Optimization and Simulation for the Daily Operation of Renewable Energy Communities

Nathalie Frieß[1], Elias Feiner[2], Ulrich Pferschy[1], Joachim Schauer[2], and Thomas Strametz[2]

[1] University of Graz, Department of Operations and Information Systems, Universitätsstraße 15, Graz 8010, Austria
nathalie.friess@uni-graz.at, ulrich.pferschy@uni-graz.at
[2] FH Joanneum, Department of Software Design und Security, Werk-VI-Straße 46, Kapfenberg 8605, Austria
joachim.schauer@fh-joanneum.at, elias.feiner@fh-joanneum.at, thomas.strametz2@fh-joanneum.at

Abstract. Renewable Energy Communities (RECs) are an important building block for the decarbonization of the energy sector. The concept of RECs allows individual consumers to join together in local communities to generate, store, consume and sell renewable energy. A major benefit of this collective approach is a better match between supply and demand profiles, and thus, an increase in local self-consumption. The optimal exploitation of locally produced electricity raises many operational questions. In this context, we introduce a Mixed Integer Linear Program (MILP) that optimizes the energy flows within a REC. It employs the following instruments relevant for local self-consumption: (a) stationary batteries, (b) batteries of electric vehicles and (c) load shifting (i.e. moving the use of electric appliances from one time period to another). To handle the uncertainty of the involved planning parameters, we use a Model Predictive Control (MPC) approach and solve the optimization model in an iterative manner. The introduced planning framework can be applied to generate realistic performance measures of specific community configurations and to evaluate strategic investment decisions.

Keywords: mixed integer linear programming, model predictive control, energy communities

1 Introduction

Striving for an increase in the production of renewable energy, the EU Renewable Energy Directive 2018/2001, also known as RED II, laid the foundation for legal frameworks of local energy communities. In Austria, the corresponding set of laws and regulations[3] paved the way for *Renewable Energy Communities* (RECs[4]). A REC may comprise individual producers of renewable energy, mainly

[3] Erneuerbaren-Ausbau-Gesetzespaket (EAG-Paket), passed on 07.07.2021 by the Austrian parliament, came into effect 28.07.2021.
[4] Erneuerbare-Energie-Gemeinschaften (EEGs)

owners of houses with photovoltaic (PV) panels, as well as small and medium-sized enterprises (SMEs) and public institutions with their buildings. Besides so-called *prosumers* (individuals who are both producers and consumers) also consumers without the possibility of producing energy can participate in a REC. The central function of a REC is the sharing of locally produced renewable energy within the community. In this way the differences between supply and demand should be – ideally – matched inside the community, thereby reducing the strain on the power grid. The remaining demand is bought from utility companies at usual market rates. In such a setting members can realize cost savings, e.g., by receiving cheaply produced solar energy from a neighbor who currently has low demand. Prices for transactions within the community are not regulated at all but can autonomously be decided by the REC. However, the main objective of a REC is the promotion of awareness of energy consumption and the increase in the production of renewable energy through additional investments.

This framework opens interesting opportunities for citizens willing to invest in PV systems but also leaves open many aspects about the daily operation of the community. Of course, an individual member could simply consume self-produced energy, if it is currently needed, and pass on any surplus production to the community. If the community as a whole reaches a surplus or a demand, this has to be balanced from the power grid. But things get a lot more difficult – and thus more interesting – if consumption loads can be shifted in time (e.g. washing machine, hot water boiler or an energy-intensive production process of an SME), if electric cars are considered (note that electrical vehicles allowing bidirectional charging are becoming more common), and if energy storages are installed either by individual members or by the REC itself.

In such a complex system the operational decisions taken in 15-minute time steps (as given by the smart meters) can not be taken by individual members in an ad-hoc way or by a set of simple decision rules. Should I use my currently produced energy surplus to load my battery or should I feed it into the community to be consumed by other members? In case of demand, should I use electricity from my battery or from the community? Reasonable answers to questions of this kind require a longer-term perspective under multiple uncertainties. Production of renewable energy depends on solar radiation. Weather forecasts can be used, but will often be subject to changes as time proceeds. Moreover, consumption is subject to spontaneous individual behavior or unexpected events.

Among the early-stage pioneers of RECs, the strategy of daily operations turned out to be a big open question. The difficulty of how to efficiently run a REC network is often cited as a deterrent for individuals to join or found a REC. Within an applied research project[5], we aim to provide a decision support tool that allows individuals and communities to evaluate the optimized operation of a REC and thus to draw conclusions about their course of action. All relevant parameters, such as the configuration of the REC, features of each member, available PV panels, batteries, etc. can be freely configured. Computing the

[5] Funding by the *Zukunftsfonds* of the Province of Styria

optimal operation over a year allows members to realistically evaluate strategic decisions, such as buying a costly battery or installing additional PV panels.

1.1 Related Literature

The idea of exploiting collective resources and joining together in community settings (e.g. physically connected microgrids, virtual alliances,. . .) is not entirely new. Reviews on different community structures, their strengths and weaknesses, and common objectives and modeling approaches are provided in [1] and [2]. In Austria, research on RECs was contributed e.g. by Fina et al. (see, e.g., [3] for the optimization of energy flows within a REC), and by [4], [5], and [6], dealing with related optimization problems.

The concept of load scheduling (delaying the operation of controllable loads within predefined time windows) was considered, e.g., in [7], where a model incorporating the particular load profiles of household appliances was proposed. We adopt this idea and utilize the formulation of activity-based loads to integrate load scheduling for private and commercial users. Also electric vehicles (EVs) are increasingly recognized as flexible instruments to react to varying power needs, e.g., [8].

In the existing literature, planning decisions are mostly based on deterministic input values. In the field of energy research, Model Predictive Control (MPC) approaches are often used to deal with the uncertainties of forecasted parameters. MPC is a control method that considers the dynamics of a system by optimizing a set of control actions with updated input values on a rolling basis, as it has been done in [9], [10] and [11], to name just a few of related studies. However, to the best of our knowledge, MPC has not yet been applied to evaluate the actions and performance of RECs, as intended by the RED II.

2 Problem Description

Incorporating EU directives into national legislation leaves quite some room for interpretations. As Austria is among the first countries to implement RED II, the insights gained from this early realization may offer important guidance for other EU member countries. In the following we describe the optimized operation of RECs based on Austria's current legal framework.

The members of a REC can be households, small or medium-sized enterprises and local authorities with or without energy production. A producing community member with more electricity production than consumption in a 15-minute time period sends its surplus electricity to the community (see $\overrightarrow{q}^{com}$ in Figure 1), where it is redistributed to other community members ($\overleftarrow{q}^{com}$). If total production of the REC exceeds total demand, the surplus of the community is sold to the public grid ($\overrightarrow{q}^{grid}$). On the other hand, if local production does not suffice to cover the members' electricity consumption, the residual demand is covered by electricity purchased from the public grid. As consumers have the freedom to individually select their preferred electricity supplier, electricity purchase is indicated through separate $\overleftarrow{q}^{grid}$ arcs for each community member.

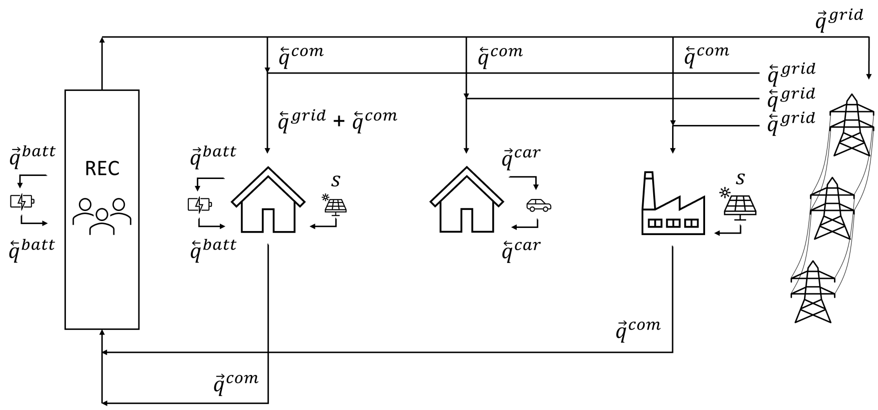

Fig. 1. Schematic structure of a REC with a community battery

Note that the amounts of energy sent from one source to another, henceforth labeled as q or *energy flow variables*, are used to describe the retrospective allocation of energy to different entities, but not to describe actual electricity flows following the laws of physics. The superscript above the q variables identifies the source or target of the energy flow and the arrow indicates the respective direction (e.g. $\overrightarrow{q}^{grid}$ stands for an energy outflow to the public grid, while $\overleftarrow{q}^{grid}$ stands for an energy inflow from the public grid).

The allocation of surplus electricity for the invoice issued by the electricity supplier is handled by the distribution system operator (DSO) in a resolution of 15-minute time intervals and can follow different allocation keys. With dynamic allocation - the preferred option for communities that pursue high internal consumption rates - the allocation takes place based on the members' current electricity demand, i.e., the ratio between the electricity received from the community and the members' electricity consumption is equal for all participants. Clearly, having an electricity demand in periods of high production leads to greater benefits within the community.

We consider the following load shifting instruments to better match the production and consumption of electricity within the community: (a) the operation of stationary batteries at the member or the community level, (b) the operation of electric cars that allow for bidirectional charging, and (c) scheduling of time-flexible loads.

Besides conventional batteries also electric vehicles with bidirectional charging can be employed as additional storage devices. In order to take full advantage of a vehicle's storage capacity, knowledge and predictability of mobility behavior take a vital role. In the proposed framework, we assume that the expected availability of a car is given by a 0/1 vector (representing typical usage patterns or input from an app). Moreover, the expected consumption rate for each trip and a desired battery reserve, must be available to allow reasonable planning.

Scheduling time-flexible loads can further ease the mismatch between supply and demand. Shiftable tasks can originate from household appliances (dishwasher, washing machine), or from larger consumers such as businesses with manufacturing machinery. Each of these shiftable tasks can be characterized by a time window, in which the task must be started and completed, and a consumption profile in 15-minutes resolution. If a detailed consumption profile is not available, the (known) total electricity consumption of the task can be split evenly over the task's duration. Based on this input, we generate a task schedule k for each feasible starting time t. Among this set of generated schedules, the most suitable schedule from a community perspective can be selected.

As there is a strong interdependence between the members' individual decisions and consumption profiles, a central optimization model is developed to determine the system-wide optimum for the community.

3 Optimization Model

The introduced optimization model seeks to control the energy use within the community by taking battery charging and discharging decisions, vehicle charging and discharging decisions, and by choosing the optimal schedule for shiftable electricity consumers. To model these decisions, a set of energy flow variables q is introduced for each member i and each time step t (see Table 1). Moreover, SoC variables are introduced to model the State of Charge (SoC) of stationary batteries and electric vehicles. The consumption profiles of shiftable demands are incorporated through binary variables x^{fload}, which select the optimal schedule among a set of predetermined options. The required input parameters, i.e., electricity supply and demand profiles, technical details about the grid connection, stationary batteries and electric cars, and expected vehicle use information, are listed in Table 2.

The overall objective of a REC can be highly versatile (e.g. profits, emissions, grid stabilization,...). As the concept of RECs evolved from the idea to better match local electricity demand and supply, our primary objective in (1) is to minimize the amount of energy exchanged with the public grid, and thus, to increase collective self-sufficiency and self-supply. In constraint (2), the balance of energy in- and outflows is ensured for each community member i and time step t. Similarly, constraint (3) maintains a balanced energy in- and outflow for the community. As injection rates of generation units are often limited in residential distribution networks, a feed-in limit for the amount of energy leaving the private power supply system is imposed in constraint (4). Moreover, for the default community member, we assume that only excess electricity is fed into the grid, i.e., the amount of electricity sent to the community is limited by the electricity surplus, if available. This relationship is modeled in constraint (5).

The community's batteries are modeled in constraints (6) - (9). In (6), the amount of charged and discharged energy is bounded by the respective batteries' in- and output rate. Constraint (7) initializes the batteries' SoC at the beginning of the planning horizon. In constraint (8), the development of the batteries SoC is tracked throughout all time steps. Finally, in constraint (9), the batteries' SoC is limited by their nominal capacity. Analogous to (6) - (9), constraints (10) -

Table 1. Introduced sets and variables for the generic member i and time step t

Sets	
$I = \{i, ...\}$	set of members i
$I^* = \{i, ..., com\}$	set of members i and community com
$T = \{t, ...\}$	set of time steps t in planning horizon
$S_i = \{s, ...\}$	set of storage devices s of member i
$V_i = \{v, ...\}$	set of vehicles v of member i
$J_i = \{j, ...\}$	set of shiftable loads j of member i
$K_i = \{k, ...\}$	set of schedules k of shiftable load j
Variables	
$\overleftarrow{q}_{i,t}^{grid} / \overrightarrow{q}_{com,t}^{grid} \in \mathbb{R}_+$	kWh obtained from/delivered to grid
$\overleftarrow{q}_{i,t}^{com} / \overrightarrow{q}_{i,t}^{com} \in \mathbb{R}_+$	kWh obtained from/delivered to community
$\overleftarrow{q}_{i,s,t}^{batt} / \overrightarrow{q}_{i,s,t}^{batt} \in \mathbb{R}_+$	kWh obtained from/delivered to battery s of member i
$\overleftarrow{q}_{i,v,t}^{car} / \overrightarrow{q}_{i,v,t}^{car} \in \mathbb{R}_+$	kWh obtained from/delivered to car v of member i
$\overrightarrow{q}_{i,t}^{lost} \in \mathbb{R}_+$	kWh lost due to feed-in limitation
$SoC_{i,s,t}^{batt} \in \mathbb{R}_+$	state of charge of battery s at end of time step t
$SoC_{i,v,t}^{car} \in \mathbb{R}_+$	state of charge of car v at end of time step t
$x_{i,j,k}^{fload} \in \{0, 1\}$	1 if schedule k of flexible load j of member i is chosen, 0 otherwise

Table 2. Required parameters

Parameters	
$s_{i,t}$ / $d_{i,t}$	supply/demand of member i in time step t
$\overline{q}_i^{out}$	feed-in limit of member i
$\overrightarrow{\gamma_{i,s}}$ / $\overleftarrow{\gamma_{i,s}}$ / $\gamma_{i,s}$	power loss factor for battery charging/discharging/over time
$\overrightarrow{\epsilon_{i,v}}$ / $\overleftarrow{\epsilon_{i,v}}$ / $\epsilon_{i,v}$	power loss factor for car charging/discharging/over time
$\overline{q}_{i,s}^{\rightarrow batt} / \overline{q}_{i,s}^{\leftarrow batt}$	input/output limitation of battery i, s per time step t
$\overline{q}_{i,v}^{\rightarrow car} / \overline{q}_{i,v}^{\leftarrow car}$	input/output limitation of car i, v per time step t
$\overline{SoC}_{i,s}^{batt}$	storage capacity of battery i, s
$\overline{SoC}_{i,v}^{car}$	storage capacity of car i, v
$\underline{SoC}_{i,v}^{car}$	minimum charge of car i, v
$a_{i,v,t}$	1 if car v of member i is available in time step t, else 0
$\{dep_1^{i,v}, dep_2^{i,v}, ...\}$	upcoming departure times of car i, v
$\{arr_1^{i,v}, arr_2^{i,v}, ...\}$	upcoming arrival times of car i, v
$\upsilon_{i,v}$	estimated consumption of car i, v's next trip
$SoC_{i,s}^{batt}$	current SoC of battery i, s (from simulation)
$SoC_{i,v}^{car}$	current SoC of car i, v (from simulation)
$start_t$	current time step (not included in planning horizon)
t'	earliest time step at which desired SoC can be technically reached
$schedule_{k,t}$	amount of energy consumed in flexible load schedule k at time step t
$task_j^{start}$	start time of task j

(14) model the community's electric vehicles. In contrast to (8), (12) computes the SoC only in time periods where the vehicle is available. Moreover, a strictly positive minimum energy level is required in (13). As the starting SoC (set by (11)) can fall below the specified lower bound, constraint (13) is only imposed for time steps, in which the desired SoC is technically feasible. Apart from the storage-related vehicle constraints, the members' vehicle usage behavior is modeled in constraints (15) and (16). For each anticipated trip within the planning horizon, departure and arrival times and the expected energy consumption are assumed to be given. At a vehicle's departure time, the battery must contain sufficient energy to fulfill the expected trip, with energy consumption v, and to return with the user-set minimum SoC. To plan charging operations after the vehicle's return in advance, the vehicle's SoC at arrival is anticipated to be equal to the SoC at departure, minus the expected trip consumption.

The selection of shiftable loads is handled in constraints (17) - (19). With (17), the amount of electricity used by schedule k of flexible load j is fixed for each time step. Constraint (18) sets variable x^{fload}, which identifies the chosen schedule for task j. Finally, constraint (19) assures that if task j already started at the beginning of the planning horizon, the associated schedule is set to 1 to ensure that the respective task can no longer be shifted in time.

$$\min \sum_{\forall i,t} \overleftarrow{q}_{i,t}^{grid} + \sum_{\forall t} \overrightarrow{q}_{com,t}^{grid} \tag{1}$$

$$\begin{aligned} s_{i,t} + \overleftarrow{q}_{i,t}^{grid} + \sum_{\forall s} \overleftarrow{q}_{i,s,t}^{batt} + \sum_{\forall v} \overleftarrow{q}_{i,v,t}^{car} + \overleftarrow{q}_{i,t}^{com} = \\ d_{i,t} + \sum_{\forall s} \overrightarrow{q}_{i,s,t}^{batt} + \sum_{\forall v} \overrightarrow{q}_{i,v,t}^{car} + \overrightarrow{q}_{i,t}^{com} + \overrightarrow{q}_{i,t}^{lost} \qquad \forall\,(i,t) \end{aligned} \tag{2}$$

$$s_{com,t} + \sum_{\forall i} \overrightarrow{q}_{i,t}^{com} + \sum_{\forall s} \overleftarrow{q}_{com,s,t}^{batt} = \sum_{\forall i} \overleftarrow{q}_{i,t}^{com} + \sum_{\forall s} \overrightarrow{q}_{com,s,t}^{batt} + \overrightarrow{q}_{com,t}^{grid} \qquad \forall t \tag{3}$$

$$\overrightarrow{q}_{i,t}^{com} \leq \overline{q}_{i}^{out} \qquad \forall\,(i,t) \tag{4}$$

$$\begin{aligned} \overleftarrow{q}_{i,t}^{com} \leq s_{i,t} - d_{i,t} \qquad \forall\,(i,t) | s_{i,t} - d_{i,t} \geq 0 \\ \overleftarrow{q}_{i,t}^{com} \leq 0 \qquad \forall\,(i,t) | s_{i,t} - d_{i,t} < 0 \end{aligned} \tag{5}$$

$$\overleftarrow{q}_{i,s,t}^{batt} \leq \overline{q}_{i,s}^{\leftarrow batt},\ \overrightarrow{q}_{i,s,t}^{batt} \leq \overline{q}_{i,s}^{\rightarrow batt} \qquad \forall\,(i^*,s,t) \tag{6}$$

$$SoC_{i,s,start_t}^{batt} = SoC_{i,s}^{batt} \qquad \forall\, i^* \tag{7}$$

$$SoC_{i,s,t}^{batt} = \gamma_{i,s} * SoC_{i,s,t-1}^{batt} + \overrightarrow{\gamma_{i,s}} * \overrightarrow{q}_{i,s,t}^{batt} - \overleftarrow{\gamma_{i,s}} * \overleftarrow{q}_{i,s,t}^{batt} \qquad \forall\,(i^*,s,t) \tag{8}$$

$$SoC_{i,s,t}^{batt} \leq \overline{SoC}_{i,s}^{batt} \qquad \forall\,(i^*,s,t) \tag{9}$$

$$\overleftarrow{q}_{i,v,t}^{car} \leq \overline{q}_{i,v}^{\leftarrow car} * a_{i,v,t},\ \overrightarrow{q}_{i,v,t}^{car} \leq \overline{q}_{i,v}^{\rightarrow car} * a_{i,v,t} \qquad \forall\,(i,v,t) \tag{10}$$

$$SoC_{i,v,start_t}^{car} = SoC_{i,v}^{car} \qquad \forall\,(i,v) \tag{11}$$

$$SoC_{i,v,t}^{car} = \epsilon_{i,v} * SoC_{i,v,t-1}^{car} + \overrightarrow{\epsilon_{i,v}} * \overrightarrow{q}_{i,v,t}^{car} - \overleftarrow{\epsilon_{i,v}} * \overleftarrow{q}_{i,v,t}^{car} \qquad \forall (i,v,t) | a_{i,v,t} = 1 \tag{12}$$

$$SoC^{car}_{i,v,t} \geq \underline{SoC}^{car}_{i,v} * a_{i,v,t} \qquad \forall\,(i,v,t)|t \geq t' \tag{13}$$

$$SoC^{car}_{i,v,t} \leq \overline{SoC}^{car}_{i,v} \qquad \forall\,(i,v,t) \tag{14}$$

$$SoC^{car}_{i,v,dep-1} \geq \underline{SoC}^{car}_{i,v} + \upsilon_{i,v} \qquad \forall\,(i,v,trips) \tag{15}$$

$$SoC^{car}_{i,v,arr-1} = SoC^{car}_{i,v,dep-1} - \upsilon_{i,v} \qquad \forall\,(i,v,trips) \tag{16}$$

$$\overrightarrow{q}^{fload}_{i,j,t} = \sum_{k} x^{fload}_{i,j,k} * schedule_{i,j,k,t} \qquad \forall\,(i,j,t) \tag{17}$$

$$\sum_{\forall k} x^{fload}_{i,j,k} = 1 \qquad \forall\,(i,j) \tag{18}$$

$$x^{fload}_{i,j,k} = 1 \qquad \forall\,(i,j,k)|task^{start}_{j} \leq start_t \tag{19}$$

4 Implementation and Results

The proposed optimization model is based on a broad set of uncertain input values, e.g., PV production profiles, fixed and controllable components of demand, car usage information, etc. To fill this information gap, different forecasting techniques can be used. However, real values can vary significantly from generated forecasts, and thus, a communities' actual performance may well deviate from theoretical planning results. To deal with the uncertain nature of the required input parameters, we have used a model predictive control (MPC) approach in our planning framework. Based on forecasts for one day (96 discrete time steps), the optimization model computes solutions for all controllable actions within the initial planning horizon $T = \{1, ..., 96\}$. The actions of the next time step $t = 1$ are assumed to be executed in reality and the corresponding values are reported to a simulation model. Based on the optimization models' target values and changes that occurred in the preceding time step t, the current system's state variables are updated and are sent back to the optimization model. Additionally, the time horizon moves forward by one period, i.e. from $T = \{1, ..., 96\}$ to $T = \{2, ..., 97\}$, and input values are updated with the latest available forecasts. The described procedure is executed in an iterative manner and operational processes are planned as data from short-term forecasts becomes available.

Table 3 provides the results of the global optimization model (OPT+SIM) and a pure simulation model (SIM), using the commonly applied "egoistic" local priority rule for the production of each member (SIM: 1. own consumption, 2. own battery, 3. community) for a reality-based REC. A detailed analysis of different representative community archetypes and performance figures will be subject of future research.

The community configuration in our test set-up consists of 10 members: There are 3 prosumer households (members 1-3), one dairy and agricultural farm with PV (member 4), 5 pure consumer households (one of them with a flexible demand appliance) and one small business with a large flexible demand. The specifications of the producing members are given in Table 3.

The general demand profiles of household members are generated with the LoadProfileGenerator provided by [12]. The demand profiles of businesses and other institutions are based on standardized load profiles provided from APCS[6]. To represent discrepancies between demand forecasts and reality, demand forecasts are taken from measurement values of the previous week. The forecast profile for Wednesday, March 7, for example, was retrieved from historical data from Wednesday, March 1.

The production profiles of PV systems are generated from real historic weather forecasts[7] and the PV profile generation tool presented in [13]. To simulate the real production profiles, the generation tool was provided with historic weather data from the assessment period. The results shown in Table 3 relate to an assessment period of one week (01.03.2023 – 07.03.2023).

The operation of the REC is modeled in a 15-minute discretization with a rolling planning horizon of 24 hours. With a computation time of ~ 1 second for the solution calculated at every single time step t, the total computation time for OPT+SIM took 696 seconds. The calculations were run on a 64-bit operating system with an Intel® Core™ i7-1065G7 CPU @ 1.30GHz processor and with 16 GB RAM. The MILPs were implemented in Python and solved with Gurobi 9.5. The pure simulation results SIM require only 0.5 seconds in total.

Table 3. Technical parameters, self-sufficiency and self-supply of individual members and community.

		self-sufficiency [%]		**self-supply [%]**	
ID	**Technology**	**SIM**	**OPT+SIM**	**SIM**	**OPT+SIM**
1	8 kWp PV 10 kWh battery	95.53	53.50	48.05	25.34
2	4 kWp PV 50 kWh EV battery[1]	48.22	40.57	44.06	37.07
3	6 kWp PV	42.79	41.56	27.82	27.03
4	16 kWp PV	45.66	45.66	18.25	18.25
REC		**29.74**	**40.05**	**36.15**	**44.00**

[1]EV with option for bi-directional charging

As can be expected, the "egoistic" strategy SIM yields higher rates of self-sufficiency (the share of total consumption covered by local production) for producing members than the centrally optimized SIM+OPT strategy, especially for those owning a battery. However, optimization can improve the overall self-sufficiency of the community in the given setting by $\approx 10\%$. The self-supply (the share of locally used electricity over total production) can be increased by about 8%. This improvement in overall performance figures is reached by sharing energy. Members without own production benefit from locally produced surplus electricity shared within the community. Producing members, on the other side, have to receive monetary compensations from the community for providing surplus electricity.

[6] https://www.apcs.at/en/clearing/physical-clearing/synthetic-load-profiles

[7] "cloudcover" collected from https://open-meteo.com/ and updated every 6 hours

In practice, a centrally optimized system will be hard to implement, as individuals are – naturally – not willing to transfer consumption decisions to a central planning unit. For this purpose, we aim to develop a suitable pricing scheme that induces members to replicate the system-optimal behavior. Moreover, we plan to extend the optimization framework to incorporate various heating technologies, as sector coupling can make a significant contribution to efficient energy use.

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