TECHNICAL IMPACTS OF THE DEPLOYMENT OF RENEWABLE ENERGY COMMUNITIES ON ELECTRICITY DISTRIBUTION GRIDS

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ABSTRACT

Renewable Energy Communities have received considerable interest in recent years. Besides the economic, social and environmental benefits for end-users and society, their implementation on the electricity distribution network entails technical impacts which still need to be correctly understood.. In this work, we quantify these impacts on a community established on a LV domestic network subject to a European grid tariff structure, in which local generation surplus are shared among members. We first develop a collaborative demand-side management model to compute operational technical indices, such as community peak-to-average ratio, line losses, etc. We then develop an investment model to analyse the impact of communities on PV adoption in LV grids. We compare results with a benchmark in which members consume and invest individually. We show that community operation tends to reduce peak power and overall exchanges at the MV/LV substation, as well as overall line losses. The PV investment model proves that a community organization tends to favour the installation of more PV generation while controlling grid impacts, provided that a constraint on the SCR is imposed in the sizing model.

INTRODUCTION

Renewable Energy Communities (RECs) consist in organized entities gathering consumers and prosumers who are allowed to exchange energy locally, without resorting to the traditional wholesale/retail market structure. Promoted by the European Union (EU) in Directive 2018/2001 [1], they aim at fostering local private investment in renewable energy production, by placing the citizen at the centre of the electricity supply chain, and at mobilizing flexibility available in Low Voltage (LV) and Medium Voltage (MV) networks. The Directive is since being transposed into decrees and laws in the member states, so that more and more pilot projects and actual communities are currently emerging.(see e.g. [2], [3] for examples in Wallonia and Brussels respectively). Citizens are interested in RECs since they can reap financial, ecological and social benefits through the mutualization of resources and the joint investment in Distributed Energy Resources (DERs). However, the massive roll-out of RECs on the electricity distribution grids entails impacts of various natures, i.e. technical, economical, regulatory as well as legal, which still need to be correctly quantified.

RECs have been intensively investigated in the literature, given the variety in terms of possible internal market designs. Short-term (operational) and long-term (investment and sizing of energy assets) economic impacts for REC members have been more particularly studied: authors in [4] investigated for instance energy bill savings, at the individual and community levels, brought by the REC. In another study [5], the added value of REC for investments in distributed generation has been quantified. Environmental concerns are often another major issue for energy community members: the influence of RECs operation on CO2 emissions is for example reported in [6].

Finally, the technical impacts that RECs may have on distribution grids has also attracted attention. In [7], grid indices (over- and undervoltage, line loading, etc.) are computed for a REC including photovoltaic and battery storage . However, the authors considered investment in community-owned assets, one battery and one PV installation for the REC. The local energy production is also exchanged for free in the REC. In [8], the impact of individually and community-owned battery storage systems on a potential reduction of the reverse flows has been studied: authors showed that the high share of PV systems at the distribution level in RECs resulted in the increase of such flows, which are detrimental to the MV-LV transformers. Nevertheless, this paper did not include any consideration about physical grid quantities as node voltages, line losses, etc.. Reference [9] explicitly models the network. . More specifically, authors address the issues of line loading and over- and undervoltage limits in a community with a peer-to-peer (P2P) mechanism.

In this paper, the REC is established on an LV feeder, constituted principally by domestic users who may own photovoltaic (PV) generation, electric vehicles, batteries and heat pumps, in addition to standard appliances. We consider an internal market design in which the local generation surplus is shared among the community members (see Fig. 1). This design is representative of community organizations which can be encountered in Belgium [10] and France [11] for instance. The public low-voltage distribution grid infrastructure is modelled ex-post for assessing the technical impacts of the REC. The main contributions of this paper are the following:

- We propose a coordinated demand-side management model (DSM) within a community in order to quantify the potentialities in terms of peak shaving, line losses reduction, and reverse power flows;
- We develop a community investment model to quantify the optimal amount of PV power to install in a community, with a constraint on the community's minimal self-consumption, and compute grid indices in the optimal sizing situation.

We compare the obtained results with a benchmark case in which the end-users optimize their operation and investment individually, without any community.

The remainder of the paper is structured as follows. Section 2 describes the community framework and the two models, along with the underlying assumptions. The use case is defined in Section 3. Section 4 presents the results in terms of technical and energy efficiency performances. Conclusions are drawn in the final section.

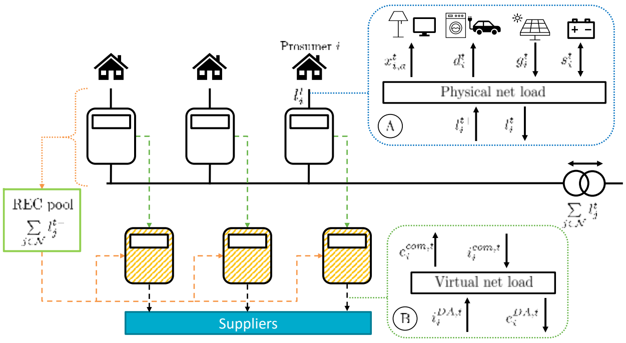

Fig. 1: Renewable Energy Community Model [12]

2. METHODOLOGY

We present the coordinated demand-side management and investment models (objective function, cost structure, constraints), along with their underlying assumptions. Grid impacts are quantified ex-post by running power flow models on the computed optimal schedules/investments.

2.1 Demand-side management model

We formulate the DSM model as a day-ahead coordinated optimal scheduling problem, aiming at minimizing the community electricity bill, by acting on the demand-side appliances. We assume a perfect forecast of generation and consumption, and that all the community members follow the recommendations of the tool. A community manager gathers data concerning the flexible loads members consent to use over the considered day.

Let $\mathcal{N} = \{1, \dots, \mathrm{N}\}$ be the set of community members connected to the same low-voltage network, and $\mathcal{T} = \{1, \dots, T\}$ the set of optimization intervals of duration Δt of the day. Every member $i \in \mathcal{N}$ can be equipped with PV panels and/or a battery storage system, and multiple flexible appliances (see below). The surplus of power production is mutualized for the other members.

2.1.1 Community demand-side model

Different devices may compose the physical net load of a community member, as represented in Fig.1.

A. *Flexible loads* are devices whose operation can be shifted either in time and/or in power. These are defined by a temporal flexibility window and operational constraints. The temporal flexibility window during which device $a \in \mathcal{A}_i$ can be operated is represented by a binary vector $\delta_{i,a} = (\delta_{i,a}^1, \dots, \delta_{i,a}^T)$. A value of 1 indicates that member i agrees to run appliance a over time slot $t \in \mathcal{T}$. Their power consumption is modelled by $x_{i,a} = (x_{i,a}^1, \dots, x_{i,a}^T)$. We model two categories of flexible loads:

1) *Time-shiftable loads* (e.g. dishwasher, washing machine, etc.). Such loads have a fixed power consumption $M_{i,a}$ and an operation duration N_a, that can be shifted along the day. We introduce binary variables, $u_{i,a}^t$, equal to 1 if time-shiftable appliance a of member $i \in \mathcal{N}$ is ON:

$$\delta_{i,a}.u_{i,a}^{\mathrm{T}} = N_a \qquad (1)$$

$$(1 - \delta_{i,a}).u_{i,a}^{\mathrm{T}} = 0 \qquad (2)$$

$$\sum_{t=t^0+1}^{t^0+N_a} u_{i,a}^t \geq N_a\left(u_{i,a}^{t^0+1} - u_{i,a}^{t^0}\right), for\ t^0 = 1{:}T - N_a \qquad (3)$$

$$x_{i,a}^t = M_{i,a}.u_{i,a}^t \qquad (4)$$

Equations (1)-(2) limit the duration of operation to one cycle and make sure that the appliance is ON during the temporal flexibility window only. Eq. (3) ensures that the appliance is run continuously until the end of the process, and (4) defines the power consumed by the time-shiftable loads.

2) *Power-shiftable loads* (e.g., Heat Pumps, Electrical Vehicles, etc.). The power consumption pattern can be controlled during usage, but total energy $E_{i,a}$. over the available time window is imposed:

$$\delta_{i,a}.x_{i,a}^{\mathrm{T}}.\Delta t = E_{i,a} \qquad (5)$$

$$(1 - \delta_{i,a}).x_{i,a}^{\mathrm{T}}.\Delta t = 0 \qquad (6)$$

$$0 \leq x_{i,a}^t \leq M_{i,a} \qquad (7)$$

Equations (5)-(6) limit the energy consumed to the predetermined total energy, and limit the operation slot to the temporal flexibility window. Eq. (7) limits the power consumed in the range $[0; M_{i,a}]$.

B. *Battery storage system* of member $i \in \mathcal{N}$ is modelled with the use of two variables: the state-of-charge (SOC) e_i^t and the charging/discharging power s_i^t.

$$s_i^t = s_{i,ch}^t - s_{i,dis}^t \qquad (8)$$

$$e_i^t = e_i^{t-1} + \left(\eta_{st} s_{i,ch}^{t-1} - \frac{1}{\eta_{st}} s_{i,dis}^{t-1}\right)\Delta t \qquad (9)$$

$$e_i^1 = R_{st}.E_{st}^{max} \qquad (10)$$

$$e_i^{T+1} \geq R_{st}.E_{st}^{max} \qquad (11)$$

$$-M_{st}^{max} \leq s_i^t \leq M_{st}^{max} \qquad (12)$$

with $s_{i,ch}^t, s_{i,dis}^t \geq 0$, respectively the power charged to and the power discharged from the battery. Equations (8)-(9) model the storage system operation. (10)-(11) impose the initial SOC to be a fixed share, R_{st}, of the total capacity, E_{st}^{max}. At the end of the day, the SOC must recover its initial level. Eq. (12) limits the charging and discharging power to M_{st}^{max}.

C. *Non-flexible loads* are aggregated and represented by $d_i = \left(d_i^1, \dots, \mathrm{d}_i^{\mathrm{T}}\right) \geq 0$ (13).

D. *PV panels electricity production* is modelled as the product between the installed PV capacity, P_{PV}, and a load factor profile, b. The solar production of member $i \in \mathcal{N}$ is therefore $g_i = P_{PV,i}.b \geq 0$ (14). Note that non-flexible loads and PV load factor profiles are deterministic.

The physical net load of member $i \in \mathcal{N}$ at time $t \in \mathcal{T}$ is then modelled as:

$$l_i^t = d_i^t + \sum_{a\in\mathcal{A}_i} x_{i,a}^t + s_i^t - g_i^t \qquad (15)$$

According to the physical net load sign, the member either imports, $l_i^t \geq 0$, or exports, $l_i^t < 0$, power from the low-voltage grid. We define the positive and negative net load as $l_i^{t+} = max(0, l_i^t)$ and $l_i^{t-} = max(0, -l_i^t)$.

For economic purposes, virtual power flows are defined. The positive net load, or power consumed, is supplied by power imported from the supplier, $i_i^{DA,t}$, and/or from the local market, $i_i^{com,t}$. Similarly the negative net load, or power injected, can be sold to the supplier, $e_i^{DA,t}$, or on the local market,$e_i^{com,t}$:

$$l_i^{t+} = i_i^{DA,t} + i_i^{com,t} \qquad (16)$$

$$l_i^{t-} = e_i^{DA,t} + e_i^{com,t} \qquad (17)$$

On the local market, the sold power must match the power bought by REC members during each time interval.

$$\sum_{i\in\mathcal{N}} e_i^{com,t} = \sum_{i\in\mathcal{N}} i_i^{com,t} \qquad (18)$$

2.1.2 Cost structure

The objective of the DSM model is to minimize the community electricity bill, which is decomposed into two main terms: commodity and grid costs. The commodity cost accounts for:

- External supplier costs: these costs cover the part of consumption not acquired on the local market. For each user $i \in \mathcal{N}$, we have $C_{sup,i}^t = \lambda_{imp} i_i^{DA,t} \Delta t$.
- Local electricity costs: these costs relate to the electricity purchased on the local REC pool, at price λ_{iloc}. For each user $i \in \mathcal{N}$, we have $C_{loc,i}^t = \lambda_{iloc} i_i^{com,t} \Delta t$.
- Revenues from exported electricity: the prosumers in the REC may sell their excess of local production either to the electricity supplier or on the local market. These sales create revenues for the prosumers expressed as $R_{sup,i}^t = \lambda_{exp} e_i^{DA,t} \Delta t$, if the energy is sold to the supplier, or as $R_{loc,i}^t = \lambda_{eloc} e_i^{com,t} \Delta t$, if it is sold on the local market.

In this paper, we consider a fixed single-supplier price. We assume also that prices for buying electricity from (selling electricity to) the community are lower (higher) than the ones proposed by the supplier.

The commodity costs of the community can therefore be aggregated as:

$$C_{com} = \sum_{t\in\mathcal{T}} \left[\sum_{i\in\mathcal{N}} C_{sup,i}^t - R_{sup,i}^t + C_{loc,i}^t - R_{loc,i}^t \right] \qquad (19)$$

The other part of the bill is related to grid usage (upstream transmission and distribution grids, and local distribution grid). We assume here a grid costs structure similar to the one that will be applied in Brussels (Belgium) starting from January 2023 [13]. For each member *i*, we have:

- Volumetric-based costs: these grid costs are charged in [€/MWh] based on the energy exchanged with the supplier during the day. For each user $i \in \mathcal{N}$, we have $C_{gr,i} = (\lambda_{distrib} + \lambda_{transp})(i_i^{DA,t} + e_i^{DA,t})\Delta t$.
- Capacity-based costs: they are charged in [€/MW] based on the peak power consumption over the day. For each user $i \in \mathcal{N}$, we have $C_{peak,i} = \lambda_{peak} \max_t (l_i^{t+})$.

The grid costs of the community can be expressed as:

$$C_{grid} = \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{N}} C_{gr,i} + \sum_{i\in\mathcal{N}} C_{peak,i} \qquad (20)$$

2.1.3 MILP formulation

The demand-side management model can be expressed as a Mixed-Integer Linear Programming (MILP) Problem.

$$\begin{cases} \min_{\Theta} B_{coll} = C_{com} + C_{grid} \\ \quad s.t. (1) - (18) \end{cases} \qquad (21)$$

The set of decision variables is defined as $\Theta = \{u_{i,a}, x_{i,a}, s_i, e_i, l_i, i_i^{DA}, e_i^{DA}, i_i^{com}, e_i^{com}\}$. We use the well-known branch-and-bound algorithm to solve (21).

2.2 Investment model

We formulate the investment problem as a long-term PV sizing tool, which aims at determining the optimal capacity of PV for each member of the community, considering the REC local market design, that would minimize the total cost for the community. The DSM model (21) is used to estimate operational costs (OPEX).

2.2.1 Cost structure

Let $\mathcal{D} = \{1, \dots, d, \dots, N_d\}$ be the set of days with N_d the number of days considered in the investment horizon. The investment cost is defined as:

$$C_{invest} = \lambda_{PV} \sum_{i\in\mathcal{N}} P_{PV,i} \qquad (22)$$

where $P_{PV,i}$ is the installed PV capacity of member $i \in \mathcal{N}$ and λ_{PV} is the equivalent annual annuity of investment charges in €/kW/year. The annual annuity is computed based on investor cost of equity and accounts for the equity invested, the debt charges and the depreciation revenues.

2.2.2 MILP formulation

The investment model can be formulated, similarly to the demand-side management model, as a MILP Problem, with the installed PV capacity as a decision variable, and with two additional constraints. Constraint (23) limits the amount of PV installed per household based on the Belgian legislation. Constraint (24) imposes a minimum community self-consumption rate (SCR, i.e. ratio between the production consumed locally and the total production) over one year, in order to control the amount of reverse power flows and avoid over-investment. We have:

$$P_{PV,i} \leq P_{PV}^{max} \qquad (23)$$

$$1 - \frac{\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{N}} e_i^{DA,d,t}}{\sum_{d\in\mathcal{D}}\sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{N}} g_i^{d,t}} \geq SCR^{min} \quad (24)$$

$$\begin{cases} \min_{\Upsilon} C_{invest} + \sum_{d\in\mathcal{D}} B_{coll}^d \\ s.t. (1)-(18)+(23)-(24) \end{cases} \quad (25)$$

where B_{coll}^d, represents the operational costs of the community. The set of decision variables is defined as $\Upsilon = \{u_{i,a}^d, x_{i,a}^d, s_i^d, e_i^d, l_i^d, i_i^{DA,d}, e_i^{DA,d}, i_i^{com,d}, e_i^{com,d}, P_{PV,i}\}$.

3. CASE STUDY

3.1 Community parameters

The studied REC is composed of 55 members connected behind the same MV-LV feeder. For the non-flexible loads, electricity consumption profiles are extracted from the Pecan Street Project dataset with a 1 hour time step [14].

The flexible loads are assigned to each member based on a penetration level. For each simulated day, their planned operation is based on the usage frequency of the devices and different temporal flexibility windows (the $\delta_{i,a}$ vector) are assigned to the operation: day flexibility, night flexibility, and peak hours. Three time-shiftable loads are considered: dishwasher, washing machine, and clothes dryer. These loads have a fixed power profile. We model two types of power-shiftable loads, i.e. electric vehicles and heat pumps. These loads have a range of operating power and predetermined energy consumed each day. For the heat pumps, different energy needs are applied according to the season. Storage system is assigned to community members according to a 50% share. The initial/final battery level parameter R_{st} is fixed at 50%.

Community parameters (tariffs, loads characteristics) are detailed in [15]. Members are connected to the Modified LV 116 buses IEEE network [16].

3.2 DSM model: Benchmark

We compare the outcomes of the DSM model when the end-users collaborate as a community (model (21)), and when each end-user performs an individual optimization of her own electricity bill. The physical net load output of the models are passed to a three-phase, balanced distribution load flow tool [17] in order to compute grid KPIs (see section 3.4) in both situations. The DSM model is run each time for 16 days (8 days with high PV generation – 8 days with low PV generation). The same installed PV capacity, between 0 and 10 kW per household, and appliances configuration are considered in both frameworks.

3.3 Investment model: Benchmark

Instead of using an arbitrary installed PV capacity, the investment model is used to determine the optimal amount of PV capacity needed by each member, in both REC and individual frameworks. They are compared for different minimum SCR levels. Two scenarios are considered for the equivalent annuity (via inflation rate) and commodity prices. One corresponds to the current situation (high commodity prices) and the other represents the pre-crisis situation (low commodity prices) [15].

The investment model is simulated on a representative year (built on 8 representative days, i.e. 1 week day and 1 week-end day for each season), replicated through a 20-years investment horizon accounting for the correct actualization rates. Similarly to the DSM case, the physical net loads of each day go through a load flow calculation.

3.4 Key performance indicators

We compute in each case the following KPIs:

- Peak-to-average ratio (PAR): This indicator quantifies the variability of the overall consumption profile, $L^t = \sum_{i\in\mathcal{N}} l_i^t$:
$$PAR = \frac{max\ L^{t+}}{mean\ L^{t+}}$$
where $L^{t+} = max(0, L^t)$.
- Peak power [kW]: Maximum global consumption of the community.
- Node voltage level [pu]: The voltage at each node of the network is observed to ensure that it remains between the $[0.9;\ 1.1]\ [pu]$ limits.
- Line losses [kW]: Total line losses on the studied distribution grid over a simulated day.
- Line loading percent: This indicator represents the fraction of the line maximum power used.
- Self-consumption rate (SCR): The ratio between the production consumed locally and the total production. It is related to the reverse power flows.
$$SCR = 1 - \frac{\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} e_i^{DA,t}}{\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} g_i^t}$$
- Self-sufficiency rate (SSR): The ratio between the load supplied locally and the total load. It is related to the import power flows.
$$SSR = 1 - \frac{\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} i_i^{DA,t}}{\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} l_i^t + g_i^t}$$

4. RESULTS AND DISCUSSION

MILP models are coded in Julia/JuMP and solved using Gurobi. Simulation times reach 25s for the DSM model, and 340s for the investment model. The results of the DSM models are summarized in Table 1. The values are averaged over the 8 high and low PV generation days. As expected, the most significant differences between REC operation and individual optimization are observed during high PV days.

Table 1: DSM benchmark results summary

	PAR [-]	Peak Power [kW]	SCR [%]	SSR [%]	Line losses [kW]
Day			High PV		
Community Opti.	2,5	55	92	75	8
Individual Opti.	1,6	68	63	51	14
Day			Low PV		
Community Opti.	1,2	88	100	2	41
Individual Opti.	1,2	100	100	2	41

For the same installed PV capacity, the community achieves higher SCR and SSR results thanks to the internal exchange market, thereby limiting exchanges with the upstream network. The REC framework also reduces the peak power as well as the line losses. However, the PAR is higher with the REC: the average tends to be smaller as the community might require external power only during cloudy and night periods, and no power from the upper grid during sunny periods. Fig. 2 shows the histogram of nodal voltages over the whole network. We see that it never exceeds the 1.1pu limit, although we tend to be closer to the limit in the individual case.

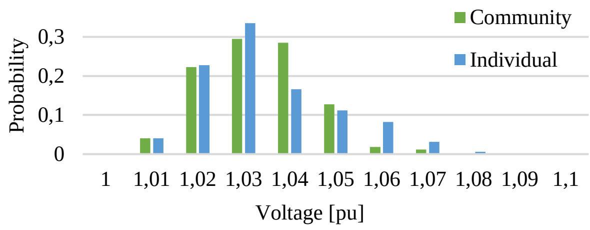

Fig. 2: Probability density of node voltage

We run the investment model for different values of the SCR constraint (see Table 2). We further compare the two price scenarii for the 80% SCR level. Results show that the economic advantages of RECs incentivize the investment in PV capacity. The higher local production induces less imports from the upstream grid (and thus better SSR values), at the cost of higher electrical lines loading. In the 80% case, the incentivization of PV investment in the REC is particularly important in a situation with high energy prices and inflation rate. This is linked to the higher supplier export prices that favor the local production despite the increased investment costs, increasing the reverse power flows through the MV/LV transformer.

Table 2. Investment model benchmark results summary

	PV capacity [kW]	Annual Grid Import [MW]	Annual Grid Exports [MW]	Max. line loading [%]
Min. SCR level	60% (Actual prices)			
Community Opti.	550	356	214	60
Individual Opti.	445	415	151	40
Min. SCR level	80% (Actual / Pre-crisis prices)			
Community Opti.	414 / 220	402 / 548	96 / 0	50 / 20
Individual Opti.	383 / 221	433 / 548	73 / 0	30 / 20
Min. SCR level	90% (Actual prices)			
Community Opti.	414	433	73	30
Individual Opti.	351	452	32	20

5. CONCLUSION AND FUTURE WORKS

This paper develops a short-term (coordinated DSM) and a long-term (PV investment) model for a REC in which members can exchange PV surplus locally, both used to assess technical impacts on the local grid. We show using the DSM model that a community operation tends to reduce peak power and overall exchanges (through the higher SCR and SSR values) at the MV/LV substation, as well as overall line losses. The PV investment model shows that a community organization tends to favour the installation of more PV generation than the individual case while controlling grid impacts, provided that a constraint on the SCR is imposed in the sizing model.

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