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Abstract

In order to mitigate climate change, the energy sector undergoes a transformation towards a climate-neutral future based on renewable energy sources. Energy system models generate insights and support decision making for this transformation. In the face of, e.g., growingly complex and important environmental assessments and stakeholder structures, considering multiple objectives in these models becomes essential to realistically reflect existing interests. However, there is a lack of highly adaptable energy system models incorporating multiple objectives. We present an implementation of the augmented epsilon-constraint method with the highly adaptable energy system optimisation framework Backbone. It enables the simultaneous optimisation of multiple objectives, such as the minimisation of costs, CO_2 emissions or self-sufficiency for a broad range of energy systems including different sectors and scales. For this purpose, new objective functions and constraints are implemented in Backbone. They are used by an external algorithm in a sequence of parallelised optimisations to cope with the complexity of real-world applications. The method is adaptable to further objectives and scalable to large and complex systems. Applications to the Western and Southern European power sector in 2050 and a sector-coupled mixed-integer household-level model demonstrate its benefits and adaptability. Pareto fronts, technology use and trade-offs are analysed and quantified. In the European power sector, emission reductions of up to 90 % can be achieved at marginal CO_2 abatement costs of below 100 EUR/(t CO_2). For the household, energy imports from the public grids can be reduced by 70 % at 20 % higher cost and average cost of self-sufficiency of 2.6 ct/kWh. We expect that the presented methods and models reveal new valuable insights to modellers and decision makers.

Keywords: Energy system modeling, Multi-objective optimization, Renewable energy, Energy planning, Pareto front, Trade-off

1. Introduction

Anthropogenic climate change has disastrous consequences for people and ecosystems (Cook et al., 2013; St Louis & Hess, 2008). Hence, a global effort to mitigate against and adapt to climate change is necessary. Many mitigation measures focus on the reduction of greenhouse gas (GHG) emissions (Intergovernmental Panel on Climate Change, 2014). The energy sector, including power, heat and

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transport, is responsible for a significant share of anthropogenic GHG emissions (EUROSTAT, 2017). Therefore, policy plans on various levels, e.g. the Paris Agreement (United Nations, 2015) or the EU Green Deal (European Commission, 2020a), aim at transforming the energy sector towards a climate-neutral future based on renewable energy sources (RES).

As part of this transformation, the energy sector undergoes a number of structural changes: (i) an increased utilisation of intermittent RES reduces the dispatchable share of electricity generation (Brouwer et al., 2014); (ii) decentralised electricity generation breaks with the paradigm of few, centralised generation sites and leads to prosumers entering the market (Allan et al., 2015; Mehigan et al., 2018); (iii) coupling of the power, transport and heat sectors is necessary to achieve emission reduction targets and creates new interactions and interdependencies (Brown et al., 2019); (iv) besides prosumers, an increased number of stakeholders with diverse and conflicting, e.g. environmental, interests or objections to energy infrastructure becomes involved in energy markets and policy (Bertsch & Fichtner, 2016). These structural changes come with technical, environmental, economic and social challenges, thus increasing the complexity of decision making in the context of energy system planning.

As one of these challenges, flexibility requirements rise in order to achieve the necessary balance of electricity supply and demand at any time and in any place. Referring to the structural changes (i), (ii) and (iii), respectively, flexibility has a temporal, a spatial and a sectoral dimension. Storages, demand response, energy transmission lines and coupling of energy sectors are some measures to provide the required flexibility (Brown et al., 2018b; Orths et al., 2019; Schreiber et al., 2021). Another challenge has been described by a shift from the *energy trilemma* (economic sustainability, ecological sustainability, energy security) towards an *energy quadrilemma* (Hauff et al., 2011), taking into account the increased importance of public acceptance in energy policy (Fitiwi et al., 2020).

In view of these challenges and the resulting increase in complexity of energy systems and related decisions, energy system models (ESMs) are an important tool. ESMs support decision making by providing analyses of and generating insights to the energy sector. Cost-minimising models are most commonly used. However, considering multiple objectives becomes increasingly important due to the above-mentioned structural changes: First, in order to balance interests of various stakeholders. Second, to account for the increasing importance of environmental sustainability. The latter is a multi-criteria concept in itself as recent efforts (Xu et al., 2020; Junne et al., 2020; Fuss & Xu, 2021) to combine ESMs with life cycle assessment (LCA) illustrate (Antunes & Henriques, 2016).

Decision makers' (DMs) preferences play an important role when optimising for multiple objectives. There are three major approaches to finding a solution desired by the DM: (i) In *a priori* methods, preferences are expressed before the optimisation. This typically leads to a single real objective function, for example by assigning weights to the individual objectives. (ii) In *a posteriori* methods, preferences are expressed after the optimisation, i.e. multiple objectives are optimised at the same time. When optimising multiple real objective functions simultaneously, the intuitive notion of optimality on $\mathbb{R}$, induced by the partial order $\leq$, does not suffice. Therefore, the notion of Pareto-optimality is employed, where, roughly speaking, a solution to an optimisation problem is called Pareto-optimal, if improvements of one objective can only be achieved by deterioration of another one. The set of all images through the objective function of Pareto-optimal solutions is called Pareto front. (iii) In *interactive* methods, preferences are expressed and optimisations are carried out iteratively (Miettinen et al., 2016).

Deciding on preferences a posteriori or interactively is advantageous compared to methods using a pure a priori or single-objective approach. First, knowing the Pareto front helps understanding the objectives' relations. Its shape shows whether objectives correlate positively or conflict with each other and further analyses allow to quantify trade-offs, see e.g. (Pelet et al., 2005; Ren et al., 2010; Cambero & Sowlati, 2016; Limleamthong & Guillén-Gosálbez, 2017; Prina et al., 2020c). If, for example, costs and emissions are two objectives, the slope of the Pareto front (or its inverse) corresponds to marginal CO_2 abatement costs. Second, knowing the Pareto front helps understanding the scope for decision-making. Boundaries of the Pareto front indicate the objectives' feasible optimal range, e.g. maximum attainable emission reductions or minimal costs, while each of its elements represents one feasible, optimal alternative. Both, knowledge of the Pareto front and trade-offs between objectives, supports decision making and preference determination (Morton & Fasolo, 2009; Eisenführ et al., 2010). Third, the feasibility of energy scenarios depends on the acceptance of various stakeholders, for example local acceptance of energy infrastructure like onshore wind turbines (Enevoldsen & Sovacool, 2016). Pure cost-minimisations fail to represent existing interests as well as societal and behavioural aspects and are therefore prone to generate practically infeasible outcomes (Bertsch et al., 2016, 2017; Roddis et al., 2018; Huckebrink & Bertsch, 2021). Considering multiple objectives can be one step towards generating *interest-optimal* energy scenarios, which therefore have increased societal feasibility. Fourth, when considering multiple objectives, solutions, which are sub-optimal with respect to each single objective, are obtained. These solutions would not be obtained in a single-objective optimisation and may exhibit large differences in variable space, but only small differences in objective space. These solutions can present appealing alternatives for decision makers and reduce systematic uncertainties (DeCarolis, 2011; DeCarolis et al., 2016). Finally, for all solutions in the Pareto front, optimality with respect to each objective is guaranteed. Generally, this is not the case for single-objective optimisations or policy plans. When considering a cost-minimal or policy plan-based scenario (see e.g. Prina et al., 2020c), for example, emissions could potentially be further reduced without increasing costs. Therefore, multi-objective optimisations can avoid inefficient decisions.

For both, a posteriori and iterative multi-objective optimisation approaches, methods to generate a subset of the Pareto front are needed. To analyse energy systems and support decision making, an ESM that incorporates such a multi-objective optimisation method would be required. To achieve high efficiency, one highly adaptable multi-objective ESM that covers the diverse range of relevant applications is desirable. However, as a following review will show—to the authors' knowledge—no ESM exists that combines multiple objectives with high adaptability. The aim of this paper is to fill that gap and to demonstrate such a model's capabilities for analysing and planning energy systems.

The remainder of this paper is organised as follows. Section 2 reviews existing ESMs. Section 3 introduces the implementation of the augmented epsilon-constraint method with the energy system optimisation framework Backbone. Section 4 presents two very distinct models, to which the implemented method is applied. Results are presented and discussed in Section 5. Section 6 concludes.

2. Reviewing energy system models

In the following, we specify relevant characteristics of ESMs and define criteria to assess their universal applicability.

2.1. Selection criteria

Arising from the structural changes and challenges in the energy sector and depending on the specific purpose, especially the research question and the energy system studied, we consider the following seven criteria to be potentially important for the suitability of ESMs. In particular, an ESM should perform well in all these criteria to be considered highly adaptable.

(i) temporal resolution significantly influences modelling results, for example storage expansion and power plant operation (Slednev et al., 2017; Cao et al., 2019);

(ii) spatial resolution and scope are important to accurately represent system characteristics like grid infrastructure (Cao et al., 2019) and balancing effects resulting from a larger number of system participants;

(iii) coverage of multiple energy sectors allows to investigate their coupling potential and interactions, for example in the form of demand response via heat pumps (Sperber et al., 2020), industrial processes (Kirchem et al., 2020) or electric vehicles (Lund & Kempton, 2008), and ensures global optimality of the pathway towards a more sustainable, integrated multi-sector system;

(iv) technological details and operational aspects significantly impact flexibility demand and provision as well as sectoral interactions (Helistö et al., 2019a, 2021);

(v) considering stochastic parameters enables treatment of uncertainties (Möst & Keles, 2010), e.g. related to extreme weather conditions;

(vi) transparency and free availability of models and associated data promotes more efficient energy research and decision support while enabling reproduction and verification of results (DeCarolis et al., 2012; Pfenninger et al., 2017);

(vii) a multi-objective approach helps to understand the range of and relation between different alternatives and increases the feasibility and efficiency of decisions.

These criteria are in line with criteria used in the existing literature, e.g. (Pfenninger et al., 2014; Hall & Buckley, 2016; Oree et al., 2017; Helistö et al., 2019a; Prina et al., 2020b) and the wiki page[1] of the *openmod initiative*, to group or categorise ESMs.

[1] `https://wiki.openmod-initiative.org/wiki/Open_Models` [Accessed 23 December 2021]

2.2. Existing models

The number of ESMs is enormous and ever increasing. A comprehensive review is therefore beyond the scope of this work. However, we refer to existing reviews and additional publications to show that—to our knowledge—no multi-objective ESM exists that performs well in all the above criteria.

Prina et al. (2020b) review 22 bottom-up ESMs. They find that many long-term models, e.g. LEAP (Heaps, 2021), MARKAL/TIMES (Loulou et al., 2004, 2005), OSeMOSYS (Howells et al., 2011), Temoa (Hunter et al., 2013), MESSAGE (IIASA, 2012), LUT (Bogdanov & Breyer, 2016; Sadiqa et al., 2018) and Mahbub et al. (2017), have high resolution in sector coupling, while only some (Balmorel (Wiese et al., 2018), Mahbub et al. (2017), LUT) have high resolution in time. All reviewed short-term models demonstrate high resolution in time and many of them also in space (Oemof (Hilpert et al., 2017a,b), Calliope (Pfenninger & Pickering, 2018), Genesys (Bussar et al., 2016), PyPSA (Brown et al., 2018a; Hörsch et al., 2018), PLEXOS (Energy Exemplar, no date), DESSTINEE (Staffell, no date), GAMAMOD (Hauser et al., 2018), Ficus (Atabay, 2017), REMix (Gils et al., 2017)) or sector coupling (EnergyPLAN (Lund, 2014), Oemof, Calliope, Ficus, REMod (Henning & Palzer, 2014; Palzer & Henning, 2014), REMix, Batas Bjelić & Rajaković (2015), Mahbub et al. (2016)). Across short- and long-term models the authors identify PyPSA, PLEXOS and eMix (Wierzbowski et al., 2016) as models with high resolution in techno-economic detail. However, the review concludes that none of the examined models achieves high resolution in all four categories time, space, techno-economic detail and sector coupling.

Helistö et al. (2019b) briefly review ESMs. Some of the reviewed models, e.g. PRIMES (E3MLab, 2016), PERSEUS (Rosen, 2008), SCOPE (Gerhardt et al., 2015) and ReEDS (Short et al., 2011), can consider multiple energy sectors while others, e.g. SMART (Powell et al., 2012) is capable of incorporating stochastic behaviour and uncertainty. The authors conclude, however, that none of the reviewed models is suited for investment and operational optimisations of large systems at high temporal and spatial resolution while taking into account stochastic phenomena.

Prina et al. (2020a) review 30 ESMs. All reviewed models, except TIMES-VTT (Pursiheimo et al., 2017), Calliope and OSeMOSYS, have hourly time steps. All but EnergyPLAN, Dorotić et al. (2019), Komušanac et al. (2016), ReMod, Oemof, OSeMOSYS, NEMO (Elliston et al., 2016) and Mahbub et al. include multiple nodes. According to the authors, EnergyPLAN, Dorotic et al., Komusanac et al., TIMES, REMix, OSeMOSYS, Enertile (Fraunhofer ISI, 2021), PyPSA-Eur, BVMC (Samsatli et al., 2015) and STeMES (Samsatli & Samsatli, 2015) cover the electricity, heat and transport sectors, while Dorotic et al., Komusanac et al., BVCM, STeMES, Samsatli & Samsatli (2018), Bracco et al. (2013), Gabrielli et al. (2018), Morvaj et al. (2016, 2017), Fazlollahi et al. (2012) and Mahbub et al. include multiple objectives. However, the authors conclude that none of the examined models includes multiple nodes, hourly time steps, multiple sectors and a suitable multi-objective optimisation approach at the same time.

Many multi-objective studies model only a very specific energy system with limited system boundaries and do therefore not meet the sectoral, technological or spatial requirements for modelling the extensive scope of a global or continental energy transition. Some focus on distributed generation systems

(Ren et al., 2010; Bracco et al., 2013), microgrids (Mohammadkhani et al., 2018; Sedighizadeh et al., 2018), district heating networks (Fazlollahi et al., 2012), bioenergy and -fuel (Hombach & Walther, 2015; Cambero & Sowlati, 2016; Cambero et al., 2016; Rabbani et al., 2018; Razm et al., 2019), scheduling of hydro-thermal-wind power systems (Yuan et al., 2015), photovoltaic-wind-battery systems (Mazzeo et al., 2020), optimal reactive power flow (Lashkar Ara et al., 2012) or general methods to further analyse Pareto fronts (Limleamthong & Guillén-Gosálbez, 2017).

The same applies to the models examined by Antunes & Henriques (2016) and Cui et al. (2017). Antunes & Henriques (2016) review multi-objective power generation expansion and operation planning models, focussing on computational methods used to calculate Pareto-optimal solutions. Many of the included studies are fairly old and the ones published in 2010 and thereafter only incorporate the electricity sector. Among these, Zangeneh et al. (2011), Niknam et al. (2011), El-Zonkoly (2011) and Soroudi & Afrasiab (2012) focus on distributed generation and model distribution grids. Arnette & Zobel (2012), Zhang et al. (2012) and Aghaei et al. (2012) have low technological detail and are not suited for operational planning while Katsigiannis et al. (2010), Dufo-López et al. (2011) and Fadaee & Radzi (2012) model stand-alone power systems. Cui et al. (2017) review the application of multi-objective methods to renewable energy generation optimisation, e.g. stand-alone, hybrid and distributed generation systems, energy saving and emission reduction. Some of the reviewed models are already discussed above. Others focus for example on the optimisation of wind farms (Rodrigues et al., 2016), stand-alone systems (Clarke et al., 2015), microgrids (Chaouachi et al., 2013; Borhanazad et al., 2014) and buildings (Asadi et al., 2012; Fesanghary et al., 2012; Asadi et al., 2014; Schwartz et al., 2016).

Other multi-objective ESMs are more generic and not limited to such a specific application. However, they exhibit some characteristics limiting their adaptability and universal applicability. Unsihuay-Vila et al. (2011) present the electricity expansion planning model MESEDES. It considers and optimises three objectives related to costs, GHG emissions and diversification of the generation mix, respectively, and uses weighting factors to obtain best compromise solutions. Prina et al. (2018, 2019, 2020c) couple the deterministic simulation model EnergyPLAN with a multi-objective evolutionary algorithm to develop the models EPLANopt and EPLANoptTP. They cover the electricity, heat and transport sectors at hourly resolution following a single-node approach. Multiple objectives are optimised, e.g. cost, CO_2 emissions and renewable energy generation share. Tietze et al. (2020) develop the model LAEND by integrating energy system modelling and environmental impact assessment, based on Oemof and openLCA. It serves for investment and dispatch optimisations of decentralised systems. Various environmental impact indicators as well as costs are used for minimisations, either as single objectives or as a weighted sum. Prina et al. (2020a) develop oemof-moea by coupling the bottom-up dispatch optimisation model Oemof to a multi-objective evolutionary algorithm for expansion planning. It incorporates the electricity, thermal and transport sectors and two objectives for costs and CO_2 emissions, respectively, at hourly resolution. However, the dispatch model neglects some technological details, e.g. regarding reserves and unit operation, and the expansion planning neglects some technologies, e.g. offshore wind turbines and hydrogen storages. Yamchi et al. (2021) present a model for integrated planning of electricity and gas networks. They optimise the expansion of solar photovoltaic and natural gas-fired units as well as electricity and gas transport infrastructure. Costs and power plant emissions are considered as two objectives and optimised simultaneously.

We acknowledge that the above review and the choice of sources is to some extent subjective and incomplete. However, it shows that—to our knowledge—no ESM exists that combines multiple objectives with high adaptability as described in Section 2.1.

3. Methodology

In this section, we present a highly adaptable multi-objective energy system optimisation model building on the open source energy system modelling framework Backbone (Helistö et al., 2019b) and the augmented epsilon-constraint method (Mavrotas, 2009).

3.1. The energy system modelling framework Backbone

Backbone is a mixed-integer linear optimisation framework for investment planning and scheduling purposes. It is highly adaptable, because the framework has a very general structure and large parts of the models are defined by input data. The network structure of Backbone, as illustrated in Figure A.8 in the Appendix, consists of *nodes*, possibly connected by *lines* and grouped into *grids*. It allows for any desired spatial resolution and mixing of scales, as defined by the input data. Nodes can have a *state*, representing stored energy, and various constraints, e.g. related to energy balances and reserve requirements, can be enforced at nodes. Typically, grids are used to group nodes with the same type of energy, e.g. electricity, gas or heat. Backbone is not limited to any predefined types of energy. Every energy type can be modelled by adequate input data. Lines can exchange energy between nodes in the same grid, either intentionally via transfer or unintentionally via diffusion. *Units* can provide and use energy at a node or convert energy between nodes in different grids. Moreover, a unit's input can come from *commodity* nodes, e.g. natural gas, or *flows*, e.g. solar radiation, where the consumption of commodities can cause *emissions*, e.g. CO_2. If desired, investments in units and lines can be permitted.

The temporal structure of Backbone allows for any desired resolution, as appropriate for the model under examination and depending on data availability, and a model can have different resolutions for different parts of the time horizon. Myopic optimisation models are also possible. Stochastic models can be realised using samples or forecasts, where samples are intended for long-term investment planning and forecasts for short-term scheduling models. The technological structure of units in Backbone includes methods to represent start-up and shutdown trajectories, detailed variable conversion efficiencies, as well as division into sub-units or aggregation. Integer variables can be used to model the online status of units or restrict unit investments to the multiple of an integer. Finally, the structure of Backbone includes ancillary services and policy-related constraints. Different frequency-related reserve categories can be included and reserve requirements can be based on other model parametersReserves can be provided by units, depending on the reserve category and the units' online status, where constraints for the time of reserve allocation decisions can be incorporated for each category. Further constraints include but are not limited to capacity margins, maximum emissions and energy provided by a certain type of unit.

The currently implemented objective function for the minimisation of total system costs in Backbone is given by

$$\begin{aligned} v^{\text{costObj}} = & \\ & \sum_{f,t} p_{f,t}^{\text{probability}} \cdot \left(v_{f,t}^{\text{vomCost}} + v_{f,t}^{\text{fuelCost}} + v_{f,t}^{\text{startupCost}} + v_{f,t}^{\text{shutdownCost}} + v_{f,t}^{\text{rampCost}} + v_{f,t}^{\text{stateCost}} + v_{f,t}^{\text{penalties}} \right) \\ & \quad + v^{\text{fomCost}} + v^{\text{unitInvestCost}} + v^{\text{lineInvestCost}} \end{aligned} \tag{1}$$

and comprises costs related to investments in units $v^{\text{unitInvestCost}}$ and lines $v^{\text{lineInvestCost}}$, operation and maintenance (variable $v_{f,t}^{\text{vomCost}}$ and fixed v^{fomCost}), start-up $v_{f,t}^{\text{startupCost}}$, shutdown $v_{f,t}^{\text{shutdownCost}}$ and ramping $v_{f,t}^{\text{rampCost}}$ of units, fuel use $v_{f,t}^{\text{fuelCost}}$ (including emissions) and change in energy state $v_{f,t}^{\text{stateCost}}$. Additionally, penalties $v_{f,t}^{\text{penalties}}$ can result from violation of certain constraints to ensure feasibility and help debugging. Cost terms depending on the model time step t and forecast f are summed over all time steps and forecasts, while using a probability factor $p_{f,t}^{\text{probability}}$ to weight different forecasts. For each emission type e, e.g. CO_2, an emission limit $p_e^{\text{emissionCap}}$ can be included in Backbone. The respective constraint is given by

$$\sum_{f,t} p_{f,t}^{\text{probability}} \cdot \left(v_{f,t,e}^{\text{generationEmission}} + v_{f,t,e}^{\text{startupEmission}} \right) \leq p_e^{\text{emissionCap}}, \tag{2}$$

where $v_{f,t,e}^{\text{generationEmission}}$ and $v_{f,t,e}^{\text{startupEmission}}$ are the emissions of type e due to energy generation and unit start up, respectively. The mathematical nomenclature, including parameters, variables, indices, sets and functions, is summarised in Table A.3 in the Appendix. For more details on the framework formulation and its GAMS implementation, please refer to (Helistö et al., 2019b) and the source code[2].

Several studies apply Backbone to models of different spatial and temporal scope and resolution and furthermore illustrate its adaptability regarding e.g. sector coupling (Rasku & Kiviluoma, 2019; Lindroos et al., 2021; Ikäheimo et al., 2022), stochastic forecasts (Rasku et al., 2020) and operational detail (O'Dwyer & Flynn, 2019; Helistö et al., 2021). From the framework description and these studies, it is clear that Backbone performs well in all above categories except from (vii), the multi-objective approach. The implementation of a multi-objective approach into Backbone is described in Section 3.3.

3.2. The augmented epsilon-constraint method (AUGMECON)

This section covers methods to solve multi-objective optimisation problems. The following definitions, as illustrated in Figure 1, form the basis for this discussion. The mathematical nomenclature is summarised in Table A.3 in the Appendix.

[2] `https://gitlab.vtt.fi/backbone/backbone` [Accessed 23 December 2021]

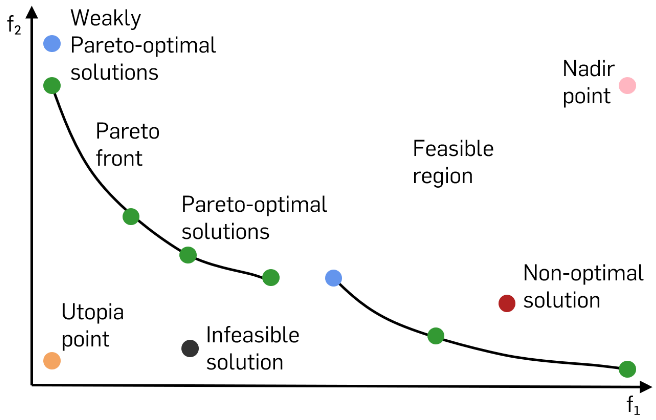


Figure 1: Illustration of relevant definitions for the minimisation of two objective functions. Note that this figure displays the objective space and the term solution refers to the image of a solution under the objective function.

Consider the following setting. Let $V \subset \mathbb{R}^n$ be the possibly constrained *feasible variable set* and $f = (f_1, f_2, \ldots, f_k) : V \to O \subset \mathbb{R}^k$ multiple objective functions, where $K = \{1, 2, \ldots, k\}$ and O is the *feasible objective set*. Further consider the multi-objective minimisation problem

$$\min_{x \in V} \quad \{f_1(x), f_2(x), \ldots, f_k(x)\}. \tag{3}$$

A solution $x \in V$ with image $f(x) = (f_1(x), \ldots, f_k(x)) \in O$ is called *Pareto-optimal* if there does not exist any $x' \neq x$ in V such that

$$f_i(x') \leq f_i(x) \ \forall \ i \in K \text{ and } f_j(x') < f_j(x) \text{ for at least one } j \in K. \tag{4}$$

Accordingly, such a solution is called *weakly Pareto-optimal* if there does not exist any $x' \neq x$ in V such that $f_i(x') < f_i(x) \ \forall \ i \in K$. The images of such solutions under the objective function are called *Pareto-optimal* or *weakly Pareto-optimal* as well. To describe not only a single solution, but the set of all optimal solutions, the set of all Pareto-optimal solutions is called *Pareto set* $P \subset V$ and its image *Pareto front* $P^* = f(P) \subset O$. Furthermore, two not necessarily feasible points in the objective space are used to describe the range of the Pareto front, the *utopia point* $U \in \mathbb{R}^k$ and the *nadir point* $N \in \mathbb{R}^k$, which are given by

$$U = \left(\min_{x \in V} f_1(x), \min_{x \in V} f_2(x), \ldots, \min_{x \in V} f_k(x)\right) \quad \text{and} \quad N = \left(\max_{x \in V} f_1(x), \max_{x \in V} f_2(x), \ldots, \max_{x \in V} f_k(x)\right). \tag{5}$$

From now on following the notation above, various methods exist to generate Pareto-optimal solutions to a multi-objective optimisation problem, see e.g. (Miettinen, 2008), (Arora, 2012), (Wiecek et al., 2016) or (Cui et al., 2017) for an overview. The weighted sum method, where weights $w_i \geq 0$, $\sum_{i \in K} w_i = 1$ are assigned to the objectives and their sum $\sum_{i \in K} w_i f_i(x)$ is minimised, or the non-dominated sorting genetic algorithm and its variants, e.g. NSGA-III (Deb & Jain, 2014; Jain & Deb, 2014), are two well known examples.

Based on the existing formulation of Backbone, containing a cost objective function and an emission constraint, the implementation of an epsilon-constraint method is arguably the most intuitive approach.

In epsilon-constraint methods, all but one objective function of the initial multi-objective optimisation problem are reformulated into constraints with upper bounds ε_i and only the remaining one is optimised:

$$\min_{x \in V} \quad f_j(x) \quad \text{s.t.} \quad f_i(x) \leq \varepsilon_i \ \forall \ i \in K \setminus \{j\}. \tag{6}$$

A solution to problem (6) is weakly Pareto-optimal but not necessarily Pareto-optimal (Miettinen, 1999). By introducing $k-1$ positive slack variables $s_i > 0, \ i \in K \setminus \{j\}$, a positive constant $c \approx 10^{-6} \ldots 10^{-3}$ and transforming the constraints from inequalities into equations, Mavrotas (2009) further reformulated this problem into

$$\min_{x \in V} \quad \left(f_j(x) + c \sum_{i \in K} s_i \right) \quad \text{s.t.} \quad f_i(x) + s_i = \varepsilon_i \ \forall \ i \in K \setminus \{j\}, \tag{7}$$

calling it augmented epsilon-constraint method (AUGMECON). A solution to problem (7) is Pareto-optimal and by varying the upper bounds ε_i, different elements of the Pareto front can be obtained. To identify the lowest and highest sensible values for ε_i, a method to determine the boundaries of the Pareto front $\min_{x \in P^*} f_i(x)$ and $\max_{x \in P^*} f_i(x)$ for $i \in K$, i.e. the utopia and nadir points, is needed. A lexicographic optimisation, for example

$$\min_{x \in V} f_k(x) \text{ s.t.} \left[f_{k-1}(x) = \min_{x \in V} f_{k-1}(x) \text{ s.t.} \left(f_{k-2}(x) = \min_{x \in V} f_{k-2}(x) \ \ldots \text{ s.t. } f_1(x) = \min_{x \in V} f_1(x) \right) \right] \tag{8}$$

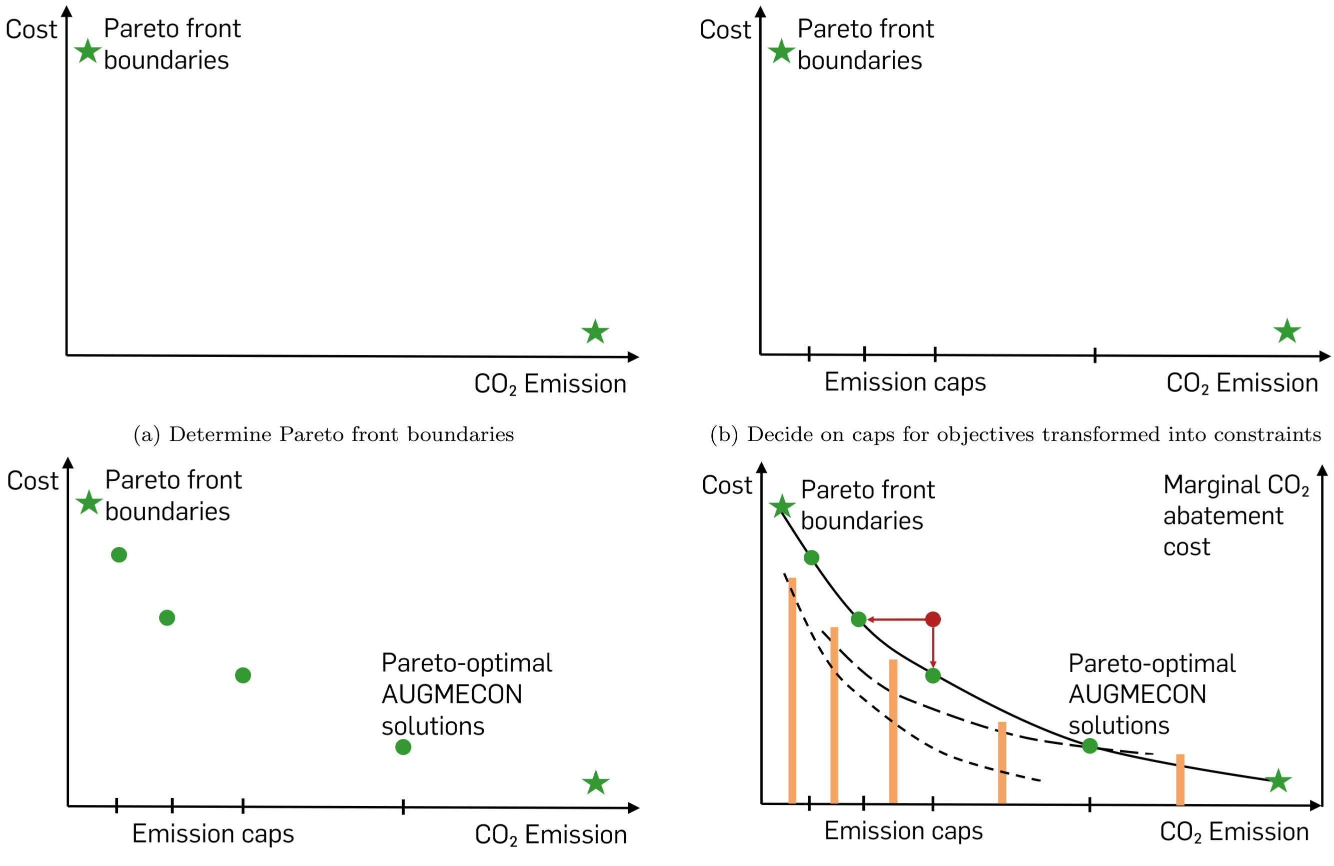
can be used for this purpose.

AUGMECON does not require convexity (Miettinen, 2008) or continuity (Mavrotas, 2009) of the optimisation problem. While convexity is given in Backbone as all constraints and objectives are linear in all variables, continuity is violated when using integer variables.

When solving problem (7) multiple times in a suitable setting, the number and distribution of Pareto-optimal solutions can well be controlled by choosing appropriate upper bounds ε_i for the constraints (Mavrotas, 2009). However, two characteristics of the optimisation problem can lead to infeasible or redundant solution attempts. First, more than two objectives in the original optimisation problem imply more than one constraint in the AUGMECON formulation, which can lead to infeasibility. AUGMECON (Mavrotas, 2009) and AUGMECON-R (Nikas et al., 2020) address this issue by introducing early exits from this constraint grid and can significantly reduce the number of infeasible model runs by avoiding solution attempts with even stricter constraints once a constraint combination turned out to be infeasible. Second, discrete or integer variables can lead to a non-connected Pareto front. Model solves using a constraint with upper bound in a gap of the Pareto front lead to the same Pareto-optimal solution at the border of this gap. AUGMECON2 (Mavrotas & Florios, 2013) and AUGMECON-R (Nikas et al., 2020) address this issue by introducing bypass coefficients to avoid this redundancy by comparing the realised value of a slack variable, which contains information about the size of a potential gap in the Pareto front, with the distance to the next closest point in the constraint grid.

3.3. Implementing the augmented epsilon-constraint method with Backbone

An implementation of AUGMECON with Backbone enables multi-objective optimisations of energy systems. Relevant objectives could be costs, global warming potential, other LCA-related impact categor-



(a) Determine Pareto front boundaries

(b) Decide on caps for objectives transformed into constraints

(c) Calculate Pareto-optimal solutions

(d) Conduct further analyses

Figure 2: Four steps for multi-objective energy system optimisations using the AUGMECON implementation. The individual steps have to be carried out successively from (a) to (d), but within each step, parallelisation is possible. The axis labels refer to costs and CO_2 emissions as examplary objectives.

ies like use of resources and land or quantities related to peoples' acceptance, e.g. effects on scenicness. In this work, we use the method for bi-objective optimisations of costs and CO_2 emissions and cost and self-sufficiency, respectively. However, newly introduced objectives and constraints[3] are formulated more generally: in the case of CO_2 emissions for any emission resulting from fuel combustion and in the case of self-sufficiency for energy in- or output from any group of units. These formulations are intended to serve as illustrative examples and can be further extended to more and other objectives.

The method has four main steps: *(a) determine Pareto front boundaries*, *(b) decide on caps for objectives transformed into constraints*, *(c) calculate Pareto-optimal solutions* and *(d) conduct further analyses*. They are illustrated in Figure 2 for the example of costs and CO_2 emissions and described in more detail in the following, where, for the sake of simplicity, we often refer explicitly only to the case of costs and emissions.

(a) Determine Pareto front boundaries. To determine the Pareto front boundaries, i.e. the components of the utopia and nadir points, two lexicographic optimisations as per Eq. (8) are carried out, e.g. in the

[3]The newly implemented objective functions and constraints are freely available from the Backbone repository `https://gitlab.vtt.fi/backbone/backbone`.

case of cost and emissions

$$\min_{x\in V} \mathrm{cost}(x) \text{ s.t. } \mathrm{emission}(x) = \min_{x\in V} \mathrm{emission}(x) \quad \text{and} \tag{9}$$

$$\min_{x\in V} \mathrm{emission}(x) \text{ s.t. } \mathrm{cost}(x) = \min_{x\in V} \mathrm{cost}(x). \tag{10}$$

Backbone can already perform single-objective cost minimisations with constrained emissions, but the single-objective minimisation of emissions and energy imports, respectively, with constrained costs are newly implemented. This is realised by introducing a new objective function

$$v_e^{\mathrm{emissionObj}} = \sum_{f,\,t} p_{f,t}^{\mathrm{probability}} \cdot \left(v_{f,t,e}^{\mathrm{generationEmission}} + v_{f,t,e}^{\mathrm{startupEmission}} + v_{f,t}^{\mathrm{penalties}} \right), \tag{11}$$

which comprises all emission terms of type e from the original emission constraint Eq. (2) as well as penalties, and a new objective function

$$v_{G,io}^{\mathrm{generationObj}} = \sum_{f,t} p_{f,t}^{\mathrm{probability}} \cdot \left(p_G^{\mathrm{weight}} \cdot \sum_{u\in G} v_{f,t,u,io}^{\mathrm{generation}} + v_{f,t}^{\mathrm{penalties}} \right), \tag{12}$$

which comprises the (possibly weighted) sum of all energy in- or outputs io from units in a group G. Additionally, a new cost constraint

$$\begin{aligned}\sum_{f,\,t} p_{f,t}^{\mathrm{probability}} &\cdot \left(v_{f,t}^{\mathrm{vomCost}} + v_{f,t}^{\mathrm{fuelCost}} + v_{f,t}^{\mathrm{startupCost}} + v_{f,t}^{\mathrm{shutdownCost}} + v_{f,t}^{\mathrm{rampCost}} + v_{f,t}^{\mathrm{stateCost}} \right) \\ &+ v^{\mathrm{fomCost}} + v^{\mathrm{unitInvestCost}} + v^{\mathrm{lineInvestCost}} \leq p^{\mathrm{costLimit}}\end{aligned} \tag{13}$$

limits the total costs from the original cost objective function Eq. (1) except penalties to a maximum $p^{\mathrm{costLimit}}$ and a new generation constraint

$$\sum_{f,t} p_{f,t}^{\mathrm{probability}} \cdot \left(p_G^{\mathrm{weight}} \cdot \sum_{u\in G} v_{f,t,u,io}^{\mathrm{generation}} + v_{f,t}^{\mathrm{penalties}} \right) \leq p_{G,io}^{\mathrm{generationLimit}} \tag{14}$$

limits the in- or outputs from a group of units to a maximum $p_{G,io}^{\mathrm{generationLimit}}$. The solution of Eq. (9) is the Pareto-optimal solution with lowest emission $p_{\mathrm{CO_2}}^{\mathrm{lowestEmission}}$ and highest cost whereas the solution of Eq. (10) is the Pareto-optimal solution with lowest cost and highest emission $p_{\mathrm{CO_2}}^{\mathrm{highestEmission}}$.

(b) Decide on caps for objectives transformed into constraints. For each further Pareto-optimal solution, a cap for the objectives not transformed into constraint is needed in the next step, e.g. an emission cap $p_{\mathrm{CO_2}}^{\mathrm{emissionCap}}$ in the case of CO_2 emissions. Depending on their desired number and distribution, the caps can be any finite subset of the interval $[p_{\mathrm{CO_2}}^{\mathrm{lowestEmission}}, p_{\mathrm{CO_2}}^{\mathrm{highestEmission}}]$.

(c) Calculate Pareto-optimal solutions. To calculate further Pareto-optimal solutions, the AUGMECON method as described by Eq. (7) is implemented in Backbone. This is realised by introducing a positve slack variable $s > 0$ and new constraints and objectives. In the case of cost and emissions, we use a cost objective

$$v_{\mathrm{AUGMECON}}^{\mathrm{costObj}} = v^{\mathrm{costObj}} + c \cdot s \tag{15}$$

based on Eq. (1) and an emission constraint

$$\sum_{f,\,t} p_{f,t}^{\mathrm{probability}} \cdot \left(v_{f,t,e}^{\mathrm{generationEmission}} + v_{f,t,e}^{\mathrm{startupEmission}} \right) + s = p_e^{\mathrm{emissionCap}} \tag{16}$$

based on Eq. (2). In the case of cost and self-sufficiency, we use a generation objective

$$v^{\text{generationObj}}_{G,io,\text{AUGMECON}} = v^{\text{generationObj}}_{G,io} + c \cdot s \tag{17}$$

based on Eq. (12) and a cost constraint

$$\begin{aligned} &\sum_{f,t} p^{\text{probability}}_{f,t} \cdot \left(v^{\text{vomCost}}_{f,t} + v^{\text{fuelCost}}_{f,t} + v^{\text{startupCost}}_{f,t} + v^{\text{shutdownCost}}_{f,t} + v^{\text{rampCost}}_{f,t} + v^{\text{stateCost}}_{f,t} \right) \\ &\quad + v^{\text{fomCost}} + v^{\text{unitInvestCost}} + v^{\text{lineInvestCost}} + s = p^{\text{costLimit}} \end{aligned} \tag{18}$$

based on Eq. (13). For each cap from the previous step, this optimisation is done once to obtain a Pareto-optimal solution. As discussed in Section 3.2, this problem is feasible for all caps between the components of the utopia and nadir points, e.g. in the interval $[p^{\text{lowestEmission}}_{CO_2}, p^{\text{highestEmission}}_{CO_2}]$.

(d) Conduct further analyses. Building on the three previous steps, the studied energy system can be analysed further. First, all Pareto-optimal solutions represent scenarios with different realised objective values. As such, they can be compared with respect to invested energy conversion technologies, use of energy storages or any other quantity derived from Backbone variables to study for example emission reduction strategies. Second, by varying assumptions and conducting the steps *(a)* - *(c)* for each set of input data, different Pareto fronts can be generated as depicted by the dashed black lines in Figure 2d. This allows for investigating the effect of certain assumptions and to carry out sensitivity analyses.[4] Third, by putting exogenously determined solutions, e.g. policy targets or market-based projections, in the context of the Pareto front, their optimality can be analysed. As illustrated by the red dot and arrows in Figure 2d, potential cost or emission savings can be identified. Fourth, trade-offs between the two objectives can be analysed and quantified. For the example of costs and emissions, the trade-off between them can be interpreted as marginal CO_2 abatement costs. Due to emission trading and taxation mechanisms, this is a highly relevant quantity. Visually, the shape of the Pareto front gives qualitative information about trade-offs. Discretely, when interpolating linearly between two Pareto-optimal solutions, the resulting slope quantifies average trade-offs. In Figure 2d, this is illustrated by the orange bars, which refer to the right ordinate. Continuously, the Pareto front can, if it is connected, be approximated by a smooth function, as illustrated by the black solid line in Figure 2d. The trade-offs between the two objectives can then be approximated continuously by this function's derivative. Finally, the method can be used for interactive decision support as for example described by (Mavrotas, 2009). For this purpose, steps *(a)* - *(c)* are carried out once with a coarse resolution. Based on this result, the DM can express preference for some region of the Pareto front. Then, steps *(b)* and *(c)* are carried out again for the region of preference, providing a higher resolution of this region for the DM. This iterative process can be repeated until the DM is satisfied with a solution.

[4]Note that two different notions of "scenarios" (regarding objective values and regarding model assumptions) are studied together. Different assumptions lead to different Pareto fronts, each of which contains solutions with different objective values. Thereby, we can analyse and vividly illustrate combinations of assumptions and objective values. For example, the effect of varying cost prdictions across different CO_2 reduction targets can be examined.

To save computation time and modellers' resources, Python code[5] is developed as described in Algorithm 1 for the example of costs and emissions, which automatedly uses the different objectives and constraints implemented in Backbone to obtain a representative subset of m elements in the Pareto front. It follows the procedure illustrated in Figure 2: steps *(a)* - *(d)* have to be carried out successively, but within each step, parallelisation is possible. In step *(a)*, referring to lines 1 to 6 in Algorithm 1, the two lexicographic optimisations described in Equations (9) and (10), respectively, are executed in parallel, where each of the two consists of two single-objective optimisations, which have to be run successively. For step *(b)*, implicitly included in the for loop in line 7, the modeller has to provide the desired number, in this case $m-2$, and distribution of emission caps between the highest and lowest emission values determined in the previous step. This is represented by some map, e.g. $d : \mathbb{R}^2 \rightarrow (p_{\mathrm{CO_2}}^{\mathrm{lowestEmission}}, p_{\mathrm{CO_2}}^{\mathrm{highestEmission}})^{m-2}$. In step *(c)*, referring to line 8, the model has to be solved once for each cap, typically making it the most computationally heavy part of the whole method. However, after the decision on emission caps has been made in step *(b)*, the individual optimisations according to the AUGMECON method are mutually independent. Therefore, all individual optimisations in this step are parallelised. These parallelisations can reduce computation time significantly. If computational resources allow, the $m+2$ required optimisations can be carried out in only three successive blocks with 2, 2, and $m-2$ parallel optimisations, respectively. This ensures the scalability of the whole method to large or complex systems and enables the calculation of a high number of Pareto-optimal solutions.

Algorithm 1: Calculating a subset of a cost-emission Pareto front in parallel

Input: Energy system data, number and distribution of emission caps represented by $d(\cdot,\cdot)$

Output: Subset of Pareto front, energy system designs

1 **do in parallel**

2 $\quad p_{\mathrm{CO_2}}^{\mathrm{lowestEmission}} = \min_{x \in V} v_{\mathrm{CO_2}}^{\mathrm{obj}}(x)$

3 $\quad p^{\mathrm{lowestCost}} = \min_{x \in V} v_{\mathrm{BB}}^{\mathrm{obj}}(x)$

4 **do in parallel**

5 $\quad p^{\mathrm{highestCost}} = \min_{x \in V} v_{\mathrm{BB}}^{\mathrm{obj}}(x) \text{ s.t. } \mathrm{emission}(x) = p_{\mathrm{CO_2}}^{\mathrm{lowestEmission}}$

6 $\quad p_{\mathrm{CO_2}}^{\mathrm{highestEmission}} = \min_{x \in V} v_{\mathrm{CO_2}}^{\mathrm{obj}}(x) \text{ s.t. } \mathrm{cost}(x) = p^{\mathrm{lowestCost}}$

7 **for** $p_{\mathrm{CO_2}}^{\mathrm{emissionCap}}$ in $d(p_{\mathrm{CO_2}}^{\mathrm{lowestEmission}}, p_{\mathrm{CO_2}}^{\mathrm{highestEmission}})$ **do in parallel**

8 $\quad \min_{x \in V} v_{\mathrm{AUGMECON}}^{\mathrm{obj}}(x) \text{ s.t. } \mathrm{emission}(x) = p_{\mathrm{CO_2}}^{\mathrm{emissionCap}} + s$

9 **return** Energy system model outputs of all optimisations

4. Energy system models

In this section, in order to highlight the method's adaptability, we present two energy system models, which differ with respect to the selection criteria from Section 2.1 as summarised in Table 1. Although

[5] It is freely available at `https://gitlab.ruhr-uni-bochum.de/ee/backbone-tools`.

Table 1: Comparison of the two energy system models studies with respect to the selection criteria from Section 2.1.

	European power sector model	Sector-coupled household-level model
Space	14 nodes, each represents a country	1 node, represents a household
Time	one year, hourly resolution	one year, hourly resolution
Sectors	electricity	heat and electricity
Technology	linearised	integer investment variables
Statistics	none	two samples for demand profiles
Objectives	cost, CO_2 emissions	cost, self-sufficiency

they are simplified in certain aspects to focus on the extended possibilities through the multi-objective approach, they are complex models using real-world data.

4.1. Southern and Western European power sector model

First, we present a Western and Southern European power sector model for the year 2050. It includes eleven countries of Southern and Western Europe (Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Portugal, Spain and Switzerland) and one year at hourly resolution. Transmission grid infrastructure, existing conventional power plants and demand and weather time series is acquired and clustered by PyPSA-Eur (Hörsch et al., 2018) and converted into input data for Backbone. The network model is aggregated by PyPSA-Eur to a resolution of one node per country, except for Denmark, Italy and Spain, where island networks require a second node each. A map is shown in Figure A.9 in the Appendix. For further details on PyPSA-Eur, please refer to the source code[6] and documentation[7].

The second main source of data, used for costs, lifetimes and efficiencies of generation and storage units, emission factors and costs of fuels, as well as projections of annual electricity demands, is a recent work by Pietzcker et al. (2021). For each country, the demand time series from 2018 is scaled up to the year 2050 using the annual demand projections. Although specific GHG emissions from burning biomass are similar to those from coal, their contribution to global warming is discussed controversially (e.g. by Millward-Hopkins & Purnell, 2019) and they are not counted towards the European Union's Emission Trading System (EU ETS) (Pietzcker et al., 2021). Thereofore, we assume specific emissions of $0\,\mathrm{t\,CO_2/MWh}$ from biomass-based electricity generation. Furthermore, a maximum installable capacity of $2\,\mathrm{MW/km^2}$ is used for onshore and offshore wind turbines (Center for Sustainable Systems, University of Michigan, 2021). For all storages, cyclic bounds are enforced, i.e. the energy content of a storage can be non-zero at the start of the model as long as it has the same value at the end. For the investable hydrogen and battery storages, first, charging and discharging capacities have to be equal at each node for each of the two technologies, and, second, the energy to power ratio is fixed to the default value of

[6] `https://github.com/PyPSA/pypsa-eur` [Accessed 23 December 2021]

[7] `https://pypsa-eur.readthedocs.io/en/latest/` [Accessed 23 December 2021]

PyPSA-Eur, namely 6 h for batteries and 168 h for hydrogen. A collection of techno-economic data used is given in Table A.2 in the Appendix.

For this power sector model, Backbone carries out an investment and dispatch planning. Investment options are onshore and offshore wind turbines, solar photovoltaic (PV) systems and closed cycle gas turbines for electricity generation as well as battery and hydrogen storages. For these technologies, except gas turbines, a green field planning is done, i.e. no capacities are already installed. Because marginal CO_2 abatement costs are determined as a result for different CO_2 emission caps, no CO_2 price is included in the model. To analyse energy systems across the whole Pareto front without wide-ranging political restrictions, the planned phase outs of coal and nuclear power plants are excluded from the base scenario. Thereby, it serves as a reference for the coal exit and nuclear exit scenarios, which are considered separately based on current political decisions.

In addition to the base scenario, four further scenarios are studied: a sensitivity analysis for storage costs with a high and a low cost scenario and the already mentioned coal and nuclear exit scenarios. For the storage cost sensitivity analysis, the investment and fixed operation and maintenance costs are varied by $\pm 15\,\%$ for hydrogen and $\pm 25\,\%$ for batteries. For the coal exit scenario, based on the National Energy and Climate Plans (NECPs) (European Commission, 2020b), it is assumed that no country uses coal for electricity generation in 2050. This assumption is based on the submitted by each member state to the European Union in 2019. For the nuclear exit scenario, it is assumed that Belgium, Germany and Spain, according to their NECPs (European Commission, 2019), operate no nuclear power plants in 2050 and that the nuclear generation capacities in the other countries remain unchanged.

With regard to model complexity, the optimisation problem has approximately 5.5 million variables, 15.5 million non-zeros and 4 million equations.

4.2. Sector-coupled household-level model

Second, we present a sector-coupled model of a residential building. Synthetic electricity and heat demand profiles are taken from Forschungsstelle für Energiewirtschaft e.V. (FfE) (2020a,b) based on measurements from the year 2015. To reflect uncertainty regarding the house's residents, e.g. from a landlady's point of view, two demand profiles, each comprising a full year at hourly resolution, are used as samples with equal weight: one for a household with two pensioners and one for a household with a full-time, a part-time working person and a child. For PV generation, weather data from the year 2015 for a location in Munich, Germany is used (Pfenninger & Staffell, 2016). The building is connected to the public electricity and gas grids and has a gas boiler already installed. As objectives, total system cost and energy consumption from the public grids (electricity and natural gas) should be minimised, i.e. maximising self-sufficiency is the second objective. To achieve this, investments in rooftop solar PV, battery storage and an air-sourced heat pump are possible. Techno-economic data from PyPSA-Eur (Hörsch et al., 2018) is used for the PV, battery, heat pump and gas boiler units. This includes costs, efficiencies, lifetimes and discount rates. Electricity and gas prices of 32.63 ct/kWh and 6.68 ct/kWh, respectively, are used based on average end-user prices in Germany in 2021 (Bundesnetzagentur and Bundeskartellamt, 2022). To reflect the effect of discrete unit sizes for small-scale systems, all investment variables are integers. Up to 20 PV panels with a capacity of 0.3 kW each, up to 6 batteries with 1 kW (dis)charging and 6 kWh storage capacity each and an air-sourced heat pump with a capacity of none, 1/3, 2/3 or all of the peak demand of approximately 10.5 kW can be installed.

5. Results and discussion

In this section, we present and discuss the results of applying the implementation of AUGMECON with Backbone from Section 3 to the two energy system models from Section 4.

5.1. Southern and Western European power sector model

A subset of 20 Pareto-optimal solutions is obtained and the whole Pareto front is approximated continuously by fitting costs as a polynomial in the logarithm of emissions. The results are shown in Figure 3 in objective space. The objective values of Pareto-optimal solutions range approximately from 110×10^9 EUR to 160×10^9 EUR and $0\,\mathrm{t\,CO_2}$ to $5.2 \times 10^8\,\mathrm{t\,CO_2}$. Marginal CO_2 abatement costs are displayed at the right ordinate of Figure 3 with logarithmic scale and range approximately from $4\,\mathrm{EUR/(t\,CO_2)}$ to $2000\,\mathrm{EUR/(t\,CO_2)}$. They are calculated in two different ways, first by linearly interpolating between each two elements of the Pareto front and second as the derivative of the continuous Pareto front approximation. Emission reductions[8] of up to 90 %, as compared to the Pareto-optimal solution with lowest costs and highest emissions, have marginal costs of less than $100\,\mathrm{EUR/(t\,CO_2)}$.

The Pareto-optimal solutions represent different emission reduction scenarios. Across these scenarios, the use of different technologies for electricity generation and storage is illustrated in Figures 4 and 5, respectively. Emission reductions are mainly achieved by replacing the dispatchable and CO_2-intensive energy sources hard coal, lignite and natural gas with intermittent RES, predominantly solar PV. The RES share reaches its maximum of approximately 75 % at zero emissions. For emission caps above approximately 50 %, more than 10 % of the total electricity demand is met by hard coal and lignite together. This value decreases with stricter emission caps and equals less than 1 % for emission caps below 15 %. This leads to increased flexibility requirements, which can, in our model, be met by investments in storages and, as a transitional substitution, natural gas turbines. Since generation through gas is less CO_2-intensive and, without a CO_2 price, more costly than coal-based generation, it is phased out together with coal for slight emission reductions. For significant reductions, when coal is phased out almost completely, natural gas-based generation increases again until, finally, flexibility provision through natural gas turbines decreases for very ambitious emission targets and is infeasible for the zero emission target. This is reflected by a peak at around 15 % of the maximum emissions and, besides the global minimum at zero emissions, a second local minimum at around 40 %.

[8] In this section, the reference for realised emissions, their reductions and caps $p_{\mathrm{CO_2}}^{\mathrm{emissionCap}}$ is always the value of the Pareto-optimal solution with lowest costs and highest emissions, $p_{\mathrm{CO_2}}^{\mathrm{highestEmission}}$.

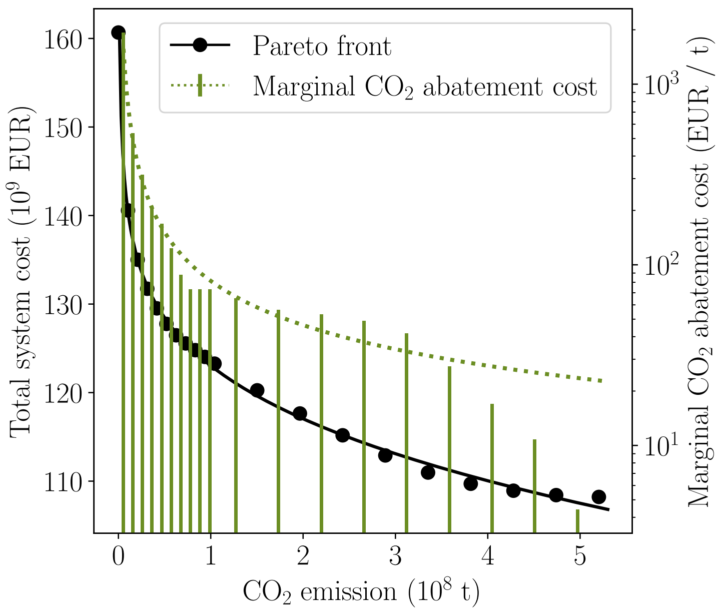


Figure 3: Pareto front (left ordinate) and marginal CO_2 abatement costs (right ordinate). The discrete Pareto-optimal solutions (black dots) result directly from applying the presented AUGMECON implementation to the Southern and Western European power sector model. The Pareto front (black solid line) is continuously approximated by fitting costs as a function of emissions to the discrete solutions. The marginal CO_2 abatement costs are determined in two ways. First, by linearly interpolating between the discrete solutions, resulting in the green bars, and second, as the derivative of the Pareto front approximation, resulting in the green dashed line.

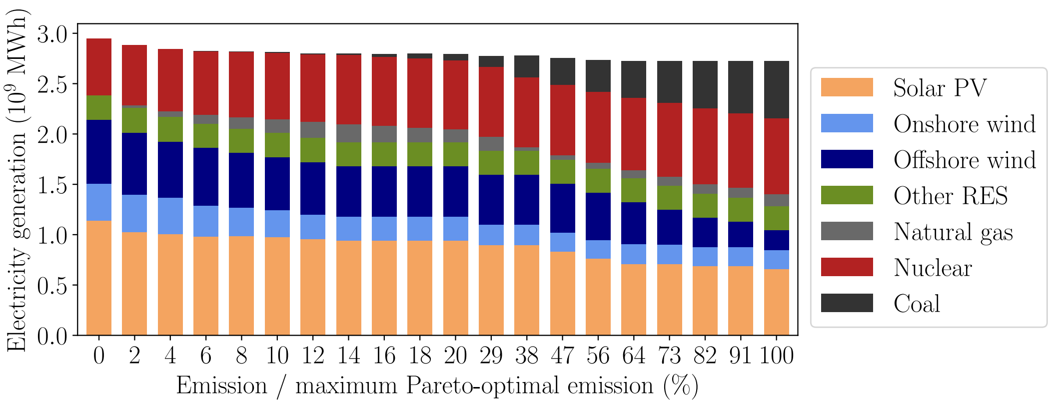


Figure 4: Electricity generation by technology across different Pareto-optimal emission reductions scenarios. Values on the abscissa represent the emissions of the respective scenario as a share of the maximum emission across all Pareto-optimal scenarios. All values are aggregated for all countries and the whole time horizon. The following technologies are aggregated: hard coal and lignite to “Coal”; biomass, run of river and hydro damns to “Other RES”; open and closed cycle gas turbines to “Natural gas”.

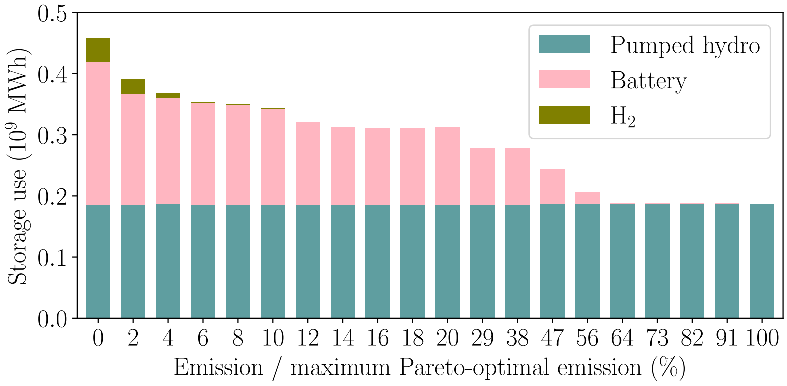


Figure 5: Electricity released from storages by technology across different Pareto-optimal emission reduction scenarios. The values are aggregated for all countries and the whole time horizon.

Significant investments in storages are made in all scenarios with emissions below approximately 60 %, referring to a renewable electricity share of 45 % to 50 %. For higher emissions and lower renewable shares, only the existing pumped hydro storage (PHS) capacities are used. Generally, storage use, i.e. the amount of energy released from storages, increases with decreasing emissions. The use of newly invested storages never exceeds approximately 1.5 times the use of already installed pumped hydro storages. Hydrogen storage is used less than batteries and only for very low emissions. Due to conversion losses, the overall electricity generation increases with decreasing emissions from approximately 2.7×10^9 MWh to 2.9×10^9 MWh.

For some of the Pareto-optimal alternatives, differences in decision variable space are significantly larger than in objective space. Consider, for example, all solutions with costs of not more than 5 % above the global minimum, i.e. the seven rightmost bars in Figure 4. Across these scenarios, electricity generation from offshore wind turbines and coal varies approximately by a factor of two each. Similarly, consider the solutions with emissions from 38 % to 56 % of the global maximum in Figure 5. Across these, the objective value varies by a factor of approximately 1.5, but the battery use by a factor of 5.

The sensitivity analysis for storage investment costs and the nuclear and coal exit scenarios are shown in Figure 6. For solutions with emissions above 3×10^8 t CO_2, where no storage investments are made in the base scenario, the Pareto fronts of all three storage cost scenarios coincide. With decreasing emissions, and increasing storage investments, the cost difference between the scenarios rises up to the maximum of approximately ±5 % at zero emissions. The nuclear exit scenario exhibits higher costs of approximately 5 % to 10 % across the different emission reductions, with larger cost differences for lower emissions. Further analyses show that the reduced nuclear capacities are compensated by higher renewable investments and use of gas turbines. For emissions below approximately 0.7×10^7 t CO_2, when no coal is used in the base scenario, the coal exit scenario coincides with the latter. Due to higher cost and lower emissions of gas as compared to coal, high emissions of above approximately 1.1×10^8 t CO_2 cannot be realised in a Pareto-optimal way in this scenario.

The model is run on a Linux machine with a total of 96 AMD 2.30 GHz processor cores and 256 GB

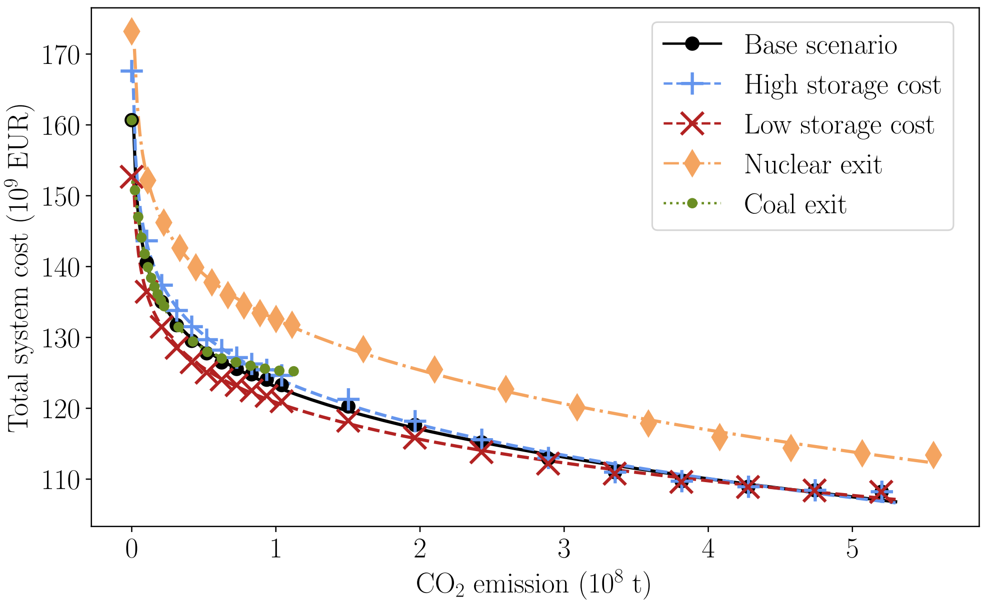


Figure 6: Pareto fronts of the base, high storage cost, low storage cost, nuclear and coal exit scenarios. The lines are polynomials in $\log x$ fitted through the respective discrete Pareto-optimal solutions. For the high and low storage cost scenarios, investment and fixed operation and maintenance costs are varied by $\pm 15\,\%$ for hydrogen storage and $\pm 25\,\%$ for batteries. For the nuclear exit scenario, the existing nuclear electricity generation capacities in Belgium, Germany and Spain are set to zero. For the coal exit scenario, the existing hard coal and lignite electricity generation capacities are set to zero.

memory. As Backbone itself is not optimised for utilising many cores efficiently, we restrict each model solve to using 2 processor cores and 2.5 GB memory. Under these conditions, the computation time for each single optimisation varies from approximately 1 h to 10 h.

5.2. Sector-coupled household-level model

A number of Pareto-optimal solutions to the household-level model is shown in Figure 7. Total system costs and energy imported from the public grids range from 1800 EUR to 3200 EUR and 3.6 MWh to 18.3 MWh, respectively. Marginal costs of self-sufficiency range approximately from 1.5 ct/kWh to 865 ct/kWh not consumed from the public grids. Due to integer investment variables, the Pareto front is not connected with three large and more smaller gaps. The large gaps are due to heat pump investments, which increase monotonically with decreasing imports, and are indicated by orange solid arrows. The smaller gaps associated with marginals above 300 ct/kWh around 5 MWh and below 4 MWh are due to battery investments, which change non-monotonically across the Pareto front, and are indicated by blue dotted arrows and ellipses. Battery investments are constantly 2 kW across the linear and connected parts of the Pareto front from 3.7 MWh to 5 MWh and from 5 MWh to 11 MWh. Towards the left end of these parts, there is a small kink, where it increases to 3 kW and the following three disconnected points are linked to increasing investments of 4, 5 and 6 kW, respectively. The number of PV panels is 10 for the least-cost solution, increases quickly and monotonically for decreasing energy imports and attains the maximum of 20 for imports of 11.4 MWh and below. The two linear and connected parts of the Pareto front, indicated by purple dashed lines and ellipses, are related to an increased utilisation of the heat pump, and thus a shift in imports from gas to electricity. With a coefficient of performance above one,

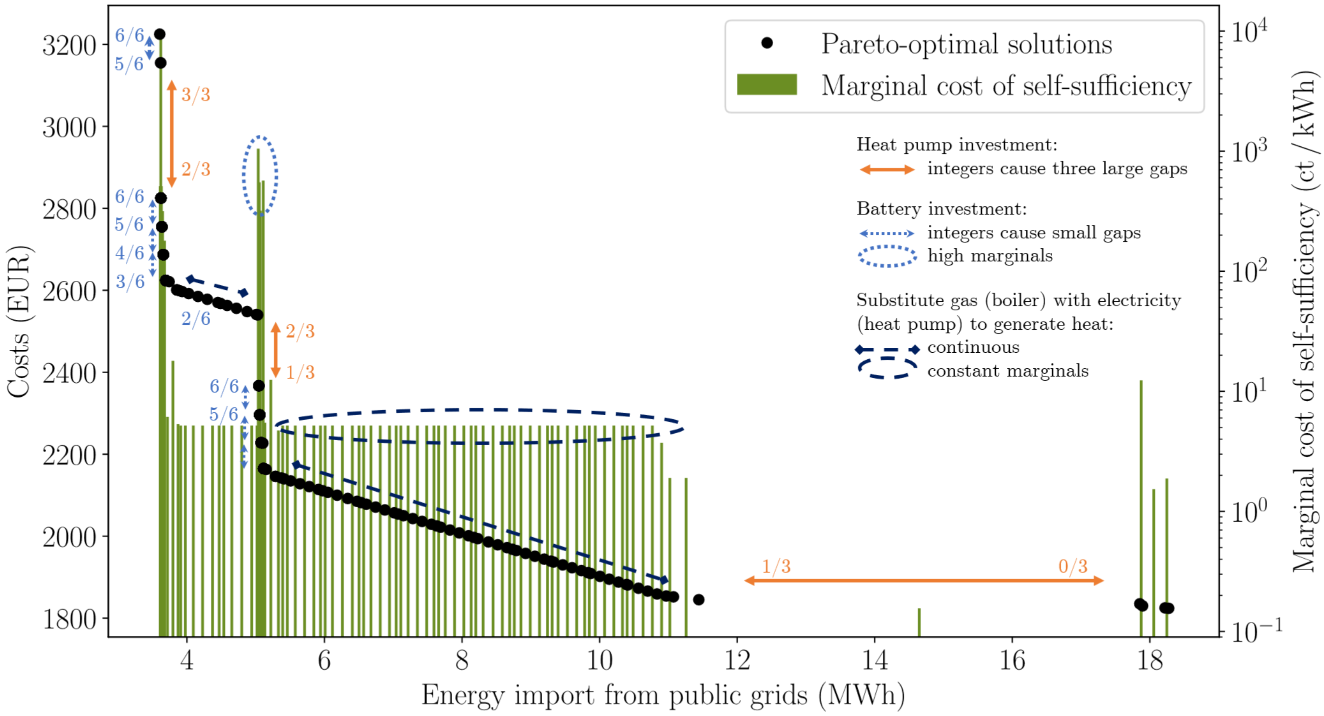


Figure 7: Pareto-optimal solutions (left ordinate) and marginal cost of self-sufficiency (right ordinate) for the household-level model. The discrete Pareto-optimal solutions result directly from applying the presented AUGMECON implementation to the sector-coupled household-level model. The marginal cost of self-sufficiency is determined by linearly interpolating between the discrete solutions. The orange and blue fractions refer to installed and maximum installable capacities of heat pumps and batteries, respectively.

this can reduce total energy imports, but comes with higher costs due to the electricity price, which is approximately five times higher than the gas price. The resulting constant marginal cost of self-sufficiency is 5 ct/kWh.

The additional cost of increased self-sufficiency, when calculated not as a "marginal" but between two more distant elements of the Pareto front, varies significantly. Between the lowest and highest level of self-sufficiency, it amounts to approximately 9.6 ct/kWh, while slightly lower import reductions to 3.8 MWh come at about 800 EUR additional annual cost and on average 5.4 ct/kWh as compared to the least-cost solution and can be achieved by investing in a 7 kW heat pump, 6 kW PV and 2 kW batteries. By investing in a 3.5 kW heat pump, 6 kW PV and 3 kW batteries, energy imports can be reduced to 5.1 MWh at average cost of 2.6 ct/kWh.

Around the Pareto front gaps related to heat pump and battery investments, solutions are similar in one objective, but differ significantly with respect to investment variables and the other objective. Identifying this variety of alternatives across the Pareto front is essential to a cost-efficient increase of self-sufficiency, but difficult when using a single-objective approach.

5.3. Discussion

As for all studies using data-driven models, the main purpose of the modelling is not to obtain results per se but to generate insights. The case studies demonstrate the capability of the AUGMECON extension of the ESM Backbone to generate new insights for very diverse energy systems and different objectives. These are related to (non-connected) Pareto fronts, trade-offs between alternative Pareto-optimal solutions, the impacts of exogenous political and techno-economic factors across different emission reduction targets as well as the relation of variations in objective and decision variable space. While some aspects of the systems have been simplified for illustrative reasons, the data used are real-world data leading to complex multi-objective optimisation problems.

Besides the general trends of generation and storage use under different emission reductions and scenario assumptions, findings of the European power sector model are in line with other studies, e.g. CO_2 prices from Pietzcker et al. (2021), generation shares of solar PV and wind for zero emissions from Child et al. (2019) and the order of magnitude of total system costs from Zappa et al. (2019). However, there are some limitations to this model. First, although an increased electricity demand due to sector coupling is included in the demand data, only the electricity sector is modelled explicitly. Changing load profiles are not considered. Second, the geographical scope of the model is only a part of the synchronous grid of Continental Europe and investments in transmission lines are not allowed. This underestimates the provision of sectoral and spatial flexibility, respectively. Third, bio- and nuclear energy as two low-carbon and dispatchable technologies are not considered as investment options, which underestimates the provision of temporal flexibility. Especially at high shares of variable renewable generation, this threefold underestimation could result in higher storage investments, higher renewable generation investments in sub-optimal technologies or sub-optimal locations as well as increased curtailment of variable RES. As a consequence, system costs and thus marginal CO_2 abatement costs would be overestimated. However, the spatial, sectoral and technological limitations can also have other, even contrary, effects. For example, if the limited countries or time period considered exhibit particularly favourable conditions for renewable electricity generation, marginal CO_2 abatement costs could be underestimated. While the cost objective considers operation- and investment-related costs, the objective for CO_2 emissions only takes into account the operation phase. This can benefit investments in new, mainly renewable, generation as compared to utilising existing, mainly conventional, capacities.

For this model, five scenarios with 20 solutions each are studied. Algorithm 1 has only three successive steps with multiple parallelised model solves each. Therefore, provided resources allow, the computation time for each scenario is only three times the amount for a single model solve. This parallelisation leads to time savings of approximately 85 % as compared to a total of 22 successive runs per scenario.

For the sector-coupled household-level model, the maximum PV capacity of 6 kW together with 2 kW to 3 kW batteries and heat pump capacities equal to one to two thirds of the peak heat demand seem to be the most cost-efficient technology mix for increasing self-sufficiency. Additional heat pump or battery investments come with significantly higher marginal cost, while generally, utilising ambient air as a second "internal" energy source is necessary to significantly decrease energy imports from the public grids. Only limited extrapolation to regional or national systems is possible as the model is not representative for the existing building stock on any larger scale. Although it is generally limited by the choice of parameters and available technologies, real-world data is used and the building and technologies are typical for existing residential single-household buildings.

For this model, the use of AUGMECON is particularly beneficial. First, where integer variables lead to large gaps in the Pareto front filled with weakly Pareto-optimal solutions, it ensures that all obtained solutions are Pareto-optimal and thus avoids inefficient system designs. Second, AUGMECON ensures that Pareto front boundaries are known and a representative subset is obtained. Due to non-connectedness and drastically varying marginals, this is essential for informed and efficient decision making.

6. Conclusion and outlook

The undergoing energy sector transformation comes with technical, environmental, economic and social difficulties and imposes new challenges for decision making. Environmental sustainability and public acceptance become increasingly important objectives and each involve many criteria. Therefore, energy system models considering multiple objectives are a key tool to inform and support decision makers. However, existing energy system models are not sufficiently adaptable to the diverse range of relevant energy systems and objectives. This refers in particular to openly available models optimising systems with multiple sectors and stochastic phenomena at high temporal and spatial resolution and a high level of technological detail for environmental and other acceptance-related objectives.

The main contribution of this paper is the efficient implementation of AUGMECON with the energy system optimisation framework Backbone as a way to equip an already very flexible energy system model with an adaptable multi-objective optimisation method. It enables the optimisation of a broad range of energy systems with respect to various objectives and is at the same time parallelisable and therefore scalable. In this paper, we incorporate costs, direct CO_2 emissions and self-sufficiency as three illustrative objectives and apply them to two energy system models including different sectors, scales, technologies and statistics and linear as well as integer variables. The implementation extends and improves possibilities for energy system analyses, in particular regarding optimality with respect to all considered objectives, quantification of trade-offs, scenario analyses across entire Pareto fronts and varying energy system designs leading to similar objective values.

The method is first applied to a Southern and Western European power sector model with several million variables, non-zeros and equations. It shows different cost-emission-optimal emission reduction scenarios for the year 2050 and quantifies trade-offs between them. Heeding the call for climate protection, it demonstrates that CO_2 emission reductions of up to 90 % can be achieved at approximately 20 % higher total system costs and marginal abatement costs of below 100 EUR/(t CO_2). The use of electricity generation and storage technologies is analysed across different emission reduction targets and linked to the implications of four scenarios for coal exit, nuclear exit and high and low storage investment cost, respectively. Furthermore, some Pareto-optimal alternatives with similar costs or emissions, but significant differences in energy system design are highlighted.

The method is then applied to a sector-coupled household-level model to obtain cost-self-sufficiency-optimal system designs under uncertain energy demand. Emphasising the relevance of integer variables for small-scale systems, it shows a non-connected Pareto front with drastically and non-monotonously varying trade-offs between the two objectives. The results highlight that a single-objective approach could lead to highly inefficient decisions and that, in combination with high investments in solar PV, moderate installations of heat pumps and batteries are a cost-efficient way of increasing self-sufficiency.

We suggest three main directions for future work. First, more and other objectives could be incorporated. This includes environmental impacts, for example life cycle assessments of land or metal use, or aspects related to behaviour and acceptance, e.g. comfort or scenicness. Secondly, the method could be advanced for three and more objectives. This includes reducing computation time by avoiding redundant optimisations. Furthermore, analysing and visualising a more than three-dimensional Pareto front comes with challenges. Using a real-time interactive method like Pareto navigation (Monz et al., 2008) could ease these difficulties and further support decision making. Thirdly, because solutions might be similar in objective space but differ significantly in decision variable space, incorporating aspects of *Modelling to Generate Alternatives* (DeCarolis, 2011; DeCarolis et al., 2016) into the method could further enrich the alternatives available for decision making and reduce systematic uncertainties of the modelling process.

Author contributions

J.F.: Conceptualisation, Investigation, Methodology, Software, Visualisation, Writing – Orignial Draft, Writing – Review & Editing. V.B.: Conceptualisation, Supervision, Writing – Review & Editing.

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Declaration of interest

The authors declare that they have no known competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Availability of code and data

To the best of the authors' knowledge, all data and code used is openly available. All data are from openly available sources, as described in Section 4. The energy system optimisation framework Backbone is openly available at `https://gitlab.vtt.fi/backbone/backbone`. Further developments of Backbone, as described in Section 3, are available from the same repository. The python code, as described in Algorithm 1, is openly available at `https://gitlab.ruhr-uni-bochum.de/ee/backbone-tools`.

References

Aghaei, J., Akbari, M. A., Roosta, A., Gitizadeh, M., & Niknam, T. (2012). Integrated renewable–conventional generation expansion planning using multiobjective framework. *IET Generation, Transmission & Distribution*, *6*, 773. doi:10.1049/iet-gtd.2011.0816.

Allan, G., Eromenko, I., Gilmartin, M., Kockar, I., & McGregor, P. (2015). The economics of distributed energy generation: A literature review. *Renewable and Sustainable Energy Reviews*, *42*, 543–556. doi:10.1016/j.rser.2014.07.064.

Antunes, C. H., & Henriques, C. O. (2016). Multi-Objective Optimization and Multi-Criteria Analysis Models and Methods for Problems in the Energy Sector. In S. Greco, M. Ehrgott, & J. R. Figueira (Eds.), *Multiple Criteria Decision Analysis* International Series in Operations Research & Management Science (pp. 1067–1165). New York, N.Y: Springer New York. doi:10.1007/978-1-4939-3094-4_25.

Arnette, A., & Zobel, C. W. (2012). An optimization model for regional renewable energy development. *Renewable and Sustainable Energy Reviews*, *16*, 4606–4615. doi:10.1016/j.rser.2012.04.014.

Arora, J. S. (2012). Chapter 17 - Multi-objective Optimum Design Concepts and Methods. In J. S. Arora (Ed.), *Introduction to optimum design* (pp. 657–679). Waltham and Oxford: Elsevier Academic Press. doi:10.1016/B978-0-12-381375-6.00017-6.

Asadi, E., Da Silva, M. G., Antunes, C. H., & Dias, L. (2012). A multi-objective optimization model for building retrofit strategies using TRNSYS simulations, GenOpt and MATLAB. *Building and Environment*, *56*, 370–378. doi:10.1016/j.buildenv.2012.04.005.

Asadi, E., Da Silva, M. G., Antunes, C. H., Dias, L., & Glicksman, L. (2014). Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. *Energy and Buildings*, *81*, 444–456. doi:10.1016/j.enbuild.2014.06.009.

Atabay, D. (2017). An open-source model for optimal design and operation of industrial energy systems. *Energy*, *121*, 803–821. doi:10.1016/j.energy.2017.01.030.

Batas Bjelić, I., & Rajaković, N. (2015). Simulation-based optimization of sustainable national energy systems. *Energy*, *91*, 1087–1098. doi:10.1016/j.energy.2015.09.006.

Bertsch, V., & Fichtner, W. (2016). A participatory multi-criteria approach for power generation and transmission planning. *Annals of Operations Research*, *245*, 177–207. doi:10.1007/s10479-015-1791-y.

Bertsch, V., Hall, M., Weinhardt, C., & Fichtner, W. (2016). Public acceptance and preferences related to renewable energy and grid expansion policy: Empirical insights for Germany. *Energy*, *114*, 465–477. doi:10.1016/j.energy.2016.08.022.

Bertsch, V., Hyland, M., & Mahony, M. (2017). What drives people's opinions of electricity infrastructure? Empirical evidence from Ireland. *Energy Policy*, *106*, 472–497. doi:10.1016/j.enpol.2017.04.008.

Bogdanov, D., & Breyer, C. (2016). North-East Asian Super Grid for 100% renewable energy supply: Optimal mix of energy technologies for electricity, gas and heat supply options. *Energy Conversion and Management*, *112*, 176–190. doi:10.1016/j.enconman.2016.01.019.

Borhanazad, H., Mekhilef, S., Gounder Ganapathy, V., Modiri-Delshad, M., & Mirtaheri, A. (2014). Optimization of micro-grid system using MOPSO. *Renewable Energy*, *71*, 295–306. doi:10.1016/j.renene.2014.05.006.

Bracco, S., Dentici, G., & Siri, S. (2013). Economic and environmental optimization model for the design and the operation of a combined heat and power distributed generation system in an urban area. *Energy*, *55*, 1014–1024. doi:10.1016/j.energy.2013.04.004.

Brouwer, A. S., van den Broek, M., Seebregts, A., & Faaij, A. (2014). Impacts of large-scale Intermittent Renewable Energy Sources on electricity systems, and how these can be modeled. *Renewable and Sustainable Energy Reviews*, *33*, 443–466. doi:10.1016/j.rser.2014.01.076.

Brown, T., Hörsch, J., & Schlachtberger, D. (2018a). PyPSA: Python for Power System Analysis. *Journal of Open Research Software*, *6*. doi:10.5334/jors.188.

Brown, T., Schäfer, M., & Greiner, M. (2019). Sectoral Interactions as Carbon Dioxide Emissions Approach Zero in a Highly-Renewable European Energy System. *Energies*, *12*, 1032. doi:10.3390/en12061032.

Brown, T., Schlachtberger, D., Kies, A., Schramm, S., & Greiner, M. (2018b). Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system. *Energy*, *160*, 720–739. doi:10.1016/j.energy.2018.06.222.

Bundesnetzagentur and Bundeskartellamt (2022). Monitoringbericht 2021. URL: https://www.bundesnetzagentur.de/SharedDocs/Mediathek/Monitoringberichte/Monitoringbericht_Energie2021.pdf?__blob=publicationFile&v=7.

Bussar, C., Stöcker, P., Cai, Z., Moraes Jr., L., Magnor, D., Wiernes, P., van Bracht, N., Moser, A., & Sauer, D. U. (2016). Large-scale integration of renewable energies and impact on storage demand in a European renewable power system of 2050—Sensitivity study. *Journal of Energy Storage*, *6*, 1–10. doi:10.1016/j.est.2016.02.004.

Cambero, C., & Sowlati, T. (2016). Incorporating social benefits in multi-objective optimization of forest-based bioenergy and biofuel supply chains. *Applied Energy*, *178*, 721–735. doi:10.1016/j.apenergy.2016.06.079.

Cambero, C., Sowlati, T., & Pavel, M. (2016). Economic and life cycle environmental optimization of forest-based biorefinery supply chains for bioenergy and biofuel production. *Chemical Engineering Research and Design*, *107*, 218–235. doi:10.1016/j.cherd.2015.10.040.

Cao, K.-K., von Krbek, K., Wetzel, M., Cebulla, F., & Schreck, S. (2019). Classification and Evaluation of Concepts for Improving the Performance of Applied Energy System Optimization Models. *Energies*, *12*, 4656. doi:10.3390/en12244656.

Center for Sustainable Systems, University of Michigan (2021). Wind Energy Factsheet. URL: http://css.umich.edu/sites/default/files/Wind%20Energy_CSS07-09_e2021_0.pdf [Accessed 23 December 2021].

Chaouachi, A., Kamel, R. M., Andoulsi, R., & Nagasaka, K. (2013). Multiobjective Intelligent Energy Management for a Microgrid. *IEEE Transactions on Industrial Electronics*, *60*, 1688–1699. doi:10.1109/TIE.2012.2188873.

Child, M., Kemfert, C., Bogdanov, D., & Breyer, C. (2019). Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in Europe. *Renewable Energy*, *139*, 80–101. doi:10.1016/j.renene.2019.02.077.

Clarke, D. P., Al-Abdeli, Y. M., & Kothapalli, G. (2015). Multi-objective optimisation of renewable hybrid energy systems with desalination. *Energy*, *88*, 457–468. doi:10.1016/j.energy.2015.05.065.

Cook, J., Nuccitelli, D., Green, S. A., Richardson, M., Winkler, B., Painting, R., Way, R., Jacobs, P., & Skuce, A. (2013). Quantifying the consensus on anthropogenic global warming in the scientific literature. *Environmental Research Letters*, *8*, 024024. doi:10.1088/1748-9326/8/2/024024.

Cui, Y., Geng, Z., Zhu, Q., & Han, Y. (2017). Review: Multi-objective optimization methods and application in energy saving. *Energy*, *125*, 681–704. doi:10.1016/j.energy.2017.02.174.

Deb, K., & Jain, H. (2014). An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part I: Solving Problems With Box Constraints. *IEEE Transactions on Evolutionary Computation*, *18*, 577–601. doi:10.1109/TEVC.2013.2281535.

DeCarolis, J. F. (2011). Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. *Energy Economics*, *33*, 145–152. doi:`10.1016/j.eneco.2010.05.002`.

DeCarolis, J. F., Babaee, S., Li, B., & Kanungo, S. (2016). Modelling to generate alternatives with an energy system optimization model. *Environmental Modelling & Software*, *79*, 300–310. doi:`10.1016/j.envsoft.2015.11.019`.

DeCarolis, J. F., Hunter, K., & Sreepathi, S. (2012). The case for repeatable analysis with energy economy optimization models. *Energy Economics*, *34*, 1845–1853. doi:`10.1016/j.eneco.2012.07.004`.

Dorotić, H., Doračić, B., Dobravec, V., Pukšec, T., Krajačić, G., & Duić, N. (2019). Integration of transport and energy sectors in island communities with 100% intermittent renewable energy sources. *Renewable and Sustainable Energy Reviews*, *99*, 109–124. doi:`10.1016/j.rser.2018.09.033`.

Dufo-López, R., Bernal-Agustín, J. L., Yusta-Loyo, J. M., Domínguez-Navarro, J. A., Ramírez-Rosado, I. J., Lujano, J., & Aso, I. (2011). Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV–wind–diesel systems with batteries storage. *Applied Energy*, *88*, 4033–4041. doi:`10.1016/j.apenergy.2011.04.019`.

E3MLab (2016). PRIMES Model: Version 6, 2016–2017: Technical Report.

Eisenführ, F., Weber, M., & Langer, T. (2010). *Rational decision making*. Berlin and London: Springer.

El-Zonkoly, A. M. (2011). Optimal placement of multi-distributed generation units including different load models using particle swarm optimisation. *IET Generation, Transmission & Distribution*, *5*, 760. doi:`10.1049/iet-gtd.2010.0676`.

Elliston, B., Riesz, J., & MacGill, I. (2016). What cost for more renewables? The incremental cost of renewable generation – An Australian National Electricity Market case study. *Renewable Energy*, *95*, 127–139. doi:`10.1016/j.renene.2016.03.080`.

Energy Exemplar (no date). PLEXOS®: The Unified Energy Market Simulation Platform. URL: `https://www.energyexemplar.com/plexos` [Accessed 23 December 2021].

Enevoldsen, P., & Sovacool, B. K. (2016). Examining the social acceptance of wind energy: Practical guidelines for onshore wind project development in France. *Renewable and Sustainable Energy Reviews*, *53*, 178–184. doi:`10.1016/j.rser.2015.08.041`.

European Commission (2019). National energy and climate plans (NECPs): Final NECPs. URL: `https://ec.europa.eu/energy/topics/energy-strategy/national-energy-climate-plans_en` [Accessed 7 September 2021].

European Commission (2020a). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Commitee and the Committee of the Regions: Stepping up Europe's 2030 climate ambition. Investing in a climate-neutral future for the benefit of our people: COM(2020) 562 final. URL: `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0562&from=EN` [Accessed 28 January 2021].

European Commission (2020b). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: An EU-wide assessment of National Energy and Climate Plans. Driving forward the green transition and promoting economic recovery through integrated energy and climate planning: COM(2020) 564 final. URL: `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0564&from=EN` [Accessed 05 September 2021].

EUROSTAT (2017). Greenhouse gas emission statistics. URL: `http://ec.europa.eu/eurostat/statistics-explained/index.php/Greenhouse_gas_emission_statistics` [Accessed 23 December 2021].

Fadaee, M., & Radzi, M. (2012). Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review. *Renewable and Sustainable Energy Reviews*, *16*, 3364–3369. doi:10.1016/j.rser.2012.02.071.

Fazlollahi, S., Bungener, S. L., Becker, G., & Maréchal, F. (2012). Multi-Objectives, Multi-Period Optimization of district heating networks Using Evolutionary Algorithms and Mixed Integer Linear Programming (MILP). In I. D. L. Bogle, & M. Fairweather (Eds.), *Computer Aided Chemical Engineering : 22 European Symposium on Computer Aided Process Engineering* (pp. 262–266). Elsevier volume 30. doi:10.1016/B978-0-444-59519-5.50053-8.

Fesanghary, M., Asadi, S., & Geem, Z. W. (2012). Design of low-emission and energy-efficient residential buildings using a multi-objective optimization algorithm. *Building and Environment*, *49*, 245–250. doi:10.1016/j.buildenv.2011.09.030.

Fitiwi, D. Z., Lynch, M., & Bertsch, V. (2020). Power system impacts of community acceptance policies for renewable energy deployment under storage cost uncertainty. *Renewable Energy*, *156*, 893–912. doi:10.1016/j.renene.2020.03.110.

Forschungsstelle für Energiewirtschaft e.V. (FfE) (2020a). Synthetic Sample Electric Load Profile (Three-Phase) by Household Types (Germany). URL: http://opendata.ffe.de/dataset/synthetic-sample-electric-load-profile-three-phase-by-household-types-germany/.

Forschungsstelle für Energiewirtschaft e.V. (FfE) (2020b). Synthetic Sample Thermal Load Profile by Household Types (Germany). URL: http://opendata.ffe.de/dataset/synthetic-sample-thermal-load-profile-by-household-types-germany/.

Fraunhofer ISI (2021). enertile®. URL: https://www.enertile.eu/enertile-en/ [Accessed 23 December 2021].

Fuss, M., & Xu, L. (2021). Unintended Environmental Impacts at Local and Global Scale—Trade-Offs of a Low-Carbon Electricity System. In D. Möst, S. Schreiber, A. Herbst, M. Jakob, A. Martino, & W.-R. Poganietz (Eds.), *The Future European Energy System: Renewable Energy, Flexibility Options and Technological Progress* (pp. 237–255). Cham: Springer International Publishing. doi:10.1007/978-3-030-60914-6_13.

Gabrielli, P., Gazzani, M., Martelli, E., & Mazzotti, M. (2018). Optimal design of multi-energy systems with seasonal storage. *Applied Energy*, *219*, 408–424. doi:10.1016/j.apenergy.2017.07.142.

Gerhardt, N., Sandau, F., Scholz, A., Hahn, H., Schumacher, P., Sager, C., Bergk, F., Kämper, C., Knörr, W., Kräck, J., & et al. (2015). Interaktion EE-Strom, Wärme und Verkehr: Endbericht: Technical Report.

Gils, H. C., Scholz, Y., Pregger, T., Luca de Tena, D., & Heide, D. (2017). Integrated modelling of variable renewable energy-based power supply in Europe. *Energy*, *123*, 173–188. doi:10.1016/j.energy.2017.01.115.

Hall, L. M., & Buckley, A. R. (2016). A review of energy systems models in the UK: Prevalent usage and categorisation. *Applied Energy*, *169*, 607–628. doi:10.1016/j.apenergy.2016.02.044.

Hauff, J., Heider, C., Arms, H., Gerber, J., & Schilling, M. (2011). Public acceptance as a mainstay of energy policy planning; Gesellschaftliche Akzeptanz als Saeule der energiepolitischen Zielsetzung. *ET, Energiewirtschaftliche Tagesfragen*, *61*.

Hauser, P., Heinrichs, H. U., Gillessen, B., & Müller, T. (2018). Implications of diversification strategies in the European natural gas market for the German energy system. *Energy*, *151*, 442–454. doi:10.1016/j.energy.2018.03.065.

Heaps, C. G. (2021). LEAP: The Low Emission Analysis Platform: [Software version: 2020.1.55]. URL: https://leap.sei.org [Accessed 23 December 2021].

Helistö, N., Kiviluoma, J., Holttinen, H., Lara, J. D., & Hodge, B.-M. (2019a). Including operational aspects in the planning of power systems with large amounts of variable generation: A review of modeling approaches. *Wiley Interdisciplinary Reviews: Energy and Environment*, *8*, e341. doi:10.1002/wene.341.

Helistö, N., Kiviluoma, J., Ikäheimo, J., Rasku, T., Rinne, E., O'Dwyer, C., Li, R., & Flynn, D. (2019b). Backbone—An Adaptable Energy Systems Modelling Framework. *Energies*, *12*, 3388. doi:10.3390/en12173388.

Helistö, N., Kiviluoma, J., Morales-España, G., & O'Dwyer, C. (2021). Impact of operational details and temporal representations on investment planning in energy systems dominated by wind and solar. *Applied Energy*, *290*, 116712. doi:10.1016/j.apenergy.2021.116712.

Henning, H.-M., & Palzer, A. (2014). A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies—Part I: Methodology. *Renewable and Sustainable Energy Reviews*, *30*, 1003–1018. doi:10.1016/j.rser.2013.09.012.

Hilpert, S., Kaldemeyer, C., Krien, U., Günther, S., Wingenbach, C., & Plessmann, G. (2017a). *The Open Energy Modelling Framework (oemof) - A novel approach in energy system modelling*. doi:10.20944/preprints201706.0093.v1.

Hilpert, S., Kaldemeyer, C., Wiese, F., & Plessmann, G. (2017b). *A Qualitative Evaluation Approach for Energy System Modelling Software—Case Study Results for the Open Energy Modelling Framework (Oemof)*. doi:10.20944/preprints201708.0069.v1.

Hombach, L. E., & Walther, G. (2015). Pareto-efficient legal regulation of the (bio)fuel market using a bi-objective optimization model. *European Journal of Operational Research*, *245*, 286–295. doi:10.1016/j.ejor.2015.02.039.

Hörsch, J., Hofmann, F., Schlachtberger, D., & Brown, T. (2018). PyPSA-Eur: An Open Optimisation Model of the European Transmission System. *Energy Strategy Reviews*, *22*, 207–215. doi:10.1016/j.esr.2018.08.012.

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M., & Roehrl, A. (2011). OSeMOSYS: The Open Source Energy Modeling System. *Energy Policy*, *39*, 5850–5870. doi:10.1016/j.enpol.2011.06.033.

Huckebrink, D., & Bertsch, V. (2021). Integrating Behavioural Aspects in Energy System Modelling—A Review. *Energies*, *14*, 4579. doi:10.3390/en14154579.

Hunter, K., Sreepathi, S., & DeCarolis, J. F. (2013). Modeling for insight using Tools for Energy Model Optimization and Analysis (Temoa). *Energy Economics*, *40*, 339–349. doi:10.1016/j.eneco.2013.07.014.

IIASA (2012). Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE). URL: http://webarchive.iiasa.ac.at/Research/ENE/model/message.html [Accessed 23 December 2021].

Ikäheimo, J., Weiss, R., Kiviluoma, J., Pursiheimo, E., & Lindroos, T. J. (2022). Impact of power-to-gas on the cost and design of the future low-carbon urban energy system. *Applied Energy*, *305*, 117713. doi:10.1016/j.apenergy.2021.117713.

Intergovernmental Panel on Climate Change (2014). *Climate change 2014: Mitigation of climate change Working Group III contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. New York NY: Cambridge University Press. doi:10.1017/CBO9781107415416.

Jain, H., & Deb, K. (2014). An Evolutionary Many-Objective Optimization Algorithm Using Reference-Point Based Nondominated Sorting Approach, Part II: Handling Constraints and Extending to an Adaptive Approach. *IEEE Transactions on Evolutionary Computation*, *18*, 602–622. doi:10.1109/TEVC.2013.2281534.

Junne, T., Simon, S., Buchgeister, J., Saiger, M., Baumann, M., Haase, M., Wulf, C., & Naegler, T. (2020). Environmental Sustainability Assessment of Multi-Sectoral Energy Transformation Pathways: Methodological Approach and Case Study for Germany. *Sustainability*, *12*, 8225. doi:10.3390/su12198225.

Katsigiannis, Y. A., Georgilakis, P. S., & Karapidakis, E. S. (2010). Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables. *IET Renewable Power Generation*, *4*, 404. doi:10.1049/iet-rpg.2009.0076.

Kirchem, D., Lynch, M. Á., Bertsch, V., & Casey, E. (2020). Modelling demand response with process models and energy systems models: Potential applications for wastewater treatment within the energy-water nexus. *Applied Energy*, *260*, 114321. doi:10.1016/j.apenergy.2019.114321.

Komušanac, I., Ćosić, B., & Duić, N. (2016). Impact of high penetration of wind and solar PV generation on the country power system load: The case study of Croatia. *Applied Energy*, *184*, 1470–1482. doi:10.1016/j.apenergy.2016.06.099.

Lashkar Ara, A., Kazemi, A., Gahramani, S., & Behshad, M. (2012). Optimal reactive power flow using multi-objective mathematical programming. *Scientia Iranica*, *19*, 1829–1836. doi:10.1016/j.scient.2012.07.010.

Limleamthong, P., & Guillén-Gosálbez, G. (2017). Rigorous analysis of Pareto fronts in sustainability studies based on bilevel optimization: Application to the redesign of the UK electricity mix. *Journal of Cleaner Production*, *164*, 1602–1613. doi:10.1016/j.jclepro.2017.06.134.

Lindroos, T. J., Mäki, E., Koponen, K., Hannula, I., Kiviluoma, J., & Raitila, J. (2021). Replacing fossil fuels with bioenergy in district heating – Comparison of technology options. *Energy*, *231*, 120799. doi:10.1016/j.energy.2021.120799.

Loulou, R., Goldstein, G., & Noble, K. (2004). Documentation for the MARKAL Family of Models. URL: https://unfccc.int/resource/cd_roms/na1/mitigation/Module_5/Module_5_1/b_tools/MARKAL/MARKAL_Manual.pdf [Accessed 23 December 2021].

Loulou, R., Remne, U., Kanudia, A., Lehtila, A., & Goldstein, G. (2005). *Documentation for the TIMES model*.

Lund, H. (2014). Chapter 4 - Tool: The EnergyPLAN Energy System Analysis Model. In H. H. Lund (Ed.), *Renewable energy systems* (pp. 53–78). Amsterdam, Netherlands and Boston, Massachusetts: Academic Press. doi:10.1016/B978-0-12-410423-5.00004-3.

Lund, H., & Kempton, W. (2008). Integration of renewable energy into the transport and electricity sectors through V2G. *Energy Policy*, *36*, 3578–3587. doi:10.1016/j.enpol.2008.06.007.

Mahbub, M. S., Cozzini, M., Østergaard, P. A., & Alberti, F. (2016). Combining multi-objective evolutionary algorithms and descriptive analytical modelling in energy scenario design. *Applied Energy*, *164*, 140–151. doi:10.1016/j.apenergy.2015.11.042.

Mahbub, M. S., Viesi, D., Cattani, S., & Crema, L. (2017). An innovative multi-objective optimization approach for long-term energy planning. *Applied Energy*, *208*, 1487–1504. doi:10.1016/j.apenergy.2017.08.245.

Mavrotas, G. (2009). Effective implementation of the ϵ-constraint method in Multi-Objective Mathematical Programming problems. *Applied Mathematics and Computation*, *213*, 455–465. doi:10.1016/j.amc.2009.03.037.

Mavrotas, G., & Florios, K. (2013). An improved version of the augmented ϵ-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. *Applied Mathematics and Computation*, *219*, 9652–9669. doi:10.1016/j.amc.2013.03.002.

Mazzeo, D., Baglivo, C., Matera, N., Congedo, P. M., & Oliveti, G. (2020). A novel energy-economic-environmental multi-criteria decision-making in the optimization of a hybrid renewable system. *Sustainable Cities and Society*, *52*, 101780. doi:10.1016/j.scs.2019.101780.

Mehigan, L., Deane, J. P., Gallachóir, B., & Bertsch, V. (2018). A review of the role of distributed generation (DG) in future electricity systems. *Energy*, *163*, 822–836. doi:10.1016/j.energy.2018.08.022.

Miettinen, K. (1999). *Nonlinear multiobjective optimization* volume ISOR12 of *International Series in Operations Research & Management Science*. Boston and London: Kluwer Academic Publishers.

Miettinen, K. (2008). Introduction to Multiobjective Optimization: Noninteractive Approaches. In J. Branke, K. Deb, K. Miettinen, & R. Słowiski (Eds.), *Multiobjective Optimization* Lecture Notes in Computer Science (pp. 1–26). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-540-88908-3_1.

Miettinen, K., Hakanen, J., & Podkopaev, D. (2016). Interactive Nonlinear Multiobjective Optimization Methods. In S. Greco, M. Ehrgott, & J. R. Figueira (Eds.), *Multiple Criteria Decision Analysis* International Series in Operations Research & Management Science (pp. 927–976). New York, N.Y: Springer New York. doi:10.1007/978-1-4939-3094-4_22.

Millward-Hopkins, J., & Purnell, P. (2019). Circulating blame in the circular economy: The case of wood-waste biofuels and coal ash. *Energy Policy*, *129*, 168–172. doi:10.1016/j.enpol.2019.02.019.

Mohammadkhani, N., Sedighizadeh, M., & Esmaili, M. (2018). Energy and emission management of CCHPs with electric and thermal energy storage and electric vehicle. *Thermal Science and Engineering Progress*, *8*, 494–508. doi:10.1016/j.tsep.2018.10.005.

Monz, M., Küfer, K. H., Bortfeld, T. R., & Thieke, C. (2008). Pareto navigation: algorithmic foundation of interactive multi-criteria IMRT planning. *Physics in Medicine & Biology*, *53*, 985–998. doi:10.1088/0031-9155/53/4/011.

Morton, A., & Fasolo, B. (2009). Behavioural decision theory for multi-criteria decision analysis: a guided tour. *Journal of the Operational Research Society*, *60*, 268–275. doi:10.1057/palgrave.jors.2602550.

Morvaj, B., Evins, R., & Carmeliet, J. (2016). Optimising urban energy systems: Simultaneous system sizing, operation and district heating network layout. *Energy*, *116*, 619–636. doi:10.1016/j.energy.2016.09.139.

Morvaj, B., Evins, R., & Carmeliet, J. (2017). Decarbonizing the electricity grid: The impact on urban energy systems, distribution grids and district heating potential. *Applied Energy*, *191*, 125–140. doi:10.1016/j.apenergy.2017.01.058.

Möst, D., & Keles, D. (2010). A survey of stochastic modelling approaches for liberalised electricity markets. *European Journal of Operational Research*, *207*, 543–556. doi:10.1016/j.ejor.2009.11.007.

Nikas, A., Fountoulakis, A., Forouli, A., & Doukas, H. (2020). A robust augmented ϵ-constraint method (AUGMECON-R) for finding exact solutions of multi-objective linear programming problems. *Operational Research*, (pp. 1–42). doi:10.1007/s12351-020-00574-6.

Niknam, T., Meymand, H. Z., Mojarrad, H. D., & Aghaei, J. (2011). Multi-objective daily operation management of distribution network considering fuel cell power plants. *IET Renewable Power Generation*, *5*, 356. doi:10.1049/iet-rpg.2010.0190.

O'Dwyer, C., & Flynn, D. (2019). Impact of flexibility service requirements on investment decisions and costs. In *Electrical and Electronic Engineering Research Collection, The 18th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants*. URL: https://researchrepository.ucd.ie/handle/10197/11402 [Accessed 23 December 2021].

Oree, V., Sayed Hassen, S. Z., & Fleming, P. J. (2017). Generation expansion planning optimisation with renewable energy integration: A review. *Renewable and Sustainable Energy Reviews*, *69*, 790–803. doi:10.1016/j.rser.2016.11.120.

Orths, A., Anderson, C. L., Brown, T., Mulhern, J., Pudjianto, D., Ernst, B., O'Malley, M., McCalley, J., & Strbac, G. (2019). Flexibility From Energy Systems Integration: Supporting Synergies Among Sectors. *IEEE Power and Energy Magazine*, *17*, 67–78. doi:10.1109/MPE.2019.2931054.

Palzer, A., & Henning, H.-M. (2014). A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies – Part II: Results. *Renewable and Sustainable Energy Reviews*, *30*, 1019–1034. doi:10.1016/j.rser.2013.11.032.

Pelet, X., Favrat, D., & Leyland, G. (2005). Multiobjective optimisation of integrated energy systems for remote communities considering economics and CO2 emissions. *International Journal of Thermal Sciences*, *44*, 1180–1189. doi:10.1016/j.ijthermalsci.2005.09.006.

Pfenninger, S., DeCarolis, J., Hirth, L., Quoilin, S., & Staffell, I. (2017). The importance of open data and software: Is energy research lagging behind? *Energy Policy*, *101*, 211–215. doi:10.1016/j.enpol.2016.11.046.

Pfenninger, S., Hawkes, A., & Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, *33*, 74–86. doi:10.1016/j.rser.2014.02.003.

Pfenninger, S., & Pickering, B. (2018). Calliope: a multi-scale energy systems modelling framework. *Journal of Open Source Software*, *3*, 825. doi:10.21105/joss.00825.

Pfenninger, S., & Staffell, I. (2016). Long-term patterns of european pv output using 30 years of validated hourly reanalysis and satellite data. *Energy*, *114*, 1251–1265. URL: https://www.sciencedirect.com/science/article/pii/S0360544216311744. doi:https://doi.org/10.1016/j.energy.2016.08.060.

Pietzcker, R. C., Osorio, S., & Rodrigues, R. (2021). Tightening EU ETS targets in line with the European Green Deal: Impacts on the decarbonization of the EU power sector. *Applied Energy*, *293*, 116914. doi:10.1016/j.apenergy.2021.116914.

Powell, W. B., George, A., Simão, H., Scott, W., Lamont, A., & Stewart, J. (2012). SMART: A Stochastic Multiscale Model for the Analysis of Energy Resources, Technology, and Policy. *INFORMS Journal on Computing*, *24*, 665–682. doi:10.1287/ijoc.1110.0470.

Prina, M. G., Casalicchio, V., Kaldemeyer, C., Manzolini, G., Moser, D., Wanitschke, A., & Sparber, W. (2020a). Multi-objective investment optimization for energy system models in high temporal and spatial resolution. *Applied Energy*, *264*, 114728. doi:10.1016/j.apenergy.2020.114728.

Prina, M. G., Cozzini, M., Garegnani, G., Manzolini, G., Moser, D., Filippi Oberegger, U., Pernetti, R., Vaccaro, R., & Sparber, W. (2018). Multi-objective optimization algorithm coupled to EnergyPLAN software: The EPLANopt model. *Energy*, *149*, 213–221. doi:10.1016/j.energy.2018.02.050.

Prina, M. G., Lionetti, M., Manzolini, G., Sparber, W., & Moser, D. (2019). Transition pathways optimization methodology through EnergyPLAN software for long-term energy planning. *Applied Energy*, *235*, 356–368. doi:10.1016/j.apenergy.2018.10.099.

Prina, M. G., Manzolini, G., Moser, D., Nastasi, B., & Sparber, W. (2020b). Classification and challenges of bottom-up energy system models - A review. *Renewable and Sustainable Energy Reviews*, *129*, 109917. doi:10.1016/j.rser.2020.109917.

Prina, M. G., Manzolini, G., Moser, D., Vaccaro, R., & Sparber, W. (2020c). Multi-Objective Optimization Model EPLANopt for Energy Transition Analysis and Comparison with Climate-Change Scenarios. *Energies*, *13*, 3255. doi:10.3390/en13123255.

Pursiheimo, E., Holttinen, H., & Koljonen, T. (2017). Path toward 100% renewable energy future and feasibility of power–to–gas technology in Nordic countries. *IET Renewable Power Generation*, *11*, 1695–1706. doi:10.1049/iet-rpg.2017.0021.

Rabbani, M., Saravi, N. A., Farrokhi-Asl, H., Lim, S. F. W., & Tahaei, Z. (2018). Developing a sustainable supply chain optimization model for switchgrass-based bioenergy production: A case study. *Journal of Cleaner Production*, *200*, 827–843. doi:10.1016/j.jclepro.2018.07.226.

Rasku, T., & Kiviluoma, J. (2019). A Comparison of Widespread Flexible Residential Electric Heating and Energy Efficiency in a Future Nordic Power System. *Energies*, *12*, 5. doi:10.3390/en12010005.

Rasku, T., Miettinen, J., Rinne, E., & Kiviluoma, J. (2020). Impact of 15-day energy forecasts on the hydro-thermal scheduling of a future Nordic power system. *Energy*, *192*, 116668. doi:10.1016/j.energy.2019.116668.

Razm, S., Nickel, S., & Sahebi, H. (2019). A multi-objective mathematical model to redesign of global sustainable bioenergy supply network. *Computers & Chemical Engineering*, *128*, 1–20. doi:10.1016/j.compchemeng.2019.05.032.

Ren, H., Zhou, W., Nakagami, K., Gao, W., & Wu, Q. (2010). Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. *Applied Energy*, *87*, 3642–3651. doi:10.1016/j.apenergy.2010.06.013.

Roddis, P., Carver, S., Dallimer, M., Norman, P., & Ziv, G. (2018). The role of community acceptance in planning outcomes for onshore wind and solar farms: An energy justice analysis. *Applied Energy*, *226*, 353–364. doi:10.1016/j.apenergy.2018.05.087.

Rodrigues, S., Bauer, P., & Bosman, P. A. (2016). Multi-objective optimization of wind farm layouts – Complexity, constraint handling and scalability. *Renewable and Sustainable Energy Reviews*, *65*, 587–609. doi:10.1016/j.rser.2016.07.021.

Rosen, J. (2008). *The future role of renewable energy sources in European electricity supply: A model-based analysis for the EU-15*. KIT Scientific Publishing. doi:10.5445/KSP/1000007531.

Sadiqa, A., Gulagi, A., & Breyer, C. (2018). Energy transition roadmap towards 100% renewable energy and role of storage technologies for Pakistan by 2050. *Energy*, *147*, 518–533. doi:10.1016/j.energy.2018.01.027.

Samsatli, S., & Samsatli, N. J. (2015). A general spatio-temporal model of energy systems with a detailed account of transport and storage. *Computers & Chemical Engineering*, *80*, 155–176. doi:10.1016/j.compchemeng.2015.05.019.

Samsatli, S., & Samsatli, N. J. (2018). A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies. *Applied Energy*, *220*, 893–920. doi:10.1016/j.apenergy.2017.09.055.

Samsatli, S., Samsatli, N. J., & Shah, N. (2015). BVCM: A comprehensive and flexible toolkit for whole system biomass value chain analysis and optimisation – Mathematical formulation. *Applied Energy*, *147*, 131–160. doi:10.1016/j.apenergy.2015.01.078.

Schreiber, S., Zöphel, C., & Möst, D. (2021). Optimal Energy Portfolios in the Electricity Sector: Trade-Offs and Interplay Between Different Flexibility Options. In D. Möst, S. Schreiber, A. Herbst, M. Jakob, A. Martino, & W.-R. Poganietz (Eds.), *The Future European Energy System: Renewable Energy, Flexibility Options and Technological Progress* (pp. 177–198). Cham: Springer International Publishing. doi:10.1007/978-3-030-60914-6_10.

Schwartz, Y., Raslan, R., & Mumovic, D. (2016). Implementing multi objective genetic algorithm for life cycle carbon footprint and life cycle cost minimisation: A building refurbishment case study. *Energy*, *97*, 58–68. doi:10.1016/j.energy.2015.11.056.

Sedighizadeh, M., Esmaili, M., & Mohammadkhani, N. (2018). Stochastic multi-objective energy management in residential microgrids with combined cooling, heating, and power units considering battery energy storage systems and plug-in hybrid electric vehicles. *Journal of Cleaner Production*, *195*, 301–317. doi:10.1016/j.jclepro.2018.05.103.

Short, W., Sullivan, P., Mai, T., Mowers, M., Uriarte, C., Blair, N., Heimiller, D., & Martinez, A. (2011). Regional Energy Deployment System (ReEDS). doi:10.2172/1031955.

Slednev, V., Bertsch, V., & Fichtner, W. (2017). A Multi-objective Time Segmentation Approach for Power Generation and Transmission Models. In K. F. Doerner, I. Ljubic, G. C. Pflug, & G. Tragler (Eds.), *Operations Research Proceedings 2015* Operations research proceedings (pp. 707–714). Cham, Switzerland: Springer.

Soroudi, A., & Afrasiab, M. (2012). Binary PSO-based dynamic multi-objective model for distributed generation planning under uncertainty. *IET Renewable Power Generation*, *6*, 67. doi:10.1049/iet-rpg.2011.0028.

Sperber, E., Frey, U., & Bertsch, V. (2020). Reduced-order models for assessing demand response with heat pumps – Insights from the German energy system. *Energy and Buildings*, *223*, 110144. doi:10.1016/j.enbuild.2020.110144.

St Louis, M. E., & Hess, J. J. (2008). Climate change: impacts on and implications for global health. *American Journal of Preventive Medicine*, *35*, 527–538. doi:10.1016/j.amepre.2008.08.023.

Staffell, I. (no date). 2050 DESSTINEE. URL: https://sites.google.com/site/2050desstinee/ [Accessed 23 December 2021].

Tietze, I., Lazar, L., Hottenroth, H., & Lewerenz, S. (2020). LAEND: A Model for Multi-Objective Investment Optimisation of Residential Quarters Considering Costs and Environmental Impacts. *Energies*, *13*, 614. doi:10.3390/en13030614.

United Nations (2015). Paris Agreement. URL: https://unfccc.int/sites/default/files/english_paris_agreement.pdf [Accessed 28 January 2021].

Unsihuay-Vila, C., Marangon-Lima, J. W., Zambroni de Souza, A. C., & Perez-Arriaga, I. J. (2011). Multistage expansion planning of generation and interconnections with sustainable energy development criteria: A multiobjective model. *International Journal of Electrical Power & Energy Systems*, *33*, 258–270. doi:10.1016/j.ijepes.2010.08.021.

Wiecek, M. M., Ehrgott, M., & Engau, A. (2016). Continuous Multiobjective Programming. In S. Greco, M. Ehrgott, & J. R. Figueira (Eds.), *Multiple Criteria Decision Analysis* International Series in Operations Research & Management Science (pp. 739–815). New York, N.Y: Springer New York. doi:10.1007/978-1-4939-3094-4_18.

Wierzbowski, M., Lyzwa, W., & Musial, I. (2016). MILP model for long-term energy mix planning with consideration of power system reserves. *Applied Energy*, *169*, 93–111. doi:10.1016/j.apenergy.2016.02.003.

Wiese, F., Bramstoft, R., Koduvere, H., Pizarro Alonso, A., Balyk, O., Kirkerud, J. G., Tveten, Å. G., Bolkesjø, T. F., Münster, M., & Ravn, H. (2018). Balmorel open source energy system model. *Energy Strategy Reviews*, *20*, 26–34. doi:10.1016/j.esr.2018.01.003.

Xu, L., Fuss, M., Poganietz, W.-R., Jochem, P., Schreiber, S., Zoephel, C., & Brown, N. (2020). An Environmental Assessment Framework for Energy System Analysis (EAFESA): The method and its application to the European energy system transformation. *Journal of Cleaner Production*, *243*, 118614. doi:10.1016/j.jclepro.2019.118614.

Yamchi, H. B., Safari, A., & Guerrero, J. M. (2021). A multi-objective mixed integer linear programming model for integrated electricity-gas network expansion planning considering the impact of photovoltaic generation. *Energy*, *222*, 119933. doi:10.1016/j.energy.2021.119933.

Yuan, X., Tian, H., Yuan, Y., Huang, Y., & Ikram, R. M. (2015). An extended NSGA-III for solution multi-objective hydro-thermal-wind scheduling considering wind power cost. *Energy Conversion and Management*, *96*, 568–578. doi:`10.1016/j.enconman.2015.03.009`.

Zangeneh, A., Jadid, S., & Rahimi-Kian, A. (2011). A fuzzy environmental-technical-economic model for distributed generation planning. *Energy*, *36*, 3437–3445. doi:`10.1016/j.energy.2011.03.048`.

Zappa, W., Junginger, M., & van den Broek, M. (2019). Is a 100% renewable European power system feasible by 2050? *Applied Energy*, *233-234*, 1027–1050. doi:`10.1016/j.apenergy.2018.08.109`.

Zhang, Q., Mclellan, B. C., Tezuka, T., & Ishihara, K. N. (2012). Economic and environmental analysis of power generation expansion in Japan considering Fukushima nuclear accident using a multi-objective optimization model. *Energy*, *44*, 986–995. doi:`10.1016/j.energy.2012.04.051`.

Appendix A. Further material

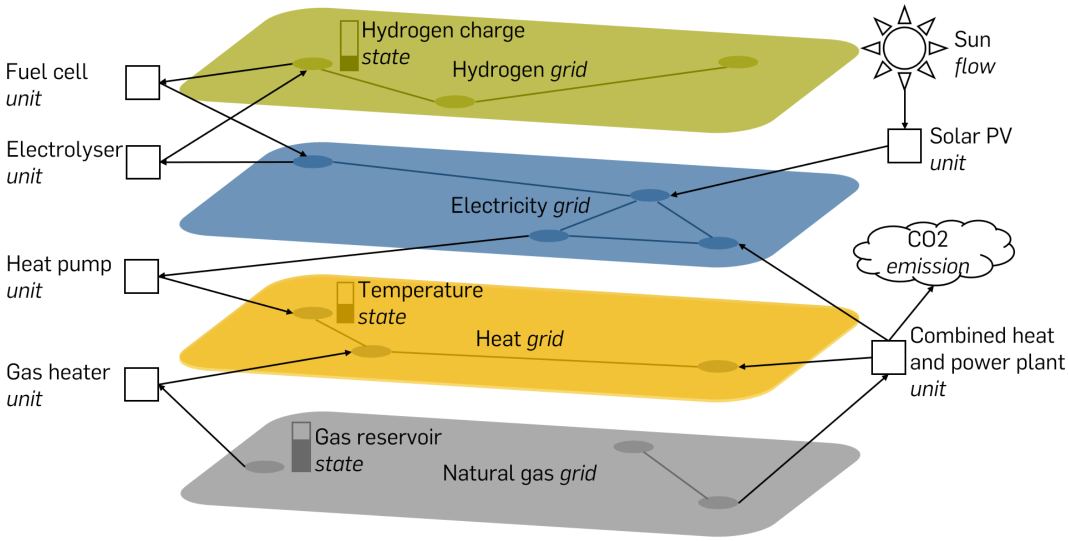

Figure A.8: An illustrative network structure in Backbone. The network consists of *nodes* (circles) in *grids* (coloured areas), connected by coloured *lines*. *Units* (black sqaures) convert energy with possibly multiple inputs and outputs (black arrows). Inputs can come from *nodes* or *flows* (sun) and outputs can go to *nodes* or *emissions* (cloud). Nodes in one grid have the same type of energy and the nodal *state* (partially filled rectangles) represents the energy content of a node.

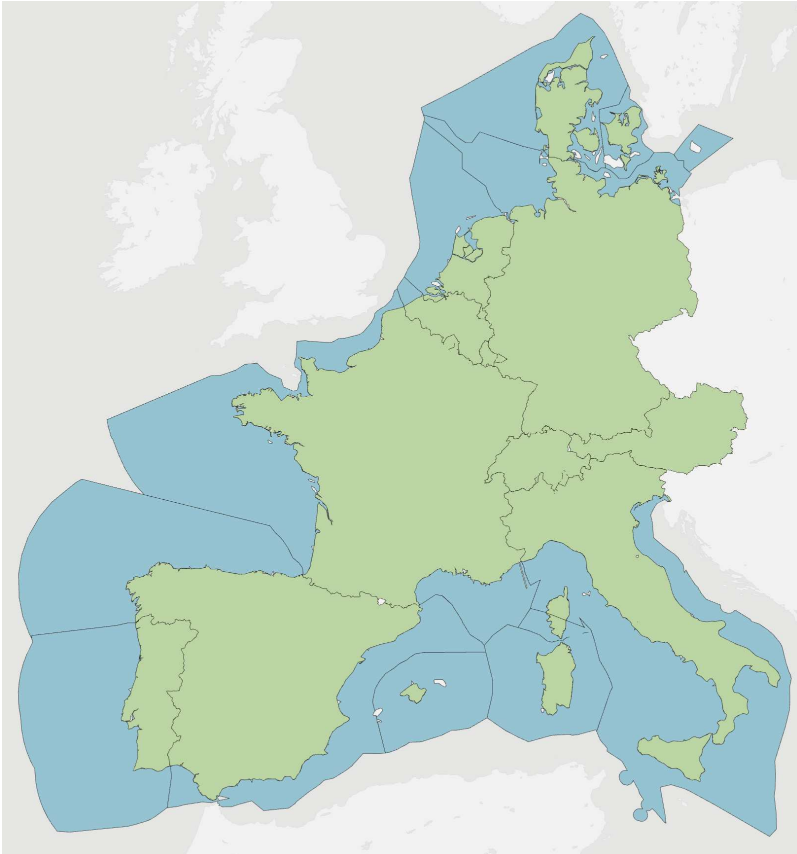

Figure A.9: Geographical scope of the Southern and Western European power sector model. For each green land area, transformer stations are aggregated to one grid node with the adjacent blue area being for offshore wind turbines. Figure created using Geo Data Viewer for Visual Studio Code.

Table A.2: Selected techno-economic data for power generation and storage units as well as fuels. The investment costs for storage units in this table are the sum of charging unit, discharging unit and reservoir. Abbreviations: O&M = operation and maintenance, PV = photovoltaic, n.a. = not applicable, CCGT = closed cycle gas turbine, OCGT = open cycle gas turbine, n.i. = not investable.

Technology	Investment cost (EUR/kW)	Fixed O&M (%/yr)	Lifetime (yr)	Variable O&M (EUR/MWh)	Efficiency (%)	Fuel cost (EUR/MWh)	Fuel emissions (kg CO_2/MWh_{th})
Solar PV	326	1	25	0	n.a.	n.a.	n.a.
Onshore wind	923	3	25	0	n.a.	n.a.	n.a.
Offshore wind	1700	3	25	0	n.a.	n.a.	n.a.
CCGT	900	3	45	4	57	32	200
Battery	768	1	20	0	64	n.a.	n.a.
H_2 storage	1246.8	2	20*	0	31.5	n.a.	n.a.
OCGT	n.i.	n.i.	n.i.	3	41	32	200
Hard coal	n.i.	n.i.	n.i.	6	44	13	347
Lignite	n.i.	n.i.	n.i.	9	41.5	3.6	387
Oil	n.i.	n.i.	n.i.	3	42	69.5	290
Nuclear	n.i.	n.i.	n.i.	5	33	7.2	0
Biomass	n.i.	n.i.	n.i.	6	42	72	0
Hydro	n.i.	n.i.	n.i.	0	100	n.a.	n.a.
Run of river	n.i.	n.i.	n.i.	0	90	n.a.	n.a.
Geothermal	n.i.	n.i.	n.i.	0	23.9	n.a.	26
Pumped Hydro	n.i.	n.i.	n.i.	0	100	n.a.	n.a.

*20 years for electrolysis and reservoir, 40 years for fuel cell

Table A.3: List of mathematical nomenclature.

Symbol	Meaning
$v^{\mathrm{costObj}}_{(\mathrm{AUGMECON})}$	Variable for cost objective function (for AUGMECON)
$v^{\mathrm{emissionObj}}_{e}$	Variable for emission objective function
$v^{\mathrm{generationObj}}_{G,io,(\mathrm{AUGMECON})}$	Variable for generation objective function (for AUGMECON)
$v^{\mathrm{vomCost}}_{f,t}$	Variable for variable operation and maintenance cost
$v^{\mathrm{fuelCost}}_{f,t}$	Variable for fuel cost
$v^{\mathrm{startupCost}}_{f,t}$	Variable for startup cost
$v^{\mathrm{shutdownCost}}_{f,t}$	Variable for shutdown cost
$v^{\mathrm{rampCost}}_{f,t}$	Variable for ramping cost
$v^{\mathrm{stateCost}}_{f,t}$	Variable for cost related to nodal state
$v^{\mathrm{penalties}}_{f,t}$	Variable for penalties
v^{fomCost}	Variable for fixed operation and maintenance cost
$v^{\mathrm{unitInvestCost}}$	Variable for unit investment cost
$v^{\mathrm{lineInvestCost}}$	Variable for transmission line investment cost
$v^{\mathrm{generationEmission}}_{f,t,e}$	Variable for generation-based emissions
$v^{\mathrm{startupEmission}}_{f,t,e}$	Variable for startup emissions
$p^{\mathrm{probability}}_{f,t}$	Parameter for probability
$p^{\mathrm{emissionCap}}_{e}$	Parameter for emission cap of e
$p^{\mathrm{costLimit}}$	Parameter for cost limit
$p^{\mathrm{generationLimit}}_{G,io}$	Parameter for generation limit
p^{Weight}_{G}	Parameter for weighting generation from group G
$p^{\mathrm{lowestEmission}}_{\mathrm{CO}_2}$	Parameter for lowest CO_2 emissions
$p^{\mathrm{highestEmission}}_{\mathrm{CO}_2}$	Parameter for highest CO_2 emissions
f, t, e	Indices for forecast, time step and emission type
G, io	Index for group and in- or output
$V \subset \mathbb{R}^n$	Variable set
$O \subset \mathbb{R}^k$	Objective set
$K = \{1, \ldots, k\}$	Index set
$P \subset V$	Pareto set
$P^* \subset O$	Pareto front
$i, j \in K$	Indices
$k, m, n \in \mathbb{N}$	Indices
$x, x' \in V$	Variables
$s, s_i \in \mathbb{R}$	Slack variables
$f = (f_1, ..., f_k)$	Objective functions
w_i	Objective weights
d	Distribution and number of emission caps
$N, U \in \mathbb{R}^k$	Nadir and utopia point
$\varepsilon_i \in \mathbb{R}$	Constraint for objective i
$c \in \mathbb{R}$	Small constant for AUGMECON