prices are borrowed from [18], with a flexibility price λ^{flex} of 0.20 €/kWh.

TABLE IV. SCENARIOS SUMMARY

Scenario	Flexibility needs			Flexible assets
	Period	Direction	Price	
BC	No flexibility	—	—	—
NF	3 days/week: 11:00h – 13:00h	DwFlex	0.20 €/kWh	BESS, PVs, EVs, EWHs
EF	3 days/week: 19:00h – 21:00h	UpFlex	0.20 €/kWh	BESS, PVs, EVs, EWHs

B. *Results*

First, we evaluate the impact of clustering by computing the optimal DER sizes and total BC cost for different numbers of clusters. Then, the impact of providing flexibility on the DER sizes and on the economic benefits is analysed by varying the DER capacities and relating them to the total EC costs. This helps to identify how adjusting DER capacities can reduce the EC costs.

The MILP was implemented in Python using PuLP [19], and the simulations performed on an AMD EPYC-Milan Processor, 2.94 GHz, 32GB RAM server using CPLEX [20].

1) *EC sizing without flexibility needs*

Using a cluster number varying from 1 to 365 (all days represented, being the reference ideal case) with steps of 20%, TABLE V. and Figure 2 relate the number of clusters to the resulting contracted power, PV and BESS capacities and total expenditure (TOTEX). As the number of clusters decreases, the algorithm underestimates the contracted power due to an overoptimization caused by a low representation of the real variability. Starting at 11.5 kVA without clustering, this value decreases, reaching 8.03 kVA for 73 clusters, an error of 30% compared to the reference case. This underestimation means that, for the EC to operate under real conditions with larger days variability, it could be necessary to raise the contracted power or schedule the assets in a suboptimal way, further increasing costs. Overoptimization for less clusters can be seen in the underestimation of PV and BESS capacities. PV capacity is 10.8 kWp without clustering and tend to decrease with the number of clusters, reaching 13.0 kWp for 146 clusters, an error of 20%. Similarly, BESS capacity starts with an optimal value of 9.42 kWh that increases to 21.8 kWh with 73 clusters, an error of over 131%. This larger BESS error may be due the larger impact of BESS, due to its flexibility, on the final operation cost of the EC. With only 1 cluster, the algorithm significantly underestimates all capacities, showing the risk of excessive data compression, where 1 representative day fails to capture the real variability for an effective EC sizing.

TABLE V. SIZING RESULTS FOR SEVERAL NUMBERS OF CLUSTERS

Clusters	Cont. P.	PV capacity	BESS capacity	TOTEX
365	11.5 kVA	10.8 kWp	9.42 kWh	54 937 €
292	10.7 kVA	11.2 kWp	14.2 kWh	56 396 €
219	9.40 kVA	11.8 kWp	14.2 kWh	56 401 €
146	9.96 kVA	13.0 kWp	21.3 kWh	57 648 €
73	8.03 kVA	11.0 kWp	21.8 kWh	58 469 €
1	2.94 kVA	8.99 kWp	4.58 kWh	58 529 €

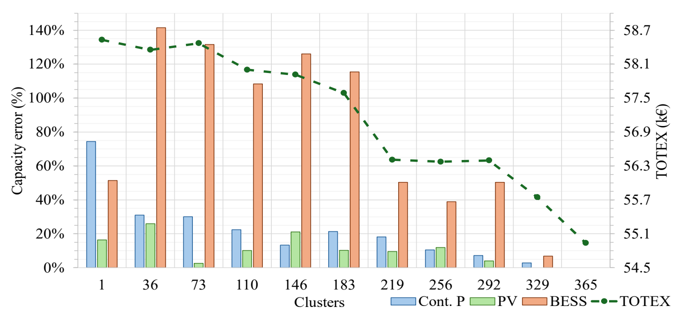

Figure 2. Capacity error and TOTEX for several numbers of clusters

Although clustering inevitably introduces deviations in contracted power and DER capacity estimations, the overall impact of clustering on the cost-effectiveness of the obtained solutions must be evaluated by calculating the TOTEX of the EC. This is also needed since multiple solutions with same TOTEX may exist, being a priori equally acceptable, so comparing resulting capacities may not be meaningful. To achieve this, the EC's operation was simulated over an entire year using the capacity values obtained from each clustering configuration. The results (Figure 2) show a clear trend between the number of clusters and TOTEX, with the TOTEX increasing when the number of clusters decreases, indicating that the sizing algorithm (designed to optimize investment and operational costs) returns more cost-effective solutions when provided with more representative days (or clusters). Clustering reduces sizing accuracy, as reflected by the increasing TOTEX error compared to reference case without clustering, but reduces significantly computation times, leading to the trade-off between time and accuracy shown in Figure 3.

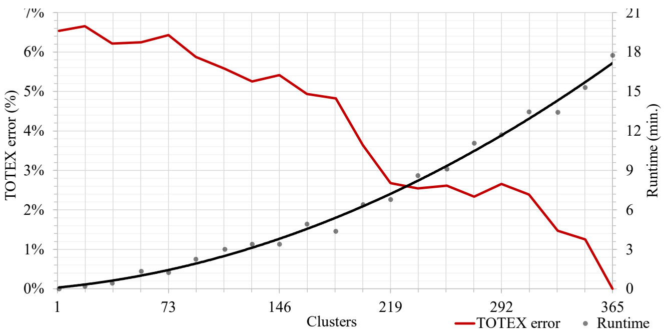

Figure 3. TOTEX error and runtime for several numbers of clusters

As can be seen, clustering substantially reduces computational effort, and as the number of clusters decreases, the runtime decays exponentially. For instance, lowering the number of clusters to 219 leads to a 40% reduction in runtime, emphasizing the effectiveness of clustering in compressing the dataset. In this case, TOTEX error remains relatively stable around 2.5% between 219 and 292 clusters, before increasing sharply. This suggests that, for this problem, 219 clusters could provide a suitable balance between computational effort and results accuracy. However, for larger EC or more DERs, it may be necessary to decrease the number of clusters to reach an acceptable sizing accuracy. However, time gains due to clustering may be particularly crucial for larger datasets, such as those involving large ECs with numerous members and DERs.

2) EC sizing considering flexibility needs

Following the initial sizing without considering flexibility, the impact of small variations in DER capacity on the TOTEX of the EC is analysed under the 2 previously introduced flexibility scenarios. As only BESS can provide both DwFlex and UpFlex, this analysis focuses solely on changes to BESS capacity. The resulting variations in TOTEX are depicted in Figure 4 (minimum TOTEX for each scenario marked with X).

As expected, in the BC, any deviation from the initially BESS capacity increases TOTEX, confirming the optimality of S1 sizing. In contrast, under the NF and EF scenarios, the BESS capacity determined by the sizing algorithm leads to different TOTEX behaviours. Specifically, the EF scenario has lower TOTEX, suggesting that this EC is more efficient at providing UpFlex than DwFlex. Besides, the results indicate that in the NF scenario, raising BESS capacity by approximately 2.8 times increases the EC's flexibility and reduces TOTEX by 10% relative to the BC. Similarly, in the EF scenario, an increase in BESS capacity by 2.3 times achieves a 16% reduction in TOTEX compared to the BC. Beyond these capacities (2.8 and 2.3), TOTEX starts to rise, as additional BESS capacity no longer delivers OPEX reductions sufficient to counterbalance the increase in CAPEX.

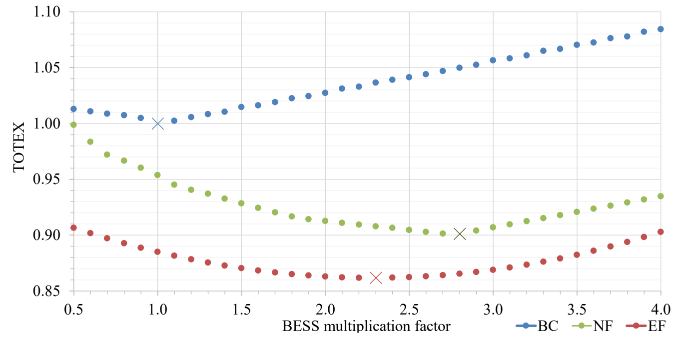

Figure 4. Uniformized TOTEX variations with BESS capacity

IV. CONCLUSION

This paper presents a 2-stage linear optimization model for sizing PV panels and BESS in ECs with both energy and CS assets. The model not only optimizes DER investments but also considers the potential participation of the EC in a LFM, integrating estimated flexibility needs and prices. This approach aligns with emerging trends in the energy sector, where LFMs offer new revenue streams for ECs.

As expected, results show data clustering significantly enhances computational efficiency but excessive compression harms accuracy by miscalculating contracted power and DER capacities. Even though clustering reduces runtime, it does so at the cost of increased TOTEX error, particularly when too few clusters are used. Hence, a beneficial clustering strategy should balance TOTEX errors and computational efficiency, ensuring that deviations stay within acceptable margins. Regarding flexibility provision, the results indicate that increasing BESS capacity beyond its initially sized value could be beneficial for ECs participating in LFMs. However, beyond a certain point, additional BESS investments may no longer justify the associated CAPEX.

Future research could explore the use of metaheuristic algorithms to iteratively refine DER capacity within the second stage of the optimization problem, test alternative clustering methods, and develop some simpler way to help solving the trade-off between computational time and sizing accuracy for more general EC structures.

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