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Indicators for the optimization of sustainable urban energy systems based on energy system modeling

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Abstract

Background: Urban energy systems are responsible for 75% of the world's energy consumption and for 70% of the worldwide greenhouse gas emissions. Energy system models are used to optimize, benchmark and compare such energy systems with the help of energy sustainability indicators. We discuss several indicators for their basic suitability and their response to changing boundary conditions, system structures and reference values. The most suitable parameters are applied to four different supply scenarios of a real-world urban energy system.

Results: There is a number of energy sustainability indicators, but not all of them are suitable for the use in urban energy system optimization models. Shortcomings originate from the omission of upstream energy supply chains (secondary energy efficiency), from limited capabilities to compare small energy systems (energy productivity), from excessive accounting expense (regeneration rate), from unsuitable accounting methods (primary energy efficiency), from a questionable impact of some indicators on the overall system sustainability (self-sufficiency), from the lack of detailed information content (share of renewables), and more. On the other hand, indicators of absolute greenhouse gas emissions, energy costs, and final energy demand are well suitable for the use in optimization models. However, each of these indicators only represents partial aspects of energy sustainability; the use of only one indicator in the optimization process increases the risk that other important aspects will deteriorate significantly, eventually leading to suboptimal or even unrealistic scenarios in practice. Therefore, multi-criteria approaches should be used to enable a more holistic optimization and planning of sustainable urban energy systems.

Conclusion: We recommend multi-criteria optimization approaches using the indicators of absolute greenhouse gas emissions, absolute energy costs, and absolute energy demand. For benchmarking and comparison purposes, specific indicators should be used and therefore related to the final energy demand, respectively, the number of inhabitants. Our example scenarios demonstrate modeling strategies to optimize sustainability of urban energy systems.

Keywords: Energy system modeling, Urban energy systems, Multi-energy systems, Optimization indicators, Multi-objective optimization, Energy sustainability, Energy efficiency, Energy sufficiency, Energy consistency

Background

Introduction

Urban energy systems are the "combined process of acquiring and using energy in a given" [1] spatial entity with a high density and differentiation of residents, buildings, commercial sectors, infrastructure [2], and energy sectors (e.g., heat, electricity, fuels) [3]. They are also called mixed-used multi-energy systems. It is often

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challenging to clearly define spatial boundaries of urban energy systems. An often-used approach is to use legally defined city districts as balance entities.

The complexity of these systems, combined with the fact that urban energy systems are responsible for 75% of global energy consumption and 70% of worldwide greenhouse gas (GHG) emissions [4], results in the need for a profound transformation of urban energy systems. Different goals and strategies are discussed with respect to various sustainability aspects.

The most prominent goal is the fulfillment of national and international climate neutrality goals and thus the mitigation of GHG emissions [5–7]. Further widespread goals with respect to urban energy systems are the minimization of energy supply costs [5, 7], the non-use of fossil fuels [7], and the increase in regional value added [8]. The objectives of network access and security of supply [5, 7] are regarded as basic requirements of well-functioning urban energy systems.

Energy system models (ESM) are important tools for the design and optimization of existing or newly planned urban energy systems [9]. Various suitable indicators need to be identified in order to address a variety of sustainability aspects. These indicators can be used as target variables in optimization models. By mathematically minimizing or maximizing them [10, 11], sustainable urban energy systems can be designed.

In addition to being used for optimization purposes, indicators can also be used for benchmarking and comparison purposes. The broad application of a set of uniform indicators to a large number of different urban energy systems allows to identify structural problems (e.g., widespread use due to subsidies for less sustainable technologies) that can be remedied by national and international regulations.

We are oriented towards the three energy sustainability strategies of energy efficiency, energy sufficiency and energy consistency [12, 13], for the identification of suitable indicators to be applied in ESM. Particularly with the focus on climate neutrality objectives, it is advisable to thoroughly explore all existing options to mitigate climate change. This includes focusing not only on consistency, but also to examine efficiency and sufficiency demand-side solutions and their potential contribution [14]. Efficiency aims at the provision of the same service with lower input, thus a relative reduction of energy demands (final, secondary, primary), material goods, or financial values by technical means [15, 16]. Sufficiency aims at a reduction of energy service demand (e.g. lower room heat) which results in an absolute reduction of final energy demand and consequently lower resource demand [15, 17], and consistency describes the quality of the energy source [12]. These three strategies are no ends in themselves but different strategies to reach sustainability objectives. Both demand-side strategies, efficiency and sufficiency aim at a reduction of energy demand, yet their approaches differ substantially from each other, and both have their own specific advantages and drawbacks [18, 19]. Overall, each of the three sustainability strategies covers different aspects, and taking all of them into account leads to a broad and manifold picture of urban energy system optimization. We therefore use the categories of efficiency, sufficiency, and consistency, as orientation for the indicator search for a broad and comprehensive perspective.

While there are a number of different indicators for measuring and evaluating the efficiency of energy systems (e.g., [16, 20–22]), only few indicators for sufficiency and consistency are described in the literature (see "Sustainability of urban energy systems").

The majority of energy system models for the optimization of urban energy systems work single-criterial [23], using either economic (e.g., least costs) or environmental (e.g., least GHG emissions) indicators as target variables [24]. In light of the multitude of goals and challenges with regard to the optimization of urban energy systems, it is questionable whether this single-indicator optimization leads to satisfactory or sustainable solutions. Indicators representing more than one goal or multi-criteria optimization could support a more balanced optimization between different goals.

There are also multi-objective models, for instance, the studies by Rieder et. al [25], Sugihara et al. [26], Karmellos and Mavrotas [27], Fonseca et al. [28], and Jing et al. [29]. Usually, an indicator for minimizing system costs (cf. Eq. 5) and an indicator for reducing greenhouse gas emissions (cf. Eq. 4) are applied as optimization criteria. In some cases, third indicators, such as primary energy efficiency ([26], cf. Eq. 2), or degree of self-sufficiency ([28], cf. Eq. 10) are complemented.

Mostly, the selected indicators are set but not further evaluated for their suitability, or whether there are better suited indicators. Within this article, we will close this gap for the specific case of optimization of urban energy systems. Therefore, existing indicators for urban energy system optimization are evaluated, and new ones proposed (see "Sustainability of urban energy systems"). These indicators are then tested for their applicability in energy system modeling. Four different energy supply scenarios are modeled to evaluate the suitability of the new indicators in energy system models (see "Methods: single-criterion simulation" and "Results: single-criterion simulation"). The scenarios include the imports of energy (scenario 1), renewable energy technologies (scenario 2), sector-coupling technologies (scenario 3), and demand reduction (scenario 4). Subsequently, possibilities to combine the most suitable indicators using multi-criteria optimization approaches are presented (see "Methods: multi-objective optimization"). Finally, indicator usage including shortcomings and advantages are discussed and conclusions are drawn.

Sustainability of urban energy systems

Definitions

Energy is a fundamental physical quantity. However, when talking about energy systems, we tend to mean the production of "desired energy services, rather than [energy] as an end in itself" [30]. It is important to distinguish between the different forms of energy (primary energy (PE), secondary energy (SE), final energy (FE), and effective energy (EE)), as well as between direct and cumulative energy demands (CED). The use of different terms of "energy" will lead to considerably varying results during the assessment process [31]. Within this contribution we refer to the definitions of energy terms from the VDI 4600 directive ("Cumulative energy demand — terms, definitions, methods of calculation") [32].

We define the energy balance boundary for the conversion processes to be considered in urban energy systems as all conversion processes up to final energy. Further transformations from final energy into effective energy take place within subsystems of buildings or plants. Although these subsystems are, strictly speaking, part of the urban energy system, they are also complex systems in their own, the interrelationships of which lie outside the scope of research on holistic urban energy systems [31]. When applying methods of energy system modeling, such delimitations and simplifications of system complexity are necessary in order to minimize the input effort for the modeler as well as the computational effort [33].

Energy sustainability: An energy system is considered sustainable if its negative impact on the society, environment, and economy is within the scope of the respective capacities [34]. Energy sustainability can be achieved by the three strategies of energy efficiency, energy sufficiency and energy consistency [12, 13].

Energy efficiency aims at improving the input–output ratio of an energy system. It can be increased either by the reduction of the resource or energy input while maintaining the same energy service, or by the increase of the service with the same input [15].

Energy sufficiency aims at the absolute reduction of energy consumption through social innovations and behavioral changes [12]. An energy system is considered to be sufficient when just as much energy is consumed as is "enough for a particular purpose" [17]. Sufficiency therefore does not aim at reducing absolute energy consumption to zero, but at limiting or reducing it to a sustainable level [15]. Part of the literature also argue for not only upper, but also lower limits to reach a sustainable level of energy service demand, referred to as "enoughness" [35, 36]. A level of "enoughness" avoids excess, especially regarding planetary boundaries but still ensures a good life [37].

In some cases, the term "energy conservation" is used synonymous with "energy sufficiency" [38]. However, since "energy conservation" is mostly used to refer to efficiency-based measures [39], we will use the term "energy sufficiency" in the following.

Energy consistency makes a qualitative assessment of production patterns of supplied energy [40]. Often, this is understood as the distinction between renewable and non-renewable primary energy sources [12]. However, also any aspects referring to the origin of supplied energy may be assessed. For example, *where* or with the help of *which* renewable technology energy is provided.

Sustainability aspects of urban energy system optimization in ESM: In order to limit the complexity of energy sustainability to a level which can be handled by ESM, this contribution will be limited to technical, economical and particular environmental aspects of an energy system, which have regional (e.g., regional value, energy supply costs) or global (e.g., climate neutrality, non-use of fossil fuels) impact. Regarding environmental aspects, GHG are the main aspect considered. As an aside, we will discuss to which extent other environmental aspects like local emissions or resource usage could be directly or indirectly covered by indicators applicable in ESM. We consider security of supply as a basic prerequisite. Furthermore, the studies in this paper are limited to the energy sectors of electricity and heat and the residential, commercial and industry demand sectors.

Efficiency indicators for urban energy systems

Patterson [16] proposed to categorize indicators for the measurement of energy efficiency into:

- Thermodynamic indicators,
- Physical indicators,
- Physical–thermodynamic indicators,
- Economic–thermodynamic indicators, and
- Economic indicators.

Thermodynamic indicators (also denoted as "technical indicators" [41]) "rely entirely on measurements derived from the science of thermodynamics" [16], and express the ratio of useful energy output to the energy input [16]:

$$\text{energy efficiency} = \frac{\text{useful energy output}}{\text{energy input}} \tag{1}$$

Purely *physical indicators* have physical input/output values [16], for example the required amount of fuel per distance traveled by car (l/km or conversely km/l). *Physical–thermodynamic indicators* are hybrid indicators measuring inputs in thermodynamic values and outputs in physical ones, or vice versa. An example is the energy content per liter of fuel (kWh/l). As they are given in physical quantities they can be easily compared [16]. *Economic–thermodynamic indicators* are hybrid indicators as well, in this case using thermodynamic and financial quantities [16], e.g. the price per energy unit (EUR/kWh). For purely *economic indicators*, both input and output are measured with financial units [16], for instance, investments per revenue (EUR/EUR).

For the classification into these terms, it is debatable if the quantity of energy (in *J* or *Wh*) is a physical or a thermodynamic term. In the following, it will be considered as thermodynamic quantity.

The *primary energy efficiency PEE* is a thermodynamic indicator, which is the inverse value of the primary energy factor *PEF* and thus calculated as the ratio of the system's final energy demand *FE* over the cumulative energy demand *CED* [42, 43]:

$$\text{PEE} = \text{PEF}^{-1} = \frac{FE}{\text{CED}} \tag{2}$$

The *secondary energy efficiency SEE* is a thermodynamic indicator as well. It is the ratio of the final energy demand over the secondary energy *SE* required for covering this demand [42]:

$$\text{SEE} = \text{SEF}^{-1} = \frac{\text{FE}}{\text{SE}} \tag{3}$$

In contrast to secondary energy efficiency, the primary energy efficiency takes into account upstream chains and their efficiency levels, which usually lie outside an urban energy system. For example, different production chains of purchased electricity with different primary energy factors (e.g., electricity from renewable sources vs. electricity from fossil-fuel power plants [32]) are considered, even though the processes lie outside the urban area. The outsourcing of an inefficient power plant to a location outside and the subsequent import of the energy would lead to an improvement of the balance sheet of secondary energy efficiency, while the primary energy efficiency would not be affected. We thus consider the primary energy efficiency to be better suited to assess energy efficiency of urban energy systems because it is a more holistic approach.

The *specific GHG emissions* m'_{GHG} are a physical–thermodynamic indicator, which relates the energy demand of the urban area to the related GHG emissions. However, this indicator is not used to calculate an input/output ratio (see Eq. 1), but an output/output ratio. Since GHG emissions should be minimized in order to avoid negative environmental impacts, we regard this indicator as an efficiency indicator. It is calculated as the ratio of the total GHG emissions m_{GHG} to the final energy demand *FE* (Eq. 4) [44]. We recommend life cycle assessments for the determination of the caused GHG emissions:

$$m'_{\text{GHG,FE}} = \frac{m_{\text{GHG}}}{FE} \tag{4}$$

Considering Eq. 1, the specific GHG emissions indicator is, strictly speaking, the *inverse value* of an efficiency indicator. We believe that the use of this indicator (g/kWh instead of kWh/g) is the more intuitive indicator, while it provides the same information content. Such inverse values are also regarded as efficiency indicators here and in the following.

For the use in optimization models, it may be appropriate to use *absolute GHG emissions* of an energy system $m_{\text{GHG,es}}$, instead of referring to a reference value. This simplifies the model, making it easier to use in ESM that are designed to minimize or maximize absolute values. A disadvantage is that the change of the final energy demand *FE*, for example by sufficiency measures, can influence the indicator, so that the indicator is no longer a pure efficiency indicator. For benchmarking and comparative purposes, a reference value should therefore certainly be applied.

The *specific energy costs* C' is an economic–thermodynamic indicator, calculated from the total system costs (including all costs for investment and operation) C and the final energy demand *FE* (Eq. 5). For optimization purposes the *absolute cost* of an energy system C_{es} may be considered (see above):

$$C'_{\text{FE}} = \frac{C}{FE} \tag{5}$$

The *energy productivity EP* is also an economic–thermodynamic indicator and is calculated from the gross domestic product *GDP* and the final energy demand *FE* [45]:

$$\text{EP} = \frac{\text{GDP}}{\text{FE}} \tag{6}$$

The energy productivity is usually used to assess national energy systems, and its significance decreases the smaller the energy system under consideration is. For example, the energy productivity of the small country of Luxembourg is strongly distorted by the strongly developed steel industry [46] and a high number of commuters and the resulting influences on the *GDP* [47]. Following analogous considerations, the suitability of this indicator for cities is doubtful.

In addition to the indicators mentioned, any other parameter can be divided by the discussed reference values, and thus be used as an energy efficiency indicator. In this way, other local emissions and resource requirements can also be included in ESM. Vera and Langlois [21] as well as Wang et al. [22], for example, list each about 30 indicators, divided into technical, social, economic and ecological aspects. In the context of energy system modeling, however, it is necessary to keep the number of indicators manageable and thus to choose a few meaningful and comparable indicators.

Sufficiency indicators for urban energy systems

The sufficiency strategy aims at limiting energy consumption to a sustainable level. There is no consensus of any value at which urban energy systems reach a state of sufficiency. There are, however, attempts to define such a level and apply them as indicator. One example is the Swiss 2000-Watt-certification standard for city districts [48]. Here, the primary energy demand including energy bound in building materials is related to the number of inhabitants [49] with the goal of reducing this value to 2 000 Watt per inhabitant.

Such absolute limits for energy consumption to a sustainable level may provide helpful orientation for the design and planning of urban energy systems. Determining those is, however, not only a complex research task on its own, but also requires a fair and detailed process that takes different city and district structures into account. The 2000-Watt-standard is applied to residential districts only [49], probably because urban areas with different sectoral structures (e.g., industrial, commercial or residential consumers) can hardly be compared with each other. We thus do not define absolute values for this indicator, but consider a reduction of energy demand generally as a contribution to sustainability.

Instead of using the primary energy demand to calculate the energy demand as done in the 2000-Watt-standard, we consider the use the final energy demand *FE* as more suitable. This excludes conversion processes from primary to final energy, and thus the efficiency of these processes, which are already represented by the efficiency indicators.

The *specific energy demand per inhabitant* ED'_{inh} is the ratio of the systems total final energy demand to the number of inhabitants n_{inh} (Eq. 7). The *absolute energy demand* of an energy system ED_{es} may be considered for optimization processes (see above):

$$ED'_{\text{inh}} = \frac{FE}{n_{\text{inh}}} \tag{7}$$

The reduction of the final energy demand can provide a rough assessment of many sustainability aspects, since the reduction of the demand leads to a reduction of resource needs. Although this is vague and not expressed in numbers here, it is conceivable that any reduction of the final energy demand reduces the environmental impact better than a sheer switch to another primary energy source. Note that renewable forms of energy also have certain resource requirements [50].

This particularly applies for demand reductions through sufficiency measures. However, the (specific) energy demand is influenced both, by the system's efficiency and sufficiency. In order to measure pure sufficiency effects with the help of this indicator, all efficiency parameters of the system must remain unchanged. For more precise statements regarding the system's energy sufficiency, parameters and indicators like heated living space per person, average room temperatures, electrical appliances per household or person, usage intensity of electrical appliances, volume of material production would have to be included. Those are beyond the scope of classic ESM, but could be included in sector models of the building or industry sectors.

Concluding, within the scope and possibilities of ESM, the indicator of (specific) energy demand (Eq. 7) provides a rough indication of sufficiency. When applying the indicator for comparison of different cities or districts, the sectoral structure needs to be taken into account.

Consistency indicators for urban energy systems

Energy consistency is mostly understood as the shift from fossil to renewable sources. Thus, the *share of renewables* (*SoR*), can be regarded as an appropriate energy consistency indicator [12, 51]:

$$SoR = \frac{\mathrm{FE}_{\text{renewable}}}{\mathrm{FE}_{\text{total}}} \tag{8}$$

In order to be considered sustainable, the utilization of an energy source should not exceed its *regeneration rate* [52, 53]. In this context, the consistency of an energy system could be assessed by considering the useful life t_{use} of materials used within an energy system in relation to its regeneration time t_{reg}:

$$t = \sum_{1}^{n} \frac{t_{\text{use,n}}}{t_{\text{reg,n}}} \tag{9}$$

Basically, this indicator is closely related to the *SoR* indicator, as both aim at the renewability (regeneration) of resources. However, this indicator goes into more detail than the *SoR* indicator and can, for example, also compare different renewable energy technologies (e.g. photovoltaic systems vs. biomass). However, in order to obtain a meaningful value, all materials used within an energy system, from the concrete in the foundation of a power plant up to the fuel, must be taken into account. Furthermore, emissions should also be considered as a "resource" and should be set in relation to the duration of mining. Such a balance would be extremely complex to compute and is a research field on its own.

Another aspect of consistency can be the locational origin of the energy source. A self-sufficient system can survive as a stand-alone unit, without any import of energy [54]. We use the location of energy supply as an evaluation of the energy origin and therefore the indicator *self-sufficiency SeS* to assess the degree to which a city or district can supply its own energy needs:

$$\mathrm{SeS} = \frac{\mathrm{FE}_{\mathrm{local}}}{\mathrm{FE}_{\mathrm{total}}} \tag{10}$$

Although the term sufficiency appears in the name of the indicator, it does not indicate a system's sufficiency in our understanding of this term. The self-sufficiency indicator is useful when considering the goals of strengthening the regional economy and reducing inter-regional grid capacities (e.g., from the wind-energy-intensive north to the south of Germany).

However, although local energy supply is indeed desirable [55], it must be questioned how an increase of self-sufficiency contributes to the fulfillment of sustainability goals in urban energy systems per se, or if a linkage to regionally connected systems is preferable from a broader sustainability perspective. Therefore, the regional reference of FE_{local} should be defined case-by-case.

Methods: single-criterion simulation

Based on the literature review and the arguments presented in the previous subsections, we consider

- Primary energy efficiency,
- (Specific) GHG emissions,
- (Specific) energy costs,
- Share of renewables,
- Self-sufficiency,
- (Specific) energy demand,

as basically suitable for the evaluation and optimization of urban energy systems. For the sufficiency indicator of specific energy demand, the restrictions discussed before need to be considered. We consider other indicators to be less suitable, due to their shortcomings of not including upstream chains (secondary energy efficiency *SEE*), their limited capability to compare small energy systems (energy productivity *EP*), or their excessive accounting expense (regeneration rate *t*). The chosen indicators will be further tested for use in energy system modeling.

The basically suitable indicators (see above) will be examined by applying them to an ESM. A real-world urban area will be simulated with different supply scenarios.

As long as the energy demand remains constant, there is a linear relationship between absolute emissions $m_{\mathrm{GHG,es}}$, costs C_{es}, and energy demand ED_{es} to specific emissions $m'_{\mathrm{GHG,FE}}$, specific costs C'_{FE}, and specific energy demand per inhabitant ED'_{inh}. Since we do not compare different systems in this case study (see "Efficiency indicators for urban energy systems"), we will use absolute values as long as the energy demand remains constant. When the energy demand changes (scenario 4), we will show both, absolute and specific values, in order to represent both efficiency and sufficiency effects.

The urban district "Strünkede" of the municipality of Herne (North Rhine-Westphalia, Germany) will be used as a real-world test area. This district has about 3 600 inhabitants and consists of 500 buildings (residential and non-residential).

We simulate a total of four energy supply scenarios and analyze how the chosen sustainability indicators behave depending on the intensity of the implementation of certain measures. Each of the four scenarios focuses on a different type of measure, all of them aiming to improve the district's energy sustainability. Namely, the share of renewable energy imports (scenario 1), the use of renewable energy technologies (scenario 2), the use of sector-coupling technologies (scenario 3), and the reduction of energy demands (scenario 4). Although the mobility/transport sector accounts for 30% of Germany's energy consumption [56], it is not examined in these scenarios. Due to its different structure, other indicators and model functionalities would be required to adequately cover the transport sector. Grey energy — i.e. the *CED* of consumer goods — is also not investigated due to similar reasons.

We use the "Spreadsheet Energy System Model Generator" (SESMG) v0.0.4, respectively v.0.2.0 [57], a model generator based on the "Open Energy Modeling Framework" (oemof) [58], for the simulation. The applied model uses a bottom-up analytical approach, methods of simulation and optimization, and the mathematical approach of linear programming. A district-sharp spatial resolution, a 1-hourly temporal resolution, and a 1-year time horizon is used. The operating modes of the plants in the model are dispatch-optimized with respect to the respective indicator under investigation. Investment optimization is not performed within this section. For detailed description of modeling methods, we refer to the documentation of oemof [59] and the SESMG [57]. The underlying Open

Energy Modelling Framework (oemof) and its sub-modules have undergone several validations [60].

Standard load profiles (SLP) are used to simulate the course of the electricity [61] and heat demand [62]. The annual electricity demand (11 000 MWh/a) and heat demand (32 000 MWh/a, see Table 2 in Appendix) are estimated on the basis of the type of building, building area, number of floors and number of residents. Photovoltaic systems (scenario 2 and 3) are simulated on the basis of weather data obtained from the German Weather Service [63]. The year 2012, an average solar year [64], was chosen as reference. We account for the GHG emission scopes listed in Table 1.

All other model parameters (plant efficiencies, costs, emissions) are estimated based on databases [63, 66, 67], legal bases [68], standards [32, 69], research articles [70], technical studies [71–73], comparison of market energy tariffs, data from the municipality of Herne and the German federal state of North Rhine-Westphalia as well as expert estimates. The model parameters used are listed in Appendix.

Results: single-criterion simulation

Scenario 1 — energy import

The first scenario (Fig. 1) reflects a typical current state of a German district energy system. It is assumed that the electricity demand is covered by electricity imports and the heat demand is covered by gas heating systems, operated with imported natural gas. The average German electricity mix (42% renewable energies [74]) is used.

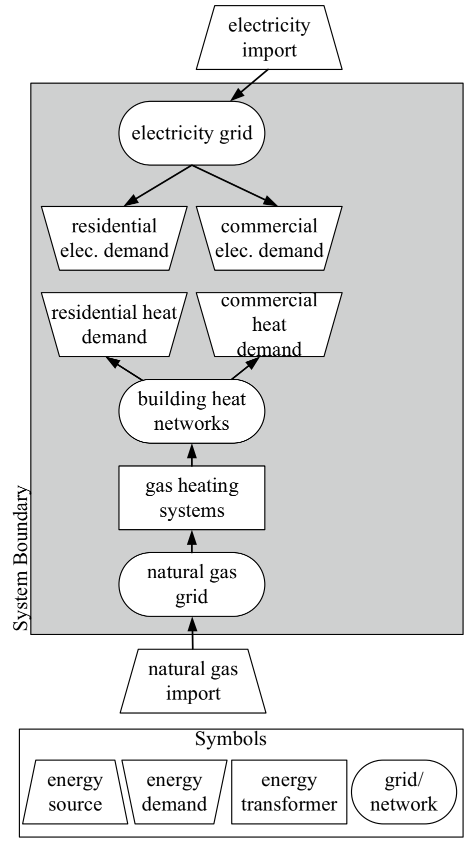

Fig. 1 Scenario 1

We analyze the response of sustainability indicators to the share of renewable energies within the imported electricity (with an otherwise unchanged electricity mix) from zero (no renewable electricity) to one (100% renewable electricity) (Fig. 2). The indicators shown in Fig. 2 refer to the total energy supply, i.e. electricity and heat.

The primary energy efficiency increases from 0.68 to 0.88 due to the lower primary energy factor of renewable energies [32]. The share of renewables increases to a lesser extent than the share of imported electricity. The total share of renewables thus results from the share of renewables in the imported electricity, multiplied by the share of electricity in the total energy demand (about 2%). A further increase of this value is only possible if the heat supply (0% renewable) is substituted by renewable sources. The specific GHG emissions m'_{GHG} decrease due to the lower carbon footprint of renewables compared to other technologies of the German electricity mix. The required energy is still completely imported ($SeS = 0$) and thus remains the same. The energy demand ED_{es} remains constant because no changes have been made on the consumption side.

Table 1 Considered GHG emission scopes. Terms based on definitions of the World Resource Institute [65] and adapted for the purpose of analyzing urban energy systems

Scope	Definition
1	"Direct GHG emissions occur from sources that are" within the model domain, "for example, emissions from combustion in owned or controlled boilers, [...], etc." [65].
2	"GHG emissions from the generation of [imported] electricity", consumed within the model domain. "Scope 2 emissions physically occur at the facility where electricity is generated" [65]. For exported electricity a GHG emission credit is granted, accordingly.
3	GHG emissions of energy suply facilities which "occur from sources not owned or controlled" [65] within the model domain, e.g. for the production of photovoltaic modules.

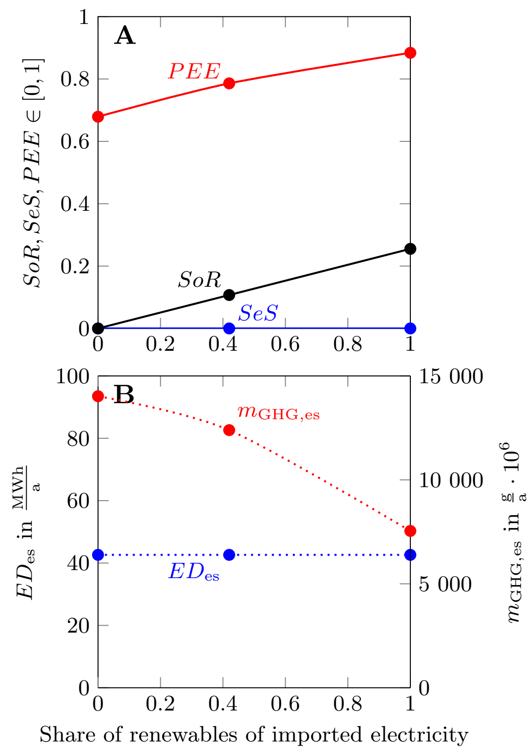

Fig. 2 Indicators in scenario 1. The simulated values are represented as dots and connected by lines. Abbreviations: *PEE* = primary energy efficiency, *SoR* = share of renewables, *SeS* = self-sufficiency, $m_{\mathrm{GHG,es}}$ = absolute GHG emissions, ED_{es} = absolute energy demand

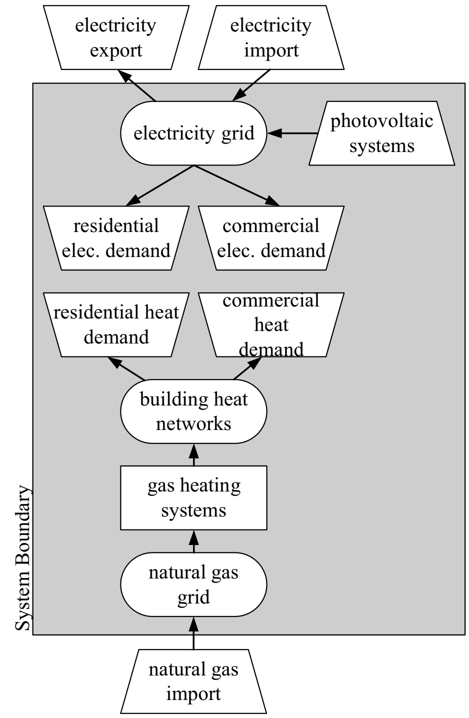

Fig. 3 Scenario 2. Symbol legend see Fig. 1

With the change in the share of renewable energies in the German electricity mix, the price of imported electricity will change due to macro-economic correlations. These relationships cannot be described with the model used in this study. For this reason, no curve for the energy costs C_{es} is presented for this scenario.

Scenario 2 — local renewable generation

In the second scenario, photovoltaic systems for decentralized provision of renewable electricity are added to the energy system. Energy required beyond that (electricity and natural gas) is imported like scenario 1. Electricity produced in excess of demand can be exported (Fig. 3).

Most indicators show a saturation effect after an installed PV capacity of 5 MW (Fig. 4). This is because PV systems only supply electricity at certain times. At times when no electricity can be supplied (e.g., at night), electricity still needs to be imported, no matter what PV capacity is installed. If in turn the demand of the system is exceeded (the maximum demand is 2.1 MW), electricity has to be exported. Exported electricity may have a positive influence on energy systems elsewhere. If the installed systems were thus to be related to a global energy system, no saturation behavior is expected.

The absolute energy cost curve does not show saturation effects, since electricity that is produced within the system boundary but not used by internal consumers, can be sold at a fixed rate due to the German renewable energies act (EEG [68]), and can thus be sold with profit. Although a credit is also granted for emissions, this does not generate any "emission profit" (the credit granted for exports is exactly the same as the emissions taken into account for production, see Table 1), which also leads to saturation behavior of the absolute emissions.

The decrease of the energy costs C_{es} is limited by the availability of space within the system area that can be used for installation. The exact cost values as well as the slope of the C_{es}-curve furthermore depend on the remuneration rate taken into account (changes for example, due to revised EEG frameworks). This remuneration is allocated to end-consumers in the form of the EEG compensation-fees. If the share of renewable energies in the electricity grid increases, this apportionment may rise. A nationally uniform expansion in the same proportion to the district under consideration could thus lead to an increase in the price of purchased energy, which in turn would increase the specific

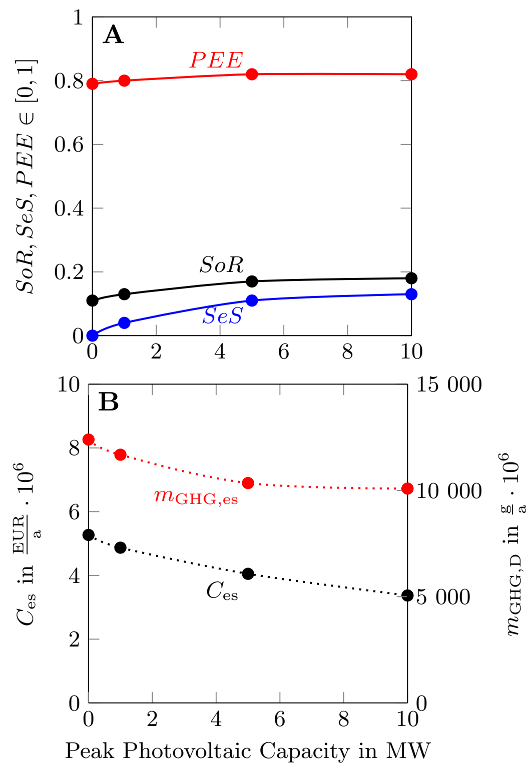

Fig. 4 Indicators in scenario 2. The simulated values are represented as dots and connected by lines. Abbreviations: *PEE* = primary energy efficiency, *SoR* = share of renewables, *SeS* = self-sufficiency, $m_{\text{GHG,es}}$ = absolute GHG emissions, C_{es} = absolute energy costs

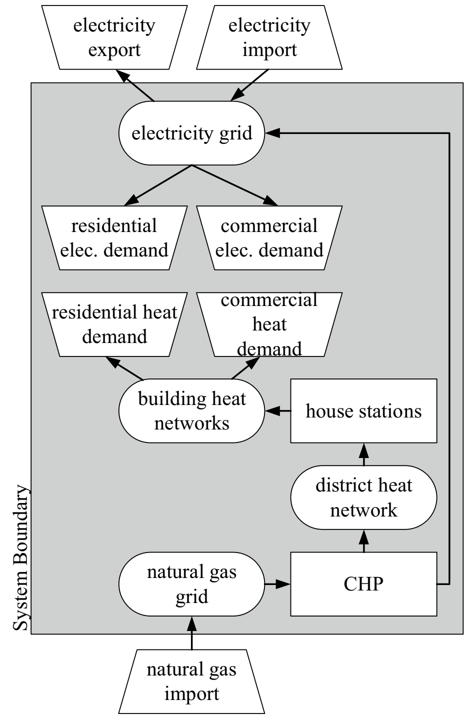

Fig. 5 Scenario 3. Symbol legend see Fig. 1

energy costs. A model with national balance limits is needed to investigate this relationship in more detail.

As in scenario 1, the (specific) energy demand remains constant and is for the sake of clarity not displayed here.

Scenario 3 — sector coupling

In the third scenario, a measure is considered which affects not only the electricity sector but also the heat sector. The entire energy supply is secured by combined heat and power plants (CHP) with an electric performance of 16 MW (thermal performance of 25 MW) in combination with a district heating network (Fig. 5). The CHPs can be operated either with biogas or natural gas. For the supply of both gases (natural gas import, biogas production) the same costs are assumed.

Figure 6 shows the development of the indicators depending on the share of (electrical) capacity of biogas, respectively natural gas-fired CHPs. Again, the specific energy demand remains constant and is therefore not displayed.

The primary energy factor of biogas CHPs is lower than that of natural gas CHPs [66]. Therefore the primary energy efficiency decreases with increasing biogas input, showing a saturation behavior. This can be explained by the fact that the lower capacity ranges are needed more frequently during the year than the higher ones (frequency quartiles of the CHP's electricity output: Q1: 1.7 MW, Q2: 3.6 MW, Q3: 6.0 MW, Q4: 16.0 MW). Thus higher biogas CHP capacities (especially above 6 MW) have less influence on the indicator.

In contrast to the scenarios discussed before, the increase of the share of renewables *SoR* and the self-sufficiency *SeS* is no longer limited to the share of the electricity sector. If the CHP units are solely operated with biogas which has its origin within the system area, both *SoR* and *SeS* increase to the maximum of 1. Again, there is a saturation effect for the same reason as for the primary energy factor. It has to be noted that in the real-world system, the availability of space for biogas production is probably limited and thereby restricts the increase of self-sufficiency *SeS* and share of renewables *SoR*.

Due to the higher purchase costs for biogas compared to natural gas, the energy costs C_{es} increase with increasing biogas usage. From approximately 8 MW electric biogas capacity on, the increase in costs becomes steeper. This can be explained by the above-mentioned frequency distribution of the CHP output and the dispatch optimization of the cost indicator (see "Methods:

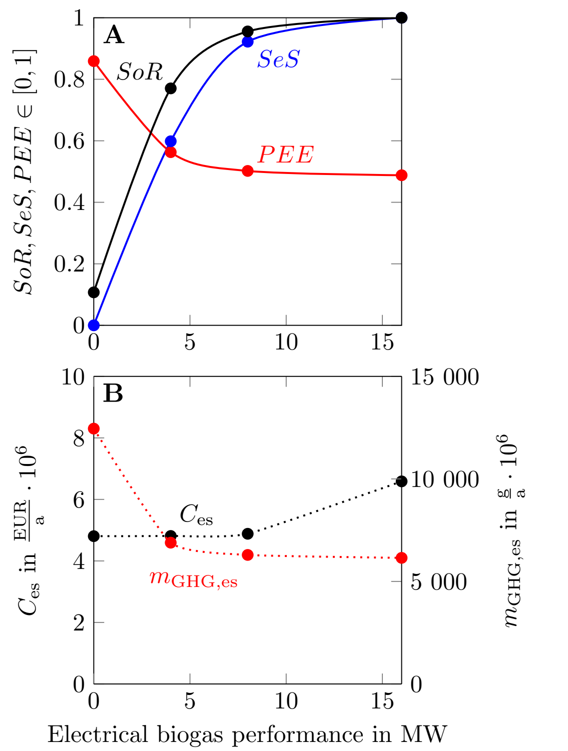

Fig. 6 Indicators in scenario 3. The simulated values are represented as dots and connected by lines. Abbreviations: *PEE* = primary energy efficiency, *SoR* = share of renewables, *SeS* = self-sufficiency, $m_{GHG,es}$ = absolute GHG emissions, C_{es} = absolute energy costs

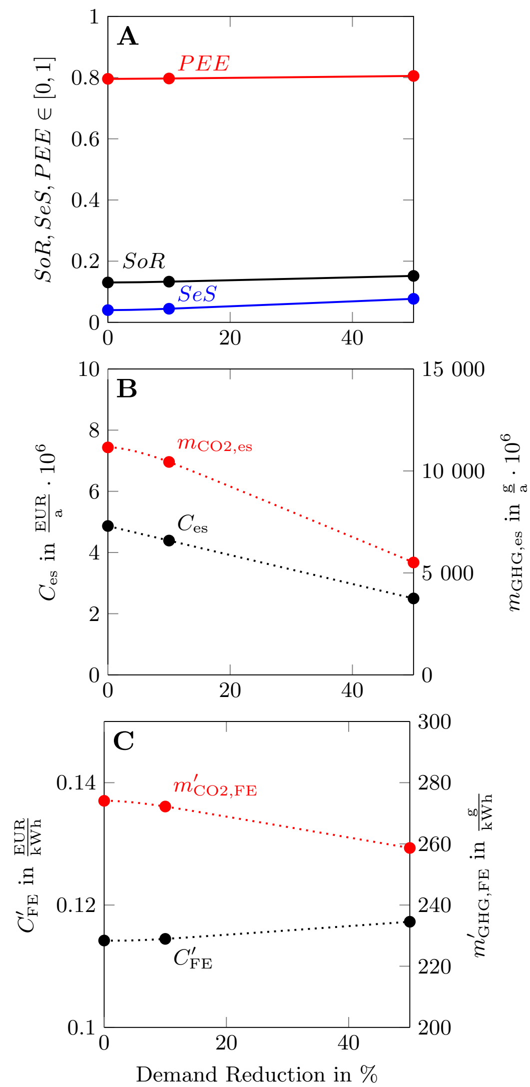

Fig. 7 Indicators in scenario 4: demand reduction, based on scenario 2 (1 MW photovoltaic systems). The simulated values are represented as dots and connected by lines. Abbreviations: *PEE* = primary energy efficiency, *SoR* = share of renewables, *SeS* = self-sufficiency, $m_{GHG,es}$ = absolute GHG emissions, $m'_{GHG,FE}$ = specific GHG emissions per final energy demand, C_{es} = absolute energy costs, C'_{FE} = specific energy costs per final energy demand

single-criterion simulation"). The (low-cost) available natural gas CHP capacity is used first, followed by the biogas CHP capacity. If the biogas CHP is only used to cover infrequent load peaks, the influence on the total system costs is relatively small, but if it is needed for the frequent base load capacities — which is the case in Fig. 6 above about 8 MW — the influence is correspondingly greater and causes the curve to rise more steeply.

Scenario 4 — demand Reduction

In the fourth scenario, the effect of changing energy demand on the district's sustainability indicators is analyzed. On the basis of scenario 2 (including 1 MW of PV systems), it is assumed that the energy demand is reduced by up to 50% for each simulated hour, both in the heating and electricity sector (Fig. 7).

The reduction in demand — which can be a result of sufficiency and efficiency measures lowers the energy demand (absolute and specific). The reduction in consumption ensures an absolute reduction in GHG emissions $m_{GHG,es}$ (Fig. 7, B). The GHG emissions are not only reduced linearly with the demand reduction, but also the GHG emissions per final energy $m'_{GHG,FE}$ (Fig. 7, C) are reduced, resulting in a exponential reduction of the total GHG emissions. This can be explained by the fact that a fixed capacity of PV systems (in this scenario we consider a fix capacity of 1 MW) can provide a higher share of the electricity supply when energy demand decreases. The reduction in consumption thus ensures that sources with high GHG emissions are used to a lesser extent, which leads to a reduction in GHG emissions. This effect also ensures a slight improvement in all other indicators (except for specific costs per final energy demand C'_{FE}).

With increasing PV capacity, the specific indicators (Fig. 7C) would change even more, and thus lead to an increasing de-linearization of the absolute indicators (Fig. 7B).

The reduction of the demand initially leads to a slight increase of the specific costs per final energy demand C'_{FE} (Fig. 7C). This is because higher consumption leads to an increased use of PV-electricity, which allows a higher profitability of PV electricity (import costs minus PV electricity production costs) than its sale (export price of PV electricity, see Appendix). However, this is a very small effect and becomes negligible when considering the absolute energy costs C_{es} (Fig. 7B).

Evaluation of the indicators

Energy efficiency indicators: The modeling results show that the primary energy efficiency *PEE* rather reflects the share of renewable than efficiency. Its increase in scenarios 1 and 3 is mainly due to the low primary energy factors used for (imported) renewable energies due to the VDI 4600 directive [32, 66]. Thus, the observed increase of primary energy efficiency is less driven by an improvement of the district's technical efficiency than by the accounting method, which grants an advantage to renewable energies. With increasing shares of renewables, the primary energy efficiency loses its original meaning of displaying efficient use of energy. Another criticism is that the primary energy efficiency factors to be applied according to the VDI 4600 directive do not distinguish between different forms of renewable energy.

With respect to the compliance with national and international climate protection targets, it is more appropriate to use the physical–thermodynamic indicator of (specific) GHG emissions as optimization criterion in ESM. Furthermore, it is not only suitable for the assessment of fundamental trends, but also for the identification of either limits that improvement measures may meet (e.g. saturation effect in scenario 3) or of a decrease of system performance.

Economic aspects play a significant role in planning practice. Economic indicators thus have a decisive influence on whether and which measures and technologies are implemented in urban energy systems. The indicator of (specific) energy costs is well suited for this purpose and should be taken into account.

Energy sufficiency indicators: The identification of suitable sufficiency indicators for ESM is difficult, since sufficiency targets at a reduction of energy service demand (e.g. heated living space per person), which is not directly considered in energy system models. However, the specific energy demand per inhabitant ED'_{inh} can give an impression of the contribution of demand-side measures. Although it cannot be distinguished between the contribution of efficiency or sufficiency, the indicator provides indications of absolute demand reduction, which is the more decisive information in terms of sustainability. Since this indicator is strongly dependent on external circumstances (sector structure, building efficiency, etc.), it should always be given together with structural information about the urban area under study. In addition, it is much less the *fixed value* of this indicator than its *change* that should be rated.

The increase of sufficiency of an urban energy system has several advantages: In addition to the absolute reduction of consumption and the associated savings, the specific costs and emissions are reduced. Since these values (consumption and its specific emissions or specific costs) are multiplied with each other to calculate the total emissions or total costs, the total savings through sufficiency measures not only exert a linear effect, but rather a quadratic effect on the savings (see "Scenario 4").

Energy consistency indicators: The share of renewables *SoR* is a clear and straightforward indicator. Nevertheless, increasing renewable energy is not a sustainability goal per se, but rather a way to reduce greenhouse gas emissions and conserve fossil fuels. The indicator does not provide any information on the improvement of these sustainability goals. Furthermore, it does not distinguish between different types of renewable energy and their different impacts on the main sustainability goals. Therefore, the indicator share of renewables is only conditionally suitable for measuring the energy sustainability of urban energy systems.

The indicator of self-sufficiency *SeS* is suitable for evaluating the increase of the local value. Nevertheless, it is questionable whether increasing self-sufficiency contributes to the sustainability of urban energy systems (see "Consistency indicators for urban energy systems"). The indicator is more suitable for evaluating entire regions, and less for individual urban areas or cities.

Methods: multi-objective optimization

As shown, there are a number of indicators that can evaluate various sub-goals of energy sustainability of urban energy systems in ESM, or can be used for optimization. But there is no single indicator for the evaluation of urban energy systems which combines various aspects and thus represents a broader perspective of different sustainability aspects. Therefore, multi-criteria optimization approaches are required for enabling such a broader perspective.

In classical single-criterion optimization, the scenario is determined which allows the minimization or maximization of the target value, other boundary parameters are completely left out [75]. Multi-objective optimization approaches in turn consider several, usually competing criteria for the optimization [75]. Therefore, the methods of combined indicators or adding constraints in single-criterion models (hereafter referred as "constraint optimization") may be considered.

By using the *combined indicator* approach, individual indicators are combined to a single value [76]. Two common approaches are the weighted sum (Eq. 11), and weighted product method (Eq. 12) [76].

Indicators formed by the *weighted sum approach* (Eq. 11) can usually be used in single-criterion optimization models. This is possible because the different indicator values (e.g., costs or emissions) — even if they occur at different process points — are simply added up to an overall indicator value. The original multi-criteria problem is thus transformed into a single-criterion problem. However, the drawback of the weighted sum method is, that the single indicators must have the same unit in order for Eq. (11) to be mathematically solvable [77]:

$$F(\vec{x}) = \sum_{i=1}^{k} w_i f_i(\vec{x}) \tag{11}$$

$F(\vec{x})$ multi-criteria function, $\vec{x}$ set of decision variables, k number of applied criteria, $f_i(\vec{x})$ function of criterion i, w_i weighting of criterion i.

The weighted product approach works similarly to the weighted sum approach [78], except that the individual indicators f_i are multiplied and the weights w_i are taken into account as potencies [76]:

$$F(\vec{x}) = \prod_{i=1}^{k} f_i(\vec{x})^{w_i} \tag{12}$$

The weighted product approach can possibly not easily be applied to single-criterion ESM tools, if the tool does not allow multiplying indicator values that apply at different process points (e.g. costs for purchasing natural gas vs. emissions from burning the gas). It has to be individually checked whether the respective modeling tool permits the use of such multi-indicators. Further note that multi-criteria functions could possibly complicate the system of equations to be solved by the model and thus increase the computing time. This may result in the need to simplify model structures in order to reduce the computing time, which may in turn reduce model accuracy.

With *constraint optimization* (also known as ϵ-constraint method [79]), the classical approach of single-criterion optimization is extended by restricting the possible solution space of the model. Therefore, for at least one additional criterion, limits (constraints) are defined by the modeler. A single-criterion solution algorithm can then determine the remaining solution space for the minimum of the primary optimization criterion.

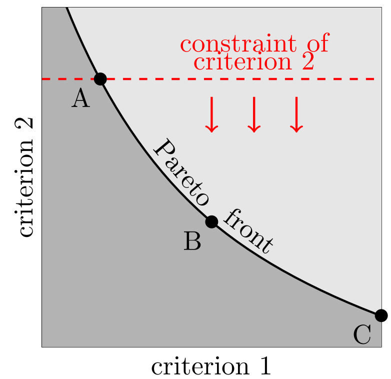

Fig. 8 Exemplary two-criteria Pareto front. Solution space in light gray (infinite number of possible scenarios), not realizable space respectively scenarios in dark gray. Three exemplary best-known Pareto points (A, B, C) are shown

In this way, a multi-criteria optimization can be performed without using a multi-criteria indicator. Constraint optimization has the disadvantage that the modeling effort is greater, since each constraint limit must be set manually. In the case of an iterative reduction of this value, this can require a large number of model runs. Moreover, it should be noted that single-criterion energy system modeling tools sometimes can only apply constraints that are related to the main optimization criterion, but not for further criteria.

The solution of a multi-criteria solution function $F(\vec{x})$ does not — as in the case of a single-criterion function $f_i(\vec{x})$ — result in a single solution scenario $\vec{x}$, but in a set of (in the sense of the function) equivalent solution scenarios [80]. The function of these scenarios is known as *Pareto front* (Fig. 8, black) [81], which has one graphical dimension per selected sub-criterion.

By adjusting constraint optimization, several different scenarios, which lie on the Pareto front, can be determined. These are also often called "*best-known Pareto points*" [75]. By, for instance, successively moving the constraints shown in Fig. 8 (red) downwards, the scenarios A, B, and C could be determined.

Multi-objective optimization approaches are of particular importance in the context of sustainable optimization of urban energy systems, especially because the previous overview has shown that there is no single indicator for holistic quantification.

Combined indicator

In compliance with the design goals for urban energy systems (see "Introduction") and the discussion within "Evaluation of the indicators" Section, we consider specific energy costs, specific GHG emissions, and specific energy demand as the most appropriate indicators to be combined within an multi-objective optimization. Due to their shortcomings, the indicators of primary energy efficiency (unsuitable accounting method), share of renewables (not fulfilling climate protection goals per se and no differentiation of different types of renewables) and self-sufficiency (questionable impact on the overall system sustainability) will not considered further for the multi-criteria optimization approach.

Since the selected indicators have different units, they can only be combined using the weighted product method (Eq. 12):

$$F(\vec{x}) = \prod_{i=1}^{k} f_i(\vec{x})^{w_i} \tag{12}$$

$$F(\vec{x}) = (C'_{\mathrm{FE}})^{w_{\mathrm{C}}} \cdot (m'_{\mathrm{GHG,FE}})^{w_{\mathrm{m}}} \cdot (ED'_{\mathrm{inh}})^{w_{\mathrm{ED}}} \tag{13}$$

$$F(\vec{x}) = \frac{C^{w_{\mathrm{C}}}}{FE^{w_{\mathrm{C}}}} \cdot \frac{m_{\mathrm{GHG}}^{w_{\mathrm{m}}}}{FE^{w_{\mathrm{m}}}} \cdot \frac{FE^{w_{\mathrm{ED}}}}{n_{\mathrm{inh}}^{w_{\mathrm{ED}}}} \tag{14}$$

$$F(\vec{x}) = \frac{C^{w_{\mathrm{C}}} \cdot m_{\mathrm{GHG}}^{w_{\mathrm{m}}} \cdot FE^{w_{\mathrm{ED}}}}{FE^{w_{\mathrm{C}}} \cdot FE^{w_{\mathrm{m}}} \cdot n_{\mathrm{inh}}^{w_{\mathrm{ED}}}} \tag{15}$$

A further simplification is possible, if $w_i = 1$ applies for all weighting variables:

$$F(\vec{x}) = \frac{C \cdot m_{\mathrm{GHG}}}{FE \cdot n_{\mathrm{inh}}} \tag{16}$$

For the application of absolute values applies:

$$F(\vec{x}) = C^{w_{\mathrm{C}}} \cdot m_{\mathrm{GHG,es}}^{w_{\mathrm{m}}} \cdot FE^{w_{\mathrm{ED}}} \tag{17}$$

If nuclear power play a role in the energy system under study, it is recommended to additionally use either the share of renewables (Eq. 8) or the resources regeneration time (Eq. 9).

Constraint optimization model

For the optimization, the model used for the single-criterion simulations is extended by investment decision variables. Specifically, the model has the possibility to design the capacities of decentralized gas heating systems (scenario 1 and 2), photovoltaic systems (scenario 2, max. 10 MW) and central natural gas or biogas CHPs (scenario 3, max. 16 MW). As within the single-criterion model, dispatch optimization is performed as well.

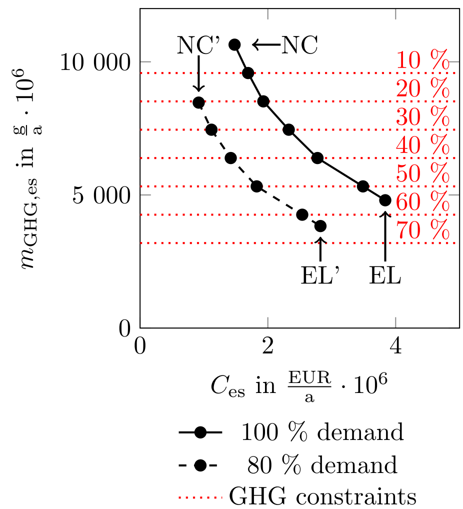

Fig. 9 Best-known Pareto points of a constraint optimization using absolute energy costs C_{es} as primary optimization criterion and absolute GHG emissions $m'_{\mathrm{GHG,es}}$ as well as absolute energy demand *ED* as constraints. The scenarios without an emission constraint (NC and NC') and the lower emission limits (EL and EL') of the solution space are marked separately. The constraint values are to be understood as percentage reductions of the initial value NC

As most of the optimization ESM [82], our modeling approach does not support the calculation of Pareto-curve functions from multi-criteria functions like shown in Eq. 16 or 17. For this reason and the advantages outlined in sec. 9, in the following we will use the constraint optimization approach and will determine best-known Pareto point. Therefore, we will first perform a purely cost-optimized model run (no constraint, NC). Based on the resulting scenario, the permitted GHG emissions are reduced in 10% steps until the value is so low that no target scenario can be determined. In a further model run, the lower emission limit of the solution space is determined, by using the GHG emission as optimization criterion. Subsequently, the energy demand is reduced, which is equivalent to a constraint of energy consumption, and optimized for the *same* GHG emission constraints as before.

Here, the demand reduction represents an opportunity, i.e., it is not a typical constraint limitation. However, this changes when the demand in systems is limited by planning regulations or individual target values. A demand constraint becomes particularly important if demand

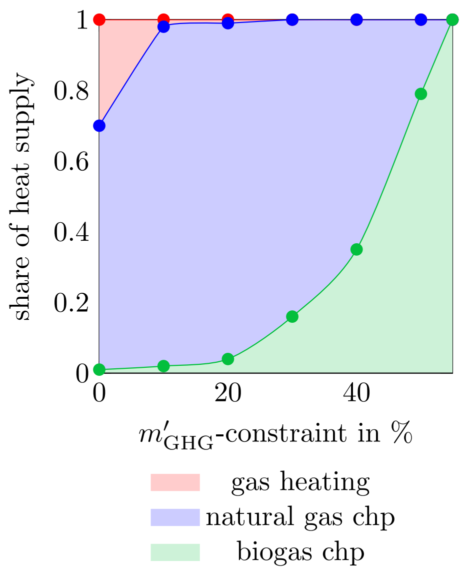

Fig. 10 Share of heat technologies available in the optimization model for heat supply with increasing GHG-constraint (in % from starting point NC, see Fig. 9)

can be reduced by an investment, e.g. by investing in better insulated windows/insulation or more efficient end-appliances (dryers, refrigerators, etc.). Then, the goal of minimizing costs would possibly get into a conflict with a demand constraint. This is a typical context for multi-criteria optimization.

Results: multi-objective optimization

The solution scenarios of the individual constraint optimization runs are best-known Pareto points. When the points are connected, the result is a typical Pareto front. In Fig. 9, slices of the actually three dimensional front (since three criteria are used) are shown. Without demand reduction, the model with 60% reduction of GHG emissions cannot be solved, because the set limits of emission free supply options are reached. Thus, such a scenario is outside the possible solution space. The lower emission limit (EL) of the solution space is below 5% of the emissions of the NC-scenario.

As the emissions constraint increases, the financial costs C' become higher. Thus, there is a conflict between cost and emission optimization in this system. The relationship is not linear.

However, the demand reduction is *not counteracting* for the other two optimization criteria, as no (investment) costs are incurred or GHG emissions are emitted for the demand reduction. Therefore, the demand reduction is an *opportunity*, which simultaneously provides a reduction in financial costs and GHG-emissions (dashed line in Fig. 7) and therefore provides a shift in the Pareto curve in Fig. 9 to the lower left. The demand reduction by 20% has the effect that even without emission constraint (NC' in Fig. 9) the emissions are lower compared to the point NC — with simultaneous reduction of costs. With the demand reduction, the solution space is extended downwards, so that also a scenario with 64% (EL') GHG emission reduction compared to NC can be enabled.

The change in the target scenarios can be attributed primarily to the cost/emission conflict in heat supply. The share of heat supply technologies available for optimization is shown in Fig. 10. Accordingly, without an emissions constraint, the heat supply is predominantly designed with natural gas CHPs with small shares of decentralized natural gas heating systems. With increasing emissions constraint, gas heating systems are not considered at all and biogas CHPs gain relevance compared to natural gas CHPs. As in the Pareto curve in Fig. 9, the progression is not linear. In each of the calculated scenarios, the investment limit of PV plants is completely used.

Discussion

The selection of suitable indicators for use in energy system modeling is influenced by several aspects. These include the selected spatial and energy system boundaries, the impact of individual indicators on the defined sustainability goals, whether indicators are used for optimization or benchmarking purposes, and whether single-criteria or multi-criteria modeling techniques are used.

System boundaries: The choice of system boundaries has decisive influence on sustainability indicators and have to be chosen carefully with respect to the effects the modeling should focus on. This applies to the used terms of energy, the applied geographical coverage, and the consideration of influences on resources other than energy. This can be used to direct the focus on certain aspects, but it can also lead to a “sham improvement” by outsourcing non-sustainable processes (see "Efficiency indicators for urban energy systems"). As outlined before, we consider upstream chains in the overall context of energy efficiency to be very important and therefore recommend the use of primary energy efficiency *PEE* over secondary efficiency *SEE*.

Awareness of the chosen system boundaries and respective effects are equally important for GHG emissions. Often the technologies used in the district have an influence outside the system boundaries, which may be considered to a given degree or neglected. This includes the emissions in the upstream chain of technologies used. Since climate change is not limited to the system boundaries of an urban area, the upstream chains need to be considered for providing a more holistic picture of emission reduction options.

Spatial system boundaries also exert an impact on the result. For example, the choice of a boundary limited to an urban area neglects positive effects of the export of renewable electricity to neighboring energy systems, national market impacts of raising energy prices due to increasing renewable energy production (see "Scenario 2 — local renewable generation"), or negative effects such as the indirect land use change effect (see below). In this case, the effect is outside the investigation area, but the *cause* is inside. Due to the limited space for energy generation, cities or districts can seldom fully meet their energy demands within their spatial boundaries. Thus, especially in the field of urban energy system modeling, system boundaries need to be carefully chosen to be able to assess sustainability of urban energy systems.

Another example of questionable sustainability contribution is the biogas usage displayed in scenario 3. There are doubts of the sustainability of land-use systems whenever a large portion of the managed land is used for biogas fuel production. A wider definition of the sustainability concept would lead to a different perspective since the choice of the balance limit neglects global impact of this scenario. In this case it can be assumed that considerable areas of land would have to be used for the biogas to be provided, which in turn may have a negative impact on the global climate balance via the indirect land use change effect [83].

Other sustainability aspects than GHG emissions (e.g., space, water, different raw materials) are not directly considered in this analysis as well. A global view is required to fully consider the respective effects. However, the indicator of (specific) energy demand can provide a first indication. Energy demand reduction in absolute terms generally leads to lower requirement of other resources as well. This might, on the one hand, be questionable for those efficiency measures which require resource-intensive technical measures and might therefore induce rebound effects, but is likely to be the case for sufficiency-induced demand reduction on the other hand. The combination of energy system modeling with complete life cycle assessment goes beyond the scope of most energy system analyses, but the various resource effects beyond GHG emissions should not be neglected in planning or political decision making. Thus, the indicator of specific energy demand and especially its change rate provides an important aspect of overall conservation of resources: the more the energy demand is reduced in absolute terms, the higher the likelihood that resource intensity and environmental impact in various aspects reduced as well.

Sustainability strategies: As a categorization of the examined indicators, we have used the trisection of efficiency, sufficiency, and consistency indicators. Thereby it became clear that there is no pure sufficiency indicator, since the indicators always depend on other strategies of energy sustainability. For example, efficiency (e.g. due to building insulation) has a significant influence on the specific energy demand ED'-sufficiency indicator. To actually measure energy sufficiency, all efficiency parameters must be kept constant, which is a quite unreasonable approach. Sufficiency rather needs to be measured on energy service level like, e.g., heated living space per person or electrical appliances per person. This requires more detailed sector models which in turn could be coupled with ESM.

Further difficulties arise when comparing different urban energy systems, as the structure (e.g. share of residential/commercial and industrial sectors) has a decisive influence on the total final energy demand of a system. A possible solution could therefore be to classify urban energy systems according to their structure so that homogeneous energy systems (e.g., purely residential areas) can be compared.

Reference values: Depending on the purpose of use, different reference values or absolute values may be used. We used final energy FE, the number of inhabitants n_{inh} as reference values, as well as absolute values. Absolute values are favorable for use in optimization models, since the equation of the respective indicators is usually rather simple. When compared to the reference value number of inhabitants n_{inh} (for the indicator specific energy demand ED'), absolute values are influenced by changes in the number of inhabitants. Thus, a decreasing number of inhabitants can improve this indicator value, although this does not provide a real sustainability benefit. Furthermore, compared to the reference value FE (e.g. for the indicators specific costs C' and specific GHG emissions m'_{GHG}), decreasing final energy demand has an influence on this indicator — thus also on sufficiency effects, although it is an efficiency indicator. Thus, absolute values ensure easy handling in optimization models, but for benchmarking and comparison purposes we recommend the use of the reference values of final energy demand *FE* and number of inhabitants n_{inh}.

Multi-criteria optimization: Energy sustainability of urban energy systems can be improved by various measures, e.g. by regenerative energy systems, sector coupling, demand reduction, demand-side management, energy storages and many more. Some of these measures have been exemplified within the modeling runs in this contribution. Depending on the weighting of the applied indicator, the combination of several measures and energy sustainability strategies in particular leads to the minimization of the applied optimization criterion.

If only a single target indicator is applied, the optimization of this value can simultaneously lead to a deterioration of other important indicators (as for example the cost and emission indicators in Fig. 6). While this conflict does not always become evident when using too few indicators in ESM, the application of a multi-criteria approach enables a more holistic view and trade-offs are quantified.

By applying multi-criteria optimization models, several equivalent scenarios in the form of a Pareto front can be compared and the conditions under which technology change occurs can be analyze (as shown, for example, in Fig. 10). Such an approach provides valuable insights for specialist planners, which can decide on a case-by-case basis which goals are most important to follow to which degree for urban energy systems.

Nevertheless, the number of indicators applied should be limited to a tolerable level: If too many indicators are used, it will be difficult to understand the interdependencies of the model and bears the potential of over-fitting. Furthermore, Pareto fronts with more than three indicators have more than three graphical dimensions. This in turn is difficult or impossible to visualize and thus also complicates the interpretation of the results. Further research on result communication of multi-objective optimization of various differently weighted indicators for urban energy systems is required.

As outlined in "Introduction", today's multi-criteria optimization models usually work with a cost and a greenhouse gas emission related indicator. In the context of urban energy system optimization, we recommend complementing them with the (specific) energy demand indicator. We further recommend that models that do not consider any measures of energy demand reduction, should be complemented. Due to the indirect effects of demand reduction (see "Sufficiency indicators for urban energy systems" and "Scenario 4 — demand reduction"), they will have decisive influence on the sustainability of urban energy systems.

Conclusion

Based on a theoretical evaluation and subsequent practical tests in an urban energy system model, various indicators were analyzed for the purposes of optimization as well as benchmarking and comparison of different urban energy systems.

As a result, there are indicators that are well suited for various aspects of the energy sustainability, but none that is able to represent overall energy sustainability of urban energy systems. The use of only one sub-indicator in the optimization process increases the risk that other important indicators will deteriorate significantly, leading to unrealistic scenarios in practice. To avoid this, multi-criteria approaches should be used to enable a more holistic optimization and planning of sustainable urban energy systems.

The evaluation of an exemplary urban energy system using the multi-objective ϵ-constraint optimization approach shows that a typical Pareto optimization curve (Fig. 9) and a clearly visible technology shift (Fig. 10) emerge for the competing optimization criteria of cost and greenhouse gas emission minimization. The optimization criterion of minimizing energy demand does not conflict with the other criteria, but actually supports them. Thus, minimizing demand provides an opportunity to improve the other objectives, within the available energy demand reduction potential. However, in subsequent studies it has to be examined to which extent costs and emissions, which are necessary for the reduction of the energy demand (e.g., investment costs of building insulation or financial incentives for consumption changes), impact the results of the multi-criteria optimization.

In conclusion, we recommend the use of multi-criteria models combining the indicators of absolute greenhouse gas emissions, energy costs, and energy demand, for the optimization of urban energy systems. For benchmarking and comparison purposes, specific indicators should be used and therefore related to the reference values of final energy (Eqs. 4 and 5), respectively, number of inhabitants (Eq. 7).

Appendix

Model parameters

See Table 2.

Table 2 System parameters used for modeling

Components	Periodical costs EUR/(kW·a)	Variable costs EUR/kWh	PEF	Periodical GHG emissions g/(kW·a)	Variable GHG emissions g/kWh	Efficiency
Electricity import (residential, 0% renewables)	0	0.3106	2.3	–	624	–
Electricity import (commercial, 0% renewables)	0	0.2156	2.3	–	624	–
Electricity import (residential, 42% renewables)	0	0.3106	1.6	–	474	–
Electricity import (commercial, 42% renewables)	0	0.2156	1.6	–	474	–
Electricity import (residential, 100% renewables)	0	0.3106	1	–	28	–
Electricity import (commercial, 100% renewables)	0	0.2156	1	–	28	–
Electricity export (PV)	0	− 0.1293	− 1.2	–	− 56	–
Electricity export (CHP, biogas)	0	− 0.0892	− 2.91	–	− 125	–
Electricity export (CHP, natural gas)	0	− 0.0505	− 1.91	–	− 414	–
Natural gas import (residential)	0	0.0644	–	–	0	–
Natural gas import (commercial)	0	0.0455	–	–	0	–
Photovoltaic systems[a]	92	0	1.2	_[d]	56	[e]
Gas heating systems	30	_[c]	1.34	–	228	0.85
Natural gas CHP (electric output)	14	_[c]	1.91	_[d]	414	0.35
Natural gas CHP (thermal output)	_[b]	_[c]	0.76	_[d]	165	0.55
Biogas CHP (electric output)	14	_[c]	2.91	_[d]	125	0.35
Biogas CHP (thermal output)	_[b]	_[c]	1.42	_[d]	100	0.55
District heat network	30	0	–	–	0	0.85
Biomass cultivation & biogas production	_[g]	0.097	_[f]	_[f]	_[f]	_[f]
Biogas production	Taken into account through life cycle analysis in the CHP					
Building heat networks	Taken into account with the gas heating system respectively the district heating network					
Electricity grid	Considered as loss-free					
Natural gas grid	Considered as loss-free					
Demands	**Annual Demand** kWh/a	**Load Profile**				
Residential electricity demand	3600000.0	h0				
Commercial electricity demand	7312390.1	g0				
Residential heat demand	20810072.5	efh/mfh				
Commercial heat demand	10927989.6	ghd				

Parameters are estimated based on databases [63, 66, 67], legal bases [68], standards [32, 69], research articles [70], technical studies [71–73], comparison of market energy tariffs, data from the municipality of Herne and the German federal state of North Rhine-Westphalia as well as expert estimates. Annualized capital costs of investment are used

[a] Azimuth: 180°, tilt: 35°, albedo: 0.18, altitude: 60 m, latitude: 52.13°, longitude: 7.36°, module: Panasonic VBHN235SA06B

[b] Costs considered with the periodical costs of the CHP's electric capacity

[c] Costs are considered with the purchase costs of the fuels

[d] Through life cycle assessments, the periodic emissions are considered with the components variable costs

[e] Depending on the operating point

[f] Taken into account through life cycle analysis in the CHP

[g] Considered with the variable costs of the biogas process

Abbreviations

C: Energy costs; CED: Cumulative energy demands; CHP: Combined heat and power plant; ED: Energy demand; EE: Effective energy; EL: Emission limit; ESM: Energy system model(s); EP: Energy productivity; es: Energy system; *F*: Multi-criteria function; f_i: Function of criterion *i*; *FE*: Final energy; *GDP*: Gross domestic product; GHG: Greenhouse gas; inh: Inhabitant; *k*: Number of applied criteria; m_{GHG}: Greenhouse gas emissions; NC: No constraint; *PE*: Primary energy; *PEE*: Primary energy demand; *PEF*: Primary energy factor; PV: Photovoltaic; *SE*: Secondary energy; *SEE*: Secondary energy demand; *SEF*: Secondary energy factor; *SeS*: Self-sufficiency; SLP: Standard load profile; *SoR*: Share of renewables; *t*: Regeneration rate; VDI: Verein Deutscher Ingenieure; w_i: Weighting of criterion *i*; *x*: Decision variable.

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Authors' contributions

CK evaluated the existing literature, created the model, evaluated the results, and drafted the manuscript. FW supervised the work, provided orientation, and edited the manuscript. Both authors read and approved the final manuscript.

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Availability of data and materials

The modeling scenarios generated and analyzed during this study are online available: https://doi.org/10.5281/zenodo.5410616. The used versions of the Spreadsheet Energy System Model Generator (SESMG) are available as well (v0.0.4: https://doi.org/10.5281/zenodo.5412027, v0.2.0: https://doi.org/10.5281/zenodo.5520513).

Declarations

Competing interests

The authors declare that they have no competing interests.

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