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Towards resilient energy communities: Evaluating the impact of economic and technical optimization

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ABSTRACT

This paper assesses the difference of optimal operation of energy communities (ECs) with respect to economic and technical goals. ECs have emerged as a promising solution for accelerating the transition to more sustainable energy systems and therefore climate change mitigation. While cost optimization (economic goal) is most commonly used in ECs, optimizing their resilience (technical goal) can be an important part of operating a distribution grid with high photovoltaic (PV) and electrical vehicle (EV) penetration in the future. This paper presents a comparative analysis of the impact of those two objective functions on overall EC costs as well as individual member costs. The findings highlight the trade-off between the flexibility measures required for a resilient EC and the cost associated with them. This study helps quantify the subsidies that would be required to incentives EC to operate in a resilient matter as a form of grid service.

1. Introduction

Energy communities (ECs) are gaining traction as key actors in the EU's energy transformation as a key element for working towards the United Nations sustainable development goal number 7: "Ensure access to affordable, reliable, sustainable and modern energy for all" [1]. By facilitating the rise of renewable energy sources and empowering individuals to take an active part in decreasing energy use, these communities also have the potential to make a substantial contribution to the EU's objective of reaching climate-neutrality by 2050 [2]. For the EU, ECs are a group of citizens who generate, store, consume, and sell energy together. It defines renewable energy communities (RECs) in the "Renewable Energy Directive II" (REDII) [3]. They operate on a local level, which means they are geographically close, and only small and medium-sized businesses are permitted to join. In recent years, member countries have incorporated this into national legislation, such as Austria with its "Renewable Energy Package" [4]. ECs are an important mechanism for the country's strategy for the integration of renewable energy sources. As a result, they also support the country's ambitious decarbonization strategy of reaching net-zero in the electricity sector by 2030 [5]. ECs are already operational in Austria under this new legal framework. The issues of energy and cost allocation among members, as well as EC subsidies via a grid tariff reduction (see [6]), have already been resolved. As a result, the Austrian framework was chosen for the implementation of an ECs optimization model.

The literature on optimization models for EC is extensive and has been increasing in recent years as shown in [7]. The topic of ECs is very multidisciplinary therefore there are a variety of possible objective functions that can be optimized. In this paper, economic and technological objective functions are discussed. For example, [8–14] minimize the overall EC cost, whereas [15–17] minimize the cost of each individual member. The possible technological objective functions are more diverse, such as minimizing energy curtailment [18], imports to the EC [19], or battery energy storage system (BESS) degradation [20]. Other objective functions include maximizing self-consumption [21,22] and energy sharing [23]. This reflects the fact that ECs can have a variety of goals other than cost minimization. This conclusion is supported by [24,25]. Out of the above-mentioned literature on EC optimization, only Refs. [9,11,12,14,15,19,20] consider an electricity grid and its constraints, which is less than half of them. While the EC is often not the balancing responsible party, and thus one could argue that modeling the grid is unnecessary, they must still adhere to the technical constraints of the grid in which they are located. What might be in the best interest of the EC could end up being very difficult for the grid and therefore for the DSO (Distribution Grid Operator) that is balancing it. On the other-hand could ECs with the right incentives also help to improve the distribution grid's resilience. Ref. [20] establishes a peer-to-peer trading system, and while resilience is not optimized, it is compared for different grid disturbance scenarios. The hybrid

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renewable energy system in [8] indirectly maximizes resilience by minimizing the hourly gap between demand and production in the EC.

Flexibility measures in the ECs are also an important part of optimizing ECs. These are most commonly found in the form of BESSs, as shown in [8,10,12,14–16,20,22,23]. Another option is to incorporate EVs into the model, as shown in [9,12,16,17,22]. However, EVs are more difficult to manage than BESSs because they are not available throughout the day and are subject to the constraints of their owners, which means they must be charged to a certain extent at a certain time. Incorporating them is important not only for their flexibility potential, but also because their load will have a significant impact on the overall demand of ECs in the future, given the increasing EV adoption as part of the decarbonization of the transport sector. A much less commonly used flexibility option is variable production via a biomass power plant (BPP). In Germany, ECs with BPPs are the most common, as shown in [26,27]. BPPs are used in the optimization of a positive energy district in [19], but only for heat production, not electricity production. In [14] a model for BPPs in hybrid renewable energy micro-grids was designed and used in a cost optimization alongside PV and BESS. Ref. [28] contains a configuration optimization of hybrid renewable energy systems that include BPPs.

While ECs are frequently viewed as a single entity, costs and profits must be allocated among its members at some point. Ref. [29] contains a performance assessment for various types of cost allocation methods in integrated community energy systems. Ref. [30] proposes an allocation method for residential energy communities that is efficient, effective, and fair. We will use allocation methods that are already in use in Austria in this work. It begins by allocating energy using a percentage allocation key or the demand share compared to total EC demand. Every EC is required to set a community energy price per MWh, which is then multiplied by the allocated energy. Section 2.5 goes into greater detail about this approach. They must pay the supplier's set price for energy that is not covered by EC and must be imported from the main grid. Members must pay grid tariffs for both, which are higher for imported energy than for EC energy. Section 2.4 contains a more detailed explanation of this. To the best of our knowledge, there is no literature on incorporating grid tariffs into EC optimization.

This work's original contributions to making electric power systems more resilient to climate change include: (1) incorporating a diverse set of production and flexibility options, such as BPPs, PV, BESS, and EVs, into a single optimization EC model while also accounting for grid constraints. (2) Including grid tariffs in the EC's cost structure. (3) Examine the difference between an economic objective function and a technical one, while also considering the impact to each member.

The remainder of this paper is structured as follows: Section 2 describes the formulation of the optimization model, including the various objective function options and constraints. Ex-post energy and cost allocation to individual EC members is also detailed here. Section 3 shows the completed case study, including its production, demand, and gird structure. Section 4 analyzes the results of cost and resilience optimization, and Section 5 concludes this work. Appendix contains the nomenclature.

2. Energy community optimization model

The EC optimization model is described in this section. It is an extension of the Low-carbon Expansion Generation Optimization Model (LEGO [31]), which is a relaxed mixed integer problem solved in GAMS with the CPLEX solver. This model takes as input demand, production, and network parameters and optimizes one of the following objective functions: cost, self-consumption, autarky (two definitions), or resilience. BESS and EVs are the models' flexibility (EVs). An optimal power flow is used to account for the constraints of the electricity grid. The EC's grid is linked to the medium voltage grid through one transmission node *itrans*. Energy can be imported and exported to and from the EC via this node. In the exceptional case that the low voltage grid has multiple connections to the medium voltage grid the model could be extended by adding the sum over the subset *itrans*. It has a high degree of temporal flexibility due to its ability to run in both representative days/periods and chronological hours. In this case, the latter is used for one year with hourly resolution. Because the cost is calculated for the entire EC, energy, and cost are distributed among the members ex-post. Main indices used are the following: Time periods h, generating units g, bus of transmission network i, j and EC member n. For the remaining exhaustive list of variables, and parameters used in the following model description can be found in the nomenclature in Appendix.

2.1. Objective functions

Historically, ECs can be driven by numerous different motives. Other than financial motivation, as shown in [25] there are various drivers to join an EC, such as self-consumption and the sharing of renewable energy. These factors will influence how an EC optimizes its operations. To reflect this, there are five different objective functions to choose from in this model.

The first objective function is minimizing the total cost. As shown in Eq. (1), it is the total of the operational costs for the entire year: These are the start-up C_t^{SU}, commitment C_t^{UP}, and variable costs C_t^{VAR} for the BPPs in €/MWh. Only operation and maintenance costs C^{OM} apply to PV, BESS, and EVs. For production from EVs their owners are reimbursed with the EC energy price C_h^{EC}. There is profit from exporting, as well as costs from importing from the grid and grid tariffs gt. In Austria, grid tariff reliefs for ECs exist; Section 2.4 describes how these work and how the various components are calculated. Finally, in order to penalize excess and unutilized energy, costs are associated with that.

$$\begin{aligned}
min\ & gt^{flat} + \sum_h \Big(\sum_t (C_t^{SU} y_{h,t} + C_t^{UP} u_{h,t} + C_t^{VAR} p_{h,t}) \\
&+ \sum_r C_r^{OM} p_{h,r} + \sum_s C_s^{OM} p_{h,s} + \sum_e (C_e^{OM} + C_h^{EC}) p_{h,e} \\
&+ C_h^{import} import_{h,itrans} - C_h^{export} export_{h,itrans} \\
&+ gt_h^{el,duty} + gt_h^{green,sub} + gt_h^{loss} + gt_h^{use} + gt_h^{bio} \\
&+ \sum_i C^{ENS} pns_{h,i} + \sum_i C^{EE} ep_{h,i} \Big) \qquad (1)
\end{aligned}$$

The second objective function is to maximize self-consumption. The goal is to consume as much locally generated energy as possible within the EC. This is accomplished by minimizing total export, as shown in Eq. (2).

$$min \sum_{h,itrans} export_{h,itrans} \qquad (2)$$

Autarky can be defined in two ways: the amount of imported energy, or, the sum of both imported and exported energy. The first definition may be sufficient for the EC, but it might result in generation peaks that the DSO must deal with. As a result, from a system standpoint, the second option is preferable. To examine the different outcomes, both options were implemented as objective function options in Eqs. (3) and (4), respectively.

$$min \sum_{h,itrans} import_{h,itrans} \qquad (3)$$

$$min \sum_{h,itrans} import_{h,itrans} + export_{h,itrans} \qquad (4)$$

The last objective function in the model is maximizing resilience. Here this is done by minimizing the maximum power peaks at the transmission node, see Eq. (5). This, as illustrated in constraint (6), is represented by the hourly import and export. The difference between this and autarky is that this is hour-specific, whereas autarky is simply the net energy over a year.

$$min\ res \qquad (5)$$

$$res \geq import_{h,itrans} + export_{h,itrans} \qquad (6)$$

2.2. Energy production and power flow constraints

This model divides energy production into renewable and thermal energy production. The LEGO model's formulation for thermal power plants was used for the implementation of biomass power plants. By changing the input parameters, this formulation can be applied to all types of thermal power plants. Hourly capacity factor profiles are used in renewable energy production.

The model employs an optimal power flow to represent the grid behind the EC. Its constraints are listed in (7). It begins with the active power balance constraint in (7a), which contains the production side, which includes thermal, renewable, BESS, and EV production, flows to and from the bus, non-supplied energy, and imports, and the demand side, which includes member, BESS, and EV demand, export, and excess production. It should be noted here that import and export are only part of the transmission node's balance constraint. This is followed by the definition and bounds of the power flow variable in (7b) and (7c) using the angle differences of the nodes and the reactance of the power lines. Finally, import and export are defined as power flows to and from the transmission node in (7d), and their bounds can be found in (7e) and (7f).

$$\sum_{gi(t,i)} p_{h,t} + \sum_{gi(r,i)} p_{h,r} + \sum_{gi(s,i)} (p_{h,s} - cs_{h,s}) + \sum_{gi(e,i)} (p_{h,e} - cs_{h,e}) + \sum_{ij(j,i)} f^P_{h,j,i} - \sum_{ij(i,j)} f^P_{h,i,j} + import_{h,i=itrans} + pns_{h,i} = D^P_{h,i} + export_{h,i=itrans} + ep_{h,i} \quad \forall h, i \tag{7a}$$

$$f^P_{h,ij} = \frac{(\theta_{h,i} - \theta_{h,j})SB}{Reac_{i,j}} \quad \forall h, ij(i,j) \tag{7b}$$

$$-\overline{T}_{i,j} \le f^P_{h,i,j} \le \overline{T}_{i,j} \quad \forall h, ij(i,j) \tag{7c}$$

$$\sum_{ij(j,i)} f^P_{h,j,i} - \sum_{ij(i,j)} f^P_{h,i,j} + import_{h,i} - export_{h,i} = 0 \quad \forall h, itrans \tag{7d}$$

$$0 \le import_{h,i} \le IMPORT^{max} \quad \forall h, itrans \tag{7e}$$

$$0 \le export_{h,i} \le EXPORT^{max} \quad \forall h, itrans \tag{7f}$$

2.3. BESS and EV constraints

The incorporation of BESSs and EVs extends the EC's flexibility options. The BESS formulation, which includes state-of-charge (SOC) constraints as well as constraints to avoid simultaneous charging and discharging, are standard constraints for BESSs and therefore they are not detailed here. The formulation for introducing EVs in the EC optimization model (8) is a new addition to the LEGO model and resembles storage constraints. In this model, EVs are seen not only as a flexible load but also as a storage technology with additional constraints via vehicle-to-grid (V2G). The EV SOC formulation in (8a)–(8c) is divided into three cases: the car is at home, the car has just arrived, and the car is not at home. In the first case (8a), the EV's SOC behaves similarly to that of a BESS. The energy used during driving must be subtracted from the SOC at the time of departure in the second (8b), and the SOC is considered zero in the third (8c) because the car is not at home and thus cannot be used. Constraint (8d) ensures that the EV has a defined minimum SOC at the time of departure, allowing it to get through the day. Constraints (8e)–(8f) define the lower and upper limits of the SOC, as well as of the production and consumption. The final constraint (8h) is responsible for prohibiting simultaneous charging and discharging of the EV.

$$soc_{h,e} = soc_{h--1,e} - p_{h,e}/\eta^{CH}_e + cs_{h,e}\eta^{DIS}_e, \text{ for } h > 1 \;\&\; \neq ARI_e, \ \forall h, e \tag{8a}$$

$$soc_{h,e} = soc_{h=DEP,e} - p_{h,e}/\eta^{CH}_e + cs_{h,e}\eta^{DIS}_e - E^{out}_e, \text{ for } h = ARI_e, \ \forall h, e \tag{8b}$$

$$soc_{h,e},\ p_{h,e},\ cs_{h,e} = 0, \ for\ DEP_e < h < ARI_e, \ \forall h, e \tag{8c}$$

$$soc_{h=DEP_e,e} \ge SOC^{min}_e, \ \forall h, e \tag{8d}$$

$$ETP_e \cdot \overline{P}_e \cdot \underline{R}_e \cdot EU_s \le soc_{h,e} \le ETP_e \cdot \overline{P}_e \cdot EU_e, \forall h, e \tag{8e}$$

$$-\overline{P}_e \cdot EU_e \le p_{h,e} - cs_{h,e} \le \overline{P}_e \cdot EU_e, \quad \forall h, e \tag{8f}$$

$$p_{h,e} \le EU_e \cdot \overline{P}_e \cdot b^{ch/d}_{h,e} \tag{8g}$$

$$cs_{h,e} \le EU_e \cdot \overline{P}_e \cdot (1 - b^{ch/d}_{h,e}) \tag{8h}$$

2.4. Grid cost constraints

Grid tariffs are a significant component of the EC's cost. Not only do they account for a sizable portion of an Austrian's electricity bill, but they are also used to incentivize energy communities. They do not have to pay the green energy surplus charge, the electricity duty, or the full grid usage charge for energy produced and consumed in the EC. The policy is to only pay for grid levels used for the ECs energy distribution. In the case of a local renewable energy community, this equates to a 57% reduction in grid usage charge. To calculate grid tariffs, the net demand for each time step has to be calculated in (9a) by adding EV and storage consumption to the participants demand. The various cost elements of Austrian grid tariffs are depicted in formulations (9b) to (9h). As previously stated, the electricity duty (9b) and green energy surplus charge (9d) must only be paid for imported energy. The $gt^{gt,flat}$ in (9c) is the summary of fees that are paid yearly by each participant and are not based on energy consumption such as the green flat fee or measurement fees. There is also a charge for grid loss (9e), which is paid for the total net energy demand. The grid use charge must be calculated twice: once for energy produced and consumed within the EC (9f) and again for imported energy (9g). The final cost component is a BPP charge (9h), which is used to fund BPP subsidies. This differs by federal state and is calculated as a percentage of the green energy surplus charge. This percentage varies between 0.7% in Tyrol and 28.5% in Salzburg. For the case study of this paper, we choose Styria where it is 9%, which is a middle ground.

$$d^{net}_h = \sum_i D^p_{h,i} + \sum_g cs_{h,g} \ \forall h, i, g \tag{9a}$$

$$gt^{el,duty}_h = C^{gt,elduty} \cdot (d^{net}_h - \sum_g p_{h,g} + export_{h,i}) \ \forall h, itrans, g \tag{9b}$$

$$gt^{gt,flat} = C^{gt,flat} \cdot card(n) \ \forall n \tag{9c}$$

$$gt^{green,sub}_h = C^{gt,green} \cdot import_{h,i} \ \forall h, itrans \tag{9d}$$

$$gt^{grid,loss}_h = C^{gt,loss} \cdot d^{net}_h \ \forall h \tag{9e}$$

$$gt^{grid,use,out}_h = C^{gt,use} \cdot import_{h,i} \ \forall h, itrans \tag{9f}$$

$$gt^{gt,use,in}_h = (1 - C^{red}) \cdot C^{gt,use} \cdot (d^{net}_h - import_{h,i}) \ \forall h, itrans \tag{9g}$$

$$gt^{bio}_h = C^{bio} \cdot gt^{green,sub}_h \ \forall h \tag{9h}$$

2.5. Ex-post energy and cost allocation

There are numerous ways to distribute energy within an EC among its members. The fixed and dynamic systems are the two types used in Austria. Note that the following allocation process corresponds to ex-post calculations, so after the optimization model has been solved. This distribution is carried out for each time step. First, the EC's energy production (12) and net demand for each participant (10) must be calculated. It is important to note that in this model, PV units and storage are considered community property, whereas EVs are considered consumer property. As a result, the consumption or production of the EV is considered for net demand. The excess production from EVs that can be allocated to all members is calculated in (11).

$$NetD_{h,n} = D_{h,n} + cs_{h,en} - p_{h,en} \ \forall h, n, en \tag{10}$$

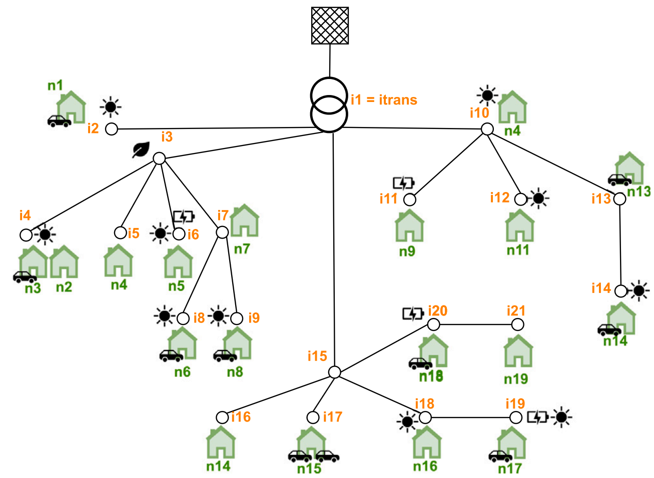

Fig. 1. Network diagram.

$$P^{eev}_h = \sum_n -NetD_{h,n} \;\; \forall h, n, NetD_{h,n} \leq 0 \tag{11}$$

$$P^c_h = \sum_t p_{h,t} + \sum_r p_{h,r} + \sum_s (p_{h,s} - cs_{h,s}) + P^{eev}_h \;\; \forall h, t, r, s \tag{12a}$$

$$P^c_h \geq 0 \tag{12b}$$

2.5.1. Fixed distribution

The idea behind fixed distribution is that members decide ahead of time how much of the produced electricity they want. This share is given in percentages. The share in MW per member ($Share^{MW}_{h,n}$, Eq. (13)) is calculated using this $Share^{f\%}_n$ and the production. The remaining grid demand $Rgd_{h,n}$ (14) is then calculated based on how much electricity is still required from the grid. The opposite is true for the excess energy $Exe_{h,n}$ in case the share is greater than consumer demand (15). Because the demand is the maximum amount of energy that can be allocated to each member, self-consumption $Sc_{h,n}$ equals net demand $NetD_{h,n}$ minus rest grid demand $Rgd_{h,n}$ (16).

$$Share^{MW}_{h,n} = Share^{f\%}_n \cdot P^c_h \;\; \forall h, n \tag{13}$$

$$Rgd_{h,n} = NetD_{h,n} - Share^{MW}_{h,n} \;\; \forall h, n \tag{14a}$$

$$Rgd_{h,n} \geq 0 \tag{14b}$$

$$Exe_{h,n} = Share^{MW}_{h,n} - NetD_{h,n} \;\; \forall h, n \tag{15a}$$

$$Exe_{h,n} \geq 0 \tag{15b}$$

$$Sc_{h,n} = NetD_{h,n} - Rgd_{h,n} \;\; \forall h, n \tag{16}$$

2.5.2. Dynamic distribution

The dynamic distribution begins with the EC demand D_c in (17), which is the sum of the member net demands. The difference between EC production P_c and demand D_c is then used to calculate the EC's excess energy Exe^c_h in (18). In Eq. (19), the excess energy from EC production is subtracted from the actual distributed energy $P^{dis,c}_h$. The dynamic aspect now enters the picture. The energy share $Share^{d,\%}_{h,n}$ is equal to the ratio of each member's net demand $NetD_{h,n}$ with respect to the demand of the EC D^c_h in (20). This can then be multiplied by the EC production P_c to obtain $Share^{MW}_{h,n}$ in (21). The actual energy received by each participant is then the self-consumption $Sc_{h,n}$ in (22), which is the share in percent $Share^{d,\%}_{h,n}$ multiplied by the distributed energy $P^{dis,c}_h$. Eq. (23) can then be used to calculate each consumer's rest grid demand by rearranging (14). While $Share^{MW}_{h,n}$ and therefore (21) is not needed for the rest of the calculations, it is an interesting result when comparing it to the actual received self-consumption.

$$D^c_h = \sum_n NetD_{h,n} \;\; \forall h, n, NetD_{h,n} \geq 0 \tag{17}$$

$$Exe^c_h = \begin{cases} P^c_h - D^c_h, & for \; P^c_h \geq D^c_h, \; \forall h, n \\ 0, & \text{else} \end{cases} \tag{18}$$

$$P^{dis,c}_h = P^c_h - Exe^c_h \tag{19}$$

$$Share^{d,\%}_{h,n} = \frac{NetD_{h,n}}{D^c_h} \tag{20}$$

$$Share^{MW}_{h,n} = Shared^{d,\%}_{h,n} \cdot P^c_h \tag{21}$$

$$Sc_{h,n} = P^{dis,c}_h \cdot Shared^{d,\%}_{h,n} \tag{22}$$

$$Rgd_{h,n} = NetD_{h,n} - Sc_{h,n} \tag{23}$$

2.5.3. Cost distribution

Following the allocation of the amount of energy received by each EC member, the individual cost can be calculated. This is also done separately for each hour. It is necessary to distinguish between the cost of energy generated within the EC and the cost of imported energy. The cost for each member is calculated in (25) by combining the EC's energy cost from (24) and grid tariffs with the member's allocated self-consumption. In the case of EV ownership, the members make a profit from EV energy production. The import cost C^{import}_h already is the cost of energy per MWh from outside the EC. The residual grid demand is the energy required from outside the EC by each member. The member cost from outside the EC is calculated using the required energy, import costs, and grid tariffs in (26). In order to compare the cost of the members with the overall cost of the EC the "Income" of the EC is calculated in (27).

$$C^{EC}_h = X^{\%} \cdot C^{import}_h \tag{24}$$

$$Cost^{in}_n = C^{gt,flat} + \sum_h Sc_{h,n} \cdot (C^{EC}_h + C^{gt,loss} + (1 - C^{reduction}) \cdot C^{gt,use}) - p_{h,en} \cdot C^{EC}_h \tag{25}$$

$$Cost^{out}_n = \sum_h Rgd_{h,n} \cdot (C^{import}_h + C^{gt,elduty} + C^{gt,green}(1 + C^{bio}) + C^{gt,loss} + C^{gt,use}) \tag{26}$$

$$Income^{EC} = \sum_n (Cost^{in}_n + Cost^{out}_n) \tag{27}$$

3. Case study

In this section, we present an illustrative case study. It consists of 19 households with 10 EVs, 10 PV units, 4 BESS, and one BPP. The system is built like a micro-gird with one connection point to the main grid. The structure of the EC is presented in Fig. 1. Due to space constraints, we will focus on cost minimization as an economic objective function and resilience maximization as a technical objective function in this case study. Also due to space limitations only the most important parameters are described in this section the others can be found in [32].

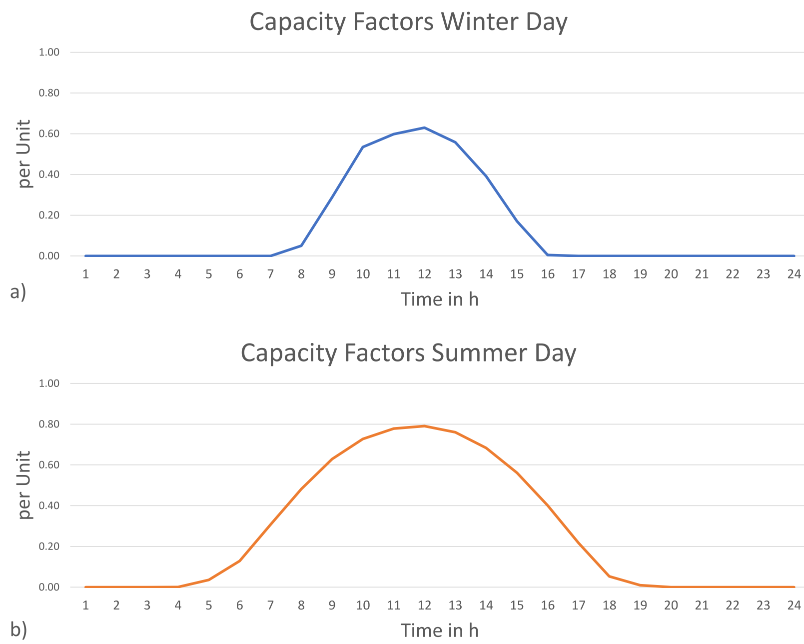

Fig. 2. Capacity factors for Rosenheim, Germany for a winter and a summer day.

3.1. Grid

The case study's EC is a stylized low-voltage grid with 21 buses that is loosely based on a distribution grid in western Austria. Bus 1 is the slack bus, as well as the transformer, which serves as the main grid's import and export point. Fig. 1 depicts the entire network diagram.

3.2. Energy production

The case study includes two types of energy production: PV and BPPs. The system has ten PV units, resulting in a PV penetration of around 50%. There are four 10.22 kWp plants and six 5.11 kWp plants. These figures are based on 28 and 14 × 365 Wp modules. The capacity factor profile for Rosenheim, Germany, was obtained from the Renewables Ninja database [33]. An example winter and summer day is shown in Fig. 2. Despite the fact that the system's policies are from Austria, a German PV profile was chosen to match the German load profiles described in Section 3.4. The EC has its own small BPPs with a capacity of 104.65 kW. The data for this plant is based on actual Austrian BPPs and was obtained from the ATLANTIS Database [34].

3.3. BESS and EVs

The system includes five small-scale household-size BESS, each with a capacity of 11 kWh and a charge and discharge efficiency of 96%. Furthermore, 50% of households own an EV. According to Statistics Austria, four different types of EVs were implemented, which correspond to four of the most commonly owned EVs in Austria. The car owners' departure and arrival times were chosen at random from 6:00–9:00 and 15:00–19:00, respectively.

3.4. Demand

The load profiles used are from the Open Power System Data project and are based on real German smart meter data [35]. They are two distinct profiles for suburban residential buildings. Because the case study included 19 households, the load profiles were scaled by a factor of 0.5 to 1.5 to produce a unique demand pattern for each consumer.

Table 1
Resilience vs. cost optimization result summary comparison.

	Resilience optimization	Cost optimization
X% of C_h^{import} [%]	120	40
$Income^{EC}$ [€]	10 333	6991
Total Cost [€]	10 336	3707
Resilience [MW]	0.00	0.27

4. Results

In this section, we compare the cost optimization of the case study EC to its resilience optimization. The findings are classified as cost-related in Section 4.1 and power-related in Section 4.2. The proposed EC has a minimum annual cost of 3707 €, compared to the EC cost of 10 336 € when resilience is optimized as presented in Table 1. This represents a 178% cost difference. This can also be seen in the C^{EC}'s requirement to recover its costs from its members in order to break even. To break even in the resilience optimization, the C^{EC} must be set to 120% of the import cost. Looking at the resilience results, it is clear that the EC's production and flexibility are sufficient to keep it independent of the grid for every hour of the year. The cost optimization's resilience of 0.27 MW is equivalent to the highest energy peak on the transmission node to the main grid.

4.1. Distribution of ECs annual cost

The annual cost distribution for the whole community is illustrated in Fig. 3. The case study's resilience optimization resulted in absolute autarky, with no export or import from the main grid. The cost optimization import results are very similar. Importing energy costs money and is thus unfavorable to the optimization unless the import energy costs are negative. This happened very rarely and only resulted in a annual profit smaller than two euros, which was less than the grid tariffs paid for the import. When compared to resilience optimization, the primary reason for cost savings for cost optimization are the export profits. Annual imported and exported energy is also depicted in Fig. 4 as well as an overall comparison of production and demand for resilience and cost optimization.

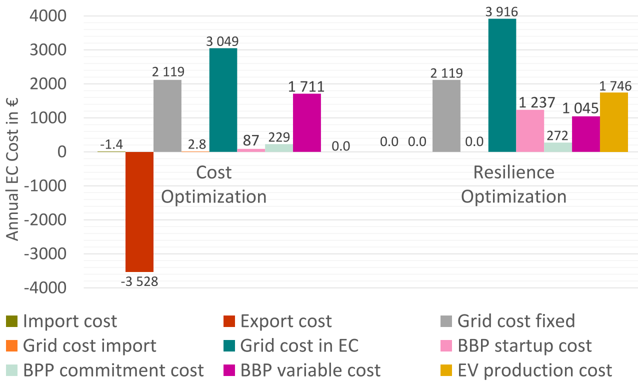

Fig. 3. Annual EC cost distribution resilience vs. cost optimization.

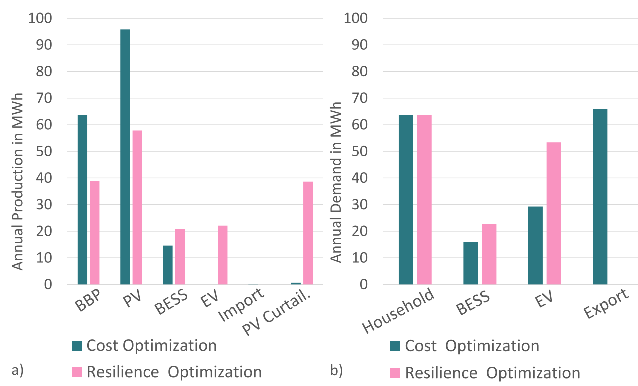

Fig. 4. Annual EC production and demand resilience vs. cost optimization.

Grid tariff costs can be divided into three categories: First, there are fixed costs that must be paid annually per household and are thus unaffected by optimization. These result in 2118.92 €. Second, there are the grid tariffs paid for the energy imported from the grid, which is irrelevant for this case study because the import is zero for resilience optimization and almost zero for cost optimization. Third, there are grid tariffs paid for energy produced and consumed within the EC. This is the most expensive component of the annual cost of the EC. Because of the increased use of storage and EVs, the overall energy demand in the resilience optimization is higher (3915.97 €) than in the cost optimization (3049.34 €), and thus the amount of grid tariffs paid is higher. For this case study, the operation, maintenance and variable (OMV) cost for PV was assumed to be zero, making the BPPs the only production with operational costs. Because it is a thermal power plant, it has start-up, commitment, and variable costs. When the two optimizations are compared, it is clear that while the power plant produced more in the cost optimization (64 MWh vs. 39 MWh, see Fig. 4), the overall production costs were higher in the resilience optimization (2027 € vs. 2554 €, see Fig. 3). This was due to the fact that the costs associated with frequently starting up and shutting down the power plant in order to avoid import and export.

Finally, there is the cost of EV production, which is derived from compensating households with EVs for their V2G energy production. In order to save money, EVs were only used as variable loads in the cost optimization and not for V2G. When maximizing resilience, on the other hand, EVs were an important flexibility option, which yields a significant corresponding EV production cost of 1746.32 €.

Table 2 shows the financial impact of the two objective functions on individual EC members. Three households with different loads are shown here as an illustrative example. The two households with EVs (N1 and N15) have higher demand and thus a higher electricity bill

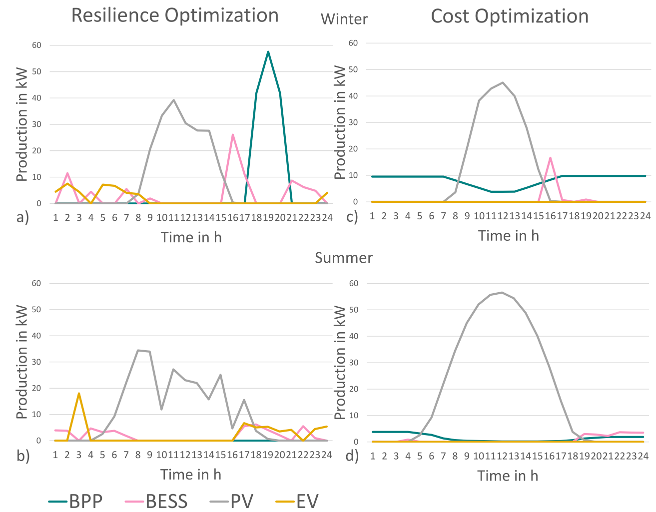

Fig. 5. Production per technology for one representative winter/summer day for cost minimization and resilience maximization.

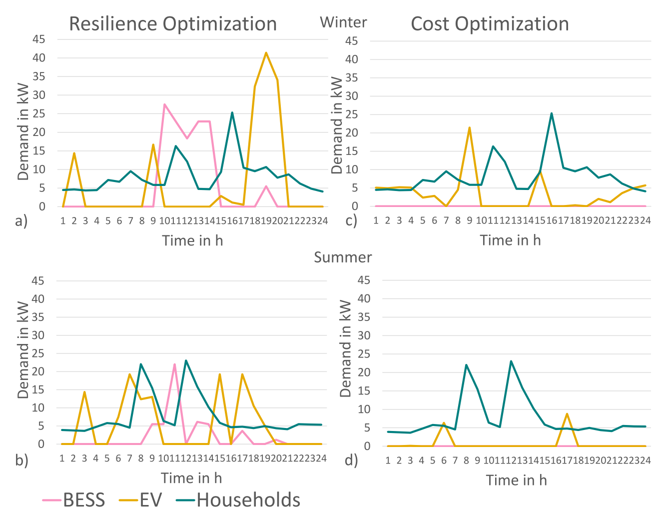

Fig. 6. Winter/Summer power demand per concept (BESS, EVs, Household demand data) for cost and resilience optimization.

Table 2
Exemplary household annual cost and demand for resilience vs. cost optimization.

	Cost optimization		Resilience optimization		Delta
	Cost in EC €	Cost out EC €	Cost in EC €	Cost out EC €	– %
N1	481.34	0.07	812.55	0	68.79
N15	812.66	0.33	1270.23	0	56.24
N19	263.43	0.03	409.1	0	55.27
	Demand EV MWh		Demand EV MWh		Demand house MWh
N1	4.66		5.27		2.57
N15	7.76		11.75		5.64
N19	–		–		2.82

than the one with an EV (N19). The cost increase between cost and resilience optimization from N19 is therefore entirely due to the EC's increased electricity price. It is more complicated for N1 and N15 because there is a price increase as well as an increase in demand because the EVs are also used for V2. On the other hand, the high EC electricity price compensates them for their production.

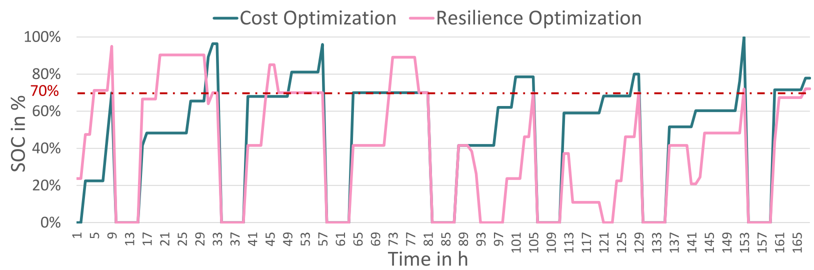

Fig. 7. State of charge (in %) of EV9 for the first week of the year for the cost (green) and resilience (pink) optimization.

4.2. Energy production and demand

Fig. 4 depicts the overall production and demand for the optimized year. As previously discussed in Section 4.1, the BPPs energy production was higher in the cost optimization, while it is producing less total energy but is used more dynamically in the resilience optimization. BESSs and EVs were heavily used as flexibility options in the resilience optimization, resulting in increased production and demand. Household demand is considered input data and therefore independent of the optimization.

As shown in Fig. 4, a significant amount of energy, i.e. 38.61 MWh, is curtailed in order to achieve a high level of resilience. The reason for curtailment in the resilience optimization was that either all of the available storage was full, or the energy was not required at a later time due to the model's perfect foresight. The reason for the small amount of curtailment in the cost minimization, where 0.65 MWh are curtailed, is simply due to the fact that export prices were negative at the time. Simply put, curtailment is less expensive than paying for energy exports.

Fig. 5 depicts the EC's energy production aggregated by production technology. Here, one example day in winter and one in summer was visualized for each optimization. The production curve for PV in the cost minimization shows the typical midday peak which is higher in the winter and lower in the summer. The broken PV production curves in the resilience optimization happen due to curtailment. In winter the BESSs are discharging to serve the afternoon demand peak in both optimizations, because of the swindling PV production at that time. EV production results in costs for the EC because the members that own the EVs need to be compensated for their production. As a result, in the cost minimization, EVs are only used as a load and never for V2G.

Fig. 6 depicts the EC's demand for the same winter and summer day used in the previous analysis. In both summer and winter, there is a charging peak of EVs in the afternoon right after they arrive, which in the case study is between 3 pm and 7 pm. The charging peaks in the morning can be explained by the requirement that EVs be 70% charged before departure. BESSs were not charged during those two days in the cost optimization. For the resilience optimization they were charged during the midday PV production peak in order to use them for the afternoon demand peak.

Fig. 7 depicts the charging pattern of EV9 for the first week of the year for the cost and the resilience optimization. When the EV is not home, therefore not available, the SOC is set to 0. The more dynamic use of the resilience optimization results in very precise meeting of the required 70% SOC just before departure. The 70% marker is highlighted in Fig. 7 by the red dotted line. It should be noted at this point that the very dynamic use of EVs results in a significantly increased number of charging/discharging cycles, which leads to a decreased battery lifetime. This is an important topic to take into account when considering using EVs to provide the necessary flexibility for increasing EC resilience. However, investigating the impact on battery lifetime unfortunately is beyond the scope of this paper. In the cost optimization however, if the electricity price at the time is low enough, the EV is charged more on one day while not being charged at all on the next, as shown in the plot on the third day.

5. Conclusions

ECs are a critical component of citizens' ability to contribute to climate change mitigation. The importance of how those ECs are operated is demonstrated in this paper. An EC optimization model with multiple objective function options is proposed. It is contributing to the current state of research by addressing multiple key aspects of ECs simultaneously. This is done by offering a diverse set of production and flexibility options, as well as considering grid constraints. By incorporating grid tariffs, the optimization model captures a significant part of the ECs annual cost structure, which enables a more comprehensive analysis of the EC's financial viability. Ex-post the model considers the impact on each individual member of the EC, thereby highlighting the varying effects that different objective functions can have on the community as a social-economic construct. The model is then used to compare the impact of an economic vs. a technological objective function on the EC. An economic objective function, in this case overall cost minimization of the EC, tends to be the obvious choice for ECs because it allows them to save money when compared to obtaining their energy from a traditional supplier. This is done with no regards to the impact on the electricity system the EC is operating in. A technological objective function, such as maximizing resilience, focuses on the system in question. This will become more important as the amount of energy production (PV) and demand through EVs in the distribution grid increases, making it more difficult for the DSO to keep it stable. By evaluating the optimization of these objective functions separately, we can elucidate the trade-offs between cost-efficiency and resilience within the EC.

The results show that the cost minimization saves a lot of money by exporting energy while the resilience optimization curtails a lot of energy instead of exporting to prevent putting strain on the main grid. The use of EVs for V2G occurs only in the resilience optimization since EV production is an additional cost point because they are owned by individual members who must be reimbursed for it. It is, an important flexibility tool for resilience optimization and is thus extensively utilized. The number of flexibility measures required for resilience optimization reflected heavily on the cost: no profit from exports, higher grid costs due to increased demand from BESSs and EVs, higher BPP costs due to increased start-up costs, and, as previously mentioned, the cost of V2G use of EVs.

The two optimizations can be viewed as two extremes. The cost optimization has the best financial outcome for the EC and its members, which is what most people would prefer. In an era of uncertain electricity prices, the EC can be considered to have the most economic resilience. However, this results in high export peaks, which have implications for the DSO responsible for grid regulation in the EC and the grid level above. The resiliency optimization demonstrates the opposite extreme: In this case study, the higher grid levels were not used at all. This does not imply that this is the "grid-friendliest" way to operate the EC. It would be more advantageous for DSOs to use the

Table A.1

Indices:			
h	Time periods (usually hours)	n	Member
g	Generating units	i, j	Bus of transmission network
$t(g)$	Subset of thermal generation units	$gi(g, i)$	Generator g connected to node i
$s(g)$	Subset of storage generation units	$itrans(i)$	Transmission bus
$r(g)$	Subset of renewable generation units	$en(e, n)$	EEV owned by member n
$e(g)$	Subset of EVs		
Parameters:			
$D^{P}_{h,i}$	Active power demand at node (MW)	EU_g	Indicator of existing unit (integer)
$D^{P}_{h,n}$	Active power demand at member (MW)	$\overline{T}_{i,j}$	Transmission line limit (MW)
η^{DIS}_{g}	Discharge efficiency of unit (p.u.)	$Reac_{i,j}$	Line Reactance
η^{CH}_{g}	Charge efficiency of unit (p.u.)	ETP_g	Energy to Power Ratio
SB	Base power (MVA)	ARI_g	Arrive time of the EV (h)
C^{EE}	Cost of excess energy (€/MWh)	DEP_g	Departure time of EV (h)
C^{ENS}	Cost of energy non-served (Meuro/MWh)	E^{out}_{e}	Energy used while out (MWh)
C^{SU}_{g}	Start-up cost of unit (€)	SOC^{min}_{e}	Minimum SOC for EVs (MW)
C^{UP}_{g}	Commitment cost of unit (€/h)	$Share^{f\%}_{n}$	Static member energy share (%)
C^{VAR}_{g}	Variable cost of energy (€/MWh)	$IMPORT^{max}$	Maximum of import (MW)
C^{OM}_{g}	OM cost (€/MWh)	$EXPORT^{max}$	Maximum of export (MW)
C^{EC}_{h}	Cost of energy in the EC (€/MWh)	$Sc_{h,n}$	Member Self-consumption (MW)
C^{import}_{h}	Cost of import (€/MWh)	P^{eev}_{h}	Excess EV production (MW)
C^{export}_{h}	Cost of export (€/MWh)	P^{c}_{h}	EC production (MW)
$C^{gt,elduty}$	Grid tariff electricity duty (€/MWh)	D^{c}_{h}	EC Demand (MW)
$C^{gt,flat}$	Grid tariff fixed costs (€/household)	$P^{dis,c}_{h}$	Distributed EC production (MW)
$C^{gt,green}$	Grid tariff green subsidy (€/MWh)	$NetD_{h,n}$	Net demand per member (MW)
$C^{gt,loss}$	Grid tariff grid loss (€/MWh)	$Share^{MW}_{h,n}$	Share of production (MW)
$C^{gt,use}$	Grid tariff grid use (€/MWh)	$Share^{d,\%}$	Dynamic share of production (%)
$C^{reduction}$	Cost reduction of grid tariff (%)	$Rgd_{h,n}$	Residual grid demand (MW)
C^{bio}	Grid tariff BPPs subsidy (%)	$Exe_{h,n}$	Member Excess Energy (MW)
$\underline{R}_{g}$	Minimum reserve of unit (p.u.)	$Exe^{c}_{h,n}$	EC Excess Energy (MW)
$\overline{P}_{g}$	Technical maximum of unit (MW)	$X^{\%}$	EC to Import cost ratio (%)
$Cost^{in}_{n}$	Cost per member from the EC (€)	$Cost^{out}_{n}$	Cost per member from supplier (€)
$Income^{EC}$	Over all cost for members (€)		
Variables:			
$p_{h,g}$	Power generation of the unit (MW)	$export_{h,itrans}$	Export to node itrans (MW)
$cs_{h,g}$	Consumption of the unit (MW)	gt^{flat}	Grid tariff fixed fees (€)
$pns_{h,i}$	Power non-served (MW)	$gt^{el,duty}_{h}$	Grid tariff electricity duty (€)
$ep_{h,i}$	Excess Power (MW)	$gt^{green,sub}_{h}$	Grid tariff green subsidy (€)
$f^{P}_{h,i,j}$	Power flow of line ij (MW)	gt^{loss}_{h}	Grid tariff grid loss (€)
$y_{h,g}$	Startup decision of the unit (integer)	gt^{use}_{h}	Grid tariff grid use (€)
$import_{h,itrans}$	Import to node itrans (MW)	gt^{bio}_{h}	Grid tariff BPPs subsidies (€)
$b^{ch/d}_{h,s}$	Charging or discharging binary	res	Resilience (MW)
$soc_{h,g}$	State of charge (MW)	d^{net}_{h}	Net demand of EC (MW)
$\theta_{h,i}$	Voltage angle		

EC for peak-shaving during times of production/demand peaks across the entire distribution grid rather than the EC not exporting/importing energy at all. The resilience optimization results can be viewed as a worst-case scenario of how much it can cost to use the EC for grid services. This means that the best solution lies somewhere between the two discussed extremes. The EC will have to be compensated for the monetary difference, and in order to do so, the government will have to pass legislation making this possible.

Future research will attempt to further this model into multi-objective optimization in order to find the ideal middle ground between multiple objective functions.

CRediT authorship contribution statement

Lia Gruber: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Ivana Kockar:** Resources, Writing – review. **Sonja Wogrin:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

As stated in the paper, the data that can be shared can be found on our git-hub.

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Appendix. Nomenclature

See Table A.1.

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