IMPACT OF DISTRIBUTED ENERGY RESOURCES INVESTMENT CAPACITIES ON THE CARBON FOOTPRINT OF RENEWABLE ENERGY COMMUNITIES

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Abstract

This paper investigates how distributed energy resources investment capacities impact the carbon footprint of a renewable energy community. The investigation is conducted through the formulation of an optimisation problem minimising an economic (cost) and an environmental (carbon footprint) objectives. It considers new investments and the carbon intensity of energy from the grid. It provides results for grid users acting alone, forming a renewable energy community but investing alone, or allowing co-investment in the community. Multiple case studies are tested to compare the effects of different tariffs and investment budgets. Various locations for renewable energy communities are also tested to see the limitations for profitability depending on the local solar intensity and carbon emission of the external electricity mix. The principal ideas are to demonstrate: that the community framework can reduce the carbon footprint of the system, that a community framework increases the benefits and that an energy bill minimization for all members (maximizing self-consumption) provides an efficient proxy for minimizing carbon footprint.

1 Introduction

In recent years, the imperative of the energy transition and its intersection with climate change has become increasingly urgent. Renewable distributed energy resources (DER) are increasingly popular and will remain so over the next few decades until energy systems align with global climate targets.

Due to the rise of energy prices and the increasing attention towards sustainability, private individuals are also investing massively in their energy production units.

In Europe, renewable energy communities (RECs) are emerging as a possible response to the challenges of energy transition. Their impact on the prosumers' habits and investment opportunities is well established [1]. By producing and consuming locally, users allow for more decentralized supervision of the network, while RECs tend to maximize self-consumption at the distribution level.

RECs also provide opportunities for aggregating flexibility, thus allowing to provide grid services (e.g., reactive power, balancing). This flexibility could either be provided by community members separately or by a bigger device supported by the whole community as a co-investment.

The increase in renewable DER penetration constitutes a challenge for power system operation since the DERs are connected mostly to low voltage (LV) level grids. Considering the weaknesses of such a system, increasing the DER penetration could bring some issues impacting the grid and its users.

In [2], a local market structure is defined to allow community members to plan their energy usage and make trades at the optimal price. Using a central coordinator for the community, trades are settled in a day-ahead local market. This model is extended in [3], with the addition of a power flow model and the consideration of new investments in the community.

In [3], three investment scenarios are considered and compared:

- Participants can invest in DERs at their location to optimize their energy usage without being part of the community;
- Participants can invest in DERs at their location to optimize their energy usage with a local EC created in the distribution grid;
- Participants can invest in DERs anywhere in the distribution grid to optimize the energy usage of the local EC.

This paper builds upon [3] and tries to quantify the impact of REC on the carbon intensity of its members' energy usage. Additionally, a locational study is conducted to see the profitability of the energy community with varying PV potential and CO_2 intensity of imported energy.

Deeper analyses of some of the key parameters will also be conducted. Two studies are conducted on the costs and CO_2 emissions (carbon footprint) variation, first with increasing investment budget in the REC, then with varying fees for energy exchanges in the community.

Life cycle assessment approach [4, 5] is usually employed to quantify the environmental impact (carbon footprint) of a product. It covers the whole lifespan of a product (starting from the extraction of raw material up to disposal and recycling).

The work presented in [6] suggests a data-driven framework to design a REC considering technical objectives and environmental impact. Formulated multi-criteria decision-making problem is solved by integrating machine learning and life cycle assessment.

A REC multi-objective planning method considering economic (total annualized costs), environmental (carbon footprint) and social (user comfort) objectives is presented in [7]. The results of this work shows improvements in economic benefits and self-sufficiency of a REC when all community members modify their behaviours towards an objective.

This paper starts by formulating the mathematical optimization problem in Section 2. The case studies and simulation parameters will be introduced in Section 3. The results are presented in Section 4. Finally, conclusions for this work are derived in Section 5.

2 Problem formulation

The models are completely detailed in [3] but repeated here with added CO_2 constraints for the sake of completeness. The optimization problem, in a descriptive form, is as follows,

$$\begin{aligned} \min \quad & \text{Cost/CO}_2 \text{ footprint of the REC (2), (3)} \qquad (1) \\ \text{subject to} \quad & \textit{Cost and CO}_2 \textit{ constraints } (4) - (6), \\ & \textit{Devices constraints } (7) - (14), \\ & \textit{Exchange constraints } (15) - (18), \\ & \textit{Sizing constraints } (19) - (25), \\ & \textit{Power flow equations, } (26), (27). \end{aligned}$$

The objective and the constraints are detailed next.

2.1 Objectives

We consider two options for the objective function, to minimize either the total REC's cost or the carbon footprint, considering impacts from both investments and operation,

$$\begin{aligned} \text{Total cost} = & \sum_{u \in \mathcal{U}} \left(\Pi_u^{\text{op}} + \frac{\Pi_u^{\text{inv}}}{I^{\text{hor}}} \right) + \pi^{\text{peak}} \overline{p} \\ & + \pi_t^{\text{igr}} \sum_{t \in \mathcal{T}} w_{d_t} \Delta_T P_t^{\text{loss}}, \qquad (2) \\ \text{Total CO}_2 = & \sum_{u \in \mathcal{U}} \left(K_u^{\text{op}} + \frac{K_u^{\text{inv}}}{I^{\text{hor}}} \right) \\ & + \kappa_t^{\text{gri}} \sum_{t \in \mathcal{T}} w_{d_t} \Delta_T P_t^{\text{loss}}. \qquad (3) \end{aligned}$$

Equation (2) models the total users' operational and weighted investment costs, peak price for the community and network losses, valued at grid import price. Equation (3), models the CO_2 emissions of the community. Where $u \in \mathcal{U}$ is the index of the member in the set of all the community, $t \in \mathcal{T}$ the time period index of the simulation, w_{d_t} weights each time period according to the representative day they are part of. I^{hor} is the investment horizon in years.

Each user's operational cost in the community writes as:

$$\begin{aligned} \Pi_u^{\text{com}} = & \Delta_T \sum_{t \in \mathcal{T}} w_{d_t} \Bigg(\pi_t^{\text{igr}} i_{u,t}^{\text{gri}} - \pi_t^{\text{egr}} e_{u,t}^{\text{gri}} \qquad (4) \\ & + \gamma^{\text{com}} \left(e_{u,t}^{\text{com}} + i_{u,t}^{\text{com}} \right) \\ & + \gamma^{\text{sto}} \left(\eta_u^{\text{cha}} P_{u,t}^{\text{cha}} + P_{d,t}^{\text{dis}} / \eta_u^{\text{dis}} \right) \Bigg) \; \forall u \in \mathcal{U}. \end{aligned}$$

To compute the CO_2 intensity of the community energy use, several sources of emissions are considered:

- CO_2 intensity of energy taken from the grid (κ^{gri}) defines the operational emissions (K^{op}):

$$K_u^{\text{op}} = \Delta_T \sum_{\forall t \in \mathcal{T}} w_{d_t} \kappa^{\text{gri}} e_{u,t}^{\text{gri}} \qquad (5)$$

- CO_2 emissions due to the new investments of the community (K^{inv}) depend on the life cycle assessment for PV (κ^{PV}) and battery storage system (BSS) (κ^{BSS}) installations and their sizes:

$$K_u^{inv} = \kappa^{\text{PV}} C_u^{\text{PV}} + \kappa^{\text{BSS}} C_u^{\text{BSS}} \qquad (6)$$

- CO_2 cost for energy losses in the LV network, with a CO_2 intensity equal to grid emissions, because these losses will be paid for by the slack bus.

2.2 Constraints

2.2.1 Photovoltaic installations: For every time period t, photovoltaic power injection ($P_{u,t}^{\text{PV}}$) is bounded with the upper bound value defined as the PV profile $\overline{P}_{u,t}^{\text{PV}}$ depending on both weather conditions and PV installation size,

$$P_{u,t}^{\text{PV}} \in [0, \overline{P}_{u,t}^{\text{PV}}] \qquad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \qquad (7)$$

2.2.2 Battery storage systems: A battery storage system state of charge evolution is modeled as,

$$\begin{aligned} & s_{u,t_{d,1}} - \Delta_T \left(\eta_u^{\text{cha}} P_{u,t_{d,1}}^{\text{cha}} - P_{u,t_{d,1}}^{\text{dis}} / \eta_u^{\text{dis}} \right) = s_{u,d}^{\text{init}} \\ & \qquad \forall u \in \mathcal{U}, \quad \forall d \in \mathcal{D}, \quad (8) \\ & s_{u,t} - s_{u,t-1} - \Delta_T \left(\eta_u^{\text{cha}} P_{u,t}^{\text{cha}} - P_{u,t}^{\text{dis}} / \eta_u^{\text{dis}} \right) = 0, \\ & \qquad \forall u \in \mathcal{U}, \quad t \in \{t_{d,2}, \dots, t_{d,T}\}, \forall d \in \mathcal{D}, \quad (9) \\ & s_{u,t_{d,T}} = s_{u,d}^{\text{init}} \qquad \forall u \in \mathcal{U}, \forall d \in \mathcal{D}, \quad (10) \end{aligned}$$

with $s_{u,t}$ the state of charge of the storage of user u at the end of period t. These are bounded by variables that depend on the sizing results introduced in the next subsection,

$$\begin{aligned} s_{u,t} & \in [\underline{S}_u; \overline{S}_u] & \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \quad (11) \\ s_{u,d}^{\text{init}} & \in [\underline{S}_u; \overline{S}_u] & \forall u \in \mathcal{U}, \forall d \in \mathcal{D}, \quad (12) \\ P_{u,t}^{\text{dis}} & \in [0; \overline{P}_u^{\text{dis}}] & \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \quad (13) \\ P_{u,t}^{\text{cha}} & \in [0; \overline{P}_u^{\text{cha}}] & \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \quad (14) \end{aligned}$$

Constraint (10) enforces an identical state of charge ($s_{d,u}^{\text{init}}$) at the beginning ($t_{d,0}$) and end ($t_{d,T}$) of each representative day $d \in \mathcal{D}$.

2.2.3 Exchange constraints: These constraints ensure that internal community power exchanges are balanced at all times (15) and determine the peak of the whole community (16),(17).

$$\begin{aligned} \sum_{u \in \mathcal{U}} \left(i_{u,t}^{\text{com}} - e_{u,t}^{\text{com}} \right) = 0 & \qquad \forall t \in \mathcal{T}, \quad (15) \\ P_{slack,t}^{\text{inj}} \leq \overline{p} & \qquad \forall t \in \mathcal{T}, \quad (16) \\ - P_{slack,t}^{\text{inj}} \leq \overline{p} & \qquad \forall t \in \mathcal{T}. \quad (17) \end{aligned}$$

The power balance for each community member defines its power exchanges depending on its internal devices and usage,

$$e^{\text{gri}}_{u,t} - i^{\text{gri}}_{u,t} + e^{\text{com}}_{u,t} - i^{\text{com}}_{u,t} = P^{\text{PV}}_{u,t} - D^{\text{nfl}}_{u,t} + P^{\text{dis}}_{u,t} - P^{\text{cha}}_{u,t} \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \tag{18}$$

where $P^{\text{PV}}_{u,t}$ and $D^{\text{nfl}}_{u,t}$ are the power produced by the PV system and the fixed power consumption of user u at time t, respectively. Variables $P^{\text{cha}}_{u,t}$, and $P^{\text{dis}}_{u,t}$ are the active powers going in and out of the BSS.

2.2.4 Sizing constraints: Each community member can invest in new PV (C^{PV}_{u}) or BSS (C^{BSS}_{u}) capacities at its location.

The PV and BSS sizes are optimized for each user considering its location and the investment costs (Π^{inv}),

$$\Pi^{\text{inv}}_{u} = \Pi^{\text{PV}}(C^{PV}_{u}) + \Pi^{\text{BSS}}(C^{BSS}_{u}) \tag{19}$$

where $\Pi^{y}(x)$ is the cost of installation for a system y of size x,

$$\Pi^{\text{y}}(x) = b^{\text{y}}_{u}\pi^{\text{y}}_{f} + x\pi^{\text{y}}_{v} \tag{20}$$

$$b^{\text{y}}_{u}\underline{x}^{\text{y}} \leq x \leq b^{\text{y}}_{u}\overline{x}^{\text{y}} \tag{21}$$

with π^{y}_{f} and π^{y}_{v} the fixed and variable cost coefficients. The fixed cost term allows the modeling of economies of scale in new investments. Equation (21) bounds the system sizes and fixes the value of b^{y}_{u}, the binary variable indicating the user's investment in technology y.

$$\sum_{\forall u \in \mathcal{U}} \Pi^{\text{inv}}_{u} \in [0; \sum_{\forall u \in \mathcal{U}} \overline{B}_{u}]. \tag{22}$$

The decision variables for investment capacities C^{PV}_{u} and C^{BSS}_{u} are used to define the bounds for the exchanged quantities for the operational planning,

$$\overline{P}^{\text{PV}}_{u,t} = C^{\text{PV}}_{u}\overline{p}^{\text{PV}}_{u,t} \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \tag{23}$$

$$[\underline{S}_{u}, \overline{S}_{u}] = [0.1C^{\text{BSS}}_{u}, 0.9C^{\text{BSS}}_{u}] \quad \forall u \in \mathcal{U}, \tag{24}$$

$$[\overline{P}^{\text{cha}}_{u}, \overline{P}^{\text{dis}}_{u}] = [\overline{P}^{\text{cha}}C^{\text{BSS}}_{u}, \overline{P}^{\text{dis}}C^{\text{BSS}}_{u}] \quad \forall u \in \mathcal{U}, \tag{25}$$

where $\overline{p}^{\text{PV}}_{u}$ is the scaled PV profile associated with user u. The newly invested capacity C^{BSS}_{u} can only be used ranging from 10 to 90% of its maximum capacity, variables $\overline{P}^{\text{cha}}_{u}$ and $\overline{P}^{\text{dis}}_{u}$ represent the maximal charging and discharging power of the new BSS per unit of capacity installed.

2.2.5 Power flow model: These constraints ensure reliable operation of the distribution network. The community operator (CO) is considered responsible for adequate grid operation through this. A relaxed DistFlow model [8] is used as the considered network has a radial configuration.

The power flow variables and constraints are linked to those of the community problem with,

$$P^{\text{inj}}_{u,t} = e^{\text{gri}}_{u,t} + e^{\text{com}}_{u,t} - i^{\text{gri}}_{u,t} - i^{\text{com}}_{u,t} \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \tag{26}$$

where $P^{\text{inj}}_{u,t}$ is the active power injected in node u at time t.

The total active power losses in the system (P^{loss}_{t}) for each time step are computed as,

$$P^{\text{loss}}_{t} = \sum_{\forall u \in \mathcal{U} \cup \text{slack}} P^{\text{inj}}_{u,t} \quad \forall t \in \mathcal{T}. \tag{27}$$

3 Experimental setup

3.1 Case study

The problem is run on a benchmark Dickert-LV network [9] consisting of three feeders for a total of 11 buses. The community spans the whole network and involves nine residential users, one industrial consumer, and PCC, which is the slack bus in the OPF model. The role of this slack bus is to provide for the net imbalance in the community and to compensate for the power losses in the network.

3.2 Simulation

The simulation is run with a one-hour resolution using 12 representative days each divided into 24 periods of one hour. This models a full one-year period with one day per month weighted with values of w_{d_t}. Data for yearly consumption and PV production come from [10]. The operational planning costs of each day are weighted to represent the annual OPEX of the system. Yearly results are obtained from a single optimization model to determine unique DER sizes and the annual CAPEX of each user.

This Mixed-Integer Second-Order Cone Problem (MISOCP) is implemented using Julia JuMP package [11] and solved by Gurobi [12]. The exact relaxation of the power flow constraints is checked *ex post*.

3.3 Scenarios

The three investment scenarios discussed in the introduction are compared to assess the impact of the energy community on members' energy bills and carbon footprints.

3.3.1 Individual model: In this model, each user can only invest at his electrical node with an amount limited by his budget. Two constraints are added to model this,

$$\Pi^{\text{inv}}_{u} \in [0; \overline{B}_{u}] \quad \forall u \in \mathcal{U}, \tag{28}$$

and community exchanges are not allowed,

$$i^{\text{com}}_{u,t} = e^{\text{com}}_{u,t} = 0 \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \tag{29}$$

The results of this model serve as a baseline for comparison with the two following REC frameworks.

3.3.2 REC without co-investment: In this scenario, each member's budget can only be used for personal DERs, ensured by constraint (28). A community is created, and constraint (29) is thus relaxed. This represents a community where each participant can invest in devices behind its energy meter. The benefits of the community mostly come from the gap between the import (π^{igr}) and export (π^{egr}) prices. When the community price is set inside this range, the community creates value for both the buyer and the seller.

3.3.3 REC with co-investment: All the community members can pool their capital together, the CO can optimally size and place the new DERs. This scenario uses the full model developed in Section 2.

3.4 Simulation parameters

This study is initially based on a Belgian case study, where the annual CO_2 emissions for the electricity taken from the grid is 175 g/kWh [13]. The new investments have a fixed CO_2 intensity per capacity: 1590 kg/kWp for PV [14], 106 kg/kWh for battery capacity [15] and 70 kg/kW for each of the inverters [16]. All these values come from life-cycle assessments for the device and depend on its capacity.

The price of imports from the grid (retailer) is valued at 40 c€/kWh and exports are sold at 10 c€/kWh, the base community fee (γ^{com}) imposed by the CO is 1 c€/kWh for both import and exports, battery fees (γ^{sto}) are valued at the same amount. Most community members willing to create the community also have an important investment budget for renewable energy resources summing up to 156 k€, including an important capital from the industrial member.

4 Results

Table 1 summarizes all six simulation results. The price-optimal results align with those expected from [3], with a REC model delivering savings and better grid performance metrics that could be further improved through a co-investment mechanism within the community. Similarly, the CO_2-optimal results are enhanced by the community and further improved through the co-investment mechanism.

Table 1 Summary of optimal results for the two objectives and three frameworks.

Optimum	Price			CO_2		
Case	Ind.	EC	Co.	Ind.	EC	Co.
Cost [k€/y]	22.9	19.4	**18.0**	25.6	20.9	**20.5**
Π^{com} [k€/y]	15.6	11.4	10.1	18.7	13.1	11.8
Π^{inv} [k€]	145.0	156.0	156.0	117.8	156.0	154.2
CO_2 [t/y]	12.3	10.7	**10.6**	11.5	10.15	**9.9**
K^{op} [t/y]	7.55	5.1	4.6	8.2	5.2	4.5
K^{inv} [t]	95.1	112.8	119.0	65.6	98.4	107.9
PV [kWp]	55.2	65.0	**68.4**	36.6	54.7	**60.0**
BSS [kWh]	27.7	40.0	**44.3**	38.7	60.7	**67.0**
Self suff [%]	52.4	70.6	**73.8**	49.1	68.9	**76.2**
Self cons [%]	71.1	83.2	**83.6**	92.5	**99.9**	**99.9**
Peak [kW]	32.7	15.2	14.8	46.8	23.82	21.43
Losses [kWh]	296.0	237.0	224.9	252.1	211.3	167.6

Comparing the two objectives, we can see that the results are not drastically different. In the optimal case (co-investment), minimizing the CO_2 instead of the energy bill provides an emission decrease of 700 kg/y for the whole community at the cost of 2500 €/y. More generally, going from objective (2) to (3) provides results around 5% better in terms of CO_2 emissions yet requires 10% higher costs.

For CO_2 minimization, the BSSs are more favorable compared to price minimisation, enhancing self-sufficiency with a lower investment penalty. Self-consumption significantly increases under the second objective because the excess energy, which is not valued, is curtailed to prevent increased grid losses.

The REC results for the following analyses are always carried out with the co-investment scenario, as it provides the best results overall.

4.1 Impact of the location of the REC

In these simulations, two key parameters are analyzed: the CO_2 intensity of the energy mix from the grid and the photovoltaic capacity of the location. The benefits of the REC when minimizing CO_2 emissions highly depend on both the efficiency of new investments and how much emissions the DER can avoid.

Here, three new models are solved for each pair of parameters with objective (3). Scenario **A**, is the individual model with no investment budget, to show what the starting point of the member would be with grid import only. Scenario **B** restores the available budgets, thus corresponding to the individual model from section 3.3.1. Scenario **C** is the full problem with REC and co-investment.

Figure 1 shows the optimal CO_2 emissions of the community for all considered energy mixes and PV potentials. As expected, the best results are obtained with higher values for the PV potential, because the same investments enable a larger energy output. The main factor for the carbon efficiency of the community's energy usage is the CO_2 emissions for the grid imports. This value directly defines all the model's operational emissions.

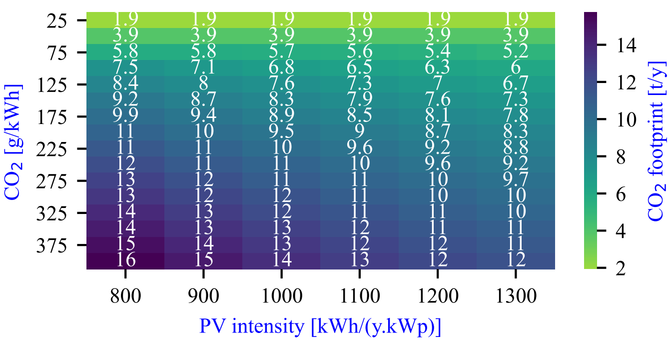

Fig. 1: Optimal CO_2 emissions of the REC framework (scenario **C**).

Figure 2 shows the impact of the community framework. It displays the difference between the optimal footprints in scenario **B** and **C**. Results show a positive impact of the REC when the grid CO_2 intensity and the PV potential increase. Indeed, in these cases, local exchanges avoid larger amounts of emissions to be avoided. At very low carbon energy mixes (25-75 g/kWh), the REC cannot further reduce the CO_2 emissions. This is because the energy imported is as clean as the energy produced by the decentralized PV resources.

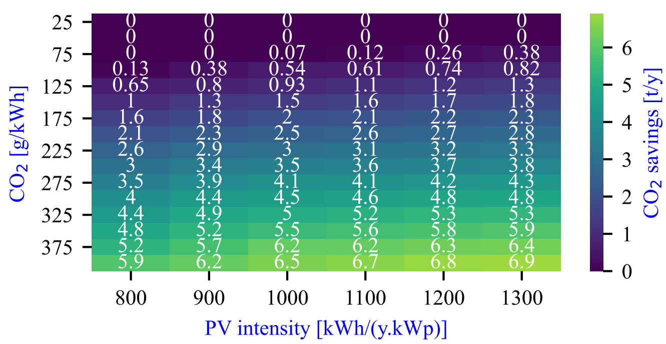

Fig. 2: CO_2 savings of the REC framework over the individual (**B**-**C**).

Table 2 depicts CO_2 emission savings for chosen countries in the EU with defined parameters for mean solar potentials from [17] and average values for energy mixes in 2024 from [13]. As expected, a country with high solar and CO_2 intensity can reach the highest emissions savings, with the impact of grid import emissions prevailing over PV potential.

Table 2 Rounded parameters and CO_2 savings for selected European countries.

Country	CO_2 [*]	PV pot. [g/kWh]	**A-B** [t/y]	**B-C** [t/y]	**A-C** [t/y]
Sweden	25	800	0.0	0.0	0.0
France	50	1100	0.0	0.0	0.0
Spain	150	1300	2.5	1.77	4.27
Belgium	175	800	1.99	1.57	3.56
Italy	350	1200	9.88	5.79	15.67
Germany	400	900	10.12	6.15	16.27

[*]: [kWh/(y.kWp)] *A-B*: *CO_2 savings from investments only.*
B-C: *CO_2 savings from REC creation.* *A-C*: *CO_2 savings overall.*

4.2 Sensitivity to available budget

The magnitude of the emission and financial savings highly depends on the investment budgets of the members. Previous results were obtained using an average budget of 15.6 k€ per member. In this section, we show financial and emission optimization results considering increasing member investment capacity. The case study is in Belgium and allows co-investment in the REC. Figure 3 shows how the minimal costs and emissions evolve with varying budgets.

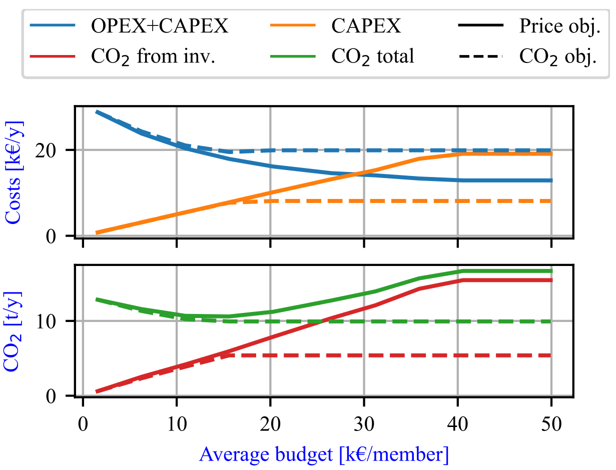

Fig. 3: Results with varying investment budgets.

These results show that with a low average budget, the price and CO_2 minimization provide the same results. All members' budget is invested in renewable to provide maximized self-sufficiency. The minimum for CO_2 emissions is reached with a budget of approximately 15 k€/member, over this value, marginal investments do not save CO_2 and the dotted curves flatten. Minimal energy costs are still decreased until a budget of 40 k€/member is reached, which results in increased CO_2 emissions due to over-investment.

The maximal useful budget value mainly depends on the ratio between capital and operational weight factors in the objective. Indeed, the ratio between CO_2 costs for grid imports and investments ($\kappa^{\text{gri}}/\kappa^{\text{PV or BSS}}$) is lower than for OPEX over CAPEX. Thus, with equal energy output, investing stops being profitable in terms of CO_2 emission before it stops being profitable for costs.

Members' ability to sell the excess energy to the grid amplifies this difference in capital/operation trade-offs between both objectives and encourages over-investment by valuing energy surplus.

4.3 Impact of community operator fees

Community operator fees are an impacting parameter of the simulation. They define what value is lost for the community members to the profit of the CO and provide a lever for incentivizing local exchanges. These fees should be well designed to ensure that the CO can pay for all grid-related costs: energy losses, grid tariffs and/or grid rent.

Figure 4 shows the impact of γ^{com} for cost minimization in the base Belgian case with co-investment. There is a small dependence of the emissions of CO_2 on the CO fee, they increase slightly until around 13 c€/kWh where internal exchanges stop being profitable due to the internal fees. Additionally, this figure shows that incentivized exchanges provide far better financial results and would promote participation in the REC and the energy transition.

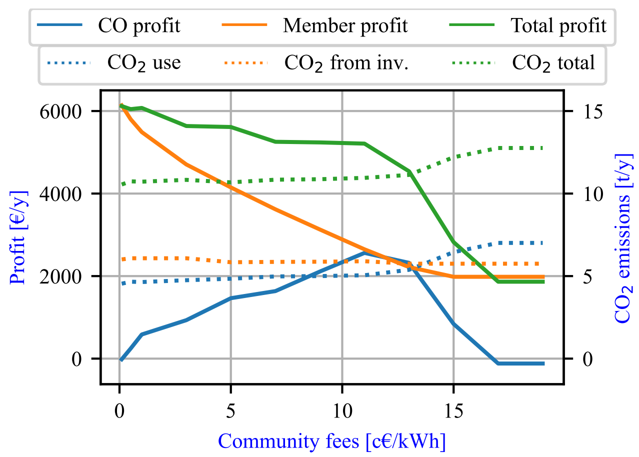

Fig. 4: Results with varying community exchange fees (γ^{com}).

5 Conclusion

This study offers some insights into the impact of distributed generation investment capacities on the carbon footprint in renewable energy communities. Based on the results stemming from multiple case studies, the following conclusions can be drawn:

- Energy communities can provide a beneficial framework for investing in distributed energy resources which is profitable for the transition to low-carbon energy.
- The magnitude of this positive impact highly depends on the solar potential and energy mix of the country where the EC is located.
- Price minimization can provide an adequate proxy and direct motivation for CO_2 efficiency. However, with large investment budgets and important monetary value for

selling energy excess, the objectives diverge. The price-minimizing investments are oversized compared to those that minimize CO_2 .

- Encouraging the internal community exchanges with reduced grid tariffs benefits the community outcome. This value still needs to be chosen adequately. Ensuring correct allocation of the benefits between members and CO, which needs to be incentivized while ensuring correct operation and payment for the grid, is crucial.

Distributed energy resource usage and REC efficiency could be further improved by unlocking community members' flexibility on demand as proposed in [18]. These results could be analyzed through CO_2 optimization with a model similar to the one presented.

References

[1] European Commission: 'Clean planet for all: a european strategic long-term vision for a prosperous, modern, competitive and climate neutral economy', *A European long-term strategic vision for a prosperous, modern, competitive and climate neutral economy*, 2018,

[2] Cornélusse, B., Savelli, I., Paoletti, S., Giannitrapani, A., Vicino, A.: 'A community microgrid architecture with an internal local market', *Applied Energy*, 2019, **242**, pp. 547–560

[3] Stegen, T., Glavic, M., Cornélusse, B., Giannitrapani, A., Paoletti, S.: 'Sizing distributed energy resources in a renewable energy community with a grid-aware internal market structure', *Electric Power Systems Research*, 2024, **234**, pp. 110797

[4] National Renewable Laboratory (NREL). 'Life Cycle Greenhouse Gas Emissions from Electricity Generation: Update'. Available from: https://www.nrel.gov/docs/fy21osti/80580.pdf

[5] Gao, C., Zhu, S., An, N., Na, H., You, H., Gao, C.: 'Comprehensive comparison of multiple renewable power generation methods: A combination analysis of life cycle assessment and ecological footprint', *Renewable and Sustainable Energy Reviews*, 2021, **147**, pp. 111255

[6] Elomari, Y., Mateu, C., Marin-Genesca, M., Boer, D.: 'A data-driven framework for designing a renewable energy community based on the integration of machine learning model with life cycle assessment and life cycle cost parameters', *Applied Energy*, 2024, **358**, pp. 122619

[7] Mariuzzo, I., Fioriti, D., Guerrazzi, E., Thomopulos, D.: 'Multi-objective planning method for renewable energy communities with economic, environmental and social goals', *International Journal of Electrical Power and Energy Systems*, 2023, **153**, pp. 109331

[8] Farivar, M., Low, S.H.: 'Branch flow model: Relaxations and convexification—Part I', *IEEE Transactions on Power Systems*, 2013, **28**, (3), pp. 2554–2564

[9] Dickert, J., Domagk, M., Schegner, P. 'Benchmark low voltage distribution networks based on cluster analysis of actual grid properties', 2013. IEEE Grenoble Powertech Conference

[10] Open Power System Data. 'Data package household data. version 2020-04-15.'. Available from: https://data.open-power-system-data.org/household_data/2020-04-15/

[11] Lubin, M., Dowson, O., Garcia, J.D., Huchette, J., Legat, B., Vielma, J.P.: 'Jump 1.0: Recent improvements to a modeling language for mathematical optimization', *Mathematical Programming Computation*, 2023,

[12] Gurobi Optimization, LLC. 'Gurobi Optimizer Reference Manual'. Available from: https://www.gurobi.com

[13] 'Electricity Maps | Live 24/7 CO2 emissions of energy consumption'. Available from: https://app.electricitymaps.com/map

[14] de Wild-Scholten, M.J.: 'Energy payback time and carbon footprint of commercial photovoltaic systems', *Solar Energy Materials and Solar Cells*, 2013, **119**, pp. 296–305

[15] Emilsson, E., Dahllöf, L.: 'Lithium-ion vehicle battery production status 2019 on energy use, co 2 emissions, use of metals, products environmental footprint, and recycling', *IVL Swedish Environmental Research Institute*, 2019,

[16] Tschümperlin.L, F.R. Stolz P.. 'Life cycle assessment of low power solar inverters (2.5 to 20 kw).'. Available from: http://treeze.ch/fileadmin/user_upload/downloads/Publications/Case_Studies/Energy/174-Update_Inverter_IEA_PVPS_v1.1.pdf

[17] Šúri, M., Huld, T.A., Dunlop, E.D., Ossenbrink, H.A.: 'Potential of solar electricity generation in the european union member states and candidate countries', *Solar Energy*, 2007, **81**, (10), pp. 1295–1305

[18] Allard, J., Stegen, T., Glavic, M., Vallée, F., De.Grève, Z., Cornélusse, B. 'Quantifying, activating and rewarding flexibility for renewable energy communities', 2024. submitted to ISGT