A generalised optimal design methodology for distributed energy systems

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Abstract

The optimal combination of energy conversion and storage technologies with local energy demand is a key but in its result not obvious challenge of distributed energy. Although a variety of possible approaches to the optimal design of limited technology selections can be found in the literature, the previous design step, the actual technology selection, and the subsequent step, the selection of the optimal operating strategy, are often neglected. We develop and demonstrate a methodology, which can optimise energy systems with arbitrary technology selection and under multi-criteria optimality definitions. The energy system modelled in *oemof.solph* is optimised using a MOEA/D approach with regard to economic, ecological and technical key performance indicators. The aim is to find trends and tendencies with a methodology that is as generalised as possible in order to integrate it into the decision-making process in energy system planning. We demonstrate the method by means of a German district for which an integrated supply concept is being sought. Different evaluation and visualisation possibilities are presented and the chances and limitations of the developed methodology are identified. We show that not only the choice of technology, but especially its sizing and operational strategy have a decisive influence on the optimality.

Keywords: Multiobjective Optimisation, Energy System Planning, Energy System Simulation, Pareto Front, District Energy Systems

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1. Introduction

The needs-based and target-oriented planning of distributed energy supply concepts can hardly be adequately represented using classical planning methods. Every supply object, be it a residential neighbourhood, a school or an industrial area, has different requirements and aspects of optimality associated with the provision of energy. At the same time, there is a wide range of different conversion and storage technologies which, alone or in combination with others, are suitable for ensuring supply according to precisely these requirements. The optimal technology choice and sizing along with the right operating strategy for a particular application, known as optimal design, is rarely obvious at first glance and depends on an large number of factors. In addition to natural law and technical regularities, these are above all economic and legal conditions which are undergoing dynamic changes and vary greatly internationally. In order to be able to react quickly to such developments in the future and to find the optimum energy supply concept for each application, planning tools are required which can evaluate and optimise the design and operational management of energy systems using computer-aided simulation and optimisation. The results of these tools can then be used to support decision-making in the usual planning processes of distributed energy supply concepts.

In the literature, various approaches are developed and discussed that design methodologies for exactly this purpose or certain subaspects. Especially in recent years, research in this area has increased massively. It is therefore not possible to provide a comprehensive description of all publications here, so the reader is referred to meta studies that provide more in-depth information on this topic [1, 2, 3, 4, 5]. However, to give an impression of the diversity of the topic, Table 1 analyses various relevant publications without any claim to completeness. It is noticeable that there is a particular focus on the design of PV/wind/battery systems. Overall, however, it can be stated that only a rather limited selection of technologies is taken into account along with the limitation to electricity or heat sector. Many of the approaches to date are relatively far from being realistic in terms of overall modelling and application as well as being difficult to transfer to other use cases. Some utilise inefficient optimisation algorithms like brute force for sizing and block diagrams for operational management. Of course, this does not apply to all publications, but it is difficult to identify a methodology which, due to its comprehensive and realistic modelling, would be suitable for a wide range of real-life projects in the long term.

In addition to these comprehensive publications on the optimal design of energy systems, there are a large number of different sub-aspects that can be found in detail in the literature.

Table 1: Overview of currently interesting publications on the optimal design of various energy systems and the classification of this publication in this context. Here ✓ describes the aspects considered in the publication, ✗ those explicitly not considered. The framework we present is only demonstrated here on a limited case study, but is actually able to cover more aspects, which are put in brackets here.

Publication	Energy Demand				Technologies											Target			Algorithms		Case Study
	Electricity	Heat	Cold	Grid Connected	Gas Boiler	Pellet Boiler	(C)CHP/Diesel	Heat Pump	Solar Thermal	Thermal Storage	Power2Heat	PV	Wind Turbine	Battery	Others	Economic	Ecologic	Technical	Sizing	Operation	
Wang et al. [6]	✓	✓	✓	✓	✓		✓			✓		✓	✓	✓	✓	✓	✓	✓	NSGA-II	Block diagram	Residential Community
Shahinzadeh et al. [7]	✓			✓			✓					✓	✓	✓		✓			HOMER		Neighbourhood
Ramli et al. [8]	✓			✗			✓					✓	✓	✓		✓		✓	MOSaDE	Block diagram	Single Household
Franco and Fantozzi [9]	✓	✓	✓	✓				✓		✓		✓						✓	Brute Force	Unclear	Single Household
Testi et al. [10, 11]	✓	✓	✓	✓				✓	✓	✓		✓			✓	✓			Brute Force	Block diagram	Hostel
Nguyen et al. [12]	✓			✗								✓	✓	✓	✓	✓	✓	✓	fuzzy-TOPSIS	EPoPA	Waste Water Treatment Plant
Das and Hasan [13]	✓	✓		✓/✗	✓			✓				✓	✓	✓		✓	✓		HOMER		Neighbourhood
Yimen et al. [14]	✓			✗			✓					✓	✓	✓		✓			Genetic Algorithm	Block diagram	Village
Li et al. [15]	✓			✓					✓	✓	✓		✓			✓			JADE	MILP	Households
Li [16]	✓			✓								✓		✓		✓			Genetic Algorithm	Genetic Algorithm	Households
Bukar et al. [17]	✓			✗			✓					✓	✓	✓		✓			Grasshopper	Rule based	Residential Microgrid
Zhou et al. [18]	✓			✓								✓		✓		✓			Genetic Algorithm	DICOPT	Housholds
Akram et al. [19]	✓			✓								✓	✓	✓		✓		✓	Brute Force	Rule based	City
Elmaadawy et al. [20]	✓			✓			✓					✓	✓	✓		✓	✓	✓	HOMER		Desalination Plant
Benalcazar [21]	✓	✓		✓	✓		✓			✓						✓			MILP	MILP	District Heating
Buchholz et al. [22]	✓	✓		✓	✓		✓			✓		✓			✓	✓	✓		Brute Force	MILP (oemof.solph)	Dairy
Berendes et al. [23]	✓			✗			✓					✓		✓		✓		✓	MILP(oemof.solph)/HOMER		Island
Wegener et al. [24]	✓	✓	✓	✓		✓	✓	✓		✓		✓		✓	✓	✓	✓		Brute Force	TRNSYS	Museum
Liu et al. [25]	✓			✓									✓	✓		✓			Genetic Algorithm	Rule based	Wind Park
Baniasadi et al. [26]	✓			✓				✓		✓		✓		✓		✓			Particle Swarm	Particle Swarm	Residential Building
Alberizzi et al. [27]	✓			✗			✓					✓	✓	✓		✓			MILP	MILP	Mountain hut
Diab et al. [28]	✓			✗			✓					✓	✓	✓		✓		✓	WOA, WCA, MFO, PSO	Block diagram	Village
Luta and Raji [29]	✓			✗								✓		✓	✓	✓		✓	HOMER		Commercial Facility
Firtina-Ertis et al. [30]	✓			✗									✓		✓			✓	Brute Force	Rule based	Household
Fathy et al. [31]	✓			✗								✓	✓	✓		✓			Social Spider	Block diagram	City
Ndwali et al. [32]	✓			✓								✓				✓		✓	MILP	Not needed	University Workshop
Das et al. [33]	✓			✗			✓					✓			✓	✓			HOMER		Residential Community
Salman et al. [34]	✓			✓/✗			✓						✓	✓		✓			GAMS		Residential Community
Mohseni and Moghaddas-Tafreshi [35]	✓			✗									✓	✓	✓	✓			Particle Swarm	Multi Agent	Residential Area
Bakhtiari and Naghizadeh [36]	✓			✗								✓	✓	✓	✓	✓		✓	ε-constraint	Unknown	Unknown
Urbanucci et al. [37]	✓	✓		✓	✓		✓			✓						✓			Genetic Algorithm	MILP	Secondary School
Zhu et al. [38]	✓			✗			✓					✓	✓	✓	✓	✓		✓	Grey Wolf	Rule based	Island
Eltamaly and Mohamed [39]	✓			✓			✓					✓	✓	✓		✓			Particle Swarm	Rule based	City
Berbaoui et al. [40]	✓			✗			✓					✓		✓		✓		✓	Virus colony	Unknown	District
Goel and Sharma [41]	✓			✗			✓								✓	✓			HOMER		Farm
Hadidian-Moghaddam et al. [42]	✓			✗												✓		✓	Ant Lion	Unknown	IEEE 33/69 bus
Khenissi et al. [43]	✓			✗								✓		✓		✓			Particle Swarm	Rule based	Household
Sawas and Farag [44]	✓			✓			✓					✓	✓		✓	✓		✓	Unknown		IEEE 30 bus
Zare and Iqbal [45]	✓			✓/✗								✓		✓		✓		✓	HOMER		Household
Our Publication	✓	✓	(✓)	✓/(✗)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	(✓)	✓	✓	✓	MOEA/D	MILP (oemof.solph)	Neighbourhood

Various meta-studies deal with the choice of suitable software to simulate operating strategies (e.g. [46, 47]), but often come to the conclusion that there is no universal remedy. The choice of the best algorithm for optimal design is also hotly debated (e.g. [48, 49]), although metaheuristics in the form of nature-inspired swarm intelligence, evolutionary or genetic methods or simulated annealing provide the best results nowadays and are suitable for a wide range of applications. For energy management, this choice does not seem to be so clear-cut and a wide variety of different approaches can be found [50, 51]. Furthermore, the modelling of plant technology for simulation (e.g. [52, 53]) as well as the methods for evaluating the energy system (e.g. [54, 55]) are already sufficiently understood and explained as sub-disciplines.

What is missing up to now is a comprehensive and, as far as possible, universally valid methodology in combination with a powerful software solution which can simulate and design distributed energy systems rather independently of their size, requirements and objectives and which is open to both manufacturers and technologies. There are other approaches to develop such methods and frameworks such as REopt Lite [56] but these are often still in the children's feet and either too complex in their use or not usable in their expressiveness and proximity to reality for real life projects. In the following, we will introduce such a methodology using an established phase-based planning process, present the software solution we have developed based on open source energy system simulation and demonstrate it using a case study. The classification of the solution developed here in the research discourse can be found at the end of Table 1 as well. The focus here is on a detailed and realistic modelling of the energy system especially in terms of regulatory and economic viability in order to be able to establish the methodology in the long term in the real world decision-making processes in planning offices and authorities. The aim here is explicitly not to obtain ready-made decisions for a specific energy system, but to find trends and recommendations that will then contribute to the objectification of decisions in the further decision-making process.

For this, a methodology is developed and presented in Chapter 2 that can optimise operation and sizing of distributed energy systems based on energy system simulation and by using different optimisation algorithms. This methodology is demonstrated by the case study of a German residential district that is briefly presented in Chapter 3. The results of this process are presented in detail in Chapter 4 and possible ways of evaluating them are shown. Finally, Chapter 5 critically examines the developed methodology and places it in the larger context of sustainable energy system planning.

2. Optimisation of distributed energy systems

According to our previous work (Schmeling et al. [57] the planning process of distributed energy supply can be divided into 4 phases (targeting, synthesis, design and operation). This publication focuses on a novel methodology for use in the third phase (design) and presents tools and processes in this phase in more detail. The two previous phases are described briefly, but the results are assumed to be given and are in regard to the case study used later. For a complete description of those phases please refer to the previous work.

2.1. Quantification of targets

Optimality of energy supply is in the eye of the beholder and can vary greatly depend on the boundary conditions and the stakeholders involved. These targets are understood as Key Performance Indicators (KPIs) of the overall technical system which thus have a decisive influence on the success of the project. In general, the methodology outlined is intended for such individual KPI definitions (as long as they can be objectively quantified) and any number of KPIs. For later demonstration and to give the reader an impression of frequently used KPIs, three dimensions (economic, ecologic and technical) are motivated and their approach to quantification is explained below. They were developed in consultation with various stakeholders of the case study that we will use later to demonstrate the methodology.

2.1.1. Economic objective function

The affordability of energy is a central problem in many countries of the world [58]. Especially low-income households often have problems to pay their energy bills [59]. The transformation of the energy sector, such as is currently taking place e.g. in the context of the German "Energiewende", is leading to a significant increase in household energy prices [60]. Making affordable energy available to the general public is therefore a major goal in the design of distributed generation when challenging classical supply solutions.

The economy of an energy supply concept can be evaluated in many different ways. Classical methods such as net present value or internal rate of return [61] can be applied or more modern, dynamic methods such as real options analysis [62]. Each of these have their own advantages and disadvantages, which is why a methodology that is objective, transparent and proven has been chosen here. For this reason, we chose an approach based on the German industrial standard VDI 2067 [63], which is based on annuity analysis. This has the advantage that, if correctly applied, the procedure and assumptions are transparent, recognised and comprehensible. With this, the annual costs A_{N} incurred on the basis of capital- ($A_{\mathrm{N,C}}$), demand- ($A_{\mathrm{N,D}}$) and operation-related ($A_{\mathrm{N,O}}$) costs and proceeds ($A_{\mathrm{N,P}}$) over an observation period T to be defined are indicated.

$$A_{\mathrm{N}} = A_{\mathrm{N,P}} - (A_{\mathrm{N,C}} + A_{\mathrm{N,D}} + A_{\mathrm{N,O}}) \tag{1}$$

The individual annuities $A_{\mathrm{N},X}$ per cost type $X \in [\mathrm{C,D,O,P}]$ result from the costs of the first year A_{X1} multiplied by an annuity factor a and a price dynamic cash value factor b_X, which in turn depends on an interest factor q and a price change factor r.

$$\begin{aligned} A_{\mathrm{N},X} &= A_{X1} \cdot a \cdot b_X \\ &= A_{X1} \cdot \frac{q^T \cdot (q-1)}{q^T - 1} \cdot \frac{1 - \left(\frac{r_X}{q}\right)^T}{q - r_X} \end{aligned} \tag{2}$$

The resulting annuity then describes the annually recurring payments of the same amount over the observation period, caused by the energy system [63, 64]. The system with the highest annuity, i.e. the lowest losses or, if the energy is supplied to third parties, the highest profits, is the best identified option for implementation. No business models of the stakeholders involved in the energy supply are imputed here, but the minimum costs over the observation period are objectively sought from the point of view of the stakeholder community.

2.1.2. Ecologic objective function

Against the background of both climate change and the finite nature of fossil fuels, a global rethink is taking place towards a responsible and moderate use of resources. Quantifying and communicating the externalities of energy consumption is therefore definitely an essential part in modern energy system planning.

Environmental impact assessment can also be carried out in different ways like Life Cycle Assessment (LCA) [65, 66]. At this point, a balancing boundary procedure based on Wehkamp et al. [62] was agreed upon in which only the operating phase is considered and the energy flows across the borders of the supplied object are assigned to the specific CO_2 emissions. The annual emission E resp. emission $E(t)$ at time t is quantified by multiplying the amount of energy $a_X(t)$ with the specific emission $e_X(t)$ at this time step for every energy type F:

$$E = \sum_t E(t) = \sum_t \sum_F a_F(t) \cdot e_F(t) \tag{3}$$

The CO_2 emissions of carbon-based energy sources are assumed to be constant, while the emissions from electricity grid purchases and feed-in are calculated dynamically on the basis of the current national energy source mix using the flow tracing method [67, 68]. Incoming quantities are counted positive, outgoing quantities negative. The emissions related to the use environmental energy (sun, wind, environmental heat) is considered to be 0 g/kWh. The time course of the specific emissions can be seen in Figure 1, whereby the emissions of the carbon-containing energy sources are taken from [69] and the dynamic emissions of electricity were calculated using a custom tool build by Windmeier [70].

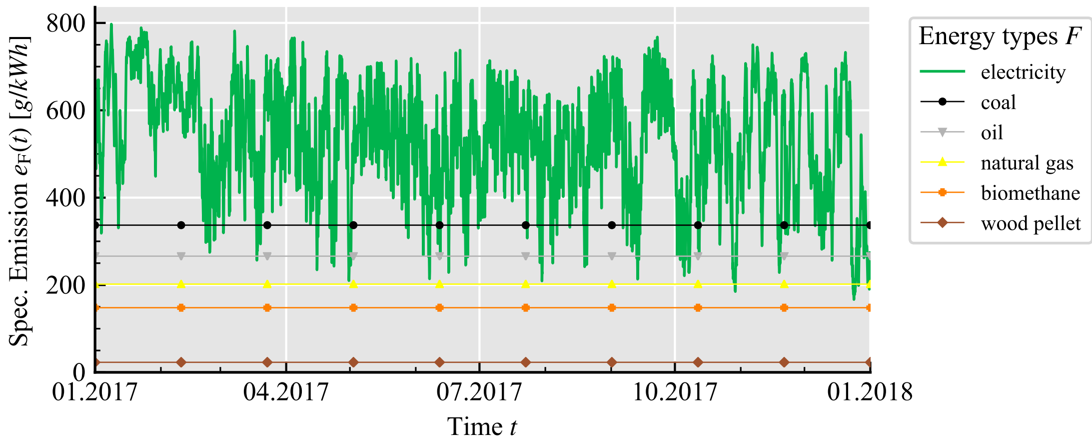


Figure 1: Time course of the specific CO_2 emissions of various energy sources to assess the ecological impact of the energy system using a balancing boundary method for Germany in the year 2017.

2.1.3. Technical objective function

Technically optimal is certainly the most controversial topic in this triad, since a varying definition can be expected depending on the external conditions and the underlying question. However, the technical side of energy use in urban areas, as relevant in the later case study, is usually characterised by limited local energy resources, often an unfavourable ratio of existing roof area for Photovoltaic (PV) or solar thermal use and energy required [71]. It is therefore a legitimate goal to use these limited resources as efficiently as possible.

This can be quantified with the help of own consumption, which is defined as the quotient of locally produced and locally used energy with the total local energy available [72]. Here B

describes the annual locally produced and consumed energy whereas C describes the annual locally produced but exported quantities. The approach is illustrated in Figure 2, the own consumption O can then be calculated as:

$$O = \frac{B}{B + C} \tag{4}$$

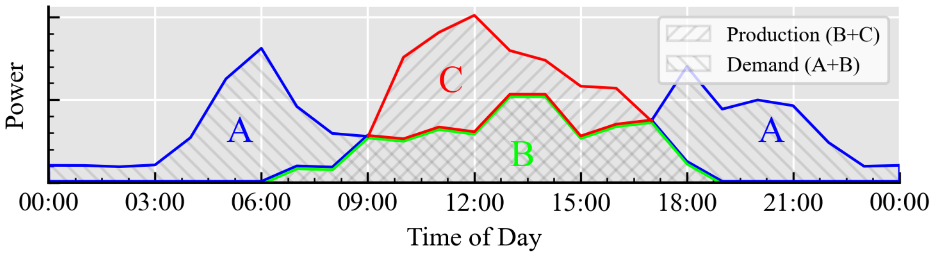


Figure 2: Graphical representation of own consumption using the example of a typical day of PV production and consumption (based on Luthander et al. [72]). Area A (blue) is the share of electricity imported from outside, area B (green) is the amount of energy produced and used locally and area C (red) is the export of locally produced energy.

The definition here is limited to the electricity sector only. In the case of locally generated thermal energy, it is assumed that this cannot be exported and is always consumed entirely locally.

2.2. Energy systems modelling

In order to be able to quantify the previously defined targets in dependence of the used technology, a simulation of the energy flows of the energy system is required. For this purpose, a model has to be built that represents both, the individual technologies, including their techno-economic properties, as well as the interaction of these technologies.

2.2.1. Superstructure

A superstructure represents all energy technologies and their interconnections that are conceivable at that planning phase, but with unspecified size, even if they are partly redundant [73]. A superstructure is the key result of the second phase of energy system planning (synthesis) acc. to Schmeling et al. [57] which can be derived as follows:

Starting with an open collection of all possible technologies involved in the energy supply system, a project-specific decision is made as to which technologies can realistically be implemented for the project under consideration. This is done both in terms of boundary conditions (e.g. resource availability or legislation) as well as technological maturity and willingness to invest of the stakeholders, until a final technology selection is made. The selected technologies must then be combined in a meaningful way, i.e. their interactions must be defined. This results in the superstructure, which is decisive for the further design process and which is shown as an example in Figure 3. Part of the superstructure are also energy-economic and legal framework conditions, such as energy prices, technical minimum requirements or funding for renewable energies (not included in the figure).

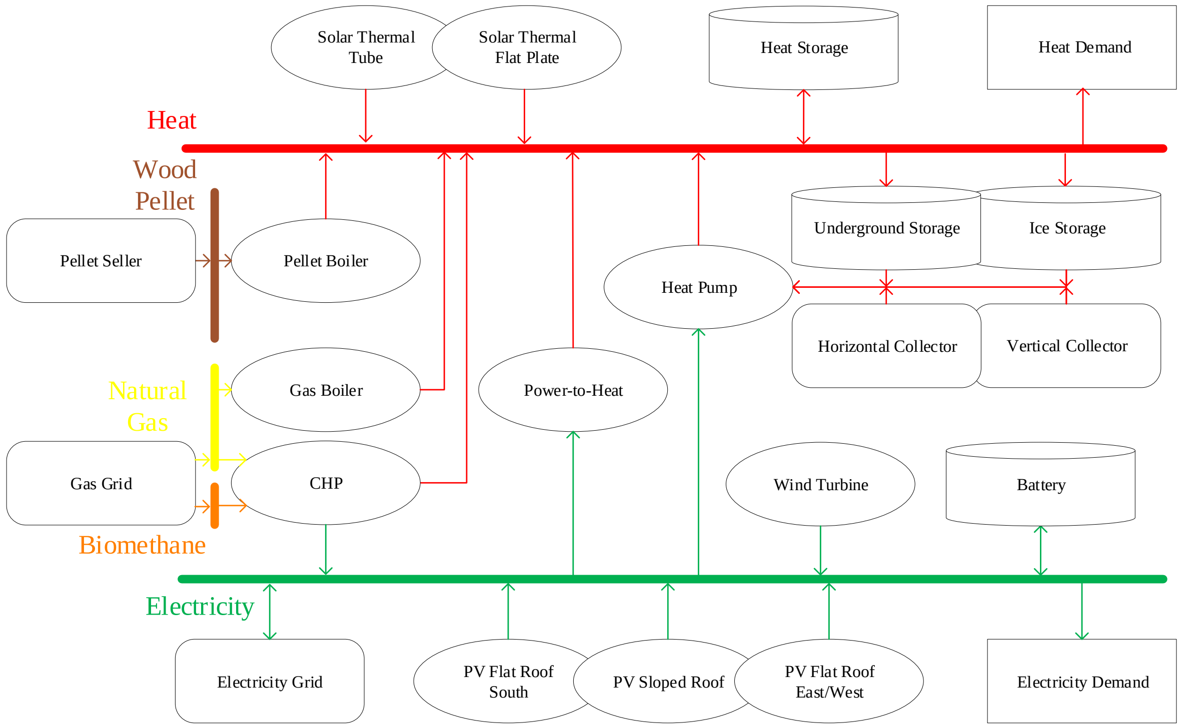


Figure 3: Exemplary representation of a superstructure as used in the later case study. Here, rounded rectangles represent energy sources, ovals energy converters, cylinders energy storage and rectangles energy demands. Details on the individual technologies can be found in Table 2.

The roof areas can be used for either solar thermal or PV. For flat roofs, we distinguish between a pure south orientation (PV Flat Roof South) and an east-west orientation (PV Flat Roof East/West) for PV. Sloped roofs are used without further elevation (PV Sloped Roof). In the case of solar thermal energy, a technological distinction is made between tube and flat plate collectors, which are always aligned to the south due to technical restrictions.

2.2.2. Energy technologies modelling

The modelling of most technologies of the superstructure is, at least at the level required here, either trivial (e.g. gas boilers) or scientifically already well understood and documented as we will show. Therefore, the approach used will only be briefly demonstrated here as an example using the Combined Heat and Power Plant (CHP).

For each technology, a manipulable variable is selected to which all other technical and economic properties are then scaled. In the case of the CHP, this is the electric power at full load, because it also serves as a distinguishing feature between different systems, e.g. on technical data sheets. The basis of the modelling in this case is a product database of different manufacturers, which comprises 54 different CHPs with electric outputs between 5 kW and 2000 kW. The manipulable variable is then plotted against all other variable values of the product database in a point cloud and regressions are performed. In other cases, such as the feed-in tariff, the product database does not have to be used, but the regulations can be translated directly into dependency of the installed capacity. This results in a mathematical continuous modelling of the average system properties as a function of only one variable. This is exemplified in Figure 4. In this way, the change of all system properties can be modelled in the later optimal design using only one degree of freedom per technology.

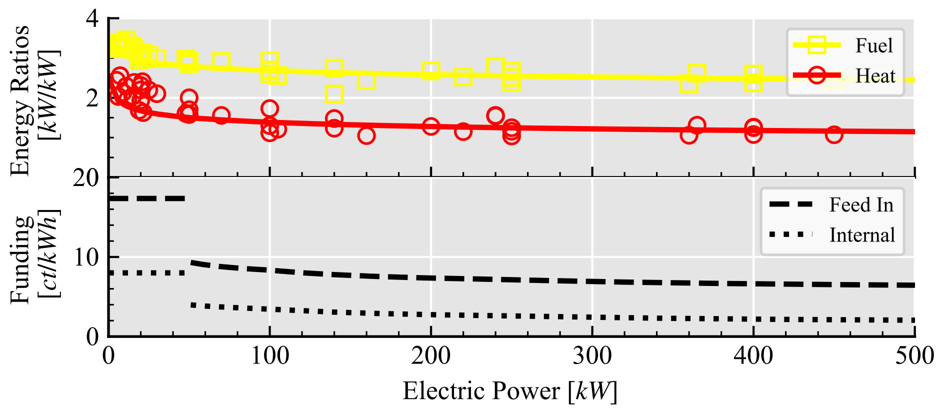


Figure 4: Representation of the continuous modelling of the CHP for the German market and under the funding conditions of the KWKG (German CHP Act). The ratio of thermal and fuel energy to electrical energy is shown above, and the state funding for own consumption and grid feed-in is shown below.

All the technologies contained in the superstructure were modelled in this or similar ways. In Table 2, we provide an overview of the technologies used in the later case study and their modelling fundamentals. This table is only intended to reflect the technology selection used in the later case study; almost any conversion and storage technologies can be modelled and optimised with this methodology due to the chosen architecture; an overview of planned as well as already implemented additions can be found in the table as well.

Table 2: Overview and description of the used and additional energy generation and storage technologies and their modelling fundamentals. In this context, technologies are referred to as trivial if they can be modelled with constant conversion efficiencies without further dependencies.

	Name	Description	References
Used in Case Study	Gas Boiler	Gas Condensing Boiler	trivial
	Pellet Boiler	Wood Pellet Boiler	trivial
	CHP	Gas Engine CHP	[74]
	PV	Roof-mounted PV (different orientations)	[75, 76]
	Solar Thermal	Flat Plate and Vacuum Tube Collectors	[75]
	Heat Pump	Brine/Water Compression Heat Pump	[77]
	Horizontal Collector	Horizontal Collector Pipes for Heat Pump	[78]
	Ice Storage	Ice Storage	trivial (only phase change energy considered)
	Vertical Collector	Geothermal Borehole for Heat Pump	[78]
	Underground Storage	Seasonal Thermal Energy Storage	[79]
	Power-to-Heat	Electrode Boiler	trivial
	Battery	Lithium-Ion Battery	[80, 81]
	Wind Turbine	Horizontal Axis Roof-mounted Wind Turbine	[82]
	Heat Storage	Water-based Sensible Heat Storage	[79]
Additional	Power-to-Gas	Electrolyser generating Hydrogen	
	Gas-to-Power	Fuel Cell for Hydrogen	
	Air Conditioning	Heat Pump for Cooling	
	PVT	Hybrid Solar Modules	
		...	

Modelling is based on power flows inside and between the technologies. As a result, aspects such as hydraulics or voltage stability are neglected. To model temperature-dependent efficiencies nonetheless, discrete temperature levels were introduced. A comprehensive description is given by Schönfeldt et al. [79], here a qualitative description will do: The main benefit of this method is, that it allows to optimise power flows and temperature at the same time using a linear model. Heat sources raise the temperature from one level to a higher one while adding energy. On the other hand, it is always possible to use energy at a higher temperature level for demands at a lower one. Where needed, virtual copies of a technology are created for every applicable temperature level. For example, a solar thermal collector can produce a certain amount of heat at one temperature or a lower amount at a higher temperature. To make sure, that the combination of these copies does not produce more heat then the real device could do, all the copies share a common resource. In the present example, it could be the solar radiation but technically it can be an abstract quantity without any physical meaning.

2.2.3. Energy demand modelling

In addition to modelling the technical systems for energy conversion and storage, the time courses of the energy demand must also be known in order to map and optimise the entire system. As already shown in Figure 3, various final energy demands can arise, primarily electricity and heat. Especially in industry, other forms of final energy such as cold, steam or compressed air may be required, all of which would have to be modelled and included into the superstructure.

The easiest way to obtain these time series would of course be to install metering equipment on site and record over a longer period of time. In many cases, however, this equipment is neither available nor is it being read out reliably and regularly enough to provide sufficient data for the upcoming simulation and optimisation of the supply concept. In addition, the reason for planning a supply concept is frequently that new energy requirements arise from the construction of new buildings or the expansion of production capacities where it has not yet been possible to measure anything. For this reason, methods must often be found to estimate load profiles and generate them synthetically. Although there are standardised load profiles, especially for electricity demand, which are used, for example, to organise small customers on energy markets or for network planning, these are usually not suitable for actual planning, so more sophisticated methods should be used [83]. Such methods differ significantly depending on the use case and are extensively described in the literature [84, 85, 86].

2.3. Optimisation algorithms

The process of optimal design consists of two parts: 1. The choice of optimal technology combinations and their sizes and 2. the choice of optimal operating strategy. There are approaches to solve these two parts simultaneously with only one algorithm (e.g. [87]), but the requirements for optimisation of our set-up can not be fulfilled with this approach. Thus, we use two separate algorithms that build on each other and exchange data. In doing so, the first optimisation step (optimisation of sizing) suggests a possible combination and dimensioning of the technologies in the superstructure. Their timely behaviour is then calculated in the second optimisation step (optimisation of operation) and the KPIs are evaluated. With this information, the first algorithm proposes new, potentially better technology sizes. The system thereby converges towards the ideal design. In Figure 5 this process is shown schematically.

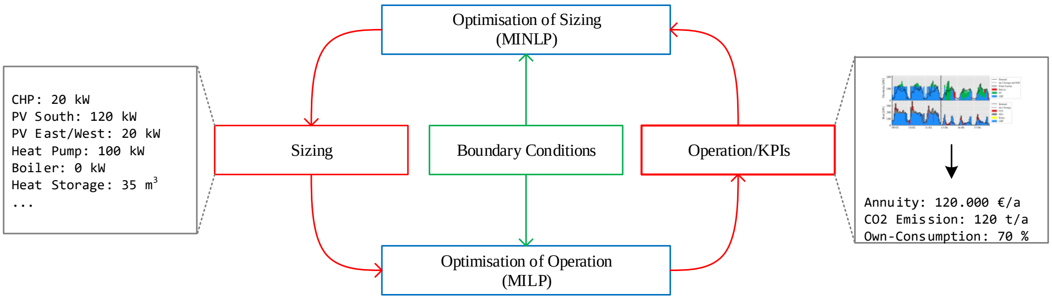


Figure 5: Schematic representation of the optimisation strategy as an iterative process between optimisation of operation and optimisation of sizing and the software used for this purpose. Exemplary data are shown. (Based on Schmeling et al. [57])

2.3.1. Optimisation of operation

In this part it is calculated how a given technology combination affects the operation and therefore the KPIs. This concerns the timely operation of each individual energy system also known as optimal dispatch. This optimisation is implemented using *oemof.solph* [88], an open source python-based tool for energy systems modelling. In *oemof.solph*, the energy system is built up from different sources and sinks as well as transformers which are connected to a directed graph. Each vertex (source, sink, transformer) can be assigned different technical properties (time series, efficiencies, ...) while the edges hold information on how an energy flow in this direction affects the optimisation function, e.g. costs. Even more complex model properties, such as minimum uptime of technologies or capacity charges can be defined. *oemof.solph* then translates this graph into a mathematically solvable Mixed Integer Linear Programming (MILP) problem where the operational status and energy flows at every timestep are degrees of freedoms of the optimisation.

The optimisation problem is solved using the python tool *pyomo* [89, 90], which in turn utilises different numerical MILP solvers of which *CBC* [91] has been used here. This solver has proven to be the most performant in comparison to other open source solvers.

Usually *oemof.solph* minimises the operating costs that are incurred for energy flows in the model. Thus, there is no static dispatch ranking or control strategy of the various technologies that could be represented in graphical form, but rather the operational management is decided anew for each point in time by mathematical optimisation. In terms of the previously introduced economic valuation using annuities (Section 2.1.1), the target function corresponds to the demand- and operation-related costs combined with the proceeds of the first year $(A_{D1} + A_{O1} - A_{P1})$. Deviating from this, an internal CO_2 penalty $p_{CO_2} \in [0\,\text{€}/\text{t}, 180\,\text{€}/\text{t}]$

payable per tonne of emitted CO_2 E is introduced for the optimisation of operation, but not for the subsequent economic KPI evaluation. In this way, it is possible to tune the operation of the system towards one or the other KPI for the same sizing. As a result, a technically identical system may be calculated several times with different operating strategies. The maximum of 180 €/t corresponds to the total external costs of the emission as determined by the German Federal Environment Agency [92], which could be internalised in this way. This is not compulsory for own consumption, as there is already enough incentive to use electricity locally due to state subsidies and the chosen CO_2 assessment approach.

The objective function of the operational optimiser can therefore be formulated as follows:

$$\min \left(A_{D1} + A_{O1} - A_{P1} + p_{\mathrm{CO_2}} \cdot E\right) \tag{5}$$

The *oemof.solph* model developed by us, including further necessary components for optimising the operation, are published under the name MTRESS ("Model Template for Residential Energy Supply Systems") as open source software [93].

With this model, we manage to optimise the large number of technologies used in the superstructure. While in the literature (Table 1) only a few technology combinations have been optimised so far, our model allows to represent this multitude and to solve it in realistic computing times. The calculation time does not increase linearly with more technologies, but increases significantly with each new technology.

2.3.2. Optimisation of sizing

Unlike the optimisation of operation, the optimal sizing has significantly less degrees of freedom (here: number of technologies), but the problem can no longer be linearised. This is mainly due to discontinuities caused by regulatory intervention (cf. Figure 4) and strong economies of scale in the costs and efficiency of technical components. Therefore this part of the optimisation is carried out as Mixed Integer Non Linear Programming (MINLP).

In addition, optimisation can no longer be carried out on the basis of just one objective as before, but all three KPIs have to be taken into account, referred to as Multi-objective (MO) optimisation. Due to the partly contradictory objectives, when comparing two solution vectors, it is not necessarily possible to determine which one is overall better, as they may differ in several dimensions. Solutions are therefore sought where one objective function cannot be improved without worsening another. The totality of these solutions is called Pareto-optimal and can be represented graphically in the form of Pareto fronts. Thus the optimisation problem can be mathematically defined in dependence on the technology sizes

$\vec{x}$ as the maximisation of annuity $A_N(\vec{x})$, minimisation of emissions $E(\vec{x})$ and maximisation of own consumption $O(\vec{x})$:

$$\max \left(A_{\mathrm{N}}\left(\vec{x}\right), -E\left(\vec{x}\right), O\left(\vec{x}\right)\right) \quad \text{s.t.} \quad \vec{x} \in X \tag{6}$$

Here, X refers to the solution space of the potential technology components sizes which, depending on the case study, would theoretically be conceivable within the superstructure. Often a value of zero, i.e. non-existence, can be assumed as the minimum plant size. At the upper end of the scale, systems such as PV or solar thermal systems are limited by the available roof area, while heat generators such as boilers or heat pumps can be limited simply by the maximum thermal load of the heat demand. The previously introduced internal CO_2 penalty is as well part of the solution space and is altered in the optimisation for different operating strategies.

Again, a fundamental problem of modelling is the large number of technologies used and the associated high mathematical optimisation effort; the choice of a suitable optimisation algorithm is thus critical in order to keep the computational effort within limits. There are many comparisons of possible approaches to solving such problems in the literature (e.g. [94, 49]), but the consensus is mostly that it depends strongly on the individual use case which approach is most successful. Therefore, various approaches such as classical optimisation algorithms as used in the optimisation of operation, swarm intelligence and genetic algorithms were tested and evaluated based on their performance. For this purpose, a shortened time period of the later case study was processed using different optimiser and their performance were compared based on convergence and computation time. In this, a Multi-objective Evolutionary Algorithm with Decomposition (MOEA/D) algorithm has proven to be best suited for the problem at hand, which will at least be briefly described here:

The basis of this algorithm is an Evolutionary Algorithm (EA), a special form of metaheuristic, which uses processes known from biological evolution to perform mathematical optimisations. Several solution vectors, which are called individuals and in their entirety population, are placed randomly in the solution space and developed by environmental pressure towards the global optimum. This is achieved by a process of population reproduction over several generations. The higher the fitness of an individual in the solution space, i.e. the better it is adapted to its environment, the more likely it is to pass on its characteristics to the next generation [95].

In these, however, usually only scalar problems are solved, so the fitness of the individuals are directly comparable. As already described, this is not necessarily the case for MO optimisation, which is why these algorithms have to be modified. In MOEA/D decomposition is used for this purpose [96, 97]. The original large problem is broken down into sub-problems, which are then solved simultaneously. We choose an approach according to Tchebycheff [98] to generate these sub-problems, in which the objectives are combined using a weight vector resulting in a scalar fitness value. The best solution of a sub-problem in the current generation is combined with neighbouring sub-problems in the course of the optimisation, leading to an exchange of information along the Pareto front.

The MOEA/D implementation in *pygmo/pagmo* [99] is used, which uses further advanced techniques in addition to the basic framework to solve MO problems reliably and efficiently. For example, the CPU architecture of modern computers is used to separately optimise populations on different islands (threads) of an archipelago, while individuals can migrate between those islands [100].

In addition, other techniques must be applied to guarantee successful optimisation. For example, non-box constraints (in this case e.g. the legal minimum requirements for the renewable heat share or the restriction that roof tops cannot be used for PV and solar thermal at the same time) have to be modelled. This is realised with a dynamic penalty approach [101], in which the target function is artificially worsened if such constraints are not met in dependence of the violation. Initial guesses were also placed on the islands at the beginning of the optimisation in order to give the optimiser a first impression of the search space. These are classically designed systems, which can be further optimised depending on their quality but do not have to.

Nevertheless, the runtime of the optimisation framework described here is several weeks to months per case study on a recent consumer hardware PC until sufficient convergence is achieved which is mainly down to the runtime of the *oemof.solph*/MILP optimisation.

3. Case study: Helleheide

The methodology shown above will now be applied in an exemplary way to demonstrate it in an application-oriented manner. The Helleheide district planned in Oldenburg, Germany, will be used for this purpose. This is a new urban district on a former military airbase, which will be used as a living lab for various Smart City activities. The living lab activities and the related stakeholder involvement in the development of innovative business models is described in detail by Brandt et al. [102]. More details about the district and the associated research projects can as well be found in Schmeling et al. [57], Wehkamp et al. [62], Klement et al. [103].

The buildings of the district are currently in the planning phase. It is to consist of seven buildings, whereby two existing buildings from military times could be preserved but have to be lavishly renovated. The district is characterised by a heterogeneous resident structure. In addition, a commercial enterprise is to be established in the neighborhood; currently, the establishment of a canteen kitchen and bistro is probable. Their energy demand profile is assumed in the following. It is also planned to create a student dormitory.

The district has to be supplied with electricity and heat for space heating and Domestic Hot Water (DHW). Cooling is rather uncommon in German residential buildings and is therefore not considered here. The process of determining the load profiles for the case study's energy demands is a multi-stage process. With the help of the software QuaSi [104], simplified cubatures, building material properties, weather data and usage profiles were used for each building to simulate the buildings energetic behaviour and thereby create hourly load profiles for space heating using a generic thermal building model based on EnergyPlus® [105]. These were compared to the annual heat demand according to energy performance certificates following DIN 4108 [106] and scaled accordingly. After validating against energy performance certificates, the buildings were simulated again, this time without internal gains due to electricity usage, because electricity and DHW hourly demand profiles were created using the LoadProfileGenerator [86]. However, since part of the space heating demand does not have to be covered by the heating system, but instead is covered by internal gains from electricity usage, the electricity demand time series was subtracted from the previous space heating time series, which, of course, can never be less than zero. The addition of this space heating time series with the DHW time series then results in the heat demand of the individual buildings. Since these buildings are to be supplied from a common heating centre, additionally the losses of a district heating network have to be taken into account. This is done according to a methodology described by Wehkamp et al. [62] and thus results in the heat time series to be provided at the outlet of the central heating system, which can then be used in the superstructure according to Figure 3. The district heating has a flow temperature of approx. 40 °C and can therefore be classified in the transition between third and fourth generation district heating [107].

Weather data of the year 2017 were used here and in any subsequent steps, since according to an internal survey, these can be regarded representative for the chosen location. The use of test reference years is not possible here, as the model also requires real electricity market data as input, which is strongly influenced by meteorological conditions. Both time series are therefore to be taken from the same year.

A graphic representation of the resulting energy demand is shown in Figure 6. Summed up over the year, this results in electricity demand of 535 MWh/a and heat demand of 541 MWh/a.

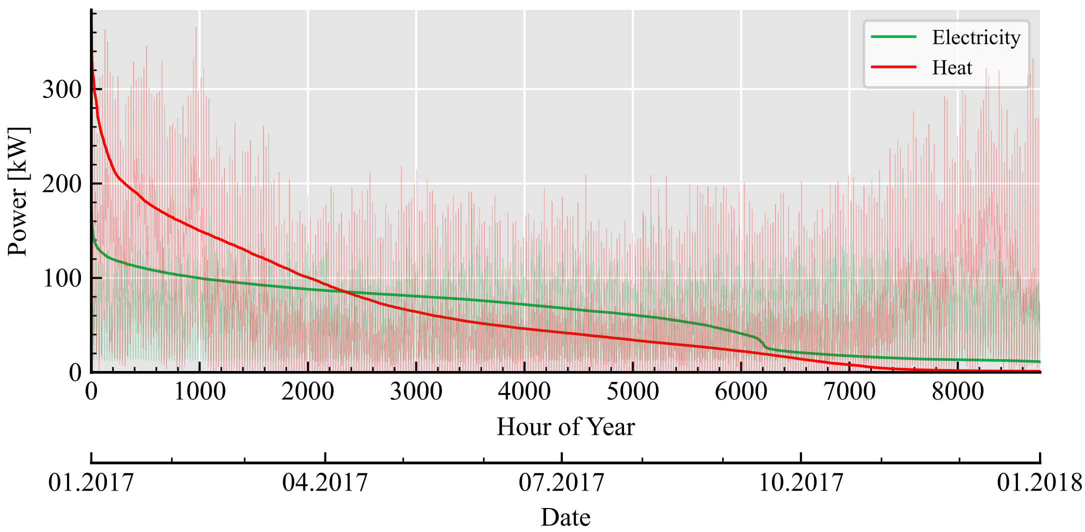


Figure 6: Time course of the hourly electricity and heat demands of the case study as time series and load duration curve.

What can be seen for heat is a seasonally strongly fluctuating demand, especially in the winter months, supplemented by a relatively constant demand for DHW. Larger load peaks are to be expected during the day. Electricity demand, on the other hand, is affected less by seasonal fluctuations and is also better distributed over the day. Here, peak loads occur mainly in the morning and evening hours.

The aim of this study is to provide a recommendation that is as application-oriented as possible. Therefore the German legal framework is implemented as accurately as possible. This includes the support regimes for PV and wind under the Renewable Energy Sources Act (EEG), the funding of CHP plants under the CHP Act (KWKG) and the minimum requirements for renewable heat supply under the Building Energy Law (GEG). Current costs for energy procurement and feed-in as well as the associated state-induced levies and taxes as of 2021 are also taken into account. Furthermore, it is assumed that electricity is bought and sold on the EEX day-ahead market, i.e. new prices have to be considered every hour. In contrast, natural gas is purchased at fixed prices.

The framework described above is of course not only suitable for such residential areas, but also for commercial and industrial environments. However, the chosen district has the advantage of combining different consumers with very different requirements, which, taken as a whole, exhibit a highly variable and counter-cyclical behaviour towards the availability of environmental energy. The design of the energy system is therefore particularly challenging. The application of this methodology to other case studies with different research questions and challenges is subject of future publications.

4. Results of the optimal design process

The results of the optimisation of operation will be demonstrated, before the results of the overall optimal design process will be discussed in detail. Therefore two different exemplary system designs will be shown and their behaviour will be explained, starting with a CHP and PV based design. Their operating behaviour can be seen in Figure 7.

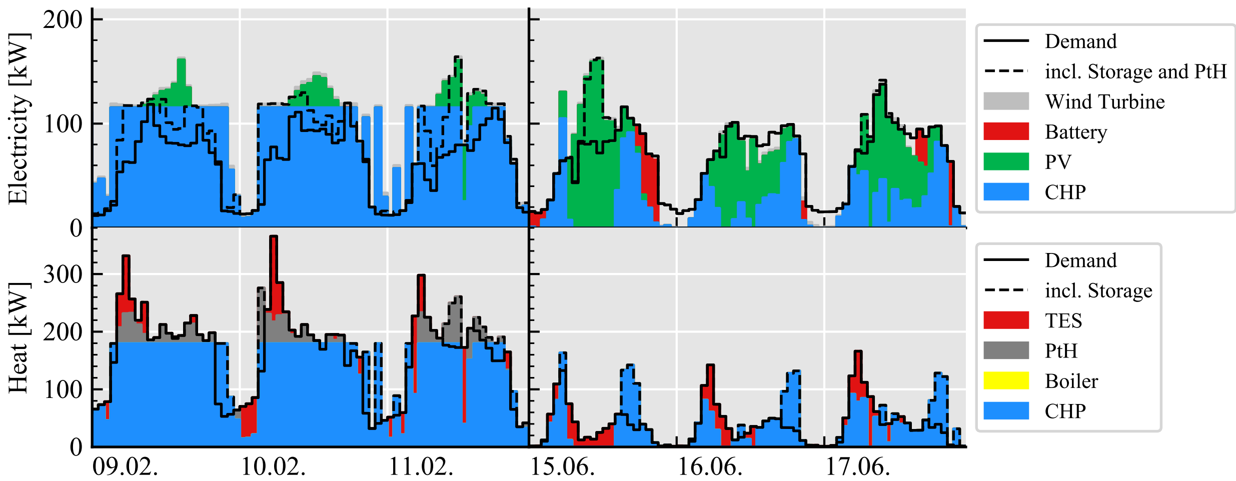


Figure 7: Exemplary illustration of the coverage of the electricity and heat demand by a CHP dominated system over three days in February and three days June with the following components: 134 kW CHP, 125 kW PV south oriented, 125 kW PV east-west oriented, 100 kW Power-to-Heat (PtH), 400 kW gas boiler, 250 kWh battery, 3.6 kW wind turbine and 15 m^3 heat storage. This results in an annuity of 165 555 €/a, CO_2-emissions of 224.4 t/a and an own consumption of 90.5 %.

We show here three days in February as an example for the heating season, and three days in June as an example for the summer time. The heating season is characterised by an extensive use of the CHP, which almost permanently meets all demands on both the electricity and heat sides. In contrast, the CHP is used much less in summer. This happens mainly in the morning and evening hours, as peak loads occur at this time that cannot yet be covered by the PV system on the electricity side. As soon as this is predominantly the case, the CHP unit switches off or reduces its output so that the district is self-sufficient. The resulting supply gap on the thermal side is then covered by the heat storage system which has been charges beforehand. In winter, on the other hand, it is necessary to provide the missing heat via the existing PtH system. The relatively low PV generation is sold externally here for the most time, as the CHP is running most of the time to supply enough heat. This is another reason why the battery is mainly only used in summer, in order to shift the solar power from the midday hours to the evening hours and thus further reduce the load on the CHP unit. The wind turbine is used permanently on the electricity side, but does not play a significant and noticeable role due to its size. The boiler on the thermal side is not used here, but heat is generated via the PtH module, which apparently delivers better operating results here. Nevertheless, there may be times in the year when the boiler turns out to be better. The KPIs are good as expected, but only become truly meaningful when compared with other systems.

Additionally the optimised operation strategy for the same timeframes of a system which is characterised by heat pumps, PV and solar thermal energy is shown in Figure 8.

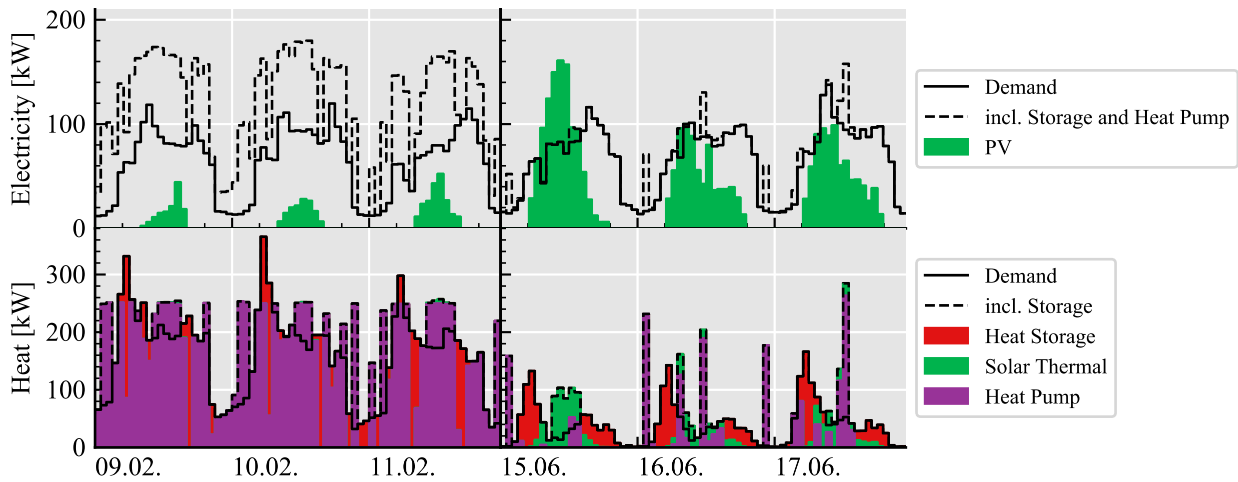


Figure 8: Exemplary illustration of the coverage of the electricity and heat demand by a heat pump dominated system over three days in February and three days June with the following components: 400 kW heat pump, 200 kW PV south oriented, 42 kW sloped PV, 200 m^2 solar thermal, 5000 m^2 horizontal ground source collector and 20 m^3 heat storage. This results in an annuity of 174 712 €/a, CO_2-emissions of 258.7 t/a and an own consumption of 87.2 %.

In this case, it is noticeable that the PV is adequately designed for the summer months, but is significantly undersized in the winter months. This is in stark contrast to the electricity demand, which is significantly higher than in the CHP case due to the heat pump and must therefore be covered mainly by grid electricity. In summer, the advantage of the large heat pump becomes apparent, as it manages to cover the needs of the district with very short running times. The combination of PV and solar thermal seems to be disadvantageous here, as a high electricity supply always coincides with a high heat production, which makes it unattractive to use the heat pump. This system is now worse than the previous one in all KPIs, if only slightly. Despite the extremely different technology combination and operation modes, the results are nevertheless comparable. This underlines the complexity of finding optimal supply design from a gut feeling.

Within the scope of the optimal design, about 53 000 such different designs were calculated and optimised multicriterially with the help of the presented methodology. Of these, about 42 000 were valid and realisable solutions which do not violate the boundary conditions. In turn, 1909 points of this are Pareto optimal. This results in the three-dimensional Pareto front shown in Figure 9 whereas in Figure 10 the same information is displayed in two-dimensional space with the technical dimension in form of a colour bar.

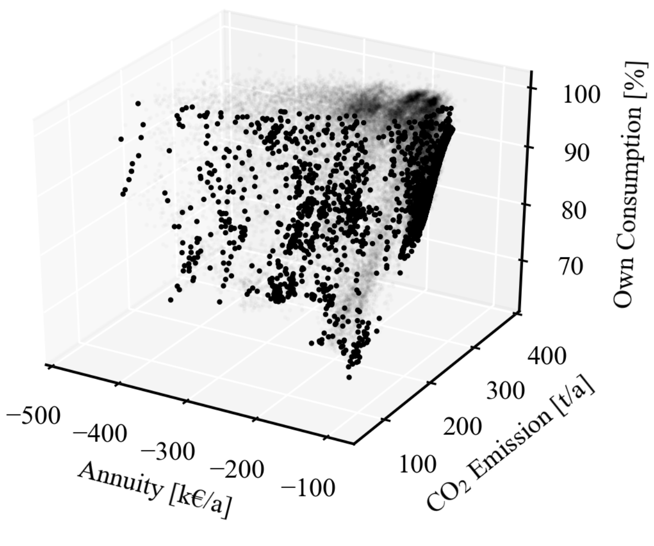


Figure 9: Visualisation of the solution vectors computed for the case study in terms of the defined KPIs, with the grey transparent dots representing all computed and feasible solutions while the black dots represent the Pareto optimal points thereof. Here it is shown in three-dimensional KPI space, the surface spanned by the Pareto-optimal points represents the three-dimensional Pareto front of the case study.

What can be seen here is the sufficient convergence of the optimisation as well as the expected broad Pareto front, which indicates a strong trade-off between the chosen KPIs. In contrast to many other studies, we do not expect a perfectly smooth front here due to

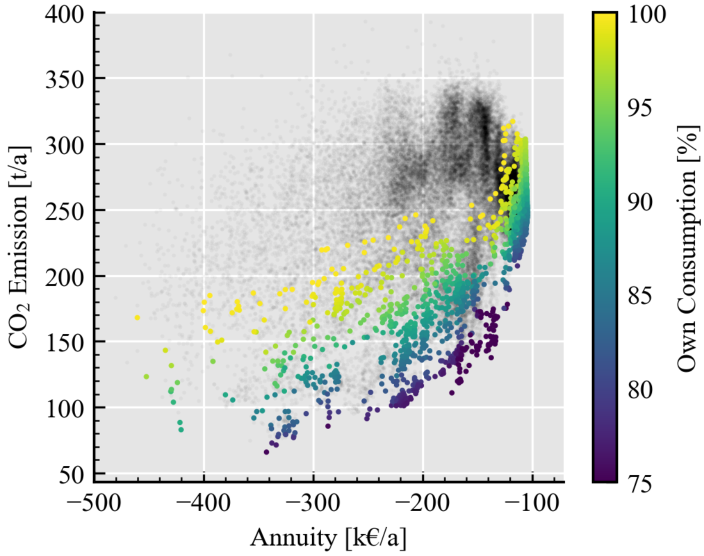


Figure 10: Visualisation of the optimisation results similar to Figure 9, whereby the technical KPI is shown as a colour bar, resulting in a 2D representation. The information displayed is the same. Anyhow, it is easier for the human eye to understand while there is a known perception bias in favour of the KPIs displayed on the axes.

the partly non-linear modelling of the individual technologies, but rather discontinuities in the representation. Further optimization would lead to further filling of the existing gaps. However, a highly precise front is not essential here, as the methodology should rather provide tendencies and recommendations for decision-making in the planning process and not bring about a final decision.

Such important tendencies can be seen in this figure, e.g. the previously assumed conflict of objectives of the selected KPIs. While the degree of self-consumption can easily be pushed close to the technical maximum of 100 % and never falls below 65 %, a wide range of solutions are conceivable in terms of costs and emissions. The most cost-effective and climate-friendly solutions differ by a factor of 3.3 in terms of costs and even by a factor of 3.7 in terms of emissions. It is interesting that despite many discontinuities in the modelling of the individual technologies, the front appears rather smooth, so it should be very easy to find satisfactory compromises later on. This can be explained by a strong change in the combination of technologies, which will be analysed later as well as by the large amount of different technologies considered, as one should always find a suitable stopgap.

Starting with this thought, and to further understand the results, we look at how many technologies are involved in the energy supply for each design. This forms an additional dimension in the representation, which is why the previous visualisation methods are only of limited use. According to Filipič and Tušar [108], other methods were chosen. Here first a scatter plot matrix (Figure 11), in which all possible combinations of KPIs are represented as a cloud of points and the number of technologies contributing to the energy supply as a colour bar. We define a contribution as a system size that reaches at least 5 % of the previously defined maximum size.

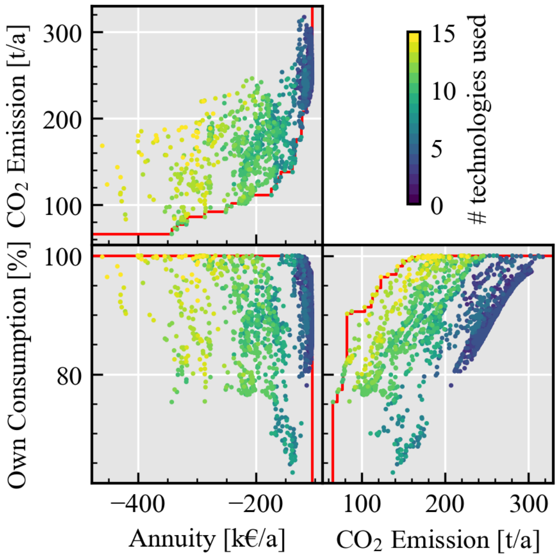
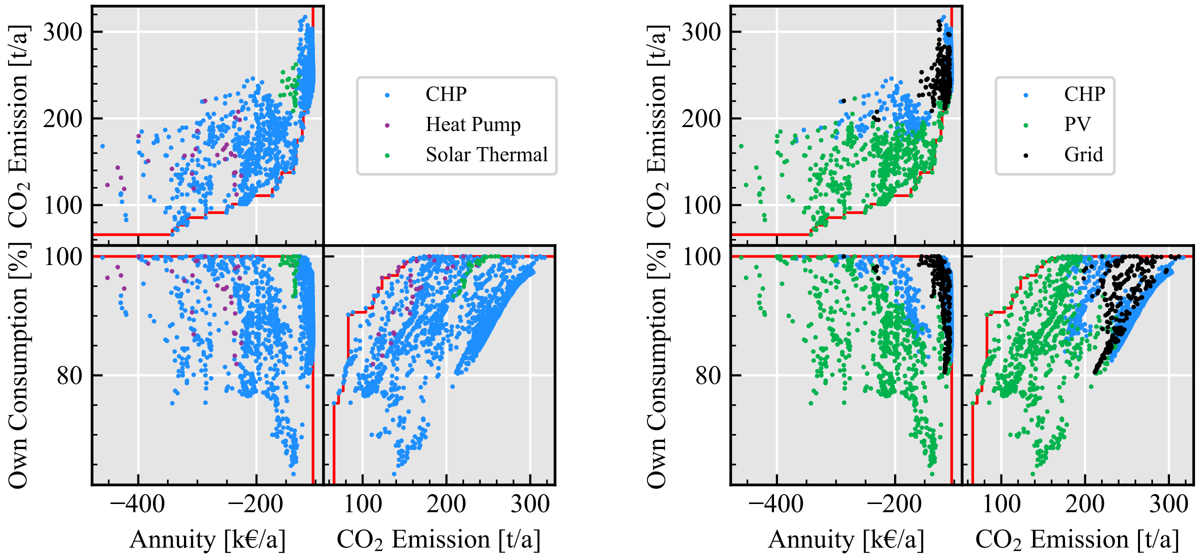


Figure 11: Renewed visualisation of the Pareto scatter matrix with the total number of plants of contributing size (>5 % of the maximum size) in the form of a colour bar.

The very clear trend in this analysis is that systems with fewer technologies involved tend to be cheaper, which is of course due to the lower capital-related costs. However, these systems also show higher emissions than systems with more components. This may be due to the lack of flexibility in generation and storage. While systems with many, sometimes very different, supply components can find an optimal mode of operation at any time, those with fewer components are unable to do so. On the other hand, the number of components seems to have less influence on the degree of own consumption. The transitions here are fluid, which strengthens the previous hypothesis: The optimiser manages to find technologies very well that allow certain KPI fulfilment levels in an adequate size without leaving large gaps.

In order to go further into the analysis of the involved technologies, we analyse which of the technologies used provide the largest amount of secondary energy, electricity or heat, and thus dominates this energy sector (Figure 12). Again, a Pareto matrix is used, one for electricity and one for heat.



(a) Heat

(b) Electricity

Figure 12: Illustration of the Pareto-optimal solutions in the form of a scatter plot matrix, in which each pair of KPIs is presented separately. The dominant technology for the two secondary energy forms, electricity and heat, is represented by a colour code. The structure of the figure at the top left corresponds to coloured points of Figure 10.

Looking first at the thermal side (Figure 12a), it emerges that of the seven potential technologies, only three, namely CHP, solar thermal and heat pump, seem to be able to dominantly provide the case study's energy supply in a pareto-optimal manner. The CHP is clearly the most common and universal solution in this, which, depending on the technology combination, results in monoobjective optima for all three KPIs. The heat pumps come into play mainly for designs with lower emissions and higher own-consumptions. Solar thermal energy merely fills a small gap between the best economic CHP systems and the other solutions. In general, the solution front seems to show discontinuities at this point, which could be due to discontinuities in government subsidies for CHPs (Figure 4). On the electrical side (Figure 12b), similarly strong tendencies can be seen. While grid-based systems lead to low costs and high levels of self-consumption, they usually emit larger amounts of CO_2. In contrast, a dominant share of PV electricity leads to low emission but slightly higher cost. The own consumption in PV based systems is rather variable. Systems dominated by CHP electricity interestingly occure at two different occasions: Firstly, as the absolutely cheapest but most climate-damaging variety, and then as a middle ground between grid and acPV-dominated systems, which again shows the changeability of the CHPs.

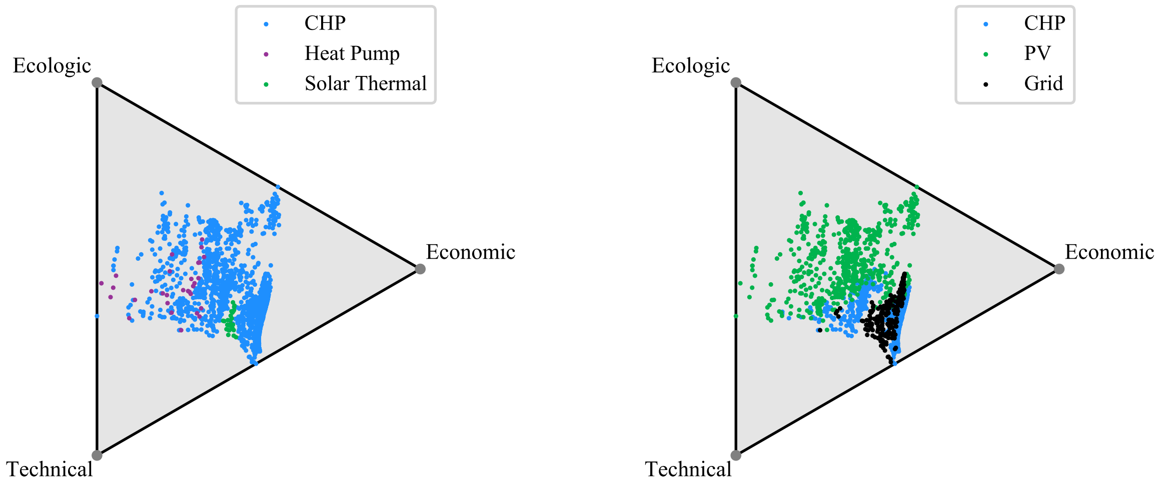
When combined considering the number of technologies (Figure 11) and the dominant technologies (Figure 12), it is noticeable that CHP units can dominate in both smaller and larger technology combinations. Solar thermal, on the other hand, tends to dominate in smaller configurations, while heat pumps tend to dominate in larger ones. This is because technologies such as heat pumps only act as energy converters, converting different local energy resources into one another, e.g. heat from deep boreholes and electricity from PV into usable heat, whereas solar thermal energy or CHP units only require backup, e.g. from a gas boiler to work. On the electrical side, PV systems also tend to show their advantages in larger systems parks. This is due to the fact that they are particularly worthwhile, for example, in combination with heat pumps or PtH for heat generation or with batteries for storage. Here, too, CHP units tend to get by with fewer other technologies or, as the case may be, a grid connection theoretically does not require any technology at all.

An alternative method of visualisation, which has not been used much in the literature so far but which visualises the tendencies just explained even better, are so-called RadViz plots ([109], Figure 13). In this method, the KPIs are evenly distributed on the unit circle, which are used as anchors. Each Pareto-optimal point is then attached to these anchors with springs, where the spring tension is proportional to the degree of achievement of the KPI. The points are positioned in the force equilibrium of these springs, so the more a solution is dominated by a certain KPI, the closer it is to this anchor point. Thus, one expects mono-optimal solutions close to the anchors, compromises midway between them.

On the thermal side (Figure 13a), it can similarly be seen that in a CHP-dominated system, it is possible to achieve optimality in all dimensions. In contrast, the heat pump-based solutions strive for good compromise between ecologic and technical KPI. Solar thermal energy again proves to be a gap-filler with high economic and potentially technical optimality. On the electricity side (Figure 13b), the important role of PVs dominance for the ecological KPI is again evident. CHPs seem to be more economically and technical optimal which is as well true for grid-based systems. Thus, the previously made statements can be confirmed here anew and the identified dominant technology islands can be understood even better.

Aside from the dominant technologies many other technologies are involved in the success of the systems, as noted earlier. Quantifying the influence of each individual component and its size is particularly difficult due to the high dimensionality. Here, a visualisation approach was chosen in which each plant size is correlated with each KPI individually and correlation coefficients are determined. The representation can be found in Figure 14.

Only rough trends can be identified as the scatter range per technology is sometimes rather high. There seem to be few completely unattractive technologies (e.g. solar thermal tubes



(a) Heat (b) Electricity

Figure 13: Illustration of the Pareto-optimal solutions in the form of a RadViz plot, where solutions are placed closer to the corresponding anchor points the more optimal they are in this respect. The dominant technology for each secondary energy form is shown by colour code.

and horizontal ground collectors), but also no completely dominant technologies, as it seemed before with CHPs. The general conclusion is confirmed that many system components lead to good emissions and few components lead to good costs, while this has little influence on own consumption. It can be seen that in the economic KPI, very small CHP units are often used, which are frequently supplemented with medium expansion stages of PV and sometime solar thermal. On the other hand, very large CHPs fired with biomethane and supplemented with large PV systems are used for ecological optimality. For further flexibility, PtH and large thermal as well as electrical storage facilities are added. As already shown, heat pumps play a role in the trade-off between economic efficiency and climate protection. There is no clearly preferred heat source for heat pumps, but they seem to be frequently combined with CHP units, at least in part and contrary to current standard concepts. Very interesting here is the replacement of the more east-west oriented PV plants for good ecological KPI with more south oriented plants for a good economic KPI. There seems to be a clear competition for roof space, which solar thermal tends to lose. In the case of own consumption, on the other hand, far less clear trends can be discerned. Although PV systems and CHP units in particular seem to have a negative influence as their size increases, while solar thermal has a slightly positive influence, it is very difficult to generalise here. The positive influence

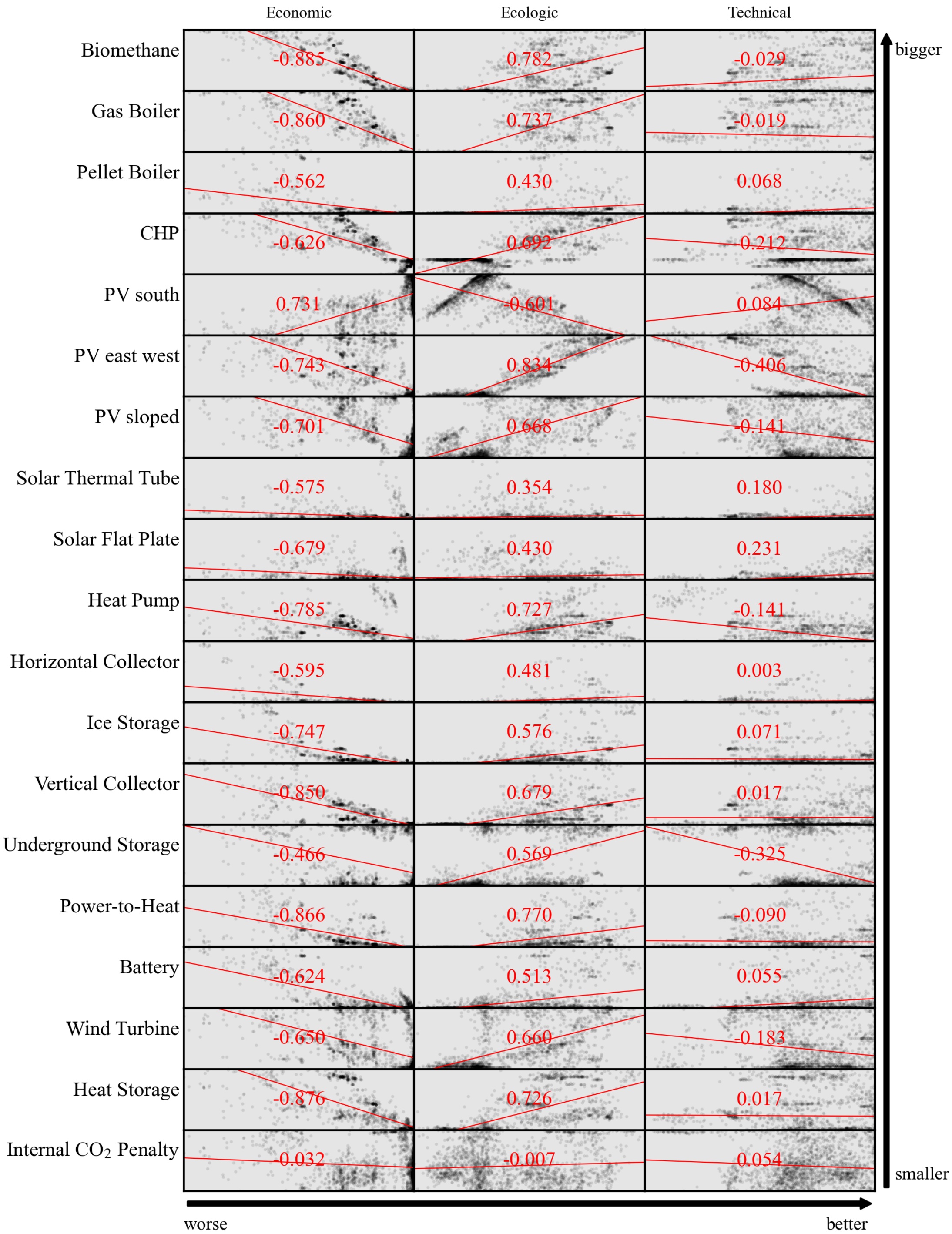


Figure 14: Correlation of KPIs and technology sizes as a scatter matrix. Only the Pareto optimal points are considered here. Linear regressions and the corresponding correlation coefficients are shown in red.

of solar thermal is interesting, which can be explained by the competition for roof space with PV. In order to optimise own-consumption, the tendency again seems to be clearly towards south-oriented PV systems. This is in line with the experience in the design of PV systems for residential buildings, which in Germany are mostly oriented east-west for good own-consumption. What is also noticeable is that the virtual CO_2 price added to manipulate operations has almost no influence on the KPIs. There are economic optima despite high CO_2 prices, which are hardly more expensive than those without this pricing. It can be deduced from this that, contrary to what was originally assumed and is already the case today, an economically optimised mode of operation of the plants coincides with good ecological optimisation.

We could now go on and pick out individual energy systems and analyse them in more detail as shown in Figure 7 and Figure 8. Similarly, one could use complex algorithmic and methods to make finite decisions for a single energy system like TOPSIS [12]. However, as already explained, the framework developed and presented here is intended to identify trends and support the decision-making process in the overall context of energy system planning. Therefore, the analysis of the results ends here.

5. Discussion

As has been shown with the case study, a simulation-based optimal design can provide interesting insights into the impact of plant sizes on KPIs and can help to make objective, valid and optimal decisions. The approach chosen here as a combination of an MILP optimiser for optimisation of operation in combination with a metaheuristic for optimisation of sizing offers the great advantage of being able to model realistic and comprehensive energy systems. The use and linkage of the two open source tools *oemof.solph* and *pygmo* has proven to be particularly beneficial in this, as it allows for a variety of necessary custom developments, improves the understanding of the results and significantly increases the transferability.

The possible insights and discernible trends that were possible due to the evaluation methods introduced do not lead to significant re-evaluations of the energy technologies studied and their raison d'être for the case study, but it is nevertheless interesting to see how to achieve similar results with very different system designs. However, this will largely be due to government influence and targeted promotion and can of course only be assessed here on the basis of a single case study. In order to be able to give conclusive assessments of the current German market situation, as well as economic analyses and possibly policy recommendations based on these, a large number of different case studies as well as sensitivity analysis are required.

The disadvantage of the chosen approach is the high computing time of several weeks due to the necessary complexity as well as the need for a lot of detailed data on the technologies used and the local conditions of the case study which are most of the times hard to collect. It is therefore essential at this point to develop further tools and, in particular, processes to either record such information on a project-specific basis or to approximate it using advanced methods. Caution is advised here, especially in the choice of KPIs, as these have a significant influence on the result. The KPIs chosen in this study are more of a national and public nature and do not, for example, reflect the actual contractual arrangements and business models of the case study. For this and many other reasons, the integration of the developed methodology into the big picture of phase-based energy system planning needs to be further investigated and the effect of such planning processes on the future national energy system needs to be quantified in more detail. In this way, a future integration of such software solutions supporting the decision-making process into the daily business of engineering offices and government agencies can be achieved in the long term, thus contributing to the efficient and sustainable energy supply of a wide variety of projects.

6. Conclusion and Outlook

It has been shown that the optimisation of energy systems in terms of technology choice, sizing and operation is a well-understood problem in certain aspects, but the need to combine these individual facets into a common framework and thus gain insights into different complex types of energy supply concepts is particularly important. With the framework presented here, it will be possible to comprehensively investigate a wide variety of different technologies and especially their interaction for various use cases in an application-oriented manner. A special focus was placed on realistic modelling in order to be able to integrate this process into existing planning processes in industry in the future. The aim is not to make final decisions for the energy system, but to be able to provide trends and recommendations on the basis of which the relevant decision-makers can then make valid choices. The framework that has been created and the case study of an urban district shown here are only the starting point for a wide range of development and analysis options that will be expanded and intensified in subsequent studies like the use in industry, the addition of innovative technologies or the effects of such methodologies on a national level.

Abbreviations

CHP	Combined Heat and Power Plant
DHW	Domestic Hot Water
EA	Evolutionary Algorithm
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non Linear Programming
MO	Multi-objective
MOEA/D	Multi-objective Evolutionary Algorithm with Decomposition
PtH	Power-to-Heat
PV	Photovoltaic

Author Contributions

Conceptualisation: LS; Methodology: LS; Software: LS and PS; Data Curation: LS, PS and LV; Formal Analysis: LS; Visualisation: LS; Writing – Original Draft Preparation: LS; Writing – Review and Editing: PS, PK, LV and BH; Project Administration: LS and PK; Supervision: BH, KvM and CA

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