



Mixed-integer linear programming based optimization strategies for renewable energy communities



Armin Cosic^a, Michael Stadler^{a, c}, Muhammad Mansoor^{a, b, *}, Michael Zellinger^a

^a BEST - Bioenergy and Sustainable Technologies GmbH, Inffeldgasse 21b, A-8010, Graz, Austria

^b Energy Economics Group, Institute of Energy Systems and Electrical Drives, Vienna University of Technology, Gußhausstraße 25 – 29/E37003, 1040, Vienna, Austria

^c Xendee Corporation, 6540 Lusk Blvd., Suite C225, San Diego, CA 92121, USA

ARTICLE INFO

Article history:

Received 5 February 2021

Received in revised form

9 July 2021

Accepted 20 July 2021

Available online 23 July 2021

Keywords:

Energy Communities

Renewable Energy

Microgrids

MILP

Optimal Planning

Decarbonization

ABSTRACT

Local and renewable energy communities show a high potential for the efficient use of distributed energy technologies at regional levels according to the Clean Energy Package of the European Union. However, until now there are only limited possibilities to bring such energy communities into reality because of several limitation factors. Challenges are already encountered during the planning phase since a large number of decision variables have to be considered depending on the number and type of community participants and distributed technologies. This paper overcomes these challenges by establishing a mixed-integer linear programming based optimal planning approach for renewable energy communities. A real case study is analyzed by creating an energy community testbed with a leading energy service provider in Austria. The case study considers nine energy community members of a municipality in Austria, distributed photovoltaic systems, energy storage systems, different electricity tariff scenarios and market signals including feed-in tariffs. The key results indicate that renewable energy communities can significantly reduce the total energy costs by 15% and total carbon dioxide emissions by 34% through an optimal selection and operation of the energy technologies. In all the optimization scenarios considered, each community participant can benefit both economically and ecologically.

© 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

The decarbonization of the energy sector requires renewable energy measures to enable a clean energy transition [1]. While there are different actions and strategies undergoing, renewable energy based microgrids are on the rise to contribute to affordable and clean energy [2]. The renewable energy based microgrids provide extensive opportunities in terms of different perspectives. The environmental perspective of such microgrids has been provided by Tabar et al. [3] by proposing the sustainable planning of hybrid microgrids towards minimizing the environmental pollution. The economic perspective of renewable energy based microgrids has been addressed by Basu et al. [4] by providing a comprehensive survey of the microgrids. The social perspective of renewable energy based microgrids has been highlighted by

Schwaegerl and Tao [5] together with technical benefits of the microgrid operation. The concept of energy sharing among different actors of microgrids to reduce carbon emissions and economic costs for infrastructure and services compared to a business as usual case is one of the major advantages of renewable energy based microgrids. This concept of energy sharing is deployed through the setup of an Energy Community (EC) [6]. The energy sharing in communities turns individual consumers into prosumers, sharing the surplus energy with other members of the microgrid.

1.1. Motivation and current status of energy communities in Austria and EU

ECs hold a significant role in the clean energy transition presented by the Clean Energy Package (CEP) [7]. There are two types of energy communities presented in CEP based on two different directives. The Directive 2018/2001 [8] presents the Renewable Energy Community (REC). The Directive 2019/944 [9] presents the Citizen Energy Community (CEC). This research work is focused on

* Corresponding author. BEST - Bioenergy and Sustainable Technologies GmbH, Inffeldgasse 21b, A-8010, Graz, Austria.

E-mail address: muhammad.mansoor@best-research.eu (M. Mansoor).

Nomenclature		Superscript	
<i>Abbreviations</i>		gc	grid connection
DER	distributed energy resources	in	input for storage
DER-CAM	distributed energy resources - customer adoption model	loss	loss of stored energy
DR	demand rates	out	output from storage
ESS	energy storage system	perf	performance
HH	household tariff	ps	purchase or sale
HWB	hot water boiler tariff	RecExp	electricity related to the renewable energy community export
LA	local authority tariff	RecPur	electricity related to the renewable energy community purchase
MILP	mixed-integer linear programming	ref	reference
OC	optimization case	stored	state of the energy in the storage
P2P	peer-to-peer	trans	transfer
PV	photovoltaic system	UtExp	electricity related to the utility export
RC	reference case	UtFix	fixed utility fee
REC	renewable energy community	UtMax	electricity related to the maximum utility purchase
SOC	state of charge	UtPur	electricity related to the utility purchase
<i>Mathematical Symbols</i>		XOR	binary variable
δ	binary variable or parameter	ESSin	electricity input to the energy storage system
η	efficiency parameter	ESSons	onsite usage of the electricity related to the energy storage system
γ	cost constraint parameter	ESSout	electricity output of the energy storage system
Π	annuity rate of the technology	ESSRecExp	exported energy storage system electricity to the renewable energy community
ρ	parameter for the state of the charge	<i>Subscripts</i>	
Θ	loss factor	char	charge rate of the storage
ζ	energy rate associated with the electricity, €/kW or €/kWh	dis	discharge rate of the storage
C	costs, €	invest	annualized investment
Cap	capacity of the technology, kW for PV and kWh for ESS	lim	limit on the costs
E	variable associated with the electricity, kW or kWh	O&M	operation and maintenance
ESS	variable associated with the energy storage system electricity, kW or kWh	tech	technologies
FixC	fixed capital cost, €	up	upfront
N	arbitrary large number	d	daytypes
PV	normalized photovoltaic performance, kW/kW _p	h	hours
VarC	variable capital cost, €/kW or €/kWh	m	months
ϕ	charging or discharging rate of the storage	n, n'	nodes: n and n' are aliases
		t	time

a real case study of a microgrid based REC in Austria. For many EU countries, the concept of energy sharing in communities is still new from a legislative point of view [10]. In order to promote decentralized energy supply and strengthen regional supply concepts, RECs receive increased attention in Austria currently. Energy communities are legally defined and anchored in the Erneuerbaren Ausbaugesetzes (EAG) [11]. According to EAG §74 paragraph 1, a REC can produce energy from renewable sources and consume, store or sell the produced energy. Therefore, for each community member it is possible to exchange energy from renewable sources (such as PV, wind power, combined heat and power systems, fuel cells and energy storage systems) within the defined community. The membership is open to private individuals, small and medium-sized enterprises (SMEs), public authorities (including municipalities), climate and energy model regions, e5-communities (a community which fulfills certain rules to be more efficient) and tourism regions. To create a financial incentive for the participants, a reduced distribution grid tariff is introduced for the electricity exchanged within the REC, as well as other financial advantages such as the cancellation of all electricity taxes and green electricity fees.

1.2. State-of-the-art literature review

The state-of-the-art literature review consists of the following subjects: energy sharing in RECs, the current state of different optimization models of RECs in microgrids and the application of these models to the optimal planning of RECs in microgrids.

Energy sharing has been discussed extensively in the literature recently, with a special focus on Peer-to-Peer (P2P) local markets where energy surplus is traded. Park and Yong [12] have provided a comprehensive review on the P2P electricity trading with a focus on providing potential development and future challenges for governments and private corporations that are interested in energy sharing. A comprehensive review of existing P2P energy trading projects has been provided by Zhang et al. in [13] with a focus on their use in local energy microgrids. Recently, P2P energy sharing has also been researched using decentralized models via bilateral contracts, auction models and blockchain based models. The Brooklyn Microgrid [14] considers a blockchain based microgrid energy market to satisfy the request of the energy management. Leong et al. [15] propose an auction based P2P energy trading mechanism via a Bayesian game bidding strategy. Morstyn et al.

[16] propose P2P energy trading via bilateral contracts for a new scalable market design. Long et al. [17] have investigated energy sharing for different Distributed Energy Resource (DER) producers in a community microgrid with PV and battery systems. Reihani et al. [18] propose a framework to consider energy sharing that allows energy buyers to reduce their energy costs by exchanging energy with neighbouring peers and local utility. Cui et al. [19] present an efficient energy sharing mechanism for various prosumers in an energy community. A recent study by Lin et al. [20] considers the optimal energy sharing of solar PV, wind power and battery among different residential houses with a time resolution of only 24-hours. The studies mentioned above consider the renewable and battery energy sharing among the microgrid participants based only on the operation phenomenon, neglecting the optimal investment of the DER technologies. It is completely different to optimally design a microgrid with DER investments and optimal energy sharing than just operate the already established microgrids. It is because of the fact that the fixed sizing of the DER technologies of the already established microgrids can pose certain limitations on the energy sharing among participants. Moreover, the variability of renewable energy technologies such as solar PV and wind power can affect the energy sharing among microgrid participants in different times of the year. Hence, an optimal renewable energy sharing mechanism can not be guaranteed. Therefore, it is important to develop certain models which consider both the optimal planning of microgrids and the optimal energy sharing from DER technologies in an energy community setup with at least a yearly time horizon.

Microgrids connect various renewable energy resources and create a dynamic and complex integrated energy system [21]. The optimal planning of such microgrids within the REC infrastructure requires advanced modeling techniques that can bring such systems into reality. It is mainly due to the large number of decision variables related to the number of community participants and the distributed technologies involved. Huang et al. [22] propose a Mixed-Integer Linear Programming (MILP) based peer-to-peer energy trading mechanism in a microgrid with a distributed PV and battery energy storage system. The objective function considered is the minimization of the total energy costs of all individual participants of the microgrid. The capacities of the technologies were assumed to be fixed in the case study. Although the previously mentioned study contributes towards renewable energy based microgrids, it can not be applied to the optimal planning of such microgrids in RECs. Fleischhacker et al. [23] use an open source model to perform portfolio optimization to establish an energy community in a city district. Although the complex multi-energy system proposed in [23] considers the minimization of the costs and carbon emissions on a district level, it is limited in providing an optimal planning of RECs with different utility tariffs, demand rates and market signals including feed-in-tariffs for a microgrid. Also, different clustering techniques have been used to disaggregate the time-series input data, which makes the optimization models vulnerable with respect to time series connectivity of technologies. To overcome this disadvantage, full-scale yearly optimization techniques based on 8760-hours have been used recently for the planning of renewable energy microgrids such as the optimal planning of a thermal energy system with a seasonal storage in [24], a performance comparison of two different MILP-based models including 8760-hours for 13 different microgrid case studies in [25] and the use of a 8760-hours modeling approach for the optimal planning of microgrid technologies including hydrogen electrolyzer, hydrogen seasonal storage and hydrogen mobility for a case study in Austria in [26]. Zwickl-Bernhard and Auer [27] have recently examined a cost minimizing energy technology portfolio using an open source energy model with MILP for an energy

community in Vienna, Austria. Although the study reported in [27] supports sustainable urban energy planning in the community structure, it is limited in not using the full-scale optimization and also not considering the yearly operational energy scheduling of the technology portfolio.

The mechanism of renewable energy sharing within the community participants can be profitable if the self-consumption of renewable electricity generated is increased. The aggregation of the load of different prosumers can also increase the profitability. Fina et al. [28] have analyzed the sharing of rooftop PV generation in multi-apartment buildings. The maximization of the value of PV in apartment buildings with different arrangements have been studied in [29]. Fleischhacker et al. [30] have proposed a game theoretic model with a welfare maximization for the shared use of a solar PV and energy storage system in a multi-apartment building. These previously mentioned studies only consider the application of renewable energy transfer in apartment buildings. It is necessary to diversify the application of the optimization models and include different kind of end users to have a genuine concept of a community setup. It is also important to have a mixture of prosumers and consumers inside an energy community to realize different energy sharing mechanisms. A recent study by Perger et al. [31] considers a linear optimization model with different prosumers (apartments, businesses, etc.) in an energy community concept for energy sharing under willingness-to-pay criteria. The energy tariffs considered by Perger et al. [31] for the purchase and sale of the energy to the grid and within the community are fixed retail electricity prices. Another recent study by Jiang et al. [32] considers a two-stage optimization model for renewable energy sharing among prosumers and consumers of an energy community setup. The optimization model considered by Jiang et al. [32] is based on a single day *i.e.* 24-hours time horizon and considers time-of-use tariffs only. Both Perger et al. [31] and Jiang et al. [32] assume same energy prices for all participants (prosumers and consumers) and do not consider demand charges and variable market signals including feed-in tariffs. Therefore, the applications of such optimization models are limited and different electricity tariff scenarios and market signals including feed-in tariffs should be considered to realize the real-life renewable energy based community microgrid setups.

1.3. Contribution beyond the state-of-the-art

This research work overcomes the above mentioned gaps in the state-of-the-art and goes beyond it. The main contribution of this research work relative to the already existing studies is provided below:

A key difference to the existing literature is the development of an advanced MILP framework for the optimal planning and the optimal operation dispatch with the option of transferring renewable energy between the energy community participants (nodes), combined with newly introduced node-specific time-of-use electricity rates and market signals using a full-scale optimization horizon. A real case study is analyzed for both the optimal investment and operation dispatch planning of a renewable energy community testbed in a microgrid setup with a leading energy service provider in Austria. Although other technologies can be considered, this REC considers multiple PV and Energy Storage System (ESS) as decentralized and centralized technologies in the community. The REC testbed considers nine diversified community participants (three households, three apartments, a government institution, a fire fighting station and a bank) connected to the utility grid. The developed MILP model considers each participant as a separate node of the microgrid system with a full-scale time horizon *i.e.* 8760-hours. Three different reference and optimization

cases are analyzed and considered with the corresponding MILP model using different electricity tariff scenarios and market signals including feed-in tariffs.

The presented MILP model considers three different reference cases without renewable energy transfer. The first reference case represents the current status of the participants and considers the existing PV systems without demand rates. The second and third reference cases are greenfield scenarios and consider only the utility purchase (no existing PV) without demand rates (second reference case) and with demand rates (third reference case). After setting up the reference cases, the optimization is performed relative to each reference case, where the renewable energy transfer is enabled among the community participants and further investment options are enabled. For all cases, the total annual energy costs and the total annual CO₂ emissions of the energy community are calculated through a cost minimization of the MILP model. The results include the optimal sizing and the full-year operational dispatch of the technologies. Furthermore, the results also include the comparisons with the reference cases in terms of the energy costs and CO₂ savings, the total annual energy costs per node and the distributed renewable energy to each node for the different tariff scenarios.

This paper is structured as follows: Section 2 describes the detailed formulation of the optimization problem. Section 3 provides the detailed information of the case study and its testing. Section 4 discusses the detailed results followed by the conclusion in Section 5.

2. Mathematical formulation of the optimization problem

The methodology considers an optimization model using a MILP framework based on the Distributed Energy Resources - Customer Adoption Model (DER-CAM) [33] and further developed within this research to include the additional decision variables for the surplus energy at a single node, the energy transfer between multiple nodes with the corresponding financial constraints and different electricity tariff scenarios with a yearly time horizon. A major difference to the existing literature is the new option for the renewable energy transfer between the nodes (community members) combined with the newly introduced node-specific time-of-use electricity rates using a full-scale optimization horizon (i.e. a full linked year). With this time horizon, volatile energy supply systems as well as seasonal energy transfer can be considered directly and hourly based electricity rates can be considered in the optimization. Therefore, this MILP framework considers the full-scale optimization i.e. 8760-hours by extending the previously MILP framework (with time series in terms of 24-hours based three representative daytypes for each month) having months $m \in \{1, 2, \dots, 12\}$, daytypes $d \in \{1, 2, 3\}$ and hours $h \in \{1, 2, \dots, 24\}$ [34] with $t \in \{1, 2, \dots, 8760\}$.

2.1. Objective function

The MILP optimization framework minimizes the total energy costs, the total CO₂ emissions of a REC and it considers different utility rates of the individual participants. In this case, the optimization is performed from the perspective of the operator of a REC and thus according to the community total energy costs. The simplified objective function related to the total annual energy costs C can be represented by eq. (1).

$$C = \sum_n C_n = \sum_n \left(\sum_{tech} DER_{invest} + \sum_t C_{utility} + \sum_t C_{O\&M} \right) \quad (1)$$

where C_n is the annual energy cost per node, DER_{invest} is the

annualized investment cost per technology $tech$ and $C_{utility}$ is related to the electrical purchase minus sales to the utility grid or to the community members. The $C_{O\&M}$ variable is related to the operation and maintenance costs.

DER_{invest} can be further described as shown in eq. (2) and eq. (3).

$$DER_{invest} = \sum_{tech} (C_{up} \Pi_{tech}) \quad (2)$$

$$C_{up} = VarC_{tech} Cap_{tech} + FixC_{tech} \quad (3)$$

where C_{up} are the upfront capital costs of the technology, Π_{tech} is the annuity rate of the technology, which gives the present value of the technology in terms of the annuity, the interest rate, and the number of annuities i.e. lifetime of the technology, $VarC_{tech}$ are the variable capital costs of the technology, Cap_{tech} is the technology capacity to be invested and $FixC_{tech}$ are the fixed capital costs of the technology. The variable capital costs vary with the amount of capacity that is invested, while the fixed capital costs are independent of the size of the technology and can cover engineering costs.

To accurately reflect the additional cost possibilities for the renewable energy transfer within a REC, two new cost variables have been added to the total $C_{utility}$ costs, which are further described in eq. (4). Furthermore, all electricity rates related to the utility purchase are node-specific in this model, so that different tariff scenarios for each node and customer can be tracked explicitly.

$$\begin{aligned} \sum_{n,t} C_{utility} = & \sum_{n,t} E_{n,t}^{UtPur} \zeta_{n,t}^{UtPur} - \sum_{n,t} E_{n,t}^{UtExp} \zeta_t^{UtExp} + \sum_n C_n^{UtFix} \\ & + \sum_{n,t} E_{n,t}^{UtMax} \zeta_{n,t}^{UtMax} + \sum_{n,t} E_{n,t}^{RecPur} \zeta^{RecPur} \\ & - \sum_{n,t} E_{n,t}^{RecExp} \zeta^{RecExp} \end{aligned} \quad (4)$$

where $E_{n,t}^{UtPur}$ is the purchased electricity from the utility at node n , $\zeta_{n,t}^{UtPur}$ is the node-specific TOU-rate for the electricity purchase from the utility, $E_{n,t}^{UtExp}$ is the exported electricity to the utility at node n and ζ_t^{UtExp} is the rate for the electricity export. C_n^{UtFix} is the yearly utility fee at node n , $E_{n,t}^{UtMax}$ is the maximum purchased electricity from the utility during the whole year at node n and $\zeta_{n,t}^{UtMax}$ is the node-specific yearly power demand rate. Note that the REC-based electricity purchase and export prices are different as described in the case study below addressed in section 3.

$E_{n,t}^{RecPur}$ is the newly introduced purchased electricity from other REC members at node n , ζ^{RecPur} is the energy community rate for the REC-based electricity purchase defined by the community operator, $E_{n,t}^{RecExp}$ is the exported electricity to the REC at node n and ζ^{RecExp} is the defined rate for the electricity export to the REC.

Furthermore, in order to avoid higher individual costs for each participant (node) in a community setup, the total annual energy costs per node C_n can also be limited in the optimization by the cost constraint of C_n^{lim} according to the eq. (5) and eq. (6) so that the individual costs per node/client in the REC are not exceeding the individual reference costs.

$$C_n^{lim} = (1 + \gamma) C_n^{ref} \quad (5)$$

$$C_n \leq C_n^{lim} \quad (6)$$

where C_n^{ref} are the costs associated with the reference case at node n and γ is the cost constraint parameter responsible for

limiting the total annual energy costs per node.

The simplified objective function related to the total annual carbon dioxide emissions can be represented by eq. (7). It is the summation of the carbon dioxide emissions occurred in providing the electricity from the grid at each node n . Carbon dioxide emissions from other technologies such as a combined heat and power system running on natural gas can be considered in principle, but only electricity from grid is considered as a source of carbon dioxide emissions in this study.

$$CO_2 = \sum_{n,t} CO_{2\text{grid}} \quad (7)$$

2.2. Technology constraints

The case study addressed in sub-section 3 considers mainly two distributed energy technologies for the production and storage of renewable energy shared within the REC, including the photovoltaic (PV) technology and the energy storage system (ESS), since this is the major focus of the current legislation.

The electricity provided by the PV technology is given by eq. (8).

$$E_{n,t}^{\text{solar}} = Cap_n^{\text{PV}} PV_{n,t}^{\text{perf}} \quad (8)$$

where $E_{n,t}^{\text{solar}}$ is the electricity provided by the solar PV technology at node n , Cap_n^{PV} is the capacity of the solar PV technology at node n and $PV_{n,t}^{\text{perf}}$ is the normalized solar PV performance at the corresponding location, which depends on the location, orientation, temperature and panel types.

The energy storage system (ESS) can be represented by eq. (9).

$$ESS_{n,t}^{\text{stored}} = ESS_{n,t-1}^{\text{stored}} + ESS_{n,t}^{\text{in}} - ESS_{n,t}^{\text{out}} - ESS_{n,t}^{\text{loss}} \quad (9)$$

where $ESS_{n,t}^{\text{stored}}$ represents the State of Charge (SoC) of the ESS at node n , $ESS_{n,t}^{\text{in}}$ is the input for ESS, $ESS_{n,t}^{\text{out}}$ is the output from the energy storage, $ESS_{n,t}^{\text{loss}}$ is the energy lost in the ESS. The energy losses can be represented by eq. (10).

$$ESS_{n,t}^{\text{loss}} = ESS_{n,t-1}^{\text{stored}} \Theta_{\text{ESS}} \quad (10)$$

where Θ_{ESS} is the coefficient of loss for the ESS. The energy storage constraints are given by eq. (11–16).

$$ESS_{n,t}^{\text{stored}} \leq Cap_n^{\text{ESS}} \quad (11)$$

$$Cap_n^{\text{ESS}} \rho_{\text{SoC}}^{\text{min}} \leq ESS_{n,t}^{\text{stored}} \leq Cap_n^{\text{ESS}} \rho_{\text{SoC}}^{\text{max}} \quad (12)$$

$$ESS_{n,t}^{\text{in}} = E_{n,t}^{\text{ESSin}} \eta_{\text{char}} \leq Cap_n^{\text{ESS}} \phi_{\text{char}}^{\text{max}} \quad (13)$$

$$ESS_{n,t}^{\text{out}} = E_{n,t}^{\text{ESSout}} \eta_{\text{dis}} \leq Cap_n^{\text{ESS}} \phi_{\text{dis}}^{\text{max}} \quad (14)$$

$$ESS_{n,t}^{\text{in}} \leq ESS_{n,t}^{\text{XOR}} N \quad (15)$$

$$ESS_{n,t}^{\text{out}} \leq (1 - ESS_{n,t}^{\text{XOR}}) N \quad (16)$$

where Cap_n^{ESS} is the capacity of the ESS at node n , $\rho_{\text{SoC}}^{\text{min}}$ and $\rho_{\text{SoC}}^{\text{max}}$ are the minimum and maximum SOC of the ESS, η_{char} and η_{dis} are the charging and discharging efficiencies of the ESS, $\phi_{\text{char}}^{\text{max}}$ and $\phi_{\text{dis}}^{\text{max}}$

are the maximum charging and discharging rates of the ESS, $ESS_{n,t}^{\text{XOR}}$ is the binary input for avoiding simultaneous charging and discharging of the ESS at node n and N is an arbitrary large number.

2.3. Energy balance and constraints

In a REC constellation the electricity provided by the solar PV technology at node n $E_{n,t}^{\text{solar}}$ can be divided into three PV electricity components, corresponding to three decision variables given by eq. (17)

$$E_{n,t}^{\text{solar}} = E_{n,t}^{\text{onsite}} + E_{n,t}^{\text{UtExp}} + E_{n,t}^{\text{RecExp}} \quad (17)$$

where $E_{n,t}^{\text{onsite}}$ is the onsite usage of the electricity provided by the PV technology at node n , which can be used to satisfy the demand or charge the onsite battery at node n , if one exists. $E_{n,t}^{\text{ExpUt}}$ is the exported PV electricity to the utility and $E_{n,t}^{\text{RecExp}}$ is the exported PV electricity to the REC participants at node n when there is a demand for electricity.

The constraints given by eqs. (18) and (19) serve to prevent simultaneous import and export to/from the utility if a grid connection exists, i.e. binary parameter $\delta^{\text{gc}} \neq 0$, otherwise both $E_{n,t}^{\text{UtPur}}$ and $E_{n,t}^{\text{UtExp}}$ will be fixed at zero.

$$E_{n,t}^{\text{UtPur}} \leq (\delta_{n,t}^{\text{ps}} \delta^{\text{gc}}) N \quad (18)$$

$$E_{n,t}^{\text{UtExp}} \leq ((1 - \delta_{n,t}^{\text{ps}}) \delta^{\text{gc}}) N \quad (19)$$

where $\delta_{n,t}^{\text{ps}}$ is related to the binary electricity purchase or sell decision variable at node n and N is an arbitrary large number.

Moreover, the electricity which is stored and provided by the ESS technology at node n can also be divided into two ESS components, corresponding to two decision variables given by eq. (20)

$$E_{n,t}^{\text{ESSout}} = E_{n,t}^{\text{ESSons}} + E_{n,t}^{\text{ESSRecExp}} \quad (20)$$

where $E_{n,t}^{\text{ESSons}}$ is the onsite usage of the electricity provided by the ESS at node n and $E_{n,t}^{\text{ESSRecExp}}$ is the exported ESS electricity to the REC. Note that in this REC model also centralized community PV and ESS technologies are possible as long as a node n for a “centralized” technology location has been specified. Thus, the model can make decisions on decentralized individual PV and ESS technologies at each node/building and also provide electricity from PV and ESS for the entire REC in one location.

For the renewable energy transfer option within the REC a new transfer variable has been introduced given by eq. (21)

$$\sum_{n'} E_{n,n',t}^{\text{trans}} = E_{n,t}^{\text{RecExp}} + E_{n,t}^{\text{ESSRecExp}} \quad (21)$$

where $E_{n,n',t}^{\text{trans}}$ is related to the renewable energy transfer from node n to node n' and is given by the sum of the total exported electricity from the PV and ESS technology within the REC. This is also the total electricity amount that can be purchased by other community members from a node n .

The higher level energy balance equation for the overall model is given by eq. (22).

$$\begin{aligned} E_{n,t}^{\text{UtPur}} + \sum_{n'} E_{n,n',t}^{\text{trans}} + E_{n,t}^{\text{onsite}} + E_{n,t}^{\text{ESSons}} + E_{n,t}^{\text{UtExp}} \\ = E_{n,t}^{\text{load}} + E_{n,t}^{\text{ESSin}} + E_{n,t}^{\text{solar}} \end{aligned} \quad (22)$$

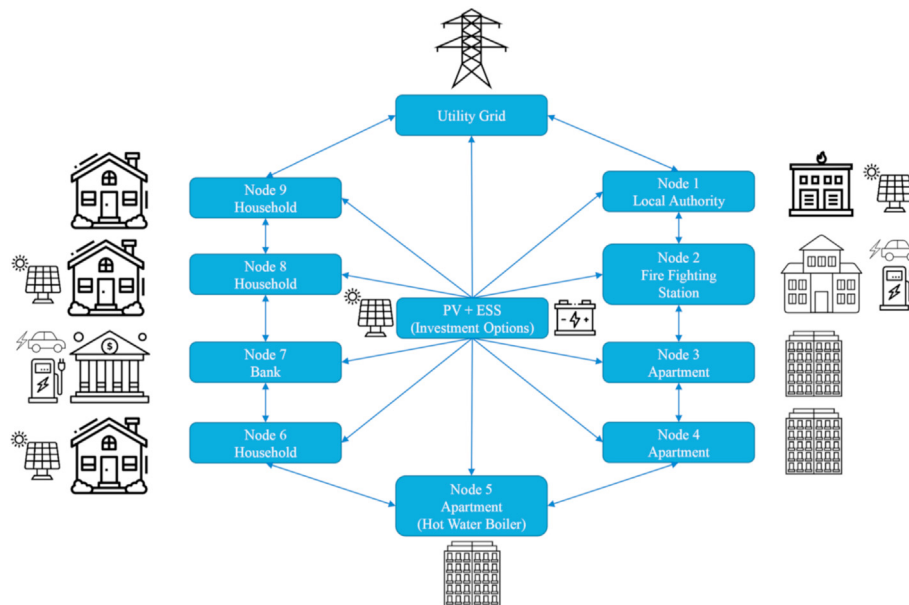


Fig. 1. The network topology of the renewable energy community testbed at a village in Carinthia (Austria) with central investment options and other existing technologies.

where $E_{n,t}^{\text{load}}$ is the electrical load demand at node n and $E_{n,t}^{\text{sales}}$ are the total remaining electricity sales to the utility at node n .

3. Case study

This section includes the details and the approach of designing the real case study for a small-scale REC testbed with nine community participants in a village in Carinthia, Austria of which six are consumers and three are prosumers with an existing PV system. It also includes the time series data analysis, the technical and economical details of the technologies, assumptions and the optimization strategy.

3.1. Renewable energy community

The setup of the testbed is based on the characteristics of a typical REC aiming to share the renewable energy produced within the community at a local level. In addition to the necessary technical setup of the REC, the project focuses on the active participation of citizens, community and local initiatives in order to create a solution that fully exploits the positive effects of a REC.

In the municipality of this village in Carinthia, a total of nine project participants have agreed to participate in a REC consisting of the local authority, a fire department, a bank, a residential building (two households and one electrical hot water boiler profile) and three single-family households. In addition, the fire department has an existing PV system with a peak power of 17.68 kW_p and two of the single-family households have already a PV system with a peak power of 4.2 kW_p and 2.6 kW_p, where the surplus PV electricity is sold to the utility at a certain feed-in tariff in the reference case. By transferring to an REC, the surplus PV electricity produced by the individual participants can be distributed to the community members (nodes) at a reduced network tariff, which means that less electricity has to be purchased from the public grid, thus saving costs and carbon emissions. Moreover, greenfield scenarios without existing PV technologies are also considered in order to find the optimal investment decisions for this REC and whether the total energy costs can be further reduced through the expansion of renewable energies. Furthermore, all

participants are located on one network level (low voltage distribution network). The current network topology of the REC testbed with the existing technologies is shown in Fig. 1. Although the investments in PV and ESS are considered in a centralized approach in this topology, further decentralized investments in PV and ESS are also possible in each individual node together with the existing decentralized technologies.

3.2. Time series input data analysis and assumptions

The responsible Distribution System Operator (DSO) in this region is the KNG-Kärnten Netz GmbH, who are co-initiators of this REC project and provided the electrical load profile data of the community. The electrical load profiles of the individual participants are synthetically generated load profiles based on real smart-meter measurements in a 15 min time interval for a whole year. The hourly based electric load data are shown in Figs. 2–3.

Moreover, the corresponding histograms for each demand are shown in Fig. 4 to provide a visual representation of the electrical

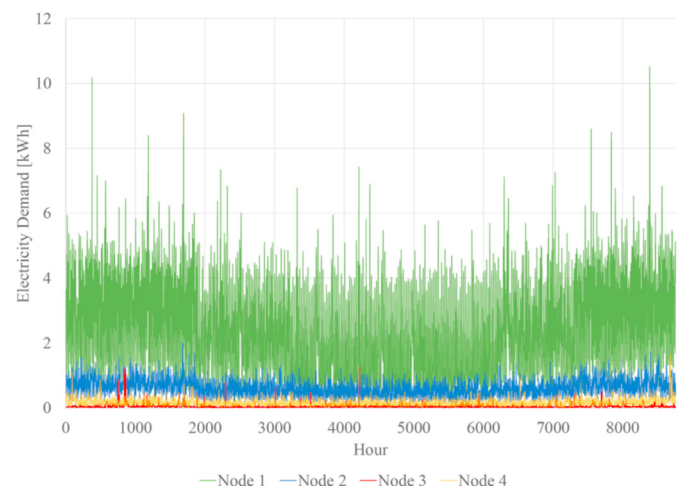


Fig. 2. The hourly electrical demand profile of node 1–4.

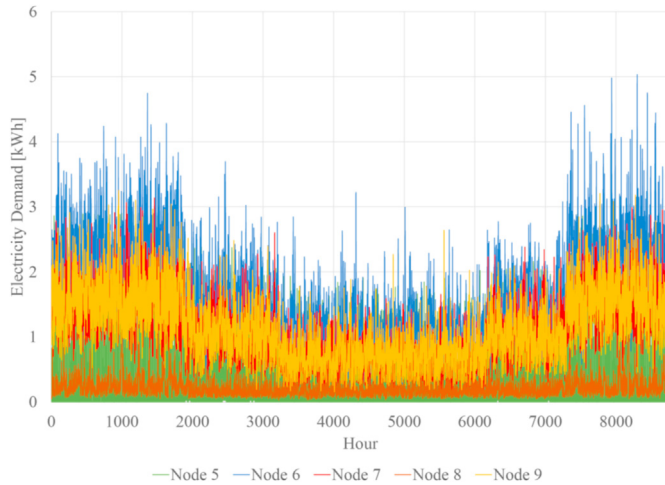


Fig. 3. The hourly electrical demand profile of node 5–9.

load data distributions in relation to the number of hours.

Furthermore, the maximum power and yearly electricity consumption for each community participant (node) and type are reported in Table 1. The total annual consumption of the whole REC is approximately 63,902 kWh/a with an hourly peak load of 18.32

kW_p when the individual electricity consumptions are aggregated to a total load.

For the determination of the electricity provided by the existing PV technologies at the location the solar PV performance is required at the site. The solar PV performance is retrieved from Meteonorm [35] with an hourly time horizon. Meteonorm explicitly provides the hourly values of the PV performance of a typical medium sized plant with crystalline silicon modules and an efficient inverter for a whole year. These data are shown in Fig. 5. The technological and economical parameters of the PV technology are addressed in sub-section 3.3.

In order to assess the CO₂ emissions correctly, the CO₂ content of the purchased electricity from the utility also needs to be considered. The marginal CO₂ emissions rate of the purchased electricity is considered in kg/kWh in this study and is shown in Fig. 6 [36] on hourly basis for the whole year. The marginal CO₂ emissions rate is based on the Austrian-mix and import-mix electricity sources. The marginal CO₂ emissions only consider the direct emissions of the fuel while generating the electricity and do not include the indirect emissions related to the fuel production and transportation.

3.3. Techno-economical parameters

The economical parameters for the solar PV and ESS include the investment parameters like fixed capital costs, variable capital costs, fixed maintenance costs and lifetime. These parameters are

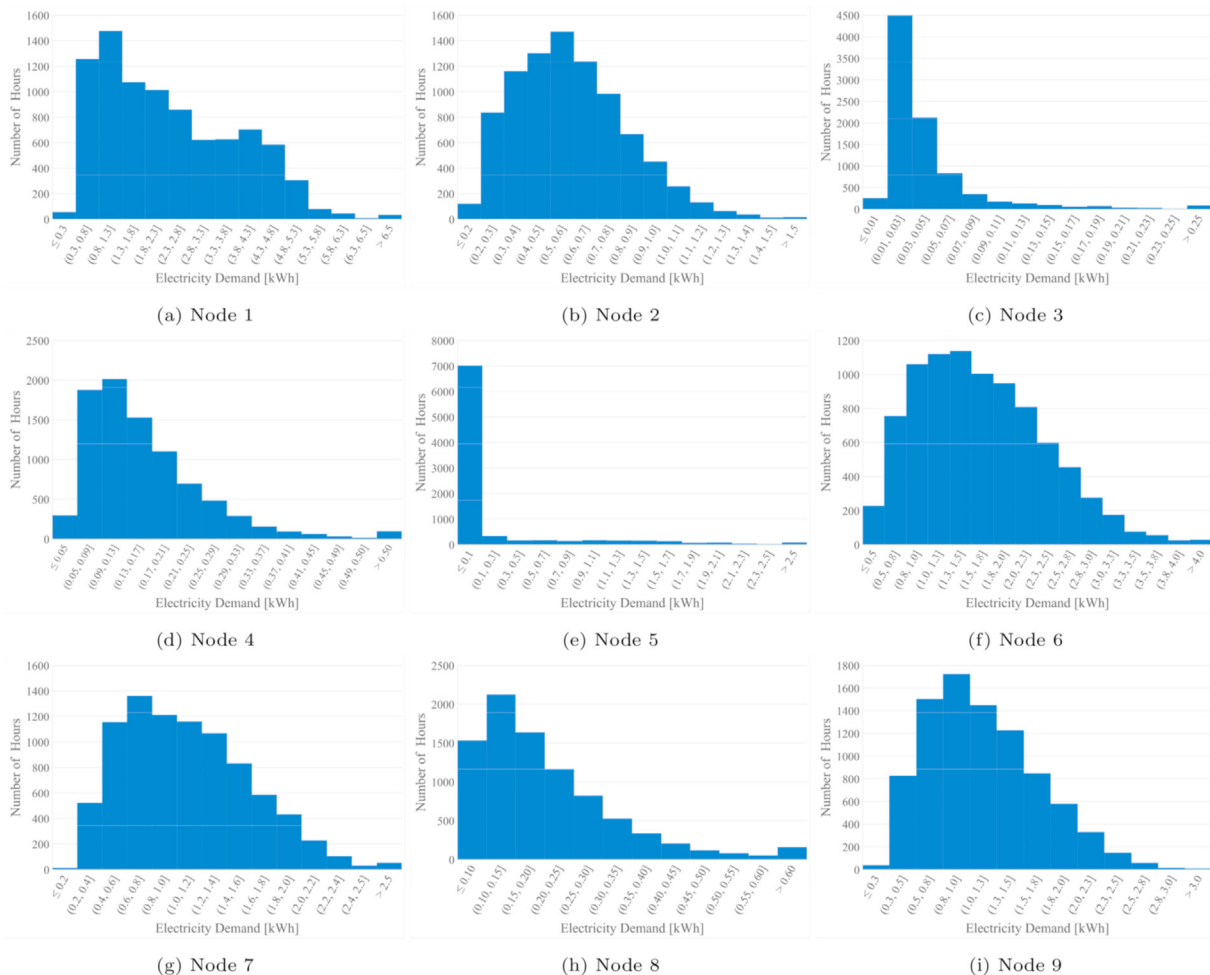
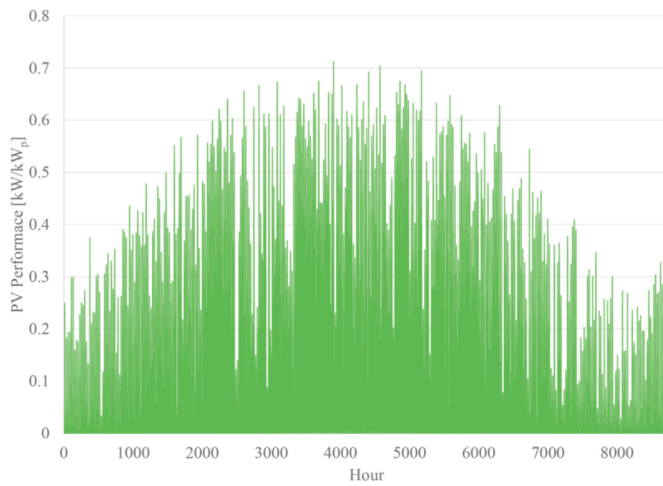
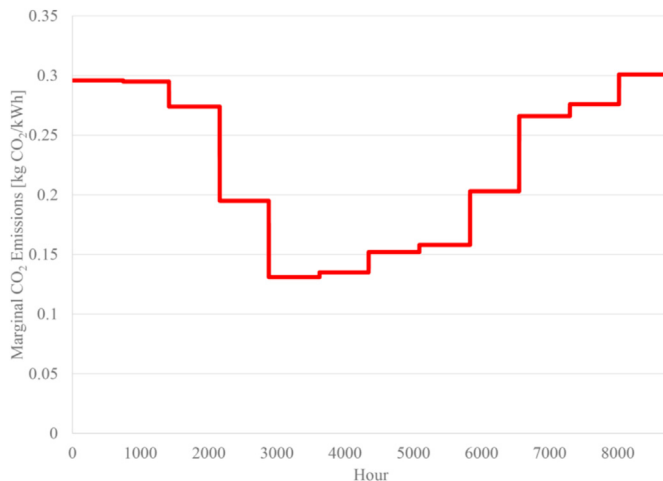


Fig. 4. The corresponding histograms for each electrical demand.

Table 1

The maximum hourly power and annual electrical load of each community participant.

Node	Type	Maximum Hourly Power [kW]	Annual Energy [kWh] per year
1	Local Authority	10.52	19,972.69
2	Fire Fighting Station	1.98	5,171.55
3	Apartment	1.26	378.10
4	Apartment	1.65	1,395.14
5	Apartment (Hot Water Boiler)	2.84	1,816.81
6	Household	5.03	14,093.83
7	Bank	3.13	9,452.83
8	Household	2.23	1,803.63
9	Household	3.25	9,817.13

**Fig. 5.** The solar PV performance data on hourly basis at the site [35].**Fig. 6.** The hourly marginal CO₂ emissions of the utility electricity [36].**Table 3**

The technical parameters of the Li-ion based ESS [39,41].

Parameter	Value
Charging Efficiency of ESS [%]	95
Discharging Efficiency of ESS [%]	95
Maximum Charge Rate [% per hour]	34
Maximum Discharge Rate [% per hour]	34
Minimum SOC of ESS [%]	20
Maximum SOC of ESS [%]	100
Self-Discharge Rate of ESS [% per hour]	0.2

given in Table 2 [37,38]. For the ESS a Lithium-ion based battery is considered. The lifetime of such Lithium-based batteries results from the stated manufacturer's warranty of ten years at a discharge depth of 100% [39]. In order to minimize battery degradation and prolong the usage of the stored renewable energy, the ESS is only operated in a SOC range of 20–100%, which according to [40] can increase the lifetime (more precisely the number of charge cycles) by 50%. Therefore a lifetime of 15 years is assumed for the ESS in this study. The interest rate is considered as 2%, which is needed for the calculation of the annuity rate for each technology.

The technical parameters for the energy storage system include the charging and discharging efficiencies, the maximum charge and discharge rates, the minimum and maximum SOC and the self-discharge rate (losses) of a typical Lithium-Ion ESS. These parameters are given in Table 3 [39,41].

In Austria, the total electricity tariff is divided into three main components consisting of an energy, a grid and a fees component with the last two components regulated by law and dependent on the respective region [42–44]. Furthermore, the Austrian sales tax of 20% must also be taken into account. The energy component of the electricity tariff for the utility purchase is based on the KELAG Home Basic tariff [45], which is commonly used for households (HH) at this site, and a special tariff for the local authority (LA) and the electrical hot water boiler (HWB) defined by the local energy supplier. Furthermore, in this case study a distinction is made between two different tariff scenarios. The first scenario refers to a pure consumption tariff without variable power demand rates for all REC members and is therefore called “Scenario Without-DR” in this study. In the second scenario there is a variable power demand rate in the grid tariff component, which refers to the yearly peak

Table 2

The economic parameters of the microgrid technologies [37,38].

Technology	Fixed Costs	Variable Costs	Fixed Maintenance Costs	Lifetime
	[€]	[€/kW or kWh for ESS]	[€/kW or kWh for ESS] per year	[Years]
PV	0	842	9	25
ESS	0	434	0	15

Table 4

The individual and summarized electricity tariff components in the REC.

Tariff Component	Unit	Without-DR			With-DR		
		HH	LA	HWB	HH	LA	HWB
Energy	€/a	39	8	0	39	8	0
	€/kWh	6.79	4.53	6.25	6.79	4.53	6.25
Grid	€/a	65.21	65.21	65.21	27.96	27.96	27.96
	€/kW _p /a	0	0	0	13.79	13.79	13.79
Fees	€/kWh	6.53	6.53	6.53	6.07	6.07	6.07
	€/a	37.35	37.35	37.35	37.35	37.35	37.35
Sales Tax	€/kWh	3.49	3.49	3.49	3.49	3.49	3.49
	%	20	20	20	20	20	20
$\zeta_{n,t}^{UtPur}$ - Variable Cost Incl. Tax	€/kWh	20.17	17.46	19.52	19.62	16.91	18.97
$\zeta_{n,t}^{UtMax}$ - Peak Load Cost Incl. Tax	€/kW _p /a	0	0	0	16.55	16.55	16.55
C_n^{UtFix} - Fixed Cost Incl. Tax	€/a	169.87	131.17	121.57	125.17	87.97	78.37

Table 5

The energy community tariff components and the summarized variable cost for the purchased electricity from the REC.

REC tariff component	Unit	Without-DR	With-DR
		HH, LA, HWB	HH, LA, HWB
Energy	€/kWh	0 or 4	0 or 4
Grid	€/kWh	2.61	2.43
Fees	€/kWh	0	0
Sales Tax	%	20	20
ζ_{REC}^{Pur} - Variable Cost Incl. Tax	€/kWh	3.13 or 7.93	2.92 or 7.72

load of each REC participant, and thus is called "Scenario With-DR". The tariffs are summarized into a variable (€/kWh), a fixed (€/a) and a peak load-related (€/kW_p/a) cost component for the optimization, which results in the following cost breakdown for the different tariff scenarios and participant types given in Table 4.

According to the current status of the negotiations surrounding the EAG, it can be assumed that the variable part of the grid component for the shared electricity within the REC will be reduced by at least 60% in order to create additional financial incentives for community members in Austria. In addition, the variable part of the fees cost component is also to be abolished. The energy price is determined by the operator of the REC or by the community participants. In this study, energy rates of 4 €/kWh are considered, which is equal to the fixed feed-in tariff to the utility of 4 €/kWh and corresponds to the current community situation with the existing PV technologies. For the greenfield investment scenarios it is assumed that no energy rates have to be paid and are therefore considered to be 0 €/kWh. The cost structure and the summarized variable energy community tariff for the purchased electricity from the REC is given in Table 5.

In addition to the fixed feed-in tariff ζ_t^{UtExp} of 4 €/kWh, also time-variable rates for the PV surplus electricity sales to the utility are considered in other greenfield optimization scenarios. This is significantly important to show how the REC reacts with different

market signals. For this the Austrian spot market prices on an hourly basis are used. This market price history is shown in Fig. 7 [46].

3.4. Optimization framework and strategy

The case study considers three different reference cases (RC) and three different optimization cases (OC) in a REC constellation related to the corresponding reference case and where the renewable energy transfer among the community participants is enabled. The different scenarios are reported in Table 6. For all cases, the total annual energy costs and the total annual CO₂ emissions are calculated through a cost minimization of the optimization model. The energy costs include the investment costs related to the PV and ESS technologies together with the electricity purchase or sales from the utility or the REC. The CO₂ emissions include the total marginal carbon dioxide emissions of the electricity purchase from the utility.

The first reference case RC-Without-DR-PV represents the current status of the participants and considers the three existing PV systems using the technical and economical parameters reported in sub-section 3.3. In this reference case, the tariff scenario without demand rates is considered for the utility purchase, which is given in Table 4. Furthermore, in this reference case, the PV surplus can only be fed into the grid at a fixed feed-in tariff of 4 €/kWh. The associated optimization case OC-Without-DR-PV determines by how much the total PV self-consumption of the REC can be increased and thus how much total annual energy costs and total annual CO₂ emissions can be saved with the prevailing tariff scenario when the renewable energy transfer between the participants is enabled.

The second and third reference cases i.e. RC-Without-DR and RC-With-DR are so-called greenfield scenarios with different tariff schemes in each case (one without and one with demand rates), where no existing PV technologies are considered. The corresponding investment and optimization cases OC-Without-DR and OC-With-DR determine how much is invested in new PV and ESS

Table 6

Different scenarios for the optimization and testing framework.

Scenario	Description
RC-Without-DR-PV	Reference case: existing PV and without demand rates
RC-Without-DR	Reference case: no existing PV; only utility purchase and without demand rates
RC-With-DR	Reference case: no existing PV; only utility purchase and with demand rates
OC-Without-DR-PV	Optimization: existing PV and without demand rates; no additional investments
OC-Without-DR	Optimization: enabled investments and without demand rates
OC-With-DR	Optimization: enabled investments and with demand rates

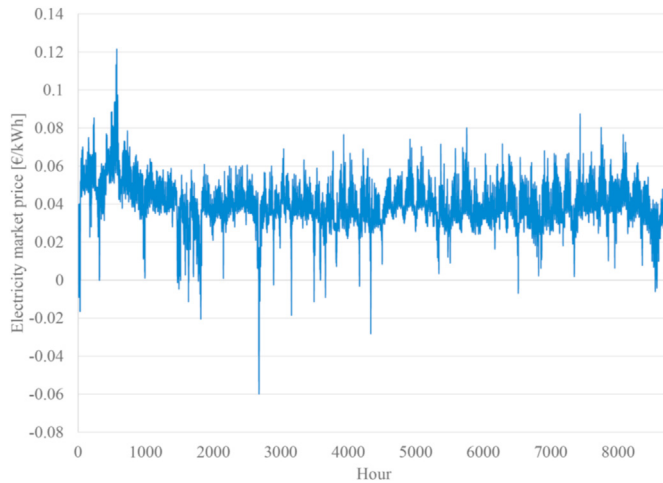


Fig. 7. The hourly EPEX spot market prices for the year 2019 in Austria [46].

technologies, and thus how much energy costs and CO₂ emissions can be saved in a REC with the optimally chosen technology capacities and enabling the renewable energy transfer. In both greenfield investment optimization cases, the spot market prices given in Fig. 7 are used for the PV surplus sales to the utility. The assumptions for all optimization scenarios are summarized in Table 7.

For all cases, the total annual energy costs and the total annual CO₂ emissions are calculated through a cost minimization of the optimization model. The results include the optimal sizing and the full-year operational dispatch of the technologies. Furthermore, the results also include the comparisons with the reference cases in terms of the energy cost and CO₂ savings, the total annual energy costs per node and the distributed renewable energy to each node for the different tariff scenarios. The optimality gap of the optimization solver was set to 0.2% for all scenarios. The MILP optimization was performed on a server with a Common KVM processor CPU 3.7 GHz and 224 GB of RAM.

4. Results

This section provides the results of the reference cases and the corresponding optimization scenarios for each node based on the different electricity tariff scenarios.

Table 7

The assumptions made regarding the REC-Purchase and Utility Sales for all optimization scenarios.

Scenario	$\zeta_{\text{REC-Pur}}^{\text{REC-Purchase}}$ [€/kWh]	$\zeta_{\text{REC-Exp}}^{\text{REC-Export}}$ [€/kWh]	$\zeta_{\text{Ut-Exp}}^{\text{Utility Sales}}$ [€/kWh]
OC-Without-DR-PV	7.93	4	4
OC-Without-DR	3.13	0	Market Prices
OC-With-DR	2.92	0	Market Prices

Table 8

The results of the reference and optimization scenarios (RC-Without-DR-PV and OC-Without-DR-PV) calculated through a cost minimization.

Scenario	PV [kW]	PV-Onsite [kWh/a]	REC-Purchase [kWh/a]	Community Energy Costs [€/a]	Cost Savings [%]	Community CO ₂ Emissions [kg-CO ₂ /a]	CO ₂ Savings [%]
RC-Without-DR-PV	24.48	6,648.19	—	12,976.25	—	13,879.25	—
OC-Without-DR-PV	24.48	6,648.19	9,694.71	11,843.70	8.73	11,839.45	14.70

4.1. Current status with existing technologies

First, the current status of the community participants is determined with the reference case scenario RC-Without-DR-PV. For this, the total electricity purchase from the grid, the produced PV electricity provided by the existing PV technologies and the respective share of the onsite PV usage, the total annual energy costs and the total annual CO₂ emissions are calculated for each node through a cost minimization using the time series input data and techno-economical parameters given in sub-sections 3.2 and 3.3 respectively.

The calculated total annual energy costs per node of the RC-Without-DR-PV reference case scenario are used as node-specific cost constraints for the optimization scenario OC-Without-DR-PV, where the renewable electricity transfer between the participants is possible. The REC participants who provide the renewable electricity to the REC ($\zeta_{\text{REC-Exp}}^{\text{REC-Export}}$) get the same energy rate as if they sold the electricity to the grid ($\zeta_{\text{Ut-Exp}}^{\text{Utility Sales}}$), i.e. 4 €/kWh. This means that the participants who sell the electricity to the other community members are not economically disadvantaged in the new REC setup. The results for the whole REC obtained from the reference (RC-Without-DR-PV) and optimization scenario (OC-Without-DR-PV) are given in Table 8. The node-specific results can be found in the Appendix A (Tables A1 and A2).

In total, an average annual PV generation of 25,083.21 kWh/a is available for the entire REC, where the existing PV systems have an aggregated peak power of 24.48 kW_p. In the reference scenario, only 6,648.19 kWh/a of the total PV generation is used for own demand (PV-Onsite), which corresponds to an average, percentage own demand coverage of approx. 26.5%. This means that the majority of the produced PV electricity is available as surplus and in this case must be fed into the grid. Through a transition to a REC, the PV own use of the community can be further increased, since in this case, the renewable electricity transfer between the community participants is enabled. Fig. 8 shows how the renewable energy is optimally distributed within the REC according to the cost minimization and how much each participant can purchase from the REC with the corresponding cost savings.

The optimization results show that the total PV own use of the REC can be increased from 6,648.19 kWh/a (26.5%) to 16,342.9 kWh/a (65.2%) as a result of the additional REC-Purchase within the community. This is due to the introduced possibility of the renewable electricity transfer between nodes, so that the electricity demand of each community participant can be satisfied with the provided renewable electricity of the PV surplus. Through this additional possibility to purchase renewable electricity from the REC, the total annual energy costs can be reduced by 8.73% as

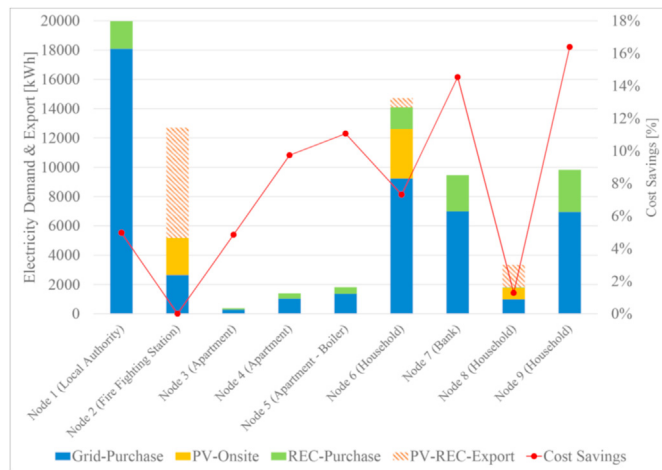


Fig. 8. The annual electricity demand of each REC participant satisfied by the calculated Grid-Purchase, PV-Onsite usage and the REC-Purchase together with the cost savings for the optimization scenario OC-Without-DR-PV. The dashed bars show how much renewable PV electricity was exported to other community participants.

the renewable electricity is purchased at a reduced energy community tariff rate (see Table 5). Moreover, since renewable electricity is purchased, the total annual CO₂ emissions can be reduced by 14.7% within the REC at the same time. Note that this only applies to CO₂ emissions within the local network and not the wider distribution grid. Furthermore, it can be seen from Fig. 8 that node 2 is exporting more PV electricity than any other node since it has the biggest PV capacity installed and, accordingly, the largest PV surplus is generated on this node, which is exported and distributed to the participants in the most cost-optimal way. Therefore, the total electricity transfer from node 2 to other nodes can be analyzed in terms of an operational dispatch through Figure A1 in the Appendix A.

4.2. Greenfield investment scenarios

In addition to the current community status, reference cases without existing PV technologies are also considered, i.e. RC-Without-DR and RC-With-DR. These scenarios correspond to the green field scenarios, where the whole electricity demand is satisfied by the purchase from the grid with the different tariff scenarios given in Table 4. The calculated total annual energy costs per node of both RC-Without-DR and RC-With-DR reference case scenarios are again used as cost constraints for the investment scenarios OC-Without-DR and OC-With-DR, where the renewable electricity transfer among the participants is enabled if a renewable generation system is selected through the performed cost optimizations. In these optimization scenarios, investments in PV generation system and ESS are considered in a centralized node. All the community nodes are connected with each other, also with this central investment node and utility grid for electricity sharing. The

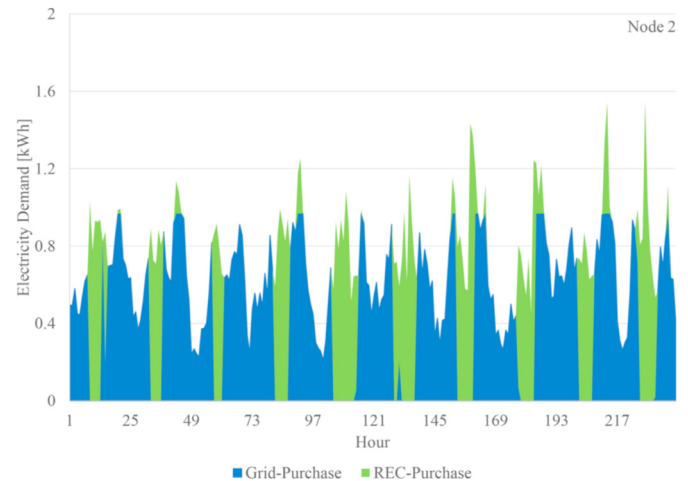


Fig. 9. The calculated electricity purchase from the grid and the REC of Node 2 determined via the optimization scenario OC-With-DR.

centralized investment node provides advantage over enabling the decentralized investments because the community can avoid the building retrofit costs and reduce the technology installation costs. Moreover, the centralized PV and ESS are much easier to maintain and monitor on the community level. The produced surplus electricity is sold to the utility at time-variable market prices on an hourly basis, which are shown in Fig. 7. The total results of the reference cases (RC-Without-DR and RC-With-DR) together with the investment decisions and objective function savings obtained from the optimization scenarios (OC-Without-DR and OC-With-DR) are given in Table 9. The node-specific results can be found in the Appendix A (Tables A3–A5).

Based on the obtained results given in Table 9, it can be seen that for both optimization scenarios, the cost minimization invests in PV technologies. In the OC-With-DR scenario, the PV capacity is being selected even larger than in the OC-Without-DR scenario. This is due to the fact that in this OC-With-DR scenario, investments are also made in a ESS technology, which means that additional PV electricity can be stored, resulting in a larger PV capacity investment and allowing more renewable electricity to be shared within the REC. Moreover, the reason for also investing in an additional ESS in the OC-With-DR scenario is that power demand rates are considered in this scenario and that power peaks can be absorbed through the use of an ESS (peak-shaving), resulting in lower peak load-related costs for each community participant. This is illustrated in Fig. 9, where the optimized electricity purchase of the first 10 days is shown. Fig. 9 shows that the Grid-Purchase is cut off by the REC-Purchase and thus flattened.

In this study, the annualized investment and maintenance costs are allocated to the community participants weighted by the amount of electricity purchased from the REC per node. This means that if a participant purchases more electricity relative to the total REC-Purchase, its investment and maintenance costs share in the

Table 9

The results of the greenfield reference (RC-Without-DR and RC-With-DR) and investment scenarios (OC-Without-DR and OC-With-DR) calculated through a cost minimization.

Scenario	PV [kW]	ESS [kWh]	REC-Purchase [kWh/a]	Community Energy Costs [€/a]	Cost Savings [%]	Community CO ₂ Emissions [kg-CO ₂ /a]	CO ₂ Savings [%]
RC-Without-DR	—	—	—	13,778.50	—	15,281.18	—
RC-With-DR	—	—	—	13,554.91	—	15,281.18	—
OC-Without-DR	46.37	—	20,129.30	11,831.10	14.13	10,899.84	28.67
OC-With-DR	52.22	14.15	23,929.76	11,481.03	15.30	10,076.12	34.06

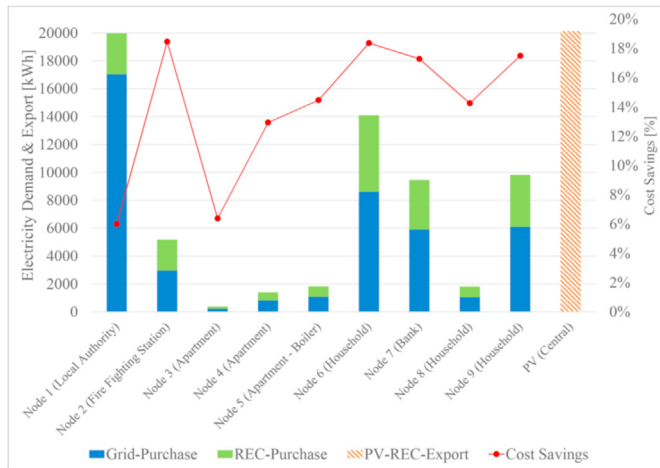


Fig. 10. The annual electricity demand of each REC participant satisfied by the calculated Grid-Purchase and the REC-Purchase together with the cost savings for the optimization scenario OC-Without-DR.

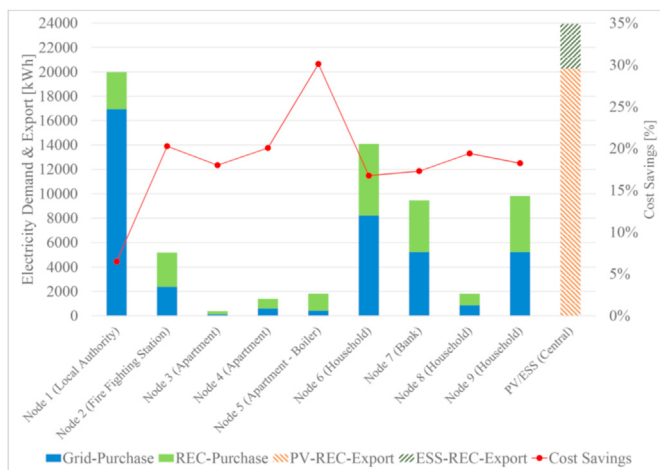


Fig. 11. The annual electricity demand of each REC participant satisfied by the calculated Grid-Purchase and the REC-Purchase together with the cost savings for the optimization scenario OC-With-DR.

technologies will also be correspondingly higher. The optimization results of each node together with the objective function savings obtained from the investment scenarios OC-Without-DR and OC-With-DR are shown in Fig. 10 and Fig. 11 respectively.

The calculated results show that with the invested technologies, the total annual community energy costs can be reduced by 14.13% and the total annual CO₂ emissions can be reduced by 28.67% within the REC in the OC-Without-DR investment scenario. Moreover, the results show that each participant in a REC constellation can benefit with a significant cost reduction of at least approx. 6% to a maximum of over 18%. In the OC-With-DR scenario with demand tariffs, the optimization results show an even higher total annual energy cost reduction of 15.3% and total annual CO₂ reduction of 34.06% within the community. This is due to the larger capacity of the invested PV technology and the additional ESS where the PV electricity can be stored, allowing more renewable electricity to be shared within the REC. This ESS allows to reduce the peak load-related costs in a targeted manner through the additional, time-limited renewable power supply of the community participants from the ESS (peak-shaving) when demand rates are used.

Furthermore, this additionally increases the total renewable energy share in the overall electricity supply of the REC, resulting in even lower CO₂ emissions when investing in a ESS. Thus, the results show that renewable energy communities can significantly reduce both energy costs and CO₂ emissions with the presented MILP-based planning approach, especially when demand-based tariffs are used for the utility purchase.

5. Conclusion

This research work addresses the decarbonization of the regional sector via targeted, MILP-based optimal planning of renewable energy communities in a microgrid constellation. It examines and analyzes a real case study, where an energy community testbed was created by a leading Austrian energy service provider in a village in Carinthia, Austria. The study considers the development of a MILP-based optimization framework, where distributed PV generation systems, energy storage systems, different electricity tariff scenarios and market signals are taken into account, so that a real REC setup can be mapped mathematically accurately and optimally planned. The case study considers in total three different reference cases and three corresponding optimization and investment scenarios in a REC setup, where the renewable energy transfer between nine community participants is enabled.

The first reference case RC-Without-DR-PV represents the current status of the participants and considers the three existing PV systems where the PV surplus can only be fed into the grid. The associated optimization case OC-Without-DR-PV determines by how much the total PV self-consumption of the REC can be increased and thus how much total annual energy costs and total annual CO₂ emissions can be saved with the prevailing tariff scenario when the renewable energy transfer between the participants is enabled. The second and third reference cases RC-Without-DR and RC-With-DR are greenfield scenarios with different tariff schemes in each case (one without and one with demand rates), where no existing PV technologies are considered. The corresponding investment and optimization cases OC-Without-DR and OC-With-DR determine how much is invested in new PV and ESS technologies, and thus how much energy costs and CO₂ emissions can be saved with the optimally chosen technology capacities. For all cases, the total annual energy costs and the total annual CO₂ emissions are calculated through a cost minimization of the optimization model.

In summary, the optimization results of the first OC-Without-DR-PV case show that the total PV own use of the REC can be increased from 26.5% to 65.2% only by enabling the renewable energy transfer between the participants. Through the additional possibility to purchase renewable electricity from the REC at a lower tariff, the total annual energy costs can be reduced by 8.73% and the total annual CO₂ emissions can be reduced by 14.7% within the REC at the same time. For the greenfield optimization scenario OC-Without-DR, the cost minimization only invests in central PV technologies, resulting in the total annual energy cost savings of 14.13% and the total annual CO₂ savings of 28.67%. However, the greatest savings are achieved in the greenfield optimization scenario OC-With-DR with demand rates. In this case, investments are also made in central ESS technologies, which are primarily used for peak shaving and thus further reducing the peak load-related costs for each community participant. Here the optimization results show a total annual energy cost reduction of 15.3% and a total annual CO₂ reduction of 34.06% within the community.

Overall, the key results of this work indicate that REC can significantly reduce the total annual energy costs and CO₂ emissions through an optimal selection and operation of the distributed energy technologies if the renewable energy is transferred and

shared between the community participants. Moreover, all optimization scenarios performed via the presented MILP-based planning approach show that each community participant can benefit both economically and ecologically with the optimal sizing and full-year operational dispatch of the corresponding technologies, regardless of the electricity tariff scenario selected. However, the greatest cost benefit can be achieved if investments in additional technologies or energy storage systems are enabled. This allows to reduce the peak load-related costs in a targeted manner through the additional, time-limited renewable power supply of the community participants from the ESS (peak-shaving) when demand rates are used.

The future research work will include the extension of this study and consider the game theoretic concepts to distribute the total cumulative cost savings and CO₂ savings among different community participants individually based on their cooperative participation. This will also help energy system planners to consider various energy sharing strategies in the field of cooperative optimization.

Credit author statement

Armin Cosic: Conceptualization, Methodology, Software, Data curation, Visualization, Writing – review & editing. **Michael Stadler:** Conceptualization, Methodology, Supervision, Resources, Writing – review & editing. **Muhammad Mansoor:** Conceptualization, Methodology, Data curation, Writing – review & editing.

Michael Zellinger: Resources, Visualization, Project administration.

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.

Acknowledgements

The authors would like to acknowledge Esther Fellingner from KELAG, a leading energy service provider in Austria, and Georg Wurzer from KNG-Kärnten Netz GmbH, the main electricity grid operator in Carinthia, for the valuable discussions on this topic and partially funding this project. Major funding was provided by the Austrian Research and Promotion Agency (FFG) under the project *OptEnGrid* (grant no. 858815), the province of Lower Austria under the project *Grundlagenforschung Smart und Microgrids* (grant no. K3-F-755/001-2017) and the COMET program 2019–2023 of BEST - Bioenergy and Sustainable Technologies GmbH under the projects *C-52-076-0-OptInvest*, *C-52-080-0-OptControl* and *C-52-077-0-SEBA/KELAG*.

Appendix A. Node-specific results

Table A1
RC-Without-DR-PV results of each node.

Node	Grid-Purchase [kWh/a]	PV-Production [kWh/a]	PV-Onsite [kWh/a]	Total Energy Costs [€/a]	Total CO ₂ Emissions [kg-CO ₂ /a]
1	19,972.69	0	0	3,618.40	4,707.04
2	2,651.8	18,115.65	2,519.75 (13.9%)	1,002.63	656.19
3	378.09	0	0	246.24	88.51
4	1,395.14	0	0	451.38	326.11
5	1,816.81	0	0	476.21	437.94
6	10,736.24	4,303.49	3,357.59 (78%)	2,516.58	2,729.55
7	9,452.83	0	0	2,076.61	2,300.86
8	1,032.78	2,664.07	770.85 (28.9%)	438.09	256.31
9	9,817.13	0	0	2,150.10	2,376.74
Total	57,253.51	25,083.21	6,648.19 (26.5%)	12,976.25	13,879.25

Table A2
OC-Without-DR results of each node.

Node	Grid-Purchase [kWh/a]	REC-Purchase [kWh/a]	PV-REC-Export [kWh/a]	Total Energy Costs [€/a]	Cost Savings [%]	Total CO ₂ Emissions [kg-CO ₂ /a]	CO ₂ Savings [%]
1	18,085.91	1,886.77	0	3,438.59	4.97	4,351.51	7.55
2	2,651.66	0.14	7,528.05	1,002.61	0	656.16	0
3	280.49	97.61	0	2,234.29	4.85	69.46	21.52
4	1,035.99	359.15	0	407.42	9.74	257.77	20.96
5	1,362.07	454.74	0	423.51	11.07	338.53	22.70
6	9,232.4	1,503.84	632.24	2,332.51	7.31	2,362.8	13.44
7	6,985.86	2,466.96	0	1,774.66	14.54	1,785.57	22.40
8	986.87	45.91	1,534.42	432.48	1.28	244.64	4.55
9	6,937.54	2,879.59	0	1,797.63	16.39	1,773.01	25.40
Total	47,558.79	9,694.71	9,694.71	11,843.70	8.73	11,839.45	14.70

Table A3

RC-Without-DR and RC-With-DR results of each node.

Node	Grid-Purchase [kWh/a]	Total CO ₂ Emissions [kg-CO ₂ /a]	Without-DR	With-DR
			Total Energy Costs [€/a]	Total Energy Costs [€/a]
1	19,972.69	4,707.04	3,618.40	3,639.43
2	5,171.55	1,205.9	1,213.08	1,172.61
3	378.10	88.51	246.24	220.23
4	1,395.14	326.11	451.38	426.28
5	1,816.81	437.94	476.21	470.09
6	14,093.83	3,416.54	3,012.70	2,973.57
7	9,452.83	2,300.86	2,076.61	2,031.58
8	1,803.63	421.54	533.77	516.00
9	9,817.13	2,376.74	2,150.10	2,105.11
Total	63,901.69	15,281.18	13,778.50	13,554.91

Table A4

OC-Without-DR results of each node.

Node	Grid-Purchase [kWh/a]	REC-Purchase [kWh/a]	Total Energy Costs [€/a]	Cost Savings [%]	Total CO ₂ Emissions [kg-CO ₂ /a]	CO ₂ Savings [%]
1	17,038.1	2,934.58	3,401.74	5.99	4,109.12	12.70
2	2,953.54	2,218.01	989.22	18.45	733.25	39.19
3	222.59	155.50	230.55	6.37	55.42	37.39
4	816.95	578.20	393.02	12.93	203.41	37.63
5	1,087.75	729.06	407.37	14.46	261.69	40.25
6	8,614.12	5,479.71	2,459.63	18.36	2,203.69	35.50
7	5,897.95	3,554.88	1,717.82	17.28	1,512.07	34.28
8	1,050.26	753.37	457.73	14.25	261.25	38.02
9	6,091.13	3,726.00	1,774.03	17.49	1,559.94	34.37
Total	43,772.39	20,129.30	11,831.10	14.13	10,899.84	28.67

Table A5

OC-With-DR results of each node.

Node	Grid-Purchase [kWh/a]	REC-Purchase [kWh/a]	Total Energy Costs [€/a]	Cost Savings [%]	Total CO ₂ Emissions [kg-CO ₂ /a]	CO ₂ Savings [%]
1	16,939.24	3,033.44	3,403.20	6.49	4,090.04	13.11
2	2,374.73	2,796.82	934.93	20.27	606.58	49.70
3	128.04	250.05	180.60	18.00	31.77	64.11
4	598.89	796.26	340.76	20.06	151.78	53.46
5	425.97	1,390.84	328.56	30.11	101.61	76.80
6	8,211.39	5,882.44	2,475.52	16.75	2,145.4	37.21
7	5,217.33	4,235.49	1,680.29	17.29	1,366.73	40.60
8	859.62	944.01	415.86	19.41	219.35	47.96
9	5,216.71	4,600.42	1,721.31	18.23	1,362.86	42.66
Total	39,971.92	23,929.76	11,481.03	15.30	10,076.12	34.06

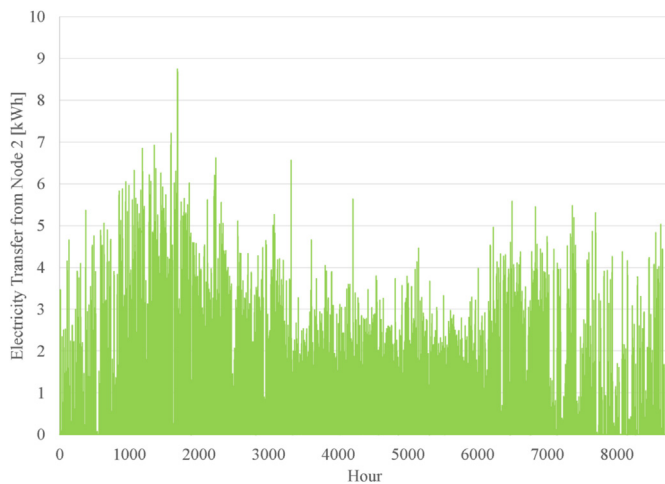


Fig. A1. The total electricity transfer from Node 2 to all other nodes for the optimization scenario OC-Without-DR-PV.

References

- [1] IRENA. Renewable energy and climate Pledges: Five Years after the Paris Agreement. Abu Dhabi: International Renewable Energy Agency; 2019.
- [2] Wang R, Hsu SC, Zheng S, Chen JH, Li XL. Renewable energy microgrids: economic evaluation and decision making for government policies to contribute to affordable and clean energy. *Appl Energy* 2020;274:115287. <https://doi.org/10.1016/j.apenergy.2020.115287>.
- [3] Tabar VS, Jirdehi MA, Hemmati R. Sustainable planning of hybrid microgrid towards minimizing environmental pollution, operational cost and frequency fluctuations. *J Clean Prod* 2018;203:1187–200. <https://doi.org/10.1016/j.jclepro.2018.05.059>.
- [4] Basu AK, Chowdhury SP, Chowdhury S, Paul S. Microgrids: energy management by strategic deployment of DERs—a comprehensive survey. *Renew Sustain Energy Rev* 2011;15(9):4348–56.
- [5] Schwaegerl C, Tao L. Quantification of technical, economic, environmental and social benefits of microgrid operation. In: *Microgrids*. John Wiley and Sons Ltd; 2013. p. 275–313. <https://doi.org/10.1002/9781118720677.ch07>.
- [6] Long C, Wu J, Zhang C, Thomas L, Cheng M, Jenkins N. Peer-to-peer energy trading in a community microgrid. In: *2017 IEEE power energy society general meeting*. IEEE; 2017, July. p. 1–5.
- [7] Directorate-General for Energy (European Commission). Clean energy for all Europeans. *Euroheat Power* 2019;14(2):3. <https://doi.org/10.2833/9937>.
- [8] European Parliament. Directive (EU) 2018/2001 of the European Parliament and of the Council on the promotion of the use of energy from renewable sources. *Off J Eur Union* 2018;2018(L 328):82–209. <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L2001&from=EN>.
- [9] European Parliament. Directive (EU) 2019/944 on Common rules for the internal market for electricity. *Off J Eur Union* 2019;L 158:18. http://www.omel.es/en/files/directive_celex_32019l0944_en.pdf.
- [10] Inès C, Guilherme PL, Esther MG, Swantje G, Stephen H, Lars H. Regulatory challenges and opportunities for collective renewable energy prosumers in the EU. *Energy Pol* 2020;138:111212.
- [11] 58/ME (XXVII. GP) - Erneuerbaren-Ausbau-Gesetz – EAG. Erneuerbaren-ausbau-gesetzespaket – EAG-Paket. 2012. https://www.parlament.gv.at/PAKT/VHG/XXVII/ME/ME_00058/index.shtml.
- [12] Park C, Yong T. Comparative review and discussion on P2P electricity trading. *Energy Procedia* 2017;128:3–9.
- [13] Zhang C, Wu J, Long C, Cheng M. Review of existing peer-to-peer energy trading projects. *Energy Procedia* 2017;105:2563–8.
- [14] Mengelkamp E, Gärtner J, Rock K, Kessler S, Orsini L, Weinhardt C. Designing microgrid energy markets: a case study: the Brooklyn Microgrid. *Appl Energy* 2018;210:870–80.
- [15] Leong CH, Gu C, Li F. Auction mechanism for P2P local energy trading considering physical constraints. *Energy Procedia* 2019;158:6613–8.
- [16] Morstyn T, Teytelboym A, McCulloch MD. Bilateral contract networks for peer-to-peer energy trading. *IEEE Trans Smart Grid* 2018;10(2):206–35.
- [17] Long C, Wu J, Zhou Y, Jenkins N. Aggregated battery control for peer-to-peer energy sharing in a community Microgrid with PV battery systems. *Energy Procedia* 2018;145:522–7.
- [18] Reihani E, Siano P, Genova M. A new method for peer-to-peer energy exchange in distribution grids. *Energies* 2020;13(4):799. <https://doi.org/10.3390/en13040799>.
- [19] Cui S, Wang YW, Shi Y, Xiao JW. An efficient peer-to-peer energy-sharing framework for numerous community prosumers. *IEEE Trans Ind Inf* 2020;16(12):7402–12. <https://doi.org/10.1109/TII.2019.2960802>.
- [20] Lin CC, Wu YF, Liu WY. Optimal sharing energy of a complex of houses through energy trading in the Internet of energy. *Energy* 2021;220:119613.
- [21] Mahmoud MS, Rahman MSU, Fouad MS. Review of microgrid architectures—a system of systems perspective. *IET Renew Power Gener* 2015;9(8):1064–78.
- [22] Huang H, Nie S, Lin J, Wang Y, Dong J. Optimization of peer-to-peer power trading in a microgrid with distributed PV and battery energy storage systems. *Sustainability* 2020;12(3). <https://doi.org/10.3390/su12030923>.
- [23] Fleischhacker A, Lettner G, Schwabeneder D, Auer H. Portfolio optimization of energy communities to meet reductions in costs and emissions. *Energy* 2019;173:1092–105. <https://doi.org/10.1016/j.energy.2019.02.104>.
- [24] Mansoor M, Stadler M, Zellinger M, Lichtenegger K, Auer H, Cosic A. Optimal planning of thermal energy systems in a microgrid with seasonal storage and Piecewise affine cost functions. *Energy* 2020;119095.
- [25] Stadler M, Pecanek Z, Mathiesen P, Fahy K, Kleissl J. Performance comparison between two established microgrid planning MILP methodologies tested on 13 microgrid projects. *Energies* 2020;13(17):4460.
- [26] Mansoor M, Stadler M, Auer H, Zellinger M. Advanced optimal planning for microgrid technologies including hydrogen and mobility at a real microgrid testbed. *Int J Hydrogen Energy* 2021;46(37):19285–302.
- [27] Zwickl-Bernhard S, Auer H. Open-source modeling of a low-carbon urban neighborhood with high shares of local renewable generation. *Appl Energy* 2020;282:116166.
- [28] Fina B, Fleischhacker A, Auer H, Lettner G. Economic assessment and business models of rooftop photovoltaic systems in multiapartment buildings: case studies for Austria and Germany. *J Renew Energy* 2018;2018.
- [29] Roberts MB, Bruce A, MacGill I. Impact of shared battery energy storage systems on photovoltaic self-consumption and electricity bills in apartment buildings. *Appl Energy* 2019;245:78–95.
- [30] Fleischhacker A, Auer H, Lettner G, Botterud A. Sharing solar PV and energy storage in apartment buildings: resource allocation and pricing. *IEEE Trans Smart Grid* 2018;10(4):3963–73.
- [31] Perger T, Wachter L, Fleischhacker A, Auer H. PV sharing in local communities: peer-to-peer trading under consideration of the prosumers' willingness-to-pay. *Sustain Cities Soc* 2021;66:102634.
- [32] Jiang A, Yuan H, Li D. A two-stage optimization approach on the decisions for prosumers and consumers within a community in the Peer-to-peer energy sharing trading. *Int J Electr Power Energy Syst* 2021;125:106527.
- [33] Mashayekh S, Stadler M, Cardoso G, Heleno M. A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids. *Appl Energy* 2017;187:154–68.
- [34] Fahy K, Stadler M, Pecanek ZK, Kleissl J. Input data reduction for microgrid sizing and energy cost modeling: representative days and demand charges. *J Renew Sustain Energy* 2019;11(6):065301.
- [35] Remund J, Müller S, Kunz S, Schilter C. METEONORM: Global meteorological database for solar energy and applied climatology. *Meteotest*; 2007.
- [36] Oib-RI 6. Energieeinsparung und Wärmeschutz, OIB-Leitfaden Energietechnisches Verhalten von Gebäuden, OIB-330.6-027/19. 2019. Retrieved November 20, 2020, from, https://www.oib.or.at/sites/default/files/erlaeuternde_bemerkungen_richtlinie_6_12.04.19_0.pdf.
- [37] IRENA. Global energy Transformation: a Roadmap to 2050. Abu Dhabi: IRENA; 2018.
- [38] IRENA. Electricity storage and renewables: costs and markets to 2030. Abu Dhabi: International Renewable Energy Agency; 2017.
- [39] Tesla. Tesla Powerwall 2. 2020. Retrieved November 20, 2020, from, https://www.tesla.com/sites/default/files/pdfs/powerwall/Powerwall%202_AC_Datasheet_de_DE.pdf.
- [40] Battery University. How to prolong Lithium-based batteries. 2020. Retrieved November 20, 2020, from, https://batteryuniversity.com/learn/article/how_to_prolong_lithium_based_batteries.

- [41] Battery University. Elevating self-discharge. 2018. Retrieved November 20, 2020, from, https://batteryuniversity.com/learn/article/elevating_self_discharge.
- [42] E-Control. Decreed grid usage rates for 2020. 2020. Retrieved November 20, 2020, from, <https://www.e-control.at/industrie/strom/strompreis/netzentgelte>.
- [43] E-Control. Taxes and charges. 2020. Retrieved November 20, 2020, from, <https://www.e-control.at/marktteilnehmer/strom/strommarkt/preise/steuern-und-abgaben>.
- [44] RIS. Ordinance of E-Control's Regulatory Commission determining the fees for grid use. 2020. Retrieved November 20, 2020, from, <https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20010107>.
- [45] KELAG. Kelag Home basic energy rate. 2020. Retrieved November 20, 2020, from, https://www.kelag.at/files/folder/Produktfolder/Privatkunden/Strom/Tarifblatt_Kelag_Home_Basic.pdf.
- [46] EPEX Spot. EPEX spot market auction prices for 2019 - Austria. 2019. Retrieved November 20, 2020, from, <https://www.epexspot.com/en/market-data>.