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Portfolio optimization of energy communities to meet reductions in costs and emissions

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ABSTRACT

Cities are expected to grow further, and energy communities are one promising approach to promote distributed energy resources and implement energy efficiency measures. To understand the motivation of those communities, this work improves two existing open source models with a Pareto Optimization and two objectives: costs and carbon emissions. Clustering algorithms support the improvement of the models' scalability and performance. The methods developed in this work gives stakeholders the tool to calculate the capabilities and restrictions of the local energy system. The models are applied to a case study using data from an Austrian city, Linz. Four scenarios help to understand aspects of the energy community, such as the lock-in effect of existing infrastructure and future developments. The results show that it is possible to reduce both objectives, but the solutions for minimum costs and minimum carbon emissions are contrary to each other. This work quantifies the highest effect of emission reduction by the electrification of the system. It may be concluded, that a steady transformation of the local energy systems is necessary to reach economically sustainable goals.

1. Introduction

Globally, 54% of the population lives in urban areas today, and this trend is expected to continue by 2045. The number of people living in cities will increase by 1.5 times to 6 billion, adding 2 billion more urban residents [1]. Cities also play an important role in tackling climate change, as they consume close to 2/3 of the worlds energy and account for more than 60–80% of global greenhouse gas emissions [2]. As stated in Ref. [3], fossil energy consumption of cities has to be reduced dramatically to meet the emission reduction targets (such as the Paris Agreement) [3]. Only in that way, sustainable development could be ensured.

Though no one-size-fits-all solution exists to ensure urban energy sustainability, compact and dense urban development and new ways of planning, financing and using energy infrastructure projects are structural prerequisites to many of the sector-specific options for carbon emissions reduction [4]. In the past years, the term energy communities (EC) has been established to promote distributed energy resources (DER) and implement energy efficiency measures. The European Commission defines an EC as a "legal entity which is effectively controlled by local shareholders or members, generally value rather than profit-driven, involved in distributed generation and in performing activities of a distribution system operator, supplier or aggregator at a local level, including across borders" [5].

For this paper, a large-scale EC covering a whole city district is considered. It is assumed that the EC owns the energy grids (e.g., electricity and district heating grid), DER and storages within the community's area. The assumption is in line with [6], where the ownership of EC projects might be: (i) 100% community owned or (ii) developed under co-ownership arrangements with the private sector (e.g., community ownership of one turbine in a larger wind farm). For the sake of simplicity, this paper assumes the first case.

This paper aims to quantify the advantages of optimizing the technology portfolio of ECs regarding cost and carbon emission reduction. The EC is modeled as a multi-energy system with the restriction of satisfying needs for electricity and heat. In this work, two verified open source models are coupled with the use of clustering algorithms. Furthermore, the open source models are expanded with three features: Pareto Optimization, economies-of-scale, and time-dependent efficiency factors. As a result of this, existing and future building stock set-ups are taken into account, as well as the implementation of energy efficiency measures (lower heat demand and electric vehicles (EV)).

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Nomenclature

Abbreviations

B	Apartment building
COP	Coefficient-of-performance
DER	Distributed energy resource
DHW	Domestic hot water
E	Single-family housing
EC	Energy community
EoS	Economies of Scale
EV	Electric vehicle
HERO	Hybrid Energy Optimization
HP	Heat pump
OSM	Open source model
PV	Photovolatic plant
SH	Space heating
ST	Solar thermal collectors
Z	Large-panel system building

Sets

$a \in A$	Distribution line
$f \in F$	Transmission process
$i \in \{Heat, Elec, Cool\}$	Energy carrier
$j \in \{1, 2, \ldots, N_m\}$	Block number
$m \in \{E, Z, B\}$	Block type
$p \in P$	Process
$r \in \mathscr{R} = \{1, \ldots, R\}$	Periods of a year
$t \in \mathscr{T} = \{1, \ldots, T\}$	Time-steps
$v \in V$	Site
$w \in \{1, \ldots, W\}$	Weeks

Variables

η, cop and Γ	Conversion efficiency
κ	Process capacity
$\overline{e}$	Emissions of minimum cost solution
$\underline{e}$	Emissions of minimum emission solution
ζ	Costs
d and D	Energy demand
q and Q	Generation
s	Binary decision
x	Continuous variable
y	Binary variables

Parameters

α	Adjusting factor for the Pareto Front
Θ	Temperature
A	Building area
K	Installed process capacity
N	Total number of processes
S	Number of stories
$share$	Share of SH

The present paper is related to at least four strands of the literature.

First, an EC is included as a multi-energy system. Various studies investigate optimum energy designs of cities and small entities of cities (such as districts and blocks) [7]. They conclude, that an important design element is an introduction of multi-energy systems (e.g., electricity, heat, cooling, fuels, transport) [8]. Such systems have become highly relevant in the last decade. Investigation of one energy carrier makes sense for detailed technical issues (such as a grid or market integration of photovoltaic (PV) systems). Multi-energy systems, as reviewed in Ref. [8], on the other hand, can feature better technical, economic and environmental performance relative to classical independent or separate energy systems at both the operational and the planning stage [8]. Ma et al. [7] show that the distributed multi-energy systems have better economic and synergistic performances than the conventional centralized energy systems. Widl et al. [9] propose a method to assess multi-carrier energy grids under a holistic scope systematically. As a proof-of-concept, the method is applied to a real-world use case of a hybrid thermal-electrical distribution grid in a central European city. The application of a multi-energy system reduces the imported heat by 20%. Consequentially, the present paper models the EC as a multi-energy system including electricity and heat, but also transport.

Secondly, various optimization models have been developed to optimize urban energy systems. DER-CAM is an optimization model that determines the optimal capacity and dispatch strategy of distributed generation technologies to minimize global annualized cost on the customer level [10]. Geidl [11] develops the energy hub concept, which is designed to couple various energy systems and manage energy flows through process conversion, storage, and distribution of energy. Nazar and Haghifam [12] use the energy hub approach of [11] to optimize an urban electricity distribution system for investment and operational costs, and availability. Fichera et al. [13] use a framework of encompassing complex networks theory and energy distribution issues. Weber and Shah [14] adapt mixed integer linear optimization techniques to design and optimize district energy systems. Mehleri et al. [15] present on a mathematical model to size decentralized energy generation systems including a district heating network. Consequentially, two types of optimization models are used in this work, one for a high temporal resolution and one for a high spatial resolution. Different scales (e.g., buildings, blocks, districts) have different requirements. This work investigates grid operation and investments highly relevant for spatial distributed energy generation and consumption. Based on these considerations, various network flow models have been developed in the past. Most models have to deal with a very long computation time when large networks are taken into account. Therefore, special tools are required to apply the model for larger districts [16]. Orehounig et al. [17] present a method of integrating energy from DES at district level using the energy hub approach. The advantage is that the energy supply systems and local energy storage systems can be evaluated in a combined way at the district scale. Eicker et al. [18] quantify energy efficiency in urban planning, based on 3D city model applied to solar energy generation. However, a clustering algorithm based on the building structure is not yet been covered by the literature.

Thirdly, in recent years, open source models (OSMs) became more relevant, and there are many OSMs in use in the energy research [19]. The advantages of such models are the ability to share modeling approaches, the improvement of quality and the decrease of adaption costs [19]. Regardless of the specific type of OSM, Ajila and Wu [20] show that open source software can generally meet high standards with little or no difference in quality relative to proprietary software. Dorfner [21] presents a suite of OSMs adapted to local energy systems. These models allow

exploring the design space of energy infrastructure on an urban scale. Four case studies demonstrated the use of these models in real-world scenarios. This work uses the OSMs "urbs" and "rivus" of Dorfner [22,23] in the work and make further improvements. These improvements aim in increasing the models' performance, as well as including new functionalities to reflect the reality more in detail.

Finally, optimization models may be solved in respect of different objectives [16]. show that objective functions at the district level are typically carbon emission, production, revenue, operation costs, investment, fuel costs, and renewable exploitation [16]. However, supply concepts with minimum costs are often incompatible with emission reduction targets. Multi-objective optimization models are frequently used in literature to tackle the problem of including different objectives. In this work, a multi-objective optimization is applied to quantify an EC's trade-off curve of costs and emissions. So, at any point on the curve, the objective's value cannot be decreased without increasing the other [24]. This so-called Pareto Front shows the most efficient solutions concerning both, costs and emissions. The results and changes in deployed technology along the Pareto Front helps, e.g., to quantify the costs of emission reduction targets. These approaches determine the optimal energy system (e.g., for district heating) from both environmental and economic perspectives. Therefore, multi-objective optimization models are preferable to support decision makers, because the effects of (often) conflicting objectives can be quantified and allow them to make reasoned (investment) decisions [10,10]. show the trade-off between cost and emission reduction and reported on the optimal investment decisions. Similar to this work, reference [10] calculates the Pareto Front within the planning optimization algorithm. Voll [25] introduce a mathematical programming framework for the operation and sizing of distributed energy supply systems based on a superstructure-based and superstructure-free methodologies. Additionally, multi-objective optimization was used to generate the Pareto Front for the objectives cumulative energy demand total investment costs. Fonseca et al. [26] developed a framework for the analysis of building energy systems at the urban scale including a multi-criteria decision based on Pareto Fronts. Wang et al. [27] applied a similar method to a university campus in Stockholm. They clearly described that the Pareto Front can give stakeholders an overview of designing the energy system and understanding the options and limitation that they face (e.g., concerning costs and emissions). Similar conclusions are drawn by Zhang et al. [28], who applied multi-objective optimization for the design of a waste heat recovery network. As the literature stated, multi-objective optimization and Pareto Fronts in particular, are beneficial to decision makers. So this work integrates this functionality to the OSMs as mentioned above.

In this paper, a framework for establishing an EC in a city district is proposed. The usage of different OSMs and scenarios help to identify how the most economic EC and, contrary, how a low carbon emission EC may look like. The main contributions of this paper are:

- The proposition of a new method to quantify the benefits of EC in city districts.
- The method describes city districts based on the building structure of city blocks. Such a method may be of practical relevance for city planners as it reduces the complexity.
- The improvement of an established OSM with features such as economies-of-scale, input data clustering algorithms and Pareto Optimization.
- Finally, as ECs might be interested in reducing the carbon emissions, different methods of emissions accounting are discussed based on the electricity market's conditions as well as the introduction of carbon taxes.

The paper is organized as follows. In Section 2, the open source models are introduced as well as the improvement of those. Section 3 presents the project site and different scenarios. Section 4 presents the results, while Section 5 discusses and concludes the paper.

2. Methods

The methods of this work base on two OSMs: "urbs"[1] [22] and "rivus"[2] [23]. The two models are chosen because they are well documented and allow the description of an EC in two dimensions, spatial and temporal. Dorfner [21] developed both models and published them on the web-based Git version control repository GitHub under the terms of the GNU General Public License. In this work, the framework "HERO"[3] is introduced, as a combination of both models "urbs" and "rivus". Fig. 1 shows the setup and the interconnection of the model's components. The video provided in the supplementary materials of this work gives a brief introduction of the methods.

As input data, three different types of data sources are used:

1. Time-series data, such as energy consumption (electricity, heat, cooling, etc.), solar radiation and the temperature depending on heat pump coefficient-of-performance (COP) as well as the energy system's emissions.
2. Geographical data, such as building area or grid length and
3. Technical (energy and emission conversion efficiency, technical limits, etc.) and economic parameters (investment, maintenance, and fuel costs).

To improve the performance and the interoperability of the models, de/-clustering algorithms are developed to meet the different requirements of the models.

The following sections describes aspects of the model. While Section 2.1 describes the clustering algorithms for varying the input data, Section 2.2 introduces improvements of the model "urbs" (such as the implementation of economies-of-scale and Pareto Optimization). Section 2.3 describes the method of modeling an EC, while Section 2.4 introduces a method to account emissions. Section 2.5 includes carbon taxes to the models' objective function. The video provided in the supplementary materials of this work gives a brief introduction of this work's methods.

2.1. Applied data clustering and aggregation methods

As mentioned above, the two models put their focus differently: While "urbs" models processes (e.g. energy conversation including the operation of storages) in a high temporal resolution, "rivus" helps to plan the EC grid infrastructure on a disaggregated spatial layer. Consequently, both models have different requirements for the input data. This encourages this work to develop different clustering algorithms to benefit from each model's strength.

The input data is clustered to reduce the size of both models as well as the computation time of solving the optimization problems. Therefore the K-Means clustering algorithm has been adopted for the "period clustering" to cluster the time-series data into R representative weeks (Section 2.1.2.1). Consequentially, another model uses "spatial aggregation" based on the method of different city blocks (Section 2.1.1). This allows the spatial aggregation of the compressed time-series data into M clusters.

[1] Latin term for city.
[2] Latin term for stream.
[3] Abbreviation of "Hybrid EneRgy Optimization".

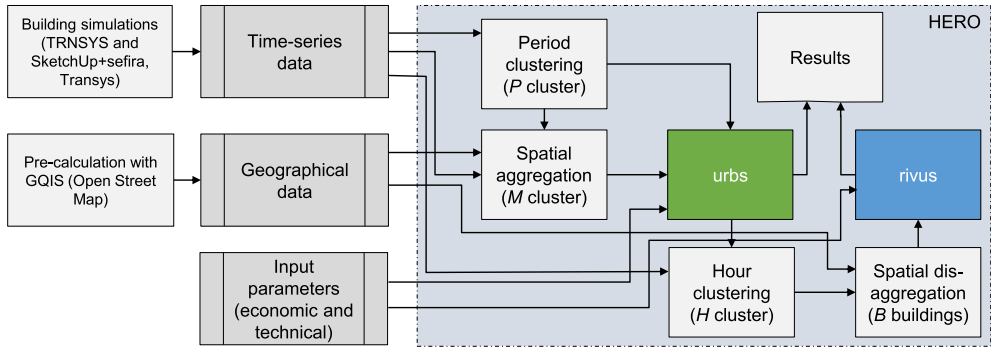

Fig. 1. Block diagram of the framework "HERO", developed in this work.

The model "rivus" requires a higher reduction of the time-series data. The second time-series clustering method "hour clustering" selects the results of "urbs" to characteristic hours (Section 2.1.2.2). The "spatial disaggregation" method prepares the input data for "rivus" on a building level (Section 2.1.1). The model "rivus" bases on the theory of graphs and consists of edges and vertexes. Each edge of "rivus" (e.g., a grid connection between two houses) is represented by a binary variable.

In the following, the applied clustering algorithms are described in detail.

2.1.1. Aggregation and disaggregation of spatial data

A novel approach of this work is the assignment of urban areas to characteristic city blocks. This approach helps to reduce the complexity of planning the urban EC. The advantage of this approach is the fact that it requires less information about the area and it may be rather easy to be collected (e.g., by a standard GIS software). Characteristic blocks are modeled in detail, e.g., in terms of a dynamic heat load.

In this work, three types of buildings and blocks, significant for the Austrian housing situation within the tested case study,[4] are defined:

Single-family housing block (E) is a city block of free-standing residential buildings. This building type is widespread in suburban or rural areas. Even though the buildings share one or more walls with another, it has direct access to a street or thoroughfare. Furthermore, it does not share heating facilities and hot water equipment with any other dwelling unit.

Apartment building block (B) is a city block of buildings with a high housing density. Apartment buildings are constructed around the border of the block, resulting in an enclosed area. Open space inside the block is used for collectively. Each building's apartments are self-contained housing units, whereby energy infrastructure could be shared (e.g., by a central heating plant) or not.

Large-panel system building or "Plattenbau" block (Z) is similar to apartment building block but consists of buildings constructed of large, prefabricated concrete slabs. In comparison, "Plattenbauten" are stand-alone buildings, resulting in limitations of energy sharing concepts.

In a first step, the city area is clustered in blocks, by using streets or another kind of obstacles (e.g., parks) as demarcation. In a second step, the blocks are assigned to the three predefined block-types. Fig. 2 shows the result of this assignment as well as the block types. While E-type blocks consist of small stand-alone buildings, B-type blocks are rather enclosed entities consisting of large buildings covering the block's border. On the opposite, Z-blocks are identifiable as stand-alone buildings, but the area covered by buildings is much higher than those of single-family buildings.

In a third step, the introduction of characteristic blocks of each type describes the remaining blocks. The assessment of the characteristic blocks bases on experts interviews [30]. Fig. 2 shows all blocks and the characteristic blocks per type, namely B1, Z1, and E1. The energy demand (including electricity, heat and hot water and cooling demand) as well as the supply of renewable generation (solar radiation) of the characteristic blocks is used to describe the corresponding demand and supply characteristics. The description to the other blocks is based on two criteria, the building area A and the number of stories S. The energy demand is described as

$$d^i_{m,j} = d^i_{m,1}\frac{A^i_{m,j}}{A^i_{m,1}}\frac{S^i_{m,j}}{S^i_{m,1}}, \quad (1)$$
$$i \in \{Heat, Elec, Cool\},\ m \in \{E, Z, B\},\ j \in \{2, 3, \ldots, N_m\}$$

With $d^i_{m,j}$ the electricity, heat and cooling demand of block type m and number j. $d^i_{m,1}$ is the demand of the characteristic block modeled by detailed building models (described in Ref. [29]).

By applying the "spatial aggregation", the results is a four-node model (three for each block types plus one central slack node). The recapture of the full spatial information of the area, spatial disaggregation is applied to reverse the approach (1) and recalculate the energy demand of each block.

2.1.2. Clustering temporal data

2.1.2.1. Period clustering for urbs. The K-Means clustering algorithm identifies P characteristic weeks. One weakness of this approach is that long-term (future) storage technologies such as hydrogen systems might not be integrated with adequate accuracy because of the lack of consecutive weeks.

As written in Ref. [31], the K-Means method minimizes the quantization error function by using the Newton algorithm, i.e., a gradient-based optimization algorithm. In this work, the K-Means method is used to cluster time-dependent inputs:

- Demand vectors of heat (space heating and hot water demand), electricity (residential and commercial demand including the charging demand of electric vehicles) and cooling d^{Heat}_m, d^{Elec}_m and d^{Cool}_m
- Supply vectors of solar PV and solar thermal collectors (ST) q^{PV}_m and q^{ST}_m and
- Conversion efficiency of electricity to heat (COP) of heat pumps $\eta^{HP_{liq-water}}_m$ and $\eta^{HP_{water-water}}_m$.

All vectors have a length of T. Firstly, time vectors are

[4] For a further description of the case study see Section 3.

Fig. 2. Geographical location of all blocks in the area of Linz a city in Austria (left) and the detailed blocks (E), (B) and (Z) created in SketchUp (right). Source [29].

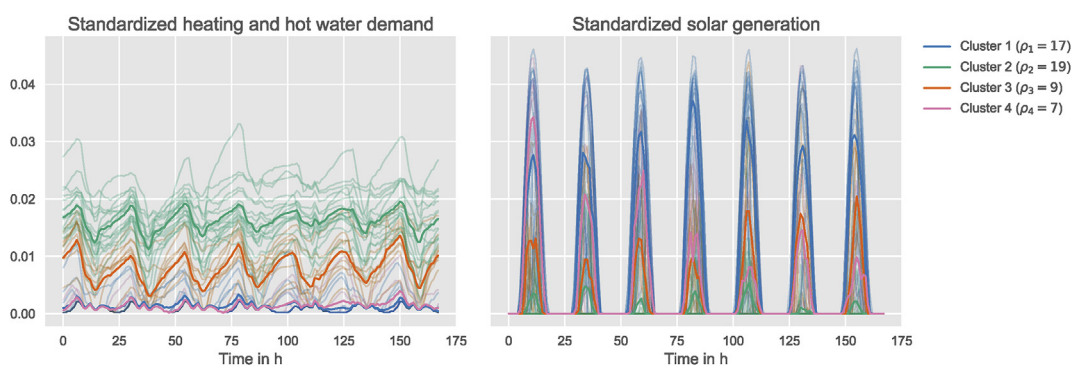

Fig. 3. Results for Linz (block E1) for heat and hot water demand and solar generation. While thin lines include the whole data set, the thick lines indicate the cluster centroids.

standardized by applying the ℓ_2 norm. Standardization improves the convergence performance of the K-Means algorithm [32]. Secondly, the time vectors are reshaped into matrices

$$D_m^{Heat}, D_m^{Elec}, D_m^{Cool}, Q_m^{PV}, Q_m^{ST}, \Gamma_m^{HP_{liq-water}}, \Gamma_m^{HP_{water-water}} \in \mathbb{R}^{T_w \times W} \tag{2}$$

With T_w of timesteps within a week $w \in \{1, \ldots, W\}$ and include them in the K-Means input matrix

$$X = \begin{bmatrix} D_1^{Heat} & & D_M^{Heat} \\ \vdots & \ddots & \vdots \\ \Gamma_1^{HP_{water-water}} & & \Gamma_M^{HP_{water-water}} \end{bmatrix}. \tag{3}$$

This algorithm requires the number of clusters to be specified. In this work, $r \in \mathscr{R} = 4$ periods (therefore four representative weeks per year) are used.

The Python Package "scikit-learn" [32,33], more in detail, the method kmeans++, is used in this work. The K-Means algorithm divides a set of W samples X into P disjoint clusters C, each described by the mean of the samples in the cluster. The means of those clusters are commonly called the cluster centroids; note that they are not, in general, points from X, although they are in the same space.

Given enough time, K-means will always converge, however, this may be to a local minimum. As a result, the computation is done several times (1000 times in this approach), with different initializations of the centroids, with varying initializations. The random initialization leads to better results as shown in Ref. [34].

Because these centroids are neither in the dataset nor the right scale (as a result of the standardization), the Euclidean distance of each centroid to its nearest neighbor is calculated and used as the new cluster center. The corresponding length of the cluster indicates each cluster center's weight ϱ_p. In total, the sum of all weights is equal to 52 weeks per year.

To give an insight in the functionality of the clustering algorithm, Fig. 3 shows the results of the period clustering from Section 4. For the sake of simplicity, only results of clustering d_{E1}^{Heat} and q_{E1}^{PV} are shown.

2.1.2.2. Hour clustering for "rivus". Similar to the approach presented before, hourly clustering is used to find representative hours in the dataset. Because of its characteristics, K-Means is not very suitable to cluster peaks or outliers of a dataset [31]. Therefore, an algorithm for both, peak detection and mean-value clustering has been developed:

(i) **Peak detection** identifies the annual peaks in the time series dataset. These parameters are essential for grid planning. Consequentially, all detected peaks from the dataset are excluded.
(ii) **K-Means** is applied to the reduced dataset (excluding the peaks). In contrast to period clustering (of Section 2.1.2.2), the clusters' size is 1 h instead of a week.

The hour clustering algorithm to the results of "urbs". The

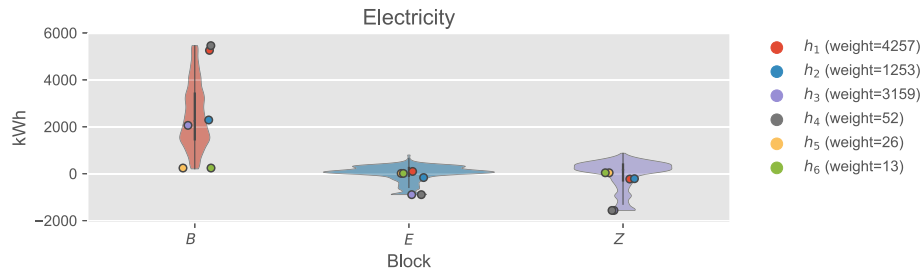

Fig. 4. Results of "urbs" (scenario "Status Quo" - minimum cost solution) of the electricity demand as violin plot and the corresponding "rivus" cluster center (including the weight) as points. The points h_4 - h_6 are the peaks of (i), while h_1 - h_3 are the centers of (ii).

model's results give insight into the optimal size and commitment of processes and storages. Consequentially, the data is used to model the required grid infrastructure. The grid infrastructure allows describing the distributed generation and sector-coupling.[5]

In addition to the period clustering, Fig. 4 shows the results of "urbs" as violin plot as well as cluster centers of the hourly clustering algorithm. Although Fig. 4 includes results, it helps to increases the understanding of the algorithm. Hours of negative energy flows indicate an excess of distributed generation. The algorithm helps to identify the peaks of positive and negative load, as well as significant hours within the distribution.

2.2. Improvements of the open source model "urbs"

In this work, the OSM additional features are added to "urbs" to handle the needs of modeling ECs. Firstly, multiple periods (e.g., weeks) with the corresponding weights, are included. As the first improvement is a standard method, it will not be described in detail. Secondly, economies-of-scale (EoS) are included to capture the investment decision on a building level. Thirdly, the time dependency of heat and solar generation is introduced. In a fourth step, the model's objective is changed to a Pareto Optimization with two objectives, costs and emissions.

2.2.1. Economies of scale

Manfren et al. [35] describe that optimization models have to be able to picture the EoS to describe the economics e.g. of DERs sufficiently. In accordance with the nomenclature introduced in Ref. [21] the process rules are expanded as follows: Total process capacity κ_{vp} (decision variable) of site $v \in V$ and process $p \in P$ consists of installed capacity K_{vp} (parameter) and new capacity $\widehat{\kappa}_{vp}$ (decision variable), as

$$\kappa_{vp} = K_{vp} + \widehat{\kappa}_{vp} \tag{4}$$

By the inclusion of binary decision variables s_{vp} the lower and upper restrictions are defined as

$$s_{vp}\overline{K}_{vp} - K_{vp} \leq \widehat{\kappa}_{vp} \leq s_{vp}\overline{K}_{vp} - K_{vp} \tag{5}$$

Both parameters $\overline{K}_{vp}$ and $\overline{K}_{vp}$ are exogenous inputs and defined e.g. by spatial restrictions (such as roof area in the case of PV).

As EoS are significant for investments in the distribution grid as well, they are implemented as

$$s_{af}\overline{K}_{af} - K_{af} \leq \widehat{\kappa}_{af} \leq s_{af}\overline{K}_{af} - K_{af} \tag{6}$$

With the corresponding index f referring to a transmission process to transfer a commodity along a distribution line a.

Finally, the investment costs of [21] are expanded by fixed investments costs

$$\zeta^{inv,fix} = \sum_{\substack{v \in V \\ p \in P}} N_{vp} s_{vp} \widehat{\kappa}_{vp}^{inv,fix} + \sum_{\substack{a \in A \\ f \in F}} s_{af} \widehat{\kappa}_{af}^{inv,fix} \tag{7}$$

Including the binary decision variables. Parameter N_{vp} includes the number of processes to be purchased, e.g. in the case of PV the number of roofs (N_{vPV}= number of buildings at site v). For the following study, it is assumed that all distributed technologies are build on a building level. The extension for storages is proceeded in the same way, but for the sake of simplicity it is not described in detail.

2.2.2. Time dependent conversion coefficients

Time dependent COP is added to "urbs" by expanding the output ratio r_{pct}^{out} by the dimension of time $t \in T$. To include generation time series of PV and ST, the efficiency is multiplied with the plants' nominal capacity κ_{vp}.

2.2.2.1. Coefficient-of-performance of heat pumps (air source and ground source). The supply temperature is used to calculate the hourly COP. As introduced in Ref. [36] the COP of process p[6] is described by a polynomial function

$$\eta_{pt}^{i} = k_0 - k_1\left(\Theta^{supply}pt - \Theta^{source}pt\right) + k_2\left(\Theta^{supply}pt - \Theta^{source}pt\right)^2 \tag{8}$$

For both, domestic hot water (DHW) and space heating (SH) ($i \in \{DHW, SH\}$) separately. Θ^{source} describes the water or air temperature, while Θ^{supply} is different for DHW or SH. The temperature of DHW is assumed to be 55 °C and SH 50°C/35.°C[7] As it is not differentiated between DHW and SH in this work's model, the mean COP is calculated as

$$\eta_{pt} = \left(1 - share_p^{SH}\right)\eta_t^{DHW} + share_p^{SH}\eta_t^{SH} \tag{9}$$

With the $share_p^{SH}$ = 84%, a typical value for Austrian heat demand [37].

2.2.2.2. Solar energy (ST and PV). Lindberg et al. [36] describe the efficiency of the ST by a polynomial function. The framework

[5] E.g., a rise of the electrical peak load resulting from the electrification of the system.

[6] $p \in \{HP(air - water), HP(water - water)\}$

[7] As presented in Ref. [37] for radiator heating in an old building stock (block type B) and floor heating for the case of a new building stock (E and Z).

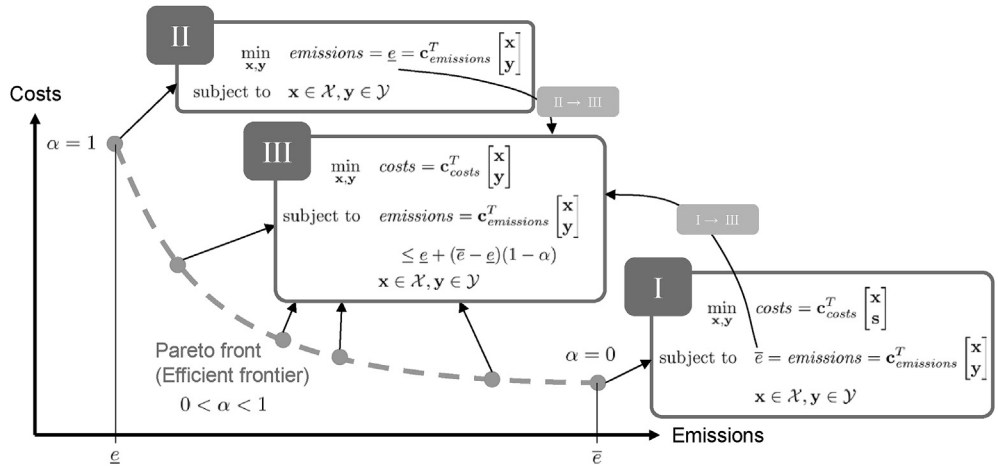

Fig. 5. The three-step approach of the Pareto Optimization applied in this work.

requires the following inputs: the solar irradiation on the tilted surface, the temperature within the ST and the ambient temperature. Additionally, the solar PV collectors' efficiency is described by a function introduced in Ref. [38]. Huld et al. [38] describe the collectors' efficiency as a function of the solar irradiation (the same as for ST), the modules temperature (calculated from the outdoor temperature) and a static power inverter's efficiency.[8]

2.2.3. Pareto Optimization

Furthermore "urbs" is expanded by a Pareto Optimization to combine two opposing objectives: *costs* and *emissions*. In the following, the model's continuous variables are named **x** and binary variables **y**, respectively. As introduced in Ref. [39], Pareto Optimization dealing with two objectives may be formulated as

$$\min_{\mathbf{x},\mathbf{y}} \quad f(\mathbf{x},\mathbf{y}) = (costs(\mathbf{x},\mathbf{y}), emissions(\mathbf{x},\mathbf{y}))$$

subject to. $\mathbf{x} \in \mathscr{X}, \mathbf{y} \in \mathscr{Y}$

With the feasible solution spaces $\mathscr{X}$ and $\mathscr{Y}$.

Both should be minimized by iterative use of the optimization model *"urbs"*. With this, a three-step approach is implemented basing on the ε-constraint method for bi-level combinatorial optimization problems[9]:

(I) The first step of the approach calculates the minimum cost solution without any restrictions concerning the emissions.
(II) Secondly, the objective is changed from costs to emissions. The result shows the solution in respect of minimal emissions.
(III) Finally, the model's objective and setup is changed back to (I), but including an upper limit of the emissions. The upper limit is a linear space between the emissions of (I) and (II) and is separated in enumerable steps.

The unit of objective of the objective function are monetary units (e.g. EUR) for (I), carbon emissions (e.g. t_{CO2}) for (II) and also monetary units for (III). Fig. 5 shows the approach graphically. The vectors of the two different objective functions are $\mathbf{c}^T_{costs}$ and $\mathbf{c}^T_{emissions}$, respectively. Starting from point (I) (causing emissions $\overline{e}$), the Pareto Front is moving along (III) to (II) (causing emissions $\underline{e}$). The movement along (III) is a result of the ε-constraint in the form

$$emissions = \mathbf{c}^T_{emissions}[\mathbf{x},\mathbf{y}]^T \leq \underline{e} + (\overline{e} - \underline{e})(1-\alpha) \tag{11}$$

by the variation of the parameter α. In this work, a variation of α in 10% steps is chosen.

2.3. Modeling of energy communities

The big advantage of an EC is the fact that ECs can conduct joint investments. To capture this effect, the EC is allowed to make investments of processes and storages on a building level (for all block types). Contrary, if there is no EC, the investments of processes and storages are on a flat (B or Z blocks) or building (E blocks) level. So, the EC can exploit the EoS of processes and storages (modeled by binary decision variables in Section 2.2.1). The investment costs in the distribution grid are unchanged between those two cases.

2.4. Merit order based accounting of emissions

One of the objectives of EC addresses emission reduction. So, the EC may consider two types of emissions: (i) mean or (ii) marginal emissions. Both types of emissions reflect the current market conditions, but marginal emissions give information of one additional unit of energy fed into or consumed from the grid. The idea behind the comparison is that the ECs might be interested in substituting certain power plants (e.g., coal), as implied by the consideration of marginal emissions.

The mean emissions are calculated by using the total carbon emissions and the total amount of electricity generated for each time-step (hour). For the introduction of marginal emissions, the marginal generator has to be defined: The marginal generator is the unit selling the last bid and setting the price.

Fig. 6 shows the result of the two types for two exemplary hours. The Emissions are based on the number of the German Bundestag [40]. While the upper part of the Figure shows the Central European merit order, the lower part shows the corresponding emissions of each power plant. So, the marginal generators are gas power plants (hour 1) and lignite power plants (hour 2). The merit order does reflect costs (and prices) but not the emissions: while the demand and electricity price for time step 1 is high, marginal and mean emissions are low and vice versa for time step 2. So, the marginal

[8] Assuming a constant power inverter's efficiency of 0.95 [36].

[9] See Ref. [39] for detailed information of the characteristics of the ε-constraint method.

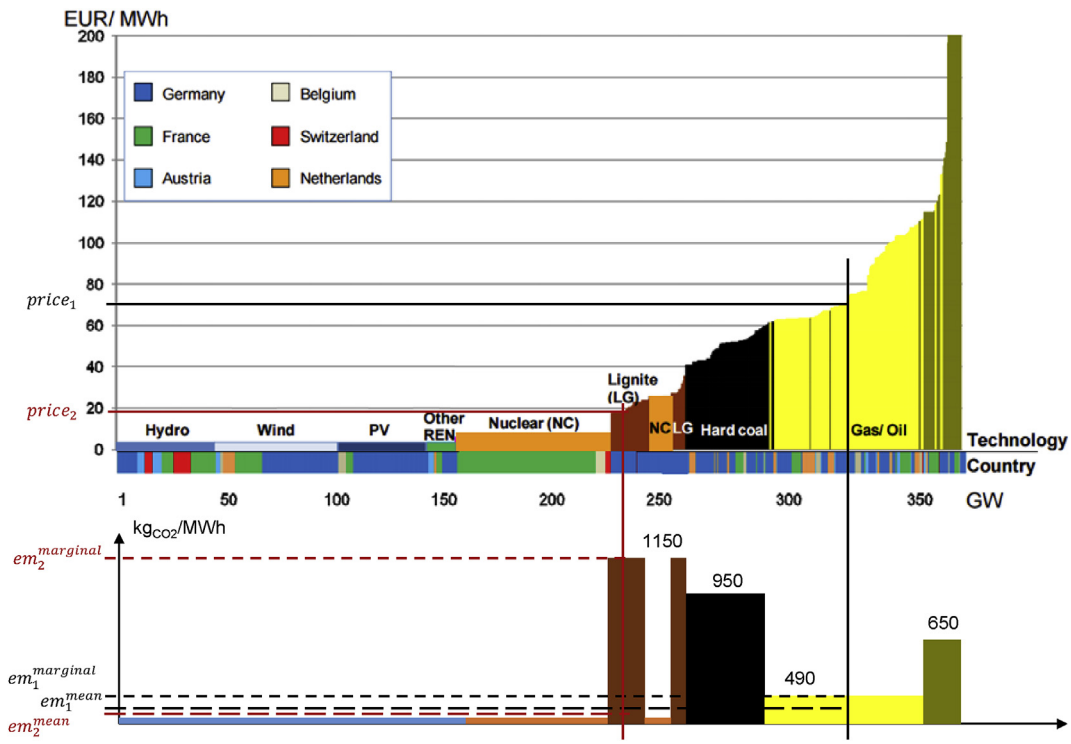

Fig. 6. Central European merit order (top) and the corresponding emissions (bottom). Own representation basing on [40,42].

emissions at time step 1 are high compared to the mean emissions, as the lignite power plant sets the price.

In the following analysis, the Austrian merit order is used because of two aspects. Firstly, the Austrian electricity market[10] has a high share of RES, therefore gives an outlook how future merit orders may look like. So, the difference between mean and marginal emissions are significant. Secondly, Austrian consumers (and therefore ECs as well) have a high affinity to buy Austrian products. Section 4 shows the effects of considering either mean or marginal emissions by the planning of local energy infrastructure of an EC. If not stated otherwise, mean emissions are used.

2.5. Carbon taxes

The European Commission proposes the introduction of carbon taxes as an effective policy measure for the reduction of carbon emissions [43]. The introduction of carbon taxes effects the objective, as it increases the costs by

$$\zeta^{CarbonTax} = \sum_{t} \sum_{c \in \{Emission\}} \sum_{v \in V} \rho_{vct} C^{CarbonTax} \tag{12}$$

of all the emissions $\rho_{vEmissiont}$ and the parameter carbon tax $C^{CarbonTax}$.

3. Definition of the case study and scenarios

In the following, an EC at a site in the city of Linz, Austria is described, as well as the corresponding scenarios regarding the available energy infrastructure, energy demand, and generation. This site is chosen because data is publicly available and all three building types, typically for Austrian building stock, are present. The assumptions in regard of the economic (such as investment, maintenance and operational costs of processes, storages, and the grid) and technical (e.g., efficiency factors) parameters are listed in this work's Appendix A.

3.1. Project site and energy infrastructure

The method defined in Section 2 is applied, to a project site in Linz, more precisely the “Andreas-Hofer-Viertel”.[11] The existing buildings (as introduced in Fig. 2 (Section 2)) are currently connected to the electricity and district heating grid [44]. Consequentially, it is assumed in one scenario that a utility company provides electricity and heat demand (via the electricity and district heating grid). The name of this scenario is “Existing Infrastructure”. Also, the possibility that no generation and distribution system is available. This scenario is named “Green Field”. In this case, the EC has to invest in the grid. The comparison of those scenarios helps to understand the “lock-in effect” given by existing energy infrastructure.

3.2. Energy demand and generation

Demand, generation, and efficiency data is described by measured and synthetic data from the year2016.[12] To understand the effects of load development, two scenarios are introduced: The scenario “Status Quo” describe the current situation at the project

[10] Installed capacity according to the Austrian TSO Austrian Power Grid: Hydro 55.16%, Wind 13.03%, PV 4.73%, Gas 20.48%, Coal 2.74% and Misc 3.86% [41].

[11] Geographical location: N 48° 17′12.2", E.14° 17′49.8″

[12] Electricity profiles: [45], heat profiles: [46], PV generation [38] and ST generation [36] and heat pump generation [36], solar radiation time series [47] a temperature time series [48]. Retail electricity, gas and heat prices from the Austrian Regulation Authority [49]. Further information regarding the building specific modeling may be found in Ref. [29].

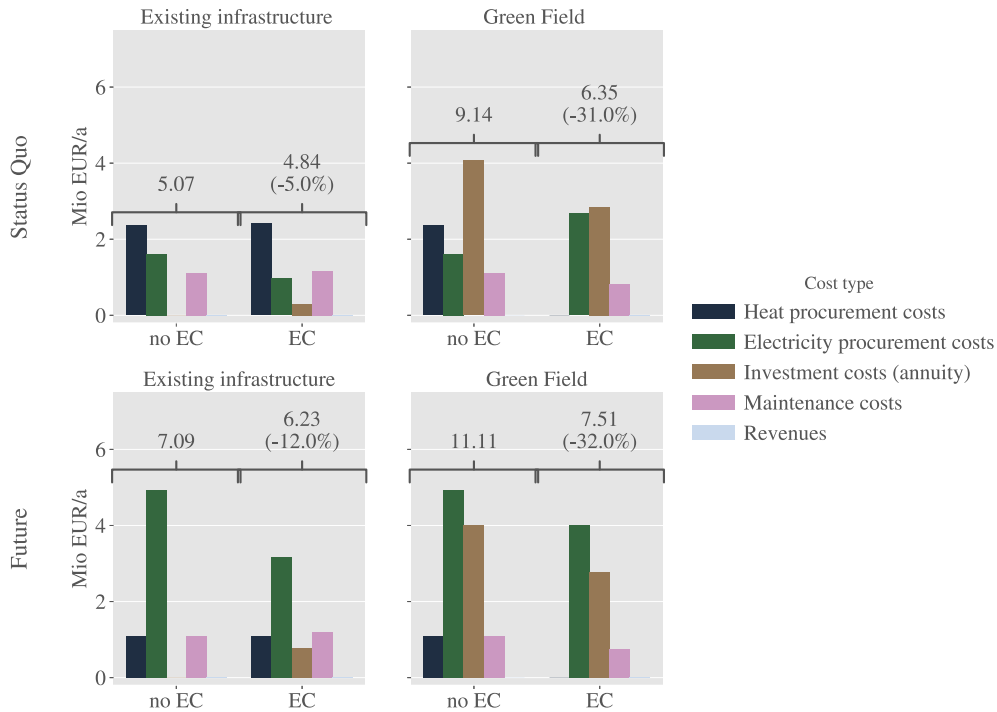

Fig. 7. Composition of the costs for the minimum costs solution.

site, while the second scenario, "Future", include a higher population density but also a higher energy efficiency standards[13] according to the current standard of legislation.[14]

Also, the future availability of electric vehicles (EV) is addressed, by introducing one EV per two inhabitants [51]. It is assumed that the electric vehicles are charged at home (without discussing the issue of parking) The charging profiles originated from an Austrian EV Study E-Mobilitätsmodellregion VLOTTE [52]. As the case study in this paper addresses an urban area, a daily demand of 4 kWh is assumed for this paper. So, the electricity demand increases more in blocks with a higher number of inhabitants (B and Z).

4. Results and discussion

In this section, firstly the minimum costs solution of the EC of the case study is shown in Section 4.1. Secondly, Section 4.2 compares the minimum costs to the minimum carbon emissions solution. Consequentially, Section 4.3 calculates the entire Pareto Front and analyze it with respect to different methods of emissions accounting. The final results in Section 4.4 address the sensitivity of the minimum cost solution in the case of carbon taxes and compare it to the Pareto Front.

4.1. The economic value of an energy community

In a first step, the economic value of an EC is discussed. Therefore, the cost minimal solution is calculated, also labeled solution (I) in Fig. 5. Fig. 7 shows the composition of annual total costs, for the cases without and with EC. Furthermore, it distinguishes between all the previously introduced scenarios.

The results show that the introduction of EC reduces the total costs by up to 32%. The highest gains are achievable in the "Green Field" scenarios, therefore showing the lock-in effect of existing investments. In the "Green Field" scenario with an EC, the EC avoid investments in the heating grid. The EC exploits the EoS by investing in one grid only, the electricity grid. This work's method describes the EoS by two components, fixed and variable investment costs (Section 2.2.1). As stated in Table A 2 the fixed investment costs of grids are very high. If the EC invests only in the electricity grid, the EC gains savings from not investing in district heating grids (reduced fixed investment costs). Additionally, to the savings from the EoS, the procurement costs of heat generated from electricity are lower than from district heating. In all cases, the revenues are minor because the distributed generation was almost entirely consumed locally.

For the following results, only the results for the EC are discussed.

4.2. Comparison of the minimum costs and minimum emissions

If the objective is switched to minimum emissions, shown as a transition from (I) to (II) in Fig. 5, the solution changes drastically. Fig. 8 shows the results for the grid deployment. It shows the results for the scenario "Status Quo/Existing Infrastructure" and the electricity grid changes strongly. The results show, that on the one hand, the grid capacity of the electricity grid gets increased massively (up to 600%). On the other hand, the heat grid capacity stays constant or gets even reduced. The video provided in the supplementary material of this work shows the grid deployment of Fig. 8 as a function of the Pareto Front.

Supplementary video related to this article can be found at https://doi.org/10.1016/j.energy.2019.02.104.

Fig. 9 shows the composition of the commodities used for electricity and heat provision (show in the first two sub-figures) and total emissions. The results indicate that the emission

[13] The implementation of energy efficiency measures allow a significant reduction of SH and DHW demand, especially for the B block type. Electricity demand (w/o any demand for heat pumps) depends on the number of inhabitants, whereas it is independent of building specific energy efficiency measures.

[14] Provincial Law of 5 May 1994, which enacts a building code for Upper Austria [50].

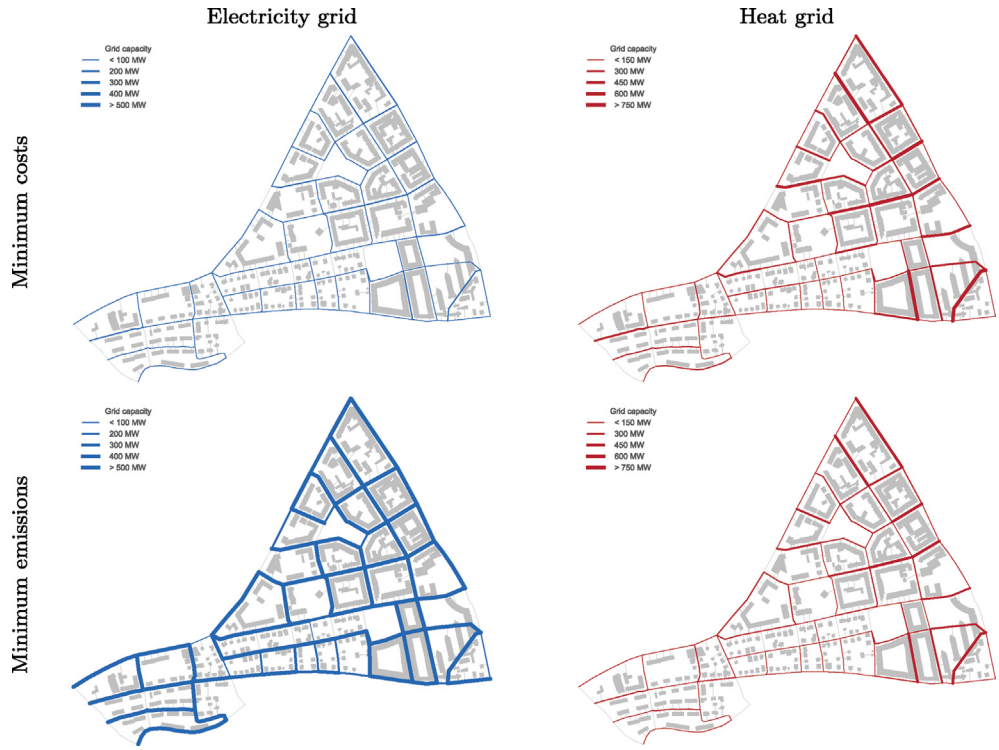

Fig. 8. Grid deployment for minimum costs and minimum emissions "Status Quo"/"Existing Infrastructure".

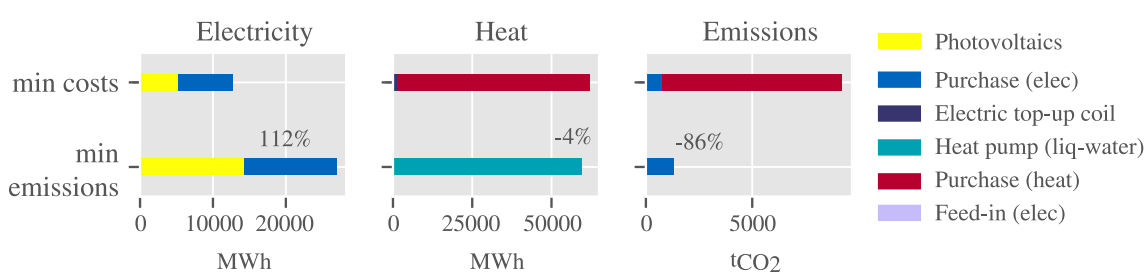

Fig. 9. Commodities created for minimum costs and minimum emissions solution.

reduction of 85% is the result of PV installations and heat pumps. Such investments require investments in electricity grid infrastructure (see Fig. 8 bottom/left) and processes (especially solar PV and heat pumps). As a result, the total costs increase by 598%. For real-world installations, such an increase in costs would be hardly manageable.

Therefore, the following results will give more information about the transition towards a renewable energy community and quantify the trade-off between costs and emissions.

4.3. Pareto Front and methods of emissions accounting

In the next step, the minimum costs and minimum emissions optimization are extended by the Pareto Optimization. Additionally, different methods of emission accounting are introduced, as introduced in Section 2.4.

Fig. 10 shows the Pareto Fronts, as well as two methods of emission accounting. The results vary highly between mean and marginal emissions (up to 389%), although the sizing of the technologies is very similar in both emission scenarios. As shown in the previous results, the highest gains of emission reduction are achieved by electrifying the EC. By accounting emissions by the method of marginal emissions, the total annual emissions increases, although there are only minor changes in the optimal technology portfolio.

As stated in Section 4.1 and 4.2 the minimum costs solution in the case of "Existing Infrastructure" is the heat procurement via the heat grid. Contrary, the heat procurement in the "Green Field" scenario, is based on heat pumps. The results show that newly designed energy infrastructure under the aspect of cost reduction benefits regarding emission reduction, named ΔE. ΔE might be interpreted as the emissions savings potential of green-field infrastructure.

The results also show that the Pareto Front of "Existing Infrastructure" converges to the Pareto Front of "Green Field", but differs in costs by ΔC (the result of an existing electricity grid). ΔC may be interpreted as the monetary value of the existing infrastructure regarding the minimum emissions solution.

4.4. Introduction of carbon taxes

For the final results, the impacts of carbon taxes on the minimum costs solution are investigated. In comparison to the Pareto Optimization, the emissions are not restricted up to the minimum

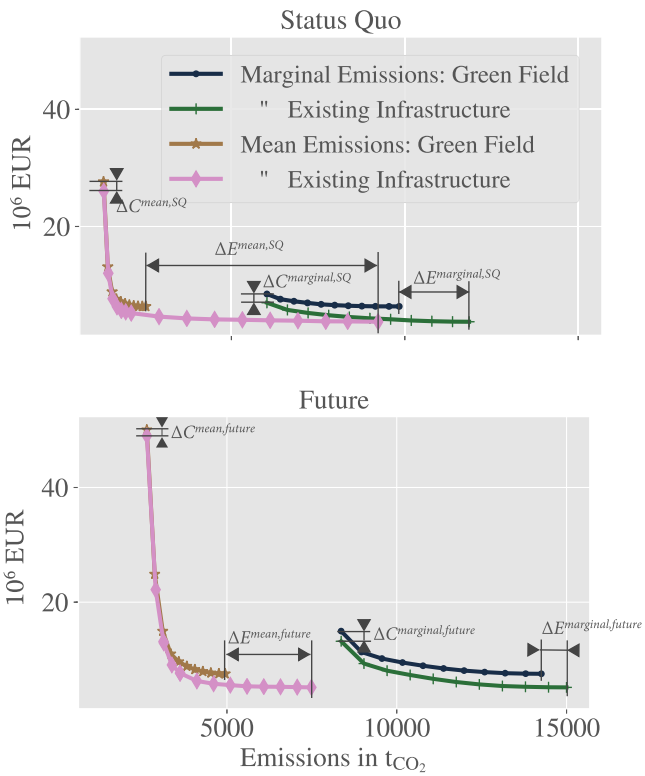

Fig. 10. Pareto Fronts with two methods of emissions accounting: mean and marginal emissions. Besides comparing the demand scenarios "Status Quo" and "Future", it is also distinguished between "Green Field" and "Existing Infrastructure". (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

from 0 to 100EUR/t_{CO_2} [15] in 20 EUR/t_{CO_2} steps. Comparing "Existing Infrastructure" with the "Green Field", it shows that "Existing Infrastructure" is more sensitive to carbon taxes. On the other hand, carbon taxes up to 100 EUR/t_{CO_2} do not provide monetary incentives to change the technology portfolio for the "Green Field" significantly. Although, the carbon taxes $C^{CarbonTax}$ are increased up to 100EUR/t_{CO_2}, it does not provide enough incentives to reduce the emissions to the level of the minimum emissions. As shown in Fig. 9 most of the emissions are the result of heat procurement. A reduction in heat load characterizes the "Future" scenario. The Future, as well as the "Green Field" scenarios do have a low sensitivity to carbon taxes. The reason is that, the heat load is lower, and the infrastructure changed in favor of low-emission technologies. So, compared to "Status Quo", the emissions are lower, as the sensitivity to carbon taxes.

5. Conclusions

To address the value of EC regarding two objectives: costs and emissions, an energy system model basing on two open-source optimization models was developed. While the focus of the first sub-model is the optimal investment decisions on a high temporal level, the second sub-model address the optimal deployment of energy grids on a building level. Also, spatial and temporal clustering algorithms have been developed to increase the models' interoperability and performance. This may make it easier for future users of the model (e.g., city planners) to apply the model. It may be concluded that the methods developed in this paper allow urban planners to analyze city districts of interest towards sustainability and costs. The block-based method developed in this paper allows future operators of the model to include and adopt city districts to low expenses.

The results show that ECs could reduce the costs as well as emissions. Not surprisingly, the solutions for minimum costs and minimum carbon emissions are contrary to each other. Therefore,

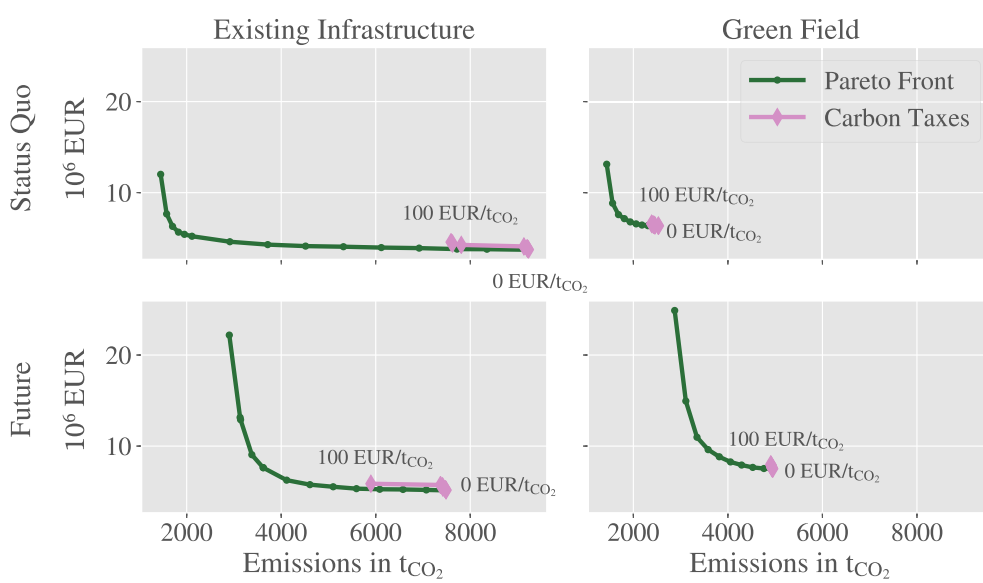

Fig. 11. Comparison of the Pareto Font with multiple minimum cost solutions with carbon taxes from 0 to 100 EUR/ t_{CO_2}, ascending in 20EUR/t_{CO_2} steps.

emissions solution (quantity based reduction of emissions); instead, carbon taxes emissions increase the total costs (price based reduction of emissions).

The results in Fig. 11 shows the results for carbon taxes starting

[15] There is an ongoing discussion about the introduction and an appropriate level of carbon taxes. So, France plans to increase the carbon tax rate to 56EUR/tCO2 in 2020 and 100 EUR/tCO2 in 2030 [53].

the calculation of the Pareto Front helps to quantify the optimal technical portfolio as a function of both objectives. The results show that a higher degree of emission reduction is mostly the result of electrification, although the use of one single energy carrier increases the risk of the EC (e.g., concerning security-of-supply or price shocks). The Pareto Front can give stakeholder (such as the local government) information about the capabilities and restrictions of the local energy system. Also, the Pareto Front helps the stakeholders to formulate and quantify emission reduction targets.

Furthermore, the lock-in effect of existing infrastructure is analyzed. It is very significant, as carbon emissions are much higher for existing infrastructure than green-field investments. Also, existing infrastructure, e.g., heat grid, make the EC more vulnerable to carbon taxes. The conclusions of the scenarios, investigated in this paper, are that a transformation of the local energy system towards sustainability is possible. The local authorities have to be aware that the transformation has to initiated in time. Otherwise, externalities (e.g., carbon taxes) and reinvestment of high-emission infrastructure leads to sunk costs and/or high emissions.

As this paper assumes that all consumers at the project site join the EC, the situation, in reality, may depend on the willingness of the consumers to join such an EC. For the practical implementation to establish an EC, the "Green Field" scenario may be more suitable: In an urban development project, an appropriate framework may provide the incentives to inhabitants to join the EC and form a sustainable EC.

Future research may include an improved modeling approach for the implementation of long-term storages and the effects of uncertainty (e.g., regarding future energy demand consumer choice). This work only investigated the building situated in one Austrian city district. Future research may study the introduction of other relevant urban blocks in cities and regions. Also, the situation for rural areas may be discussed separately.

CRediT authorship contribution statement

Andreas Fleischhacker: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Georg Lettner:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Validation. **Daniel Schwabeneder:** Methodology, Validation, Visualization, Writing - review & editing. **Hans Auer:** Project administration, Supervision.

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Appendix A. Data

Table A.1
Technical and economic parameters of processes

Process	inv-cost	inv-cost-p	fix-cost	wacc	area-per-cap	depreciation	source
	in EUR/building	in EUR/kW	in % of inv	in %	in m^2/kW	in a	
Photovoltaics	3494	1038	1	2	6.5789	25	[54]
Solarthermal	4000	2461	1	2	1.25	25	[54]
Hybrid collector	6000	3000	1	2	6.5789	25	[55]
Electrolyser	5235	4278	1	2	-	20	[56]
Fuel cell	4635	3753	1	2	-	20	[56]
Electric top-up coil	100	60	2	2	-	25	[36]
Gas boiler	1200	600	1	2	-	20	[36,54]
Heat pump (liq-water)	17,000	770	2	2	-	20	[36]
Heat pump (air-water)	3000	1150	2	2	-	18	[36]
Mikro CHP	1200	3400	3	2	-	20	[36]

Table A.2
Technical and economic parameters of grids

Grid	inv-cost	inv-cost-p	fix-cost	wacc	depreciation	source
	in EUR/m	in EUR/kW	in % of inv	in %	in a	
Elec. Grid	400	390	1	2	40	[57]
Heat grid	500	742	1	2	40	[57]
Gas grid	400	594	1	2	40	[57]

Table A.3
Technical and economic parameters of storages

Storage	eta	inv-cost	inv-cost-p	inv-cost-c	fix-cost-p	fix-cost-c	depre-	wacc	source
	in	in	in	in	in	in	ciation in	in	
	%	EUR/building	EUR/kW	EUR/kWh	EUR/kW/a	EUR/kWh/a	a	%	
Battery	96	1000	10	1200	0.5	0.5	15	2	[58]
Hot Water Storage	090	0	1	90	1	1	15	2	[36]
H2 Storage	98	0	0.1	25	0	0	25	2	[56]

References

[1] The World Bank. The world bank in urban development. 2017. http://www.worldbank.org/en/topic/urbandevelopment/overview.

[2] European Commission. Cities. 2017. https://ec.europa.eu/clima/policies/international/paris_protocol/cities_en.

[3] Allen M, Dube O, Solecki W, AragnDurand F, Cramer W, Humphreys S, et al. Framing and context. In: An IPCC Special Report on the impacts of global warming of 1.5C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty; 2018.

[4] IEA. Energy technology perspectives 2016: towards sustainable urban energy systems. 2016. https://www.iea.org/publications/freepublications/publication/EnergyTechnologyPerspectives2016_ExecutiveSummary_EnglishVersion.pdf.

[5] European Commission. Proposal for a directive of the european parliament and of the council on common rules for the internal market in electricity: IEM directive. 2016.

[6] Walker G. What are the barriers and incentives for community-owned means of energy production and use? Energy Policy 2008;36(12):4401–5. doi:"bibinfo–doi"–"url–10.1016/j.enpol.2008.09.032".

[7] Ma T, Wu J, Hao L, Lee WJ, Yan H, Li D. The optimal structure planning and energy management strategies of smart multi energy systems. Energy 2018;160:122–41. doi:"bibinfo–doi"–https://doi.org/10.1016/j.energy.2018.06.198", http://www.sciencedirect.com/science/article/pii/S0360544218312635.

[8] Mancarella P. MES (multi-energy systems): an overview of concepts and evaluation models. Energy 2014;65:1–17. doi:"bibinfo–doi"–"url–10.1016/j.energy.2013.10.041", http://www.sciencedirect.com/science/article/pii/S0360544213008931.

[9] Widl E, Jacobs T, Schwabeneder D, Nicolas S, Basciotti D, Henein S, et al. Studying the potential of multi-carrier energy distribution grids: a holistic approach. Energy 2018;153:519–29. doi:"bibinfo–doi"–https://doi.org/10.1016/j.energy.2018.04.047", http://www.sciencedirect.com/science/article/pii/S0360544218306510.

[10] Stadler M, Groissböck M, Cardoso G, Marnay C. Optimizing distributed energy resources and building retrofits with the strategic DER-CAModel. Appl Energy 2014;132:557–67. doi:"bibinfo–doi"–"url–10.1016/j.apenergy.2014.07.041", http://www.sciencedirect.com/science/article/pii/S0306261914007235.

[11] Geidl M. Integrated modeling and optimization of multi-carrier energy systems. Dissertation. ETH Zurich; 2007.

[12] Nazar MS, Haghifam MR. Multiobjective electric distribution system expansion planning using hybrid energy hub concept. Electr Power Syst Res 2009;79(6):899–911. doi:"bibinfo–doi"–"url–10.1016/j.epsr.2008.12.002", http://www.sciencedirect.com/science/article/pii/S0378779608003180.

[13] Fichera A, Frasca M, Volpe R. Complex networks for the integration of distributed energy systems in urban areas. Appl Energy 2017;193:336–45. doi:"bibinfo–doi"–"url–10.1016/j.apenergy.2017.02.065".

[14] Weber C, Shah N. Optimisation based design of a district energy system for an eco-town in the United Kingdom. Energy 2011;36(2):1292–308. doi:"bibinfo–doi"–"url–10.1016/j.energy.2010.11.014", http://www.sciencedirect.com/science/article/pii/S0360544210006407.

[15] Mehleri ED, Sarimveis H, Markatos NC, Papageorgiou LG. A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level. Integration and Energy System Engineering (1). In: European symposium on computer-aided process engineering 2011. vol. 44; 2012. p. 96–104. doi:"bibinfo–doi"–"url–10.1016/j.energy.2012.02.009", http://www.sciencedirect.com/science/article/pii/S036054421200103X.

[16] Sameti M, Haghighat F. Optimization approaches in district heating and cooling thermal network. Energy Build 2017;140:121–30. doi:"bibinfo–doi"–"url–10.1016/j.enbuild.2017.01.062".

[17] Orehounig K, Evins R, Dorer V. Integration of decentralized energy systems in neighbourhoods using the energy hub approach. Appl Energy 2015;154:277–89. doi:"bibinfo–doi"–"url–10.1016/j.apenergy.2015.04.114", http://www.sciencedirect.com/science/article/pii/S0306261915005772.

[18] Eicker U, Monien D, Duminil É, Nouvel R. Energy performance assessment in urban planning competitions. Appl Energy 2015;155:323–33. doi:"bibinfo–doi"–"url–10.1016/j.apenergy.2015.05.094", http://www.sciencedirect.com/science/article/pii/S0306261915007278.

[19] Bazilian M, Rice A, Rotich J, Howells M, DeCarolis J, Macmillan S, et al. Open source software and crowdsourcing for energy analysis. Energy Policy 2012;49:149–53. doi:"bibinfo–doi"–"url–10.1016/j.enpol.2012.06.032".

[20] Ajila SA, Wu D. Empirical study of the effects of open source adoption on software development economics. J Syst Software 2007;80(9):1517–29. doi:"bibinfo–doi"–https://doi.org/10.1016/j.jss.2007.01.011". Evaluation and Assessment in Software Engineering, http://www.sciencedirect.com/science/article/pii/S0164121207000076.

[21] Dorfner J. Open source modelling and optimisation of energy infrastructure at urban scale. Dissertationvol. 2016. München: Technische Universität München; 2016.

[22] Dorfner J. urbs: a linear optimisation model for distributed energy systems. 06.. 2017. https://github.com/ojdo/urbs.

[23] Dorfner J. rivus: a mixed integer linear optimisation model for energy infrastructure networks. 06.. 2017. https://github.com/tum-ens/rivus.

[24] Molyneaux A, Leyland G, Favrat D. Environomic multi-objective optimisation of a district heating network considering centralized and decentralized heat pumps. ECOS 2010;35(2):751–8. doi:"bibinfo–doi"–"url–10.1016/j.energy.2009.09.028", http://www.sciencedirect.com/science/article/pii/S0360544209004216.

[25] Voll P. Automated optimization-based synthesis of distributed energy supply systems; vol. 1 of *Aachener Beiträge zur Technischen Thermodynamik*. aufl ed.. 2014. p. 1. Aachen: Mainz: ISBN 978-3-86130-474-6.

[26] Fonseca JA, Nguyen TA, Schlueter A, Marechal F. City energy analyst (cea): integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts. Energy Build 2016;113:202–26. doi:"bibinfo–doi"–https://doi.org/10.1016/j.enbuild.2015.11.055", http://www.sciencedirect.com/science/article/pii/S0378778815304199.

[27] Wang C, Kilkis S, Tjernstrm J, Nyblom J, Martinac I. Multi-objective optimization and parametric analysis of energy system designs for the albano university campus in stockholm. Procedia Engineering 2017;180:621–30. doi:"bibinfo–doi"–https://doi.org/10.1016/j.proeng.2017.04.221". International High-Performance Built Environment Conference A Sustainable Built Environment Conference 2016 Series (SBE16), iHBE 2016, http://www.sciencedirect.com/science/article/pii/S1877705817317289.

[28] Zhang C, Zhou L, Chhabra P, Garud SS, Aditya K, Romagnoli A, et al. A novel methodology for the design of waste heat recovery network in eco-industrial park using techno-economic analysis and multi-objective optimization. Appl Energy 2016;184:88–102. doi:"bibinfo–doi"–https://doi.org/10.1016/j.apenergy.2016.10.016", http://www.sciencedirect.com/science/article/pii/S0306261916314404.

[29] Zelger T, Leibold J, Lettner G, Fleischhacker A, Huemer-Kals V, Kleboth A, et al. SMART CITY - MIKROQUARTIERE Energie- und lebensqualitätsoptimierte Planung und Modernisierung von Smart City-Quartieren. Endbericht; 2018. Technical report.

[30] Kleboth A, Granzow I. Interview on characteristic blocks for Linz/Austria with civil engineers. 2016.

[31] Bottou L, Bengio Yoshua. Convergence properties of the K-means algorithms. Adv Neural Inf Process Syst 1995:585–92.

[32] Garreta R. Learning scikit-learn: machine learning in Python : experience the benefits of machine learning techniques by applying them to real-world problems using Python and the open source scikit-learn library. Community experience distilled. Birmingham, UK: Packt Pub; 2013. p. 2013. ISBN 978-1783281930.

[33] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in Python. J Mach Learn Res 2011;12:2825–30.

[34] Arthur D, Vassilvitskii S. K-means++: the advantages of careful seeding. In: Proceedings of the eighteenth annual ACM-SIAM symposium on discrete algorithms. SODA '07. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics; 2007. ISBN 978-0-898716-24-5, http://dl.acm.org/citation.cfm?id=1283383.1283494.

[35] Manfren M, Caputo P, Costa G. Paradigm shift in urban energy systems through distributed generation: methods and models. Appl Energy 2011;88(4):1032–48. doi:"bibinfo–doi"–"url–10.1016/j.apenergy.2010.10.018".

[36] Lindberg KB, Doorman G, Fischer D, Korpås M, Ånestad A, Sartori I. Methodology for optimal energy system design of Zero Energy Buildings using mixed-integer linear programming. Energy Build 2016;127:194–205. doi:"bibinfo–doi"–"url–10.1016/j.enbuild.2016.05.039".

[37] Fischer D, Madani H. On heat pumps in smart grids: a review. Renew Sustain Energy Rev 2017;70:342–57. doi:"bibinfo–doi"–"url–10.1016/j.rser.2016.11.182".

[38] Huld T, Gottschalg R, Beyer HG, Topič M. Mapping the performance of PV modules, effects of module type and data averaging. Sol Energy 2010;84(2):324–38. doi:"bibinfo–doi"–"url–10.1016/j.solener.2009.12.002".

[39] Bérubé JF, Gendreau M, Potvin JY. An exact -constraint method for bi-objective combinatorial optimization problems: application to the Traveling Salesman Problem with Profits. Eur J Oper Res 2009;194(1):39–50. doi:"bibinfo–doi"–"url–10.1016/j.ejor.2007.12.014".

[40] Deutscher Bundestag. CO2-Bilanzen verschiedener Energieträger im Vergleich. 2007.

[41] APG. Installed power plant capacity. 2018. https://www.apg.at/en/markt/Markttransparenz/erzeugung/installierte-leistung.

[42] IEA Coal Industry Advisory Board. The impact of global coal supply on worldwide electricity prices. 2015.

[43] European Commission. A Clean Planet for all - a European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy. 2018.

[44] Linz AG. Kennzahlen 2016: auf einen Blick. 2016. https://www.linzag.at/media/dokumente/infomaterial_2/linzag-kennzahlen.2016.pdf.

[45] Beausoleil-Morrison I, Arndt U. An experimental and simulation-based investigation of the performance of small-scale fuel cell and combustion-based cogeneration devices serving residential buildings: final report of Annex 42 of the International Energy Agency's Energy Conservation in Buildings and Community Systems Programme. Ottawa: Natural Resources Canada; 2008. ISBN 978-0-662-47924-6.

[46] BGW. Praxisinformation P 2007/13 gastransport/betriebswirtschaft: abwicklung von Standardlastprofilen. 2007.

[47] MINES ParisTech/Transvalor. Irradiation values from helioclim-3 and

meteorological data (MERRA-2 and GFS): generated using copernicus atmosphere monitoring service information 2016. 2018.
[48] ZAMG. Meteorologische Messdaten der ZAMG. 2012-2018. https://creativecommons.org/licenses/by/3.0/at/deed.de.
[49] E-Control. Suppliers and prices. 2017. https://www.e-control.at/en/preise-vergleichen-lieferanten-auswahlen.
[50] Land Oberösterreich. Oö. bauordnung 1994 - oö. bauo 1994. 1994.
[51] Statistics Austria. Motor vehicles: vehicle stock in 2017. 21.08. 2018. https://www.statistik.at/web_de/statistiken/energie_umwelt_innovation_mobilitaet/verkehr/strasse/kraftfahrzeuge_-_bestand/index.html.
[52] Schuster A, Leitinger C, Brauner G. Begleitforschung der TU Wien in VLOTTE; 19.04. 2010. Technical report.
[53] Zimmermannová J, Hájek M, Rozenský L. Carbon taxation in the European countries. 2018. Working document, https://www.researchgate.net/publication/322315012_Carbon_taxation_in_the_European_countries.
[54] Loschan C. Marktanalyse von Skaleneffekten dezentraler Erzeugungstechnologien mit Regressionsanalyse. Bachelor Thesis. TU Wien; 2017.
[55] Adam M, Wirth P, Radosavljevic R. Verbundprojekt: standardisierung und Normung von multifunktionalen PVT Solarkollektoren (PVT–Norm): teilvorhaben: PVT–Systemanwendungen und Simulationen. 2014.
[56] Kotzur L, Markewitz P, Robinius M, Stolten D. Kostenoptimale Versorgungssysteme für ein vollautarkes Einfamilienhaus. In: Auer H, Haas R, Hiesl A, editors. Klimaziele 2050: chance für einen Paradigmenwechsel?; 2017. p. 14. eeg.tuwien.ac.at/iewt2017/.
[57] Mühlecker D. Betriebswirtschaftlich optimale Wärme- und Stromversorgung eines Stadtentwicklungsgebietes. Master Thesis. TU Wien; TU Wien; 2016. https://repositum.tuwien.ac.at/obvutwhs/content/titleinfo/1375199.
[58] Hiesl A. Kostenentwicklung dezentraler batteriespeicher - evolution oder revolution? In: Bachhiesl U, Stiegler H, editors. Neue Energie für unser bewegtes Europa; 2018. p. 17. https://www.tugraz.at/fileadmin/user_upload/Events/Eninnov2018/files/allg/EnInnov2018_Programm_180211.pdf.