EnergyScope TD:
a novel open-source model for regional energy systems*

Gauthier Limpens[†1,2], Stefano Moret[2], Hervé Jeanmart[1], and Francois Maréchal[2]

[1] *Institute of Mechanics, Materials and Civil Engineering, Université catholique de Louvain, Belgium*

[2] *Industrial Process and Energy Systems Engineering (IPESE), École Polytechnique Fédérale de Lausanne, Switzerland*

September 18, 2019

Abstract

The transition towards more sustainable, fossil-free energy systems is interlinked with a high penetration of stochastic renewables, such as wind and solar. Integrating these new energy resources and technologies will lead to profound structural changes in energy systems, such as an increasing need for storage and a radical electrification of the heating and mobility sectors. To capture the increasing complexity of such future energy systems, new flexible and open-source optimization modelling tools are needed.

This paper presents EnergyScope TD, a novel open-source model for the strategic energy planning of urban and regional energy systems. Compared to other existing energy models, which are often proprietary, computationally expensive and mostly focused on the electricity sector, EnergyScope TD optimises both the investment and operating strategy of an entire energy system (including electricity, heating and mobility). Additionally, its hourly resolution (using typical days) makes the model suitable for the integration of intermittent renewables, and its concise mathematical formulation and computational efficiency are appropriate for uncertainty applications. We present the linear programming model, detailing its formulation, and we apply it to a real-world case study to discuss advantages and disadvantages in comparison to other modelling frameworks. In particular, we model the national energy system of Switzerland to evaluate a 50% renewable energy scenario.

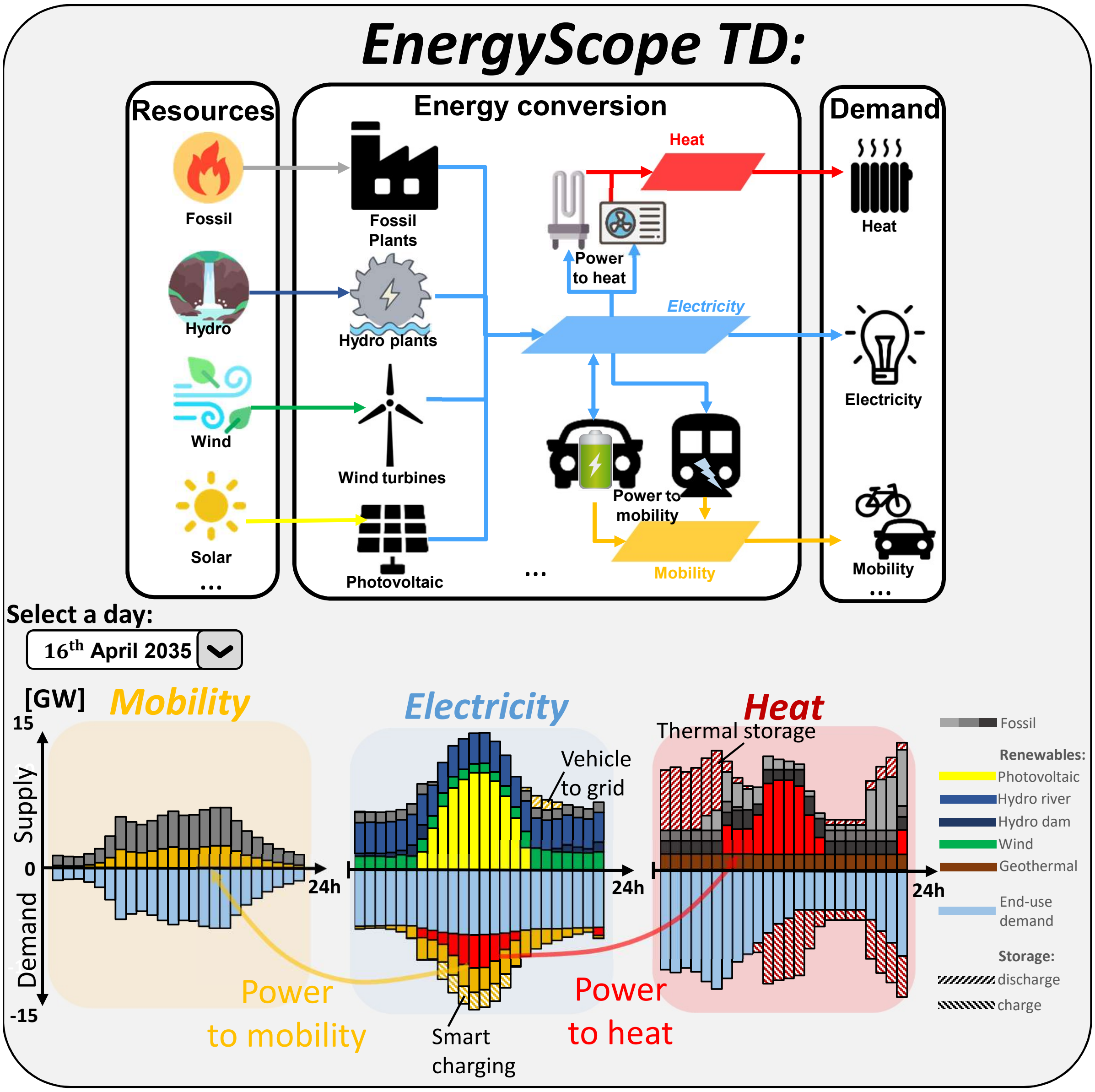
*Graphical Abstract and Supplementary Material available.

†gauthier.limpens@uclouvain.be

This is the pre-print (accepted) version of the paper.
Published version: Limpens G, Moret S, Jeanmart H, Maréchal F,
EnergyScope TD: a novel open-source model for regional energy systems.
Appl Energy 2019; Volume 255. DOI : `https://doi.org/10.1016/j.apenergy.2019.113729`

Contents

Graphical Abstract



Highlights

- Novel open-source model for long-term energy planning.
- Multi-sector modelling: electricity, heat and mobility.
- Optimization of design and operation for a target future year.
- Suitable for scenarios with high penetration rates of renewables and storage.
- Computational efficiency: hourly time resolution using typical days.

1 Introduction

The energy transition towards fossil-free energy systems requires profound structural changes - such as a novel production mix based on renewable resources, a shift to more efficient technologies as well as more sobriety in energy use. As an example, wind and solar are expected to play a major role for electricity production, as highlighted in various studies for Denmark [1], the United Kingdom [2], Belgium [3, 4], Europe [5], the United States of America [6] or even on a global scale [7]. At the same time, technologies such as heat pumps and electric vehicles can make heating and mobility more efficient [8, 9]. In addition, daily and seasonal storage technologies will be needed to ensure security of energy supply, in particular with high penetration rates of intermittent renewables. Several studies highlight the need of storage for the power grid [10, 11] or the entire energy system [12].
Overall, this transition implies a rising complexity along both the technical and socio-economic dimensions due to the increasing cross-sectoral interactions and the penetration of new technologies in the market. In this context, energy models can help understand these dynamics and thus plan future energy systems. In particular, in this paper we present EnergyScope TD, a novel open-source model for long-term energy planning, which allows to consider such dynamics in a computationally efficient way.

The paper is structured as follows. In Sections 1.1-1.3, we offer an overview of existing models and compare them in order to identify the scientific contribution of EnergyScope Typical Days (EnergyScope TD). In Section 2, we present the typical days approach and describe the model, detailing the linear programming (LP) formulation. In Section 3, we present the real-world case study of the Swiss national energy system. In Section 4, we apply the methodology to a 50% RE Swiss energy system and illustrate the performances of the model. In Section 5, we generalise the key features of the model and discuss its advantages/disadvantages compared to other models.

1.1 Overview of existing energy models

In the literature, a large variety of energy models exists. In this context, why is another energy model needed? Building on previous work by Connolly et al. [13], Pfenninger et al. [14], Prina et al. [15] and the Open Energy Modelling Initiative (Openmod) community [16], we performed an extensive review of 53 existing energy models and tools (summarised in Table 6, Appendix A). Here, we briefly summarise the results of such comparison, while the extended analysis is available in Appendix A.
Traditionally, energy models focus only on a given sector without considering cross-sectoral interactions. Examples of these models are Dispa-SET [17] or SciGRID [18] which, like many others (18 out of the 53 reviewed models), model only the electric power system. Out of the remaining 35 models, 16 partially account for the heating and the electricity sectors, and 15 partially account for the mobility sector. A major part of these models (26) consider cross-sectoral interactions in a simplified way and/or represent just a part of the energy system. Moreover, out of the 53 models, 14 are not fully open-access, such as STREAM [19, 20], NEMS [21] or MARKAL/TIMES [20], and 20 are not open-source, such as Plexos Open EU [22] or EnergyPLAN [23].
Energy models can either optimise or simulate the investment and/or the operation of the energy system. According to Wurbs [24], a simulation model is "*a representation of a system used to predict the behaviour of the system under a given set of conditions*", whereas an optimisation model is "*a mathematical formulation in which a formal algorithm is used to compute a set of decision-variable values that minimize or maximize an objective function subject to constraints*".

As a consequence, in a simulation the degrees of freedom are fixed *a priori* by the modeller, who defines a set of conditions which directly influence the results. Optimisation, instead, can reveal optimal configurations over a large number of available options and degrees of freedom, making it more suitable for analysing complex systems, where many combined alternatives need to be explored. As a drawback, optimisation is computationally more expensive, which represents a fundamental barrier for uncertainty applications [25]. In summary, optimisation and simulation are both powerful tools suitable for different applications. In this work, we adopt optimisation as a large number of options are unknown in a complex system. This approach is similar to 15 of the 53 models reviewed, which optimise - at least partially - operation and investments.

1.2 Comparison with other energy models

In Table 1, we report an extract of our detailed analysis from Table 6, comparing EnergyScope TD to the most similar energy models, i.e. a subset of the 53 reviewed models which present the following features: freely available; with a monthly to hourly time resolution; and modelling, at least partially, mobility and heat supply besides the electricity sector. The MARKAL/TIMES [20] model is added as the reference commercial model. The models are compared based on the following four criteria (also used in other reviews [13–16]): (i) Does the model include electricity, heating and mobility, considering cross-sectoral interactions? (ii) Is the model open source? (iii) Does it optimise the investment and/or the hourly operation strategy? (iv) Is the computational time acceptable for uncertainty analysis? These criteria are critical in order to identify an energy model that: (i) represents the full energy system at an urban or national scale, (ii) is open-source and open access, (iii) optimises both investments and operation while having a time resolution of at least 1h over a year and (iv) has an acceptable computational time for uncertainty analysis. Such energy model can be used to assess the promising technologies and synergies among all sectors in future energy systems with high shares of renewable energies (RE). The selected criteria is the result of the research approach presented in 2.1. Other criteria could have been applied to energy models, such as the market equilibrium or spatial resolution criteria used in reviews [13, 14]. They are discussed in Section 5.

The analysis reveals that models are neither open-source nor optimization-based except the following 7 models: DIETER [31], URBS [40, 41], Switch [38, 39], PyPSA [36, 37], OSeMOSYS [34, 35], Oemof [32, 33], Calliope [26, 27]. The first four models do not fully represent the energy sector as they focus mainly on the power system. DIETER offers a more detailed representation of the electricity system; however, the heating sector is modelled in an excessively simplified way. URBS is a LP optimisation model for capacity expansion planning and unit commitment for distributed energy systems. The Mobility sector is simplified and accounts only for interactions between the power grid and electric vehicles (EVs). Switch is a capacity-planning model for power systems with large shares of renewable energy, storage and/or demand response. Similarly to URBS, it accounts only for EVs in the mobility sector. PyPSA is "*a free software toolbox for simulating and optimising modern electrical power systems over multiple periods*" [36]: the power system is modelled in more detail, while the other sectors can be included but usually are simplified. OSeMOSYS optimises the investment strategy over multiple years, while computing partially the operation cost based on time slices. This model is suitable to study the long-run integration of technologies and energy planning; as a drawback, it simplifies the system operations to a few critical hours over the year. As an example, the proposed application in [34] uses 6 times slices which is far from the 8760 hours of the year. Oemof "*forms a toolbox to construct comprehensive energy system models*" [32]. Its active community makes it a promising toolbox for energy system modelling; however, it is not yet ready for uncertainty modelling [16]. Similarly to Oemof, Calliope [26] is rather a toolbox than an energy model. At the time of

Table 1: Comparison of existing large-scale energy planning models. Legend : ✔criterion satisfied; ✓ criterion partially satisfied; ✗ criterion not satisfied. Data from [13–16, 25].

Model	Multi-sector	Open-source	Optimisation	Comp. time
Calliope [16, 26, 27]	✓ [a]	✔	✔	mins [b]
COMPOSE [13, 28]	✔	✗	✔	- [c]
DESSTinEE [16, 29, 30]	✔	✔	✗	s
DIETER [16, 31]	✗ [d]	✔	✔	mins [b]
EnergyPLAN [13, 23]	✔	✗	Operation only	s
MARKAL/TIMES [20, 25]	✔	✗	Investment only	5-35 mins
Oemof [16, 32, 33]	✔	✔	✔	mins [b]
OSeMOSYS [16, 34, 35]	✔	✔	✓ [e]	mins
PyPSA [16, 36, 37]	✓ [a]	✔	✔	mins
STREAM [13, 19]	✓ [f]	✗	✗	- [c]
Switch [16, 38, 39]	✗ [d]	✔	✔	10-60 mins
URBS [16, 40, 41]	✗ [d]	✔	✔	20 mins
EnergyScope TD	✔	✔	✔	$\sim$ 1 min

[a]The model focuses on the power system with the possibility to implement other sectors.
[b]Not suitable for uncertainty characterisation, yet [16] .
[c]Data missing
[d]Energy system includes partially heat and transport sectors.
[e]Operation is usually not resolved on a hourly base.
[f]Energy system includes partially transport sector.

writing, no publication using Oemof [33] and Calliope [27] adopts these toolboxes to define a multi-sector energy model representing an entire energy system including electricity, heat and mobility.

As shown in Table 1, the different models proposed in the literature have multiple specific advantages but feature one or more of the following limitations: (i) being limited to only one sector (usually the electricity sector); (ii) representing sectors with different level of details (usually by simplifying heating and mobility); (iii) being commercial, i.e. not freely available nor open-source; (iv) not optimising both the investment and the hourly operation strategy; (v) not suitable for uncertainty applications.

1.3 Scientific contribution

Consequently, we propose a novel LP energy system modelling framework. The model, called EnergyScope Typical Days (EnergyScope TD)[2], builds on - and represents a major advancement compared to - previous energy system modelling work by Moret, Maréchal and coauthors [25, 42–46]. In its previous version the tool has been used in different research projects. It was first developed as an online calculator (`http://www.energyscope.ch`) to disseminate energy literacy [45] and then extended to an optimization model to support decision-makers [43]. Based on our experience with cities and industrial partners[1], even if many models exist, in the practice they are not used for regional and urban planning, where most work is done in a manual or artisanal way. Our goal is to address this urgent issue by providing a general model, such as EnergyScope TD. The model has been used to analyse the integration of deep geothermal and woody biomass conversion pathways in urban systems [47]. At a national scale, it was used

[1]Additional information provided on the website: `https://ipese.epfl.ch/`.

to assess the CO2 mititgation potential of biomass [48] or its optimal use [49]. In a broader context, the tool has been applied to optimise the integration of renewable energy [46], and for strategic energy planning under uncertainty [25, 43, 50].

Based on the reviewed literature, the contribution of EnergyScope TD is to propose an open model to optimise the design and operation of an urban or regional energy system accounting for all the energy carriers and demand with an hourly resolution over a target year. The aim of the tool is to study sectors interactions and promising technologies implementation, such as storage, during the energy transition. With respect to the listed limitations, (i-ii) the model represents with the same level of detail the heating, mobility and electricity sectors. According to the classification proposed by Codina Gironès et al. [45], the modelling framework belongs to the "snapshot" category, as it models the energy system in a target future year. This year is representative of all the years in which the system is operated. (iii) EnergyScope TD is open-source[2]. The code can be run out-of-the-box, using the data for the Swiss energy system as an example. We provide a full documentation, both in terms of formulation and data input, and a user guide (both available as Supplementary Material). (iv) The model has an hourly resolution, which allows accounting for seasonality and energy storage. (v) Resolving a complex energy system over the 8760 hours of the year is computationally not affordable for uncertainty applications. Different approaches modelling the temporal dimension have been analysed in [51], where it is shown that resorting to well chosen typical days can be a suitable approach. EnergyScope TD uses such approach, which allows the integration of intermittent renewables as well as daily to seasonal storage options, while featuring a computational time of around 1 minute on a personal laptop, which is appropriate for uncertainty applications. In fact, (vi) the proposed formulation is similar to the ones of Moret, Bierlaire, and Maréchal [43] and Moret et al. [50] where an uncertainty analysis is performed. In Section 5, we detail the contribution but also the limitations of EnergyScope TD.

2 Methodology

2.1 Research approach

Energy models can be developed in different ways. Key modelling choices typically include: optimisations vs. simulation, partial vs. entire representation of energy system, market equilibrium approach vs. energy based approach, level of granularity/resolution, target year ("snapshot") vs evolution, short vs. long computational time, etc. As no perfect strategy exists, and different strategies can suit different applications, these choices are ultimately made by the modeller after a careful evaluation.
In terms of approach, we choose an energy-based modelling approach over a market equilibrium one (such as MARKAL/TIMES [20] or NEMS [21]), as various retrospective studies (see Moret et al. [44] for a review) show the difficulty of forecasting the evolution of markets over long planning horizons. As for the implementation, we choose optimisation over simulation as the complexity of energy systems implies a large number of available options, which - as discussed in the Introduction - can be better explored by optimisation. In particular, we adopt an LP formulation which offers many practical - including computational - advantages. Similarly, in terms of level of detail, our aim is a good trade-off between model granularity and computational time. With respect to this, we choose to model the entire energy system in a target future year with an hourly level of detail, resorting to typical days (TDs) to ensure computational efficiency. Overall, these choices are appropriate for a multi-sector energy system model that can answer

[2] The code is available at: `https://github.com/energyscope/EnergyScope/tree/v2.0`

strategic planning questions such as *how to deal with the intermittency of RE?* or *what will be the role of storage technologies in the energy transition?*.

As a consequence of these choices, we have developed a methodology in two steps, as shown in Figure 1. Based on the input data (time series, scenarios and technologies), the first step consists in pre-processing them and solving a mixed-integer linear programming (MILP) problem to determine the adequate set of typical days (Section 2.2). The second step is the main energy model: it identifies the optimal design and operation of the energy system over the selected typical days (Section 2.3), i.e. technology selection, sizing and operation for a target future year. These two steps can be computed independently. Usually, first step is computed once for an energy system with given weather data whereas second step is computed several times (for each different scenario).

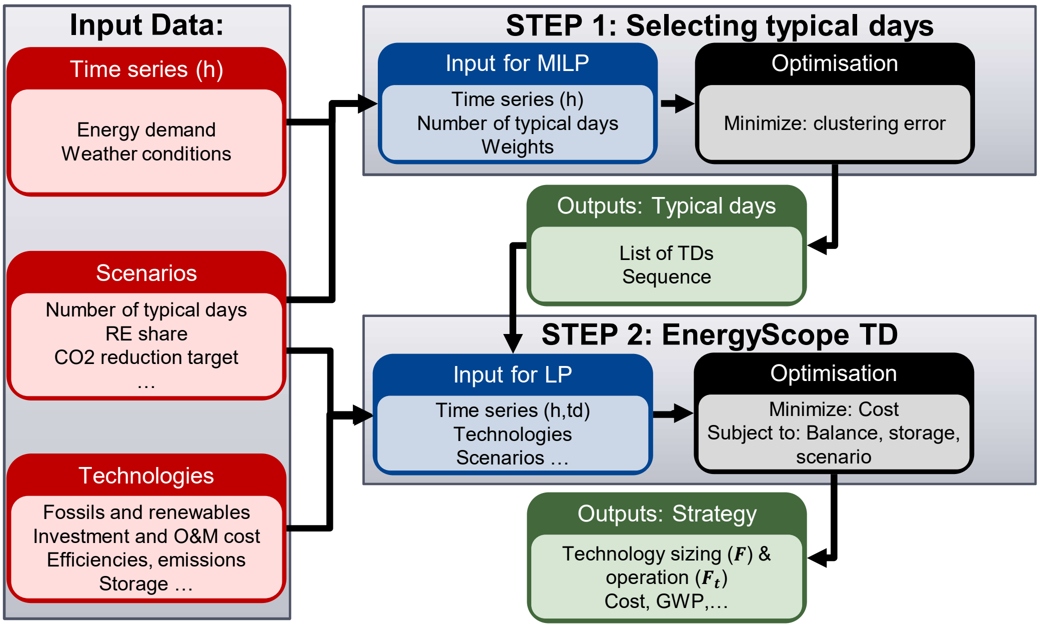


Figure 1: Overview of the two-step methodology. STEP 1: optimal selection of typical days (Section 2.2). STEP 2: Energy system model (Section 2.3). Input data used and their sources are listed in Supplementary Material. Abbreviations: typical day (TD), mixed-integer linear programming (MILP), linear programming (LP), global warming potential (GWP).

2.2 STEP 1: Selecting typical days

Due to computational restrictions, energy system models rarely optimise the 8760h of the year. As an example, running our model with 8760h time series takes more than 19 hours (from Table 5). A typical solution in this case is to use a subset of representative days called TDs; this is a trade-off between introducing an approximation error in the representation of the energy system (especially for short-term dynamics) and computational time. Resorting to TDs has the main advantage of reducing the computational time by several orders of magnitude. Usually, studies use between 6 and 20 TDs [52–55], or even less [56, 57]. As previously mentioned, using TDs can introduce some limitations. As an example, traditionally, model based on TDs are not able to include intra day or seasonal storage due to the discontinuity between the selected days. Thus, to achieve a coherent representation including seasonal storage, we first analyze different clustering methods to optimally select the TDs. Then, we include the recent method by Gabrielli et al. [52] in our framework to couple TDs and seasonal storage.

2.2.1 Clustering methods

In the literature, various approaches exist to select TDs. The simplest approaches are based on heuristic algorithms, such as selecting 2 extreme days per season, i.e. the ones with the highest and the lowest demand, respectively [56]. More advanced approaches exist, selecting TDs by clustering days which are similar based on given criteria. In this work, the criterion is to cluster days with similar demand and weather data. Hence, we consider five time series to define our clusters: two for end-use demand (electricity and space heating) and three for weather conditions (solar irradiance, wind speed and water flow in run-of-river hydro power plants). Depending on the importance of each time series, a weight can be associated to it. For every resulting cluster, the most representative existing day, also called centroid, can be taken as the TD of the cluster.

We compare four algorithms for TDs selection: a commonly used one and three recently developed algorithms. First, the k-medoids [58, 59] is a common and computationally efficient method [60] applied in similar studies [52, 57]. For every possible combination of TDs, the method clusters days by minimising their Euclidean distance. The combination of TDs offering the lowest error is thus selected as the optimum. As the problem is highly combinatorial, the solution space cannot be entirely explored; instead, a subnumber of combinations is randomly selected. The model evaluates only this subnumber of options, which results in a sub-optimal solution. The second method is a revisited version of the k-medoids algorithm developed by Domínguez-Muñoz et al. [57]. It is an integer formulation of the k-medoids problem based on an alternative method proposed by Vinod [61]: a MILP problem clusters days by minimising the distance between their time series and the optimal cluster time series. The third and fourth - here referred to as "Poncelet" and "Poncelet HYB", respectively - are both proposed by Poncelet et al. [56]. For both methods, the criterion is based on *duration curves*[3]. A MILP problem is solved to minimise the error between the real duration curve and the approximated duration curve based on TDs. Similarly to the k-medoids method, Poncelet's method tries every combination of TDs, which is again highly combinatorial. Hence, a variant called "Poncelet-HYB" is proposed, which resorts on samples of TDs. Both Poncelet and Poncelet-HYB do not cluster days and have thus been adapted to fit our application (see Appendix B for details).
These methods should normally be compared for the case study of interest, as we do in Section 4.1 for our example application.

2.2.2 Implementing seasonality with typical days

Traditional studies based on TDs, such as [56, 57], do not model inter days dynamics. This means that technologies storing energy one day to deliver it on the next day cannot be modelled with such an approach. Gabrielli et al. [52] formulated a novel approach to overcome this issue. In this approach, a TD is assigned to each day of the year; all decision variables are optimised over the TDs, apart from the amount of energy stored, which is optimised over 8760h.

From [52], we have implemented the "Coupling typical days" method (also called "Method 1" in [52]). Each day of the year is related to its TD through a sequence (TD_OF_DAY). With this approach, each day of the year is described by a given TD, and the energy stored during the last hour of every day is connected to the energy stored at the first hour of the following day.

[3] For a given hourly time series, the duration curve is a graph representing the time series sorted from the highest value (on the left) to the lowest (on the right): as an example; for the power duration curve, on a x-y graph, the peak yearly power demand hour is at $x = 1$, the lowest demand hour is at $x = 8760$.

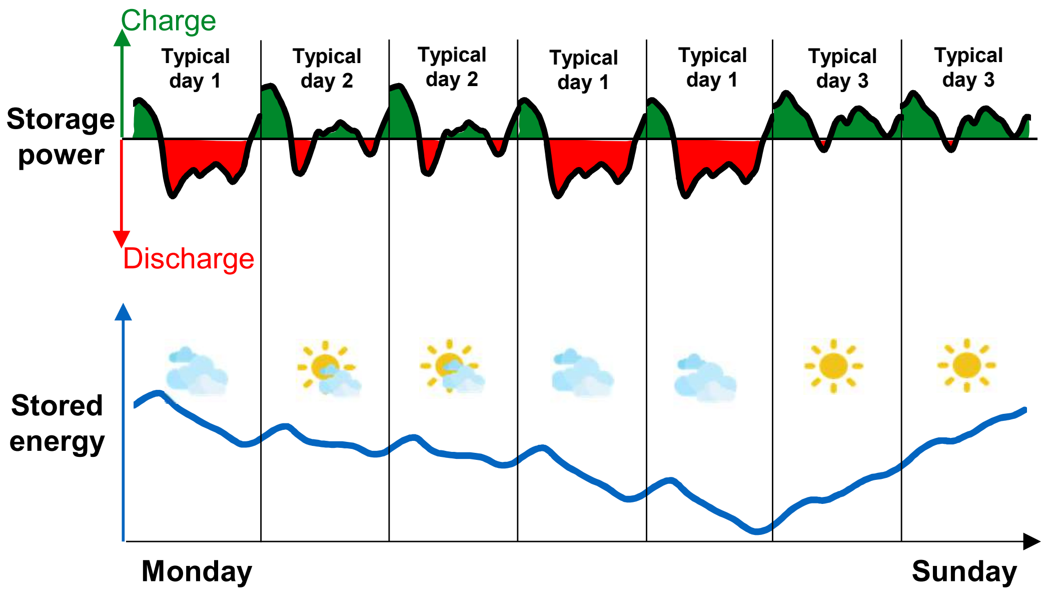


Figure 2: Illustration of the coupling method by [52] over a week. The example is based on 3 TDs: TD 1 represents a cloudy week day, such as Monday, Thursday and Friday; TD 2 is a sunny week day, such as Tuesday and Wednesday; and TD 3 represents sunny weekend days. The power profile (above) depends solely on the typical day but the energy stored (below) is optimised over the 168 hours of the week (blue curve).

Figure 2 gives an illustration of how the storage works over a week with 3 TDs. In this example, the storage is used during weekdays and more especially cloudy week days (Monday, Thursday and Friday); during the weekend, instead, the storage is refilled. The power is resolved based on independent TDs; instead, the energy is resolved over the 8760h of the year.

2.3 STEP 2: EnergyScope TD

Hereafter, we present the core of the energy model. First, we introduce the conceptual modelling framework with an illustrative example, in order to clarify as well the nomenclature adopted in the paper. Second, we introduce the key constraints of the energy model. The detailed and complete formulation with a description of sets, parameters, variables, all the constraints and data is provided in the Supplementary Material.

The energy model structure and mathematical formulation is based on previous works by Moret et al. [42] and Codina Gironès et al. [45], later extended to a MILP formulation [43] and also used for different studies about integration of RE [46, 49]. The key novelties here are the hourly resolved problem, the TDs implementation with seasonality, and the addition of multiple technologies, mostly for storage applications.

2.3.1 Conceptual modelling framework

The proposed modelling framework is a simplified representation of an energy system accounting for the energy flows within its boundaries. Its primary objective is to satisfy the energy balance constraints, meaning that the demand is known and the supply has to meet the demand. In the energy modelling practice, the energy demand is often expressed in terms of final energy consumption (FEC). According to the definition of the European commission, FEC is defined as "*the energy which reaches the final consumer's door*" [62]. In other words, the FEC is the amount of input energy needed to satisfy the end-use demand (EUD) in energy services. As an example, in the case of decentralized heat production with a natural gas (NG) boiler, the FEC is the amount of NG consumed by the boiler; the EUD is the amount of heat produced by the boiler, i.e. the heating service needed by the final user.

The input for the proposed modelling framework is the EUD in energy services, represented as the sum of three components: electricity, heating and mobility; this replaces the classical sector-based representation of energy demand. Heat is divided in three end-use types (EUTs): high temperature heat for industry demand, low temperature for space heating and low temperature for hot water. Mobility is divided in two EUTs: passenger mobility and freight.

A simplified conceptual example of the proposed energy system structure is proposed in Figure 3.

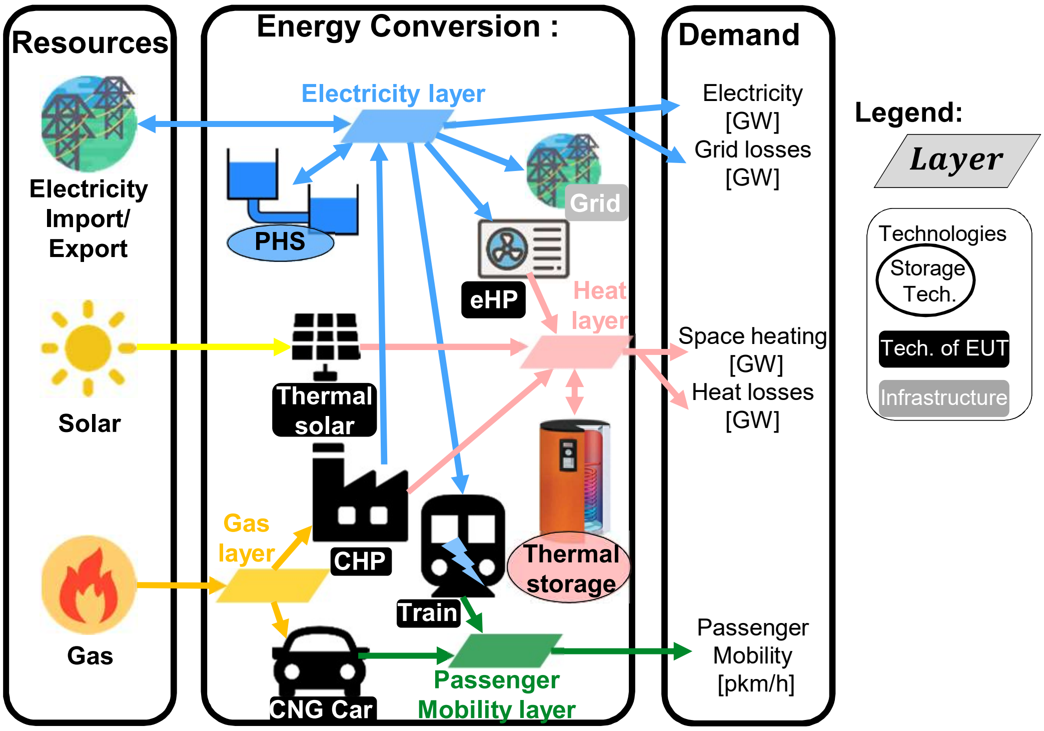


Figure 3: Conceptual example of an energy system with 3 resources, 8 technologies (of which 2 storage and 1 infrastructure) and 4 end use demand (of which 1 losses). Abbreviations: pumped hydro storage (PHS), electrical heat pump (eHP), combined heat and power (CHP), compressed natural gas (CNG). Some icons are made by Freepik from `www.flaticon.com`

The system is separated in three parts: resources, energy conversion and demand. In this illustrative example, resources are solar energy, electricity and NG. The EUD are electricity, space heating and passenger mobility. The energy system encompasses all the energy conversion technologies needed to transform resources and supply EUD. In this example, Solar and NG resources cannot be directly used to supply heat. Thus, they use technologies, such as boilers or combined heat and power (CHP) for NG, to supply the EUT layer (e.g. the high temperature industrial heat layer). *Layers* are defined as all the elements in the system that need to be balanced in each time period; they include resources and EUTs. An an example, the electricity layer must be balanced at any time, meaning that the production and storage must equal the consumption and losses. These layers are connected to each other by *technologies*. We define three types of technologies: *technologies of end-use type*, *storage technologies* and *infrastructure* *technologies*. A technology of end-use type can convert the energy (e.g. a fuel resource) from one layer to a EUT layer, such as a CHP unit that converts NG into heat and electricity. A storage technology converts energy from a layer to the same one, such as thermal storage (TS) that stores heat to provide heat. In this example, there are two storage technologies: TS for heat and pumped hydro storage (PHS) for electricity. An infrastructure technology regroups the remaining technologies including grids, such as the power grid and district heating networks (DHNs), but also technologies linking non end-use layers, such as methane production from wood gasification or hydrogen production from methane reforming.

2.3.2 Linear Programming model formulation

The energy system is formulated as a linear programming (LP) problem. It optimises the design by computing the installed capacity of each technology, as well as the operation in each period, to meet the energy demand and minimize the total annual cost of the system. In the following, we introduce the formulation by reporting the key constraints (Figure 4 and Eqs. 1-15). The complete formulation of the model is proposed in the Supplementary Material and describes sets, parameters, variables, constraints and the objective function.

End-use demand

The hourly end-use demand (**EndUses**) is computed based on the yearly end-use demand (*endUsesInput*), distributed according to a normalised time series.

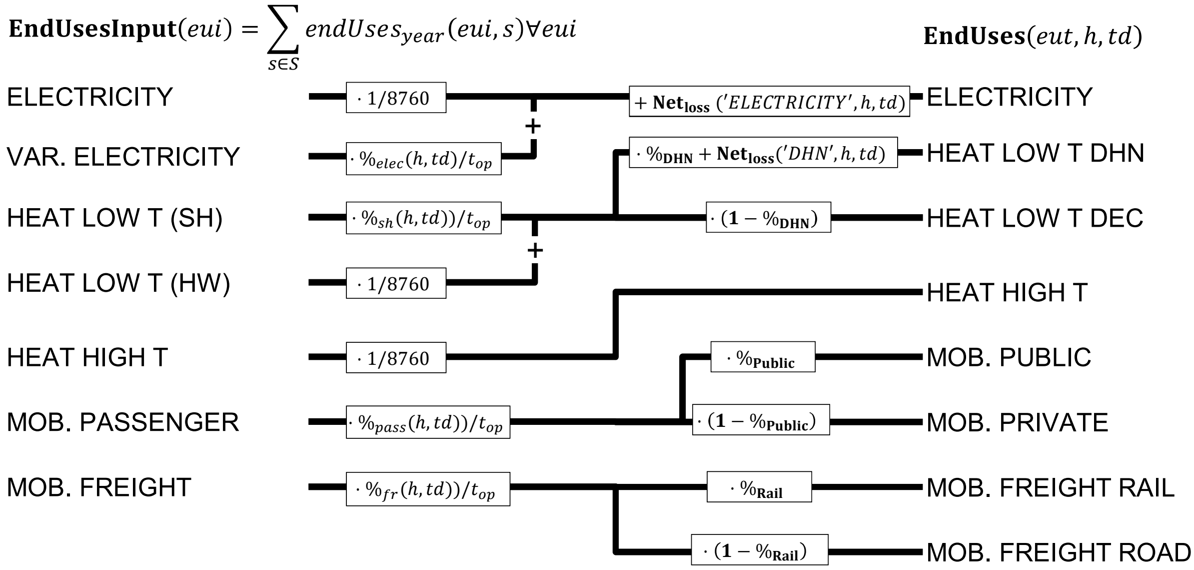


Figure 4: **EndUses** calculation starting from yearly demand model inputs (*endUsesInput*). Adapted from [25]. Abbreviations: space heating (sh), district heating network (DHN), hot water (HW), passenger (pass) and freight (fr).

Figure 4 graphically presents the constraints associated to the hourly end use demand (**EndUses**), e.g. the public mobility demand at time t is equal to the hourly passenger mobility demand times the public mobility share ($\%_{\mathbf{Public}}$).

Electricity end-uses result from the sum of the electricity-only demand, assumed constant throughout the year, and the variable demand of electricity, distributed across the periods according to $\%_{elec}$. Low-temperature heat demand results from the sum of the yearly demand for hot water (HW), evenly shared across the year, and space heating (SH), distributed across the periods according to $\%_{sh}$.

The percentage repartition between centralized (DHN) and decentralized heat demand is defined by the variable $\mathbf{\%_{DHN}}$. High temperature process heat and mobility demand are evenly distributed across the periods. Passenger mobility demand is expressed in passenger-kilometers (pkms), freight transportation demand is in ton-kilometers (tkms). The variables $\mathbf{\%_{Public}}$ and $\mathbf{\%_{Rail}}$ define the penetration of public transportation in passenger mobility and of train in freight, respectively.

Cost, emissions and objective function

The objective Eq. (1) is the minimisation of the total annual cost of the energy system ($\mathbf{C_{tot}}$), defined as the sum of the annualized investment cost of technologies (τ $\mathbf{C_{inv}}$), the operating and maintenance cost of technologies ($\mathbf{C_{maint}}$) and the operating cost of the resources ($\mathbf{C_{op}}$). The total investment cost ($\mathbf{C_{inv}}$) of each technology results from the multiplication of its specific investment cost (c_{inv}) and its installed size ($\mathbf{F}$), the latter defined with respect to the main end-uses output type Eq. (3). $\mathbf{C_{inv}}$ is annualised with the factor τ, calculated based on the interest rate (i_{rate}) and the technology lifetime (*lifetime*) Eq. (2). The total operation and maintenance cost is calculated in the same way Eq. (4). The total cost of the resources is calculated as the sum of the end-use over different periods multiplied by the period duration (t_{op}) and the specific cost of the resource (c_{op}) Eq. (5). Note that, in Eq. (5), summing over the typical days using the set *T_H_TD* is equivalent to summing over the 8760h of the year.

$$\min\ \mathbf{C_{tot}} = \sum_{j \in TECH} \Big(\tau(j)\mathbf{C_{inv}}(j) + \mathbf{C_{maint}}(j) \Big) + \sum_{i \in RES} \mathbf{C_{op}}(i) \tag{1}$$

$$\text{s.t.}\ \tau(j) = \frac{i_{rate}(i_{rate}+1)^{lifetime(j)}}{(i_{rate}+1)^{lifetime(j)}-1} \qquad \forall j \in TECH \tag{2}$$

$$\mathbf{C_{inv}}(j) = c_{inv}(j)\mathbf{F}(j) \qquad \forall j \in TECH \tag{3}$$

$$\mathbf{C_{maint}}(j) = c_{maint}(j)\mathbf{F}(j) \qquad \forall j \in TECH \tag{4}$$

$$\mathbf{C_{op}}(i) = \sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} c_{op}(i)\mathbf{F_t}(i,h,td)t_{op}(h,td) \qquad \forall i \in RES \tag{5}$$

The global annual greenhouse gas (GHG) emissions are calculated using a life cycle assessment (LCA) approach, i.e. taking into account emissions of technologies and resources "from cradle to grave". For climate change, the natural choice as indicator is the global warming potential (GWP), expressed in ktCO_2-eq./year. In Eq. (6), the total yearly emissions of the system ($\mathbf{GWP_{tot}}$) are defined as the sum of the emissions related to the construction and end-of-life of the energy conversion technologies ($\mathbf{GWP_{constr}}$), allocated to one year based on the technology lifetime (*lifetime*), and the emissions related to resources ($\mathbf{GWP_{op}}$). Similarly to the costs, the total emissions related to the construction of technologies are the product of the specific emissions (gwp_{constr}) and the installed size ($\mathbf{F}$), Eq. (7). The total emissions of resources are the emissions associated to fuels (from cradle to combustion) and imports of electricity (gwp_{op}) multiplied by the period duration (t_{op}) (Eq. 8).

$$\mathbf{GWP_{tot}} = \sum_{j \in TECH} \frac{\mathbf{GWP_{constr}}(j)}{lifetime(j)} + \sum_{i \in RES} \mathbf{GWP_{op}}(i) \tag{6}$$

$$\mathbf{GWP_{constr}}(j) = gwp_{constr}(j)\mathbf{F}(j) \quad \forall j \in TECH \tag{7}$$

$$\mathbf{GWP_{op}}(i) = \sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} gwp_{op}(i)\mathbf{F_t}(i,h,td)t_{op}(h,td) \quad \forall i \in RES \tag{8}$$

System design and operation

The installed capacity of technologies ($\mathbf{F}$) is constrained between upper and lower bounds (f_{max} and f_{min}), Eq. (9). This formulation allows accounting for old technologies still existing in the target year (lower bound), but also for the maximum deployment potential of a technology. As an example, for hydroelectric power plants, f_{min} represents the existing installed capacity (which will still be available in the future), while f_{max} represents the maximum potential .

$$f_{min}(j) \leq \mathbf{F}(j) \leq f_{max}(j) \quad \forall j \in TECH \tag{9}$$

The operation of resources and technologies in each period is determined by the decision variable $\mathbf{F_t}$. The capacity factor of technologies is conceptually divided into two components: a capacity factor for each period ($c_{p,t}$) depending on resource availability (e.g. renewables) and a yearly capacity factor (c_p) accounting for technology downtime and maintenance. For a given technology, the definition of only one of these two is needed, the other one being fixed to the default value of 1. Eqs. (10) and (11) link the installed size of a technology to its actual use in each period (F_t) via the two capacity factors. The total use of resources is limited by the yearly availability ($avail$), Eq. (12).

$$\mathbf{F_t}(j,h,td) \leq \mathbf{F}(j)c_{p,t}(j,h,td) \quad \forall j \in TECH, \forall h \in H, \forall td \in TD \tag{10}$$

$$\sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} \mathbf{F_t}(j,h,td)t_{op}(h,td) \leq \mathbf{F}(j)c_p(j) \sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} t_{op}(h,td) \quad \forall j \in TECH \tag{11}$$

$$\sum_{t \in T | \{h,td\} \in T\_H\_TD(t)} \mathbf{F_t}(i,h,td)t_{op}(h,td) \leq avail(i) \quad \forall i \in RES \tag{12}$$

The matrix f defines for all technologies and resources outputs to (positive) and inputs (negative) layers. Eq. (13) expresses the balance for each layer: all outputs from resources and technologies (including storage) are used to satisfy the EUD or as inputs to other resources and technologies.

$$\sum_{i \in RES \cup TECH \setminus STO} f(i,l)\mathbf{F_t}(i,h,td) + \sum_{j \in STO} \Big(\mathbf{Sto_{out}}(j,l,h,td) - \mathbf{Sto_{in}}(j,l,h,td)\Big) - \mathbf{EndUses}(l,h,td) = 0$$
$$\forall l \in L, \forall h \in H, \forall td \in TD \tag{13}$$

Storage

The storage level ($\mathbf{Sto_{level}}$) at a time step (t) is equal to the storage level at $t-1$ (accounting for the losses in $t-1$), plus the inputs to the storage, minus the output from the storage (accounting for input/output efficiencies (14)). Eq. (15) limits the power input/output of a storage technology based on its installed capacity ($\mathbf{F}$) and three specific characteristics. First, storage availability ($\%_{sto_{avail}}$) is defined as the ratio between the available storage capacity and the total installed capacity (default value is 1). This parameter is required to realistically represent vehicle-to-grid (V2G), for which we assume that only a fraction of the fleet can charge/discharge at the same time. Second and third, the charging/discharging time ($t_{sto_{in}}$, $t_{sto_{out}}$), which are the time to complete a full charge/discharge from empty/full storage[4]. As an example, a daily thermal storage can be fully discharged in minimum 4 hours ($t_{sto_{out}} = 4$[h]), and fully charged in maximum 4 hours ($t_{sto_{in}} = 4$[h]).

$$\mathbf{Sto_{level}}(j,t) = \mathbf{Sto_{level}}(j,t-1)\cdot(1-\%_{sto_{loss}}(j)) + t_{op}(h,td)\cdot\Big(\sum_{l\in L|\eta_{sto,in}(j,l)>0}\mathbf{Sto_{in}}(j,l,h,td)\eta_{sto,in}(j,l) - \sum_{l\in L|\eta_{sto,out}(j,l)>0}\mathbf{Sto_{out}}(j,l,h,td)/\eta_{sto,out}(j,l)\Big) \quad \forall j\in STO, \forall t\in T|\{h,td\}\in T\_H\_TD(t) \tag{14}$$

$$\mathbf{Sto_{in}}(j,l,h,td)t_{sto_{in}}(j) + \mathbf{Sto_{out}}(j,l,h,td)t_{sto_{out}}(j) \leq \mathbf{F}(j)\%_{sto_{avail}}(j) \quad \forall j\in STO, \forall l\in L, \forall h\in H, \forall td\in TD \tag{15}$$

3 Case study: the Swiss energy system

The case study represents the real-world national energy system of Switzerland. The choice of this case study is motivated by the good availability of detailed data, collected during previous work [25, 42–46]. Figure 5 shows the application of the model to the case study: the model includes 24 layers, 8 end-use demand types, and 67 technologies (including new technologies, not used today).

3.1 Demonstration

Long-term planning models are inherently non-validatable as they model an unknown future [63, 64]. However, the performance and consistency of such models can be demonstrated in representing the past or present state of the system.

Thus, we assess whether the model can reproduce the state of the Swiss energy system in the year 2011. The choice of this year is motivated by the good availability of data from previous work [25, 43–45]. The Swiss energy system in 2011 is a fossil-based system, with traditional fuels accounting for more than 80%[5] of the primary energy, with low electrification of heat (14%) and transport (4.5%) and with marginal deployment of promising technologies such as district heating network (6.4%) and heat pumps (2%) (data from the Swiss Federal Office of Energy (SFOE) [65–69]). Additional constraints are added to the model to force the 2011 configuration: (i) the end-use demand values are those from 2011; (ii) the relative annual production share of the different technologies for each type of end use demand are fixed, e.g. 20% of low temperature centralised heat provided by CHPs; (iii) the shares of public mobility ($\%_{\mathbf{Public}}$), train in freight ($\%_{\mathbf{Freight}}$) and centralized heat production ($\%_{\mathbf{DHN}}$) are those from 2011; (iv) the fuel efficiency of mobility are those from 2011.

For the comparison, 12 TDs are used, as motivated in section 4.1.2. The model output is compared to the reported values for year 2011 based on the following three indicators: (i)

[4]In this linear formulation, storage technologies can charge and discharge at the same time. On the one hand, this avoids the need of integer variables (see Supplementary Material); on the other hand, it has no physical meaning. However, in a cost minimization problem, the cheapest solution identified by the solver will always choose to either charge or discharge at any given t, as long as cost and efficiencies are defined. Hence, we recommend to always verify numerically the fact that only storage inputs or outputs are activated at each t, as we do in all our implementations.

[5]Besides fossil fuels, nuclear (11.3%), waste (6.7%) and electricity imports (1.1%) are here accounted for as traditional fuels.

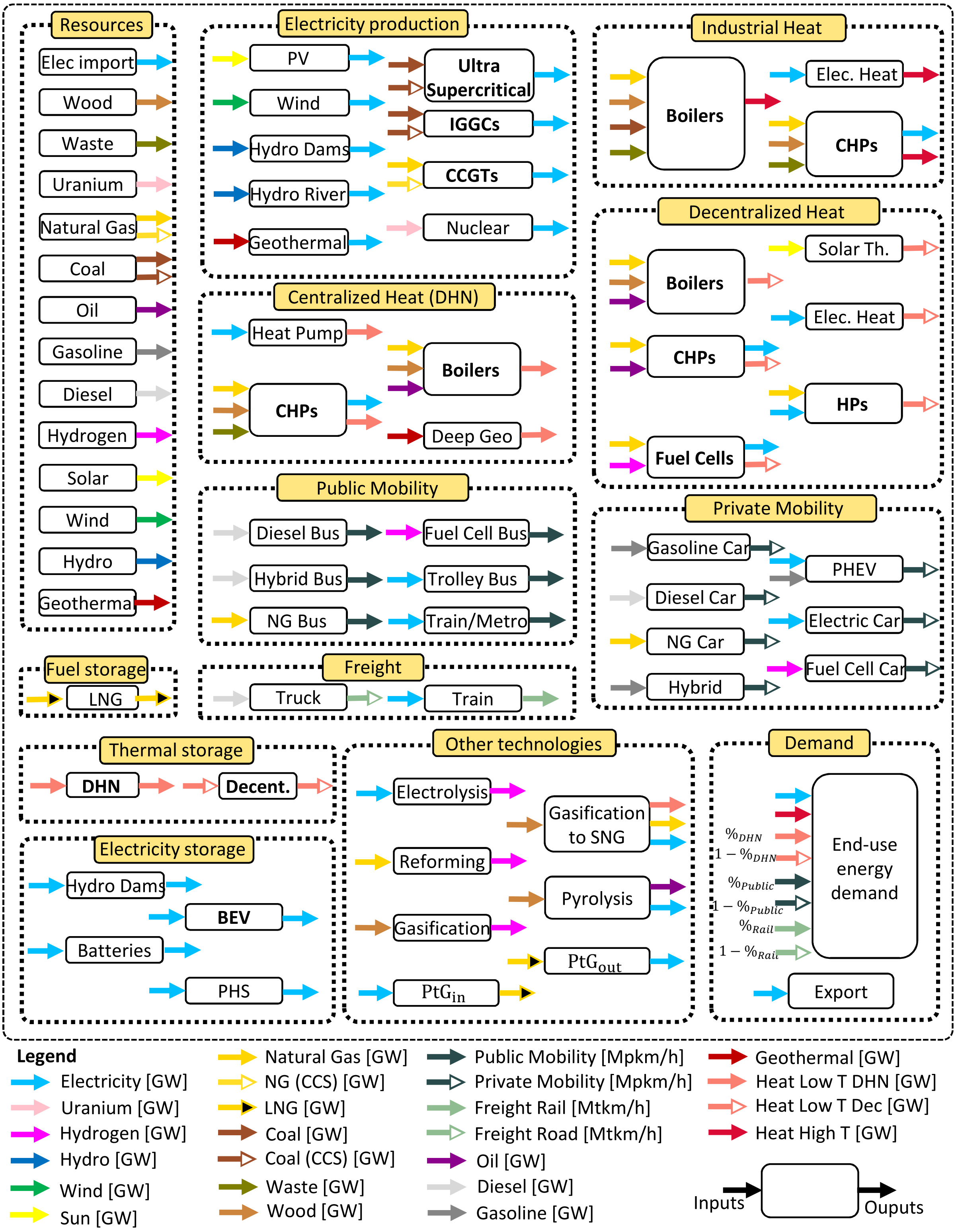


Figure 5: Application of the LP modelling framework to the Swiss energy system. **Bold** technologies represent groups of technologies with different energy inputs (e.g. **Boilers** include gas boilers, oil boilers, ...). **Decent.** represents the group of thermal storage for each decentralised heat production technology. Abbreviations: photovoltaic (PV), integrated gasification combined cycle (IGCC), combined cycle gas turbine (CCGT), combined heat and power (CHP), heat pump (HP), natural gas (NG), liquified natural gas (LNG), plug-in hybrid electric vehicle (PHEV), district heating network (DHN), battery electric vehicle (BEV), pumped hydro storage (PHS), power to gas (PtG).

primary energy consumption, global and per type of fuel; (ii) share of production per type of technology (boilers, heat pump (HP), CHP plants); (iii) global GHG emissions.

Table 2: Model demonstration: model outputs vs. actual 2011 values for the Swiss energy system. Δ_{rel} stands for the relative error.

		2011	**TDs**	Δ	Δ_{rel}	Units
Primary Energy Consumption	**Gasoline**	39.94	37.36	2.58	6.5 %	TWh
	Diesel	28.16	26.16	2.00	7.1 %	TWh
	NG	30.05	28.4	1.65	5.5 %	TWh
	Elec. Imp.	2.59	2.78	-0.19	-7.3 %	TWh
	Coal	1.66	1.43	0.23	13.9 %	TWh
	Solar	0.46	0.48	-0.02	-4.3 %	TWh
	Geothermal	0.03	0.02	0.01	33.3 %	TWh
	Waste	15.41	10.65	4.76	30.9 %	TWh
	Oil	44.34	46.2	-1.86	-4.2 %	TWh
	Wood	10.36	9.4	0.96	9.3 %	TWh
	Total	169	162.88	6.12	3.6 %	TWh
Technologies output	**Boilers**	71.59	72.53	-0.94	-1.3 %	TWh
	CHP	9.06	8.58	0.48	5.3 %	TWh
	HPs	4.02	4.23	-0.21	-5.2 %	TWh
GHG emissions (fuels)		47.51[a]	46.91	0.60	1.3 %	$MtCO_2$-eq.

[a]Total GHG emissions following the Kyoto protocol [70], removing the direct non-energy related emissions from industrial processes.

The results are reported in Table 2. In terms of energy consumption, the LP model offers an accurate approximation of the reported 2011 values. The lower values of estimated primary energy consumption are due to the fact that for electricity, heat and CHP technologies, the conversion efficiencies used for the year 2035 are also used for the validation. This difference is mostly relevant in the case of waste. Other differences are due to the fact that the LP model does not account for some minor contributions, e.g. the use of nuclear waste heat for district heating or the amount of heat classified as *other renewables* in the Swiss reports. The total GHG emissions from fuel combustion in 2011 were 50 MtCO2-eq., which includes 2.49 MtCO2-eq. due to direct non-energy related emissions from industrial processes. This number is accurately estimated by the model. In summary, EnergyScope TD can offer an accurate representation of the energy balance of a country for a past reference year.

4 Results

To verify the consistency of the methodology in Section 2, we apply the different steps to the case study. In order to represent future energy systems with high shares of RE, we impose a minimum of 50% of renewable primary energy to the system for the year 2035.

4.1 STEP 1: Choice of typical days

In this part, we first compare the clustering methods presented in Section 2.2.1, to identify the one offering the best performance for the case study. The comparison is performed using 12 TDs as a reference. As resorting to TDs can introduce errors, which can vary depending on the chosen number of TDs, we then we show how the optimal number of TDs can be identified by finding an appropriate trade-off between accuracy and computational time. Finally, in a third part, we verify the consistency of the optimal number of TDs by analysing how they represent accurately the different days of the year.

4.1.1 Clustering method selection

To select the optimal method for our application, we implemented all four methods, presented in 2.2.1, and assessed their performance based on: (i) computational cost, (ii) the clustering error, defined as the sum of the Euclidean distances within a cluster; (iii) the duration curve error, defined as the Euclidean distance between duration curves (implementations and formulas are detailed in Appendix B). As input data, we used representative time series for the Swiss energy system (provided in the Supplementary Material).

The results are summarized in Table 3 and an illustrative example of a cluster for one TD is shown in Figure 6. In this example, power and heat demand have lower errors compared to the sun power. However, one day has a very different power demand curve, but very similar errors for heat demand and sun power.

Table 3: Clustering methods performance over 12 TDs (additional results and details in Appendix B). The performance is similar, however the Domínguez-Muños method emerges as the best for every criterion.

Criteria	Units	k-medoids	Domínguez-Muños	Poncelet	Poncelet HYB
Computational cost	[s]	2500	292	3600	3125
Clustering error $\varepsilon_{cl}{}^{a}$	[-]	24.4%	9.2%	11.6%	11.6%
Duration curve error $\varepsilon_{dc}{}^{a}$	[-]	19.1%	7.7%	12.5%	12.3%

[a]Error are relatively defined as explained in Appendix B. The reference error (100%) refers to the error obtained with constant time series, such as a power demand of 1 GW over the year.

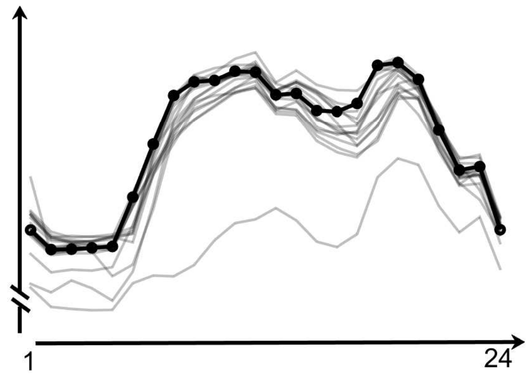
The analysis reveals that the four methods offer consistent results and have an error of the same order of magnitude. However, the method by Domínguez-Muñoz et al. [57] leads to the best results with the lowest computational time. Hence, this method will be used in the following sections.

These results are based on Swiss data, which can to some extent be considered representative of continental European countries; however, results are always case specific. For this reason, Step 1 and Step 2 should be considered as two independent and separate steps. For a new case study, both steps need to be run with the case-specific data. Also, other methods can be used to select TDs in Step 1, while still using the proposed energy model in Step 2.

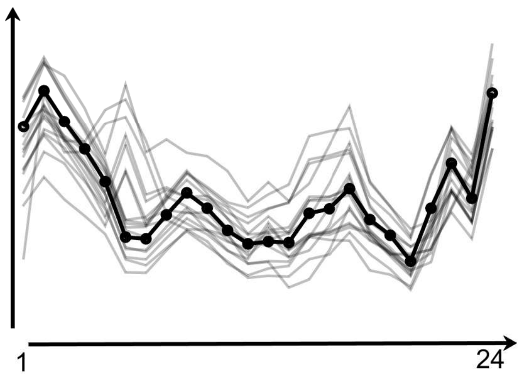
4.1.2 Comparison with the reference solution

We compare the results obtained by running our model with different numbers of TDs to the "reference" solution. This reference solution, our ground truth for this comparison, is defined as the case in which we run the model over 8760h, i.e. without resorting to TDs. The LP is solved using the commercial software IBM CPLEX 12.7 on a Intel®Core^{TM} Quad i7-6600U CPU @2.60GHz, with a memory of 16 Go, and a 64-bit system. However, the released version model can be solved using the open-source GLPSOL solver[2].

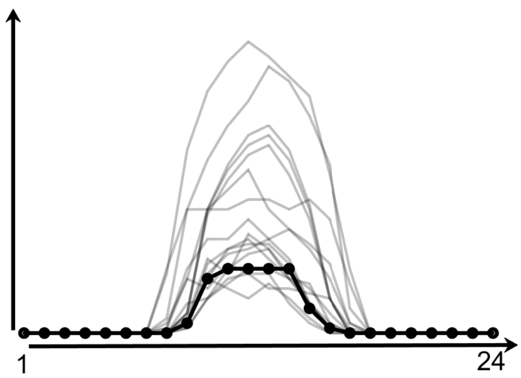
The results are reported in Table 4. Overall, the approximation offered by TDs appears appropriate. In fact, with regard to key indicators - such as energy consumption, system design,



(a) Power



(b) Heat



(c) Sun

Figure 6: Illustration of a cluster: 17 days represented by 1 TD. The thick black dotted line is the selected typical day; the grey lines are the other 16 days represented by the selected TD. X-axis represents the hour of the day.

Table 4: Comparison of results obtained with different numbers of typical days. bCHF/y stands for billion Swiss Francs per year.

		Ref.	48TDs	24TDs	12TDs	8TDs	4TDs	Units
Primary Energy Consumption	**Gasoline**	7.56	7.56	7.56	7.56	7.56	7.56	TWh/y
	Diesel	13.84	13.84	13.84	13.84	13.84	13.84	TWh/y
	NG	37.10	36.97	36.96	36.95	32.53	37.20	TWh/y
	Elec. Imp.	-	-	-	-	4.12	-	TWh/y
	Elec. Exp.	0.20	0.19	0.14	0.02	0.10	-	TWh/y
	Wind	10.68	10.68	10.68	10.68	10.68	10.68	TWh/y
	Solar	17.37	17.29	17.24	17.11	16.88	17.32	TWh/y
	Geothermal	9.69	9.69	9.69	9.67	9.66	9.66	TWh/y
	Hydro	37.18	37.18	37.18	37.18	37.18	37.18	TWh/y
	Waste	11.14	11.14	11.14	11.14	11.14	11.14	TWh/y
	Oil	5.06	5.13	5.13	5.13	5.09	5.09	TWh/y
Technologies output	**Boilers**	30.17	29.00	28.16	28.13	34.40	30.99	TWh/y
	HPs	27.33	27.60	27.60	27.60	27.42	26.57	TWh/y
GHG emissions (fuels)		22.51	22.50	22.49	22.47	23.22	22.54	$MtCO_2$-eq/y
System cost		14.34	14.38	14.39	14.33	14.36	14.27	bCHF/y

total GHG emissions from fuels and system total annual cost - the chosen number of TDs has little influence on the results.

However, we observe 3 major differences deriving from the TDs approximation, which are reported in Table 5: (i) the computational time; (ii) the thermal storage capacities; (iii) the strategy to bring flexibility in the electricity sector. The rest of the design is very similar, as presented in Table 4.

Table 5: Comparison of major differences obtained with different numbers of typical days.

		Ref.	48TDs	24TDs	12TDs	8TDs	4TDs	Units
Computational time		70240	296	135	91	91	89	s
Electricity production	**PV**	17.37	17.29	17.24	17.11	16.88	17.32	TWh/y
	Wind	10.68	10.68	10.68	10.68	10.68	10.68	TWh/y
	Hydro (all)	37.18	37.18	37.18	37.18	37.18	37.18	TWh/y
	CCGT	1.22	-	-	-	0.39	-	TWh/y
	CHP	3.68	5.00	5.38	5.40	0.20	4.24	TWh/y
	Elec. Imp.	-	-	-	-	4.12	-	TWh/y
Storage capacity	**Dec.**	41.41	35.85	35.89	35.90	26.65	23.22	GWh
	DHN daily	18.76	16.52	16.53	14.54	11.00	10.27	GWh
	DHN seas.	200.45	145.38	129.72	50.52	-	-	GWh

(i) Computational time: as expected, correlation between computational time and number of typical days is verified except for low number of typical days: With less than 12 TDs, the computational time reaches a plateau of around 90s to solve the problem.

(ii) Thermal storage capacity: the reference solution relies on daily thermal storage for decentralised and DHN heat. Moreover, it installs a seasonal thermal storage for the DHN in order to shift between days the electricity excess absorbed by the HPs. Figure 7 presents the energy stored by the DHN seasonal storage over the year for different cycle durations[6]. The reference solution shows that this technology is used for weekly to monthly cycles. By reducing the number of TDs, the energy stored for weekly cycles is reduced and even not captured with less than 12 TDs. However, resorting to 12 TDs captures some intra days event.

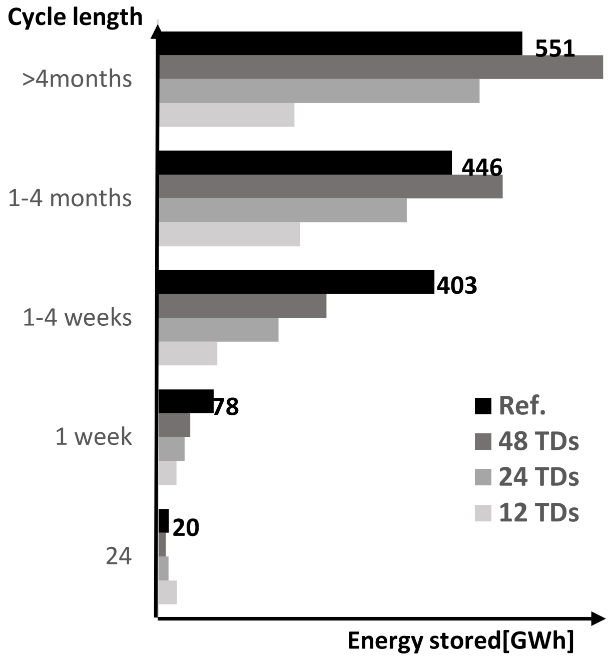


Figure 7: Energy stored in the DHN seasonal storage obtained for different cycle length and with different numbers of TDs. With less than 8 TDs, there is no capacity installed.

(iii) Strategy to bring flexibility in the electricity sector : To face the intermittency of RE, the electricity sector can find sources of flexibility in supply, demand or storage. In this scenario, the flexibility comes from hydro dams, thermal storage and electricity production. As the behavior of hydro dams is similar for the different scenarios and thermal storage has been analysed in the previous sections, here we analyse only the difference in the electricity production mix. As shown in Table 5, when varying the number of TDs, the production mix remains the same for RE technologies, whereas some differences are observed for flexible producers and imports. In the reference solution, the system relies on CHP (75%) and combined cycle gas turbine (CCGT) (25%) to back up the scarcity of intermittent renewable energy during winter. Instead, solutions resorting to TDs have different flexible producers to face lack of electricity during winter, such as CHP or more electricity imports. As an example, the optimal system with 12 TDs exclusively resorts on industrial CHP or the optimal system with 8 TDs mostly relies on electricity imports. These differences between system design strategies can be understood when looking at the objective values. They give similar results which means that solutions are almost equivalent, which is rather typical in LP problems. We thus forced the system design of TDs solution to be the same as the reference solution, and observed differences in objective values of less than 1%.

In summary, resorting to different numbers of TDs results in acceptable differences compared to the reference solution. However, with 8 TDs or less, the intra-days phenomena, such as storing

[6]The energy stored per cycle is determined as the total amount of energy which entered and left the storage within a certain period (the storage is considered as a last in first out (LIFO) stack). For example, 1 kWh entering and leaving 10 times/day a storage counts as 10kWh and is accounted in cycle length lower or equal to 24 hours.

during the weekend and restore during the week, cannot be captured and some technologies are not implemented. Therefore, 12 TDs is a good trade-off between accuracy and computational time. This number of TDs is thus used in the paper.

4.1.3 Application with 12 typical days

The previous section highlighted differences between the reference solution and the ones resorting to TDs. Figure 8 illustrates the selected 12 typical day and their relation with the days of the year for the considered case study. As described in 2.2.1, the criterion used for clustering is based on electricity demand, heat demand, solar radiation, wind speed and water flow in run-of-river hydro power plants.

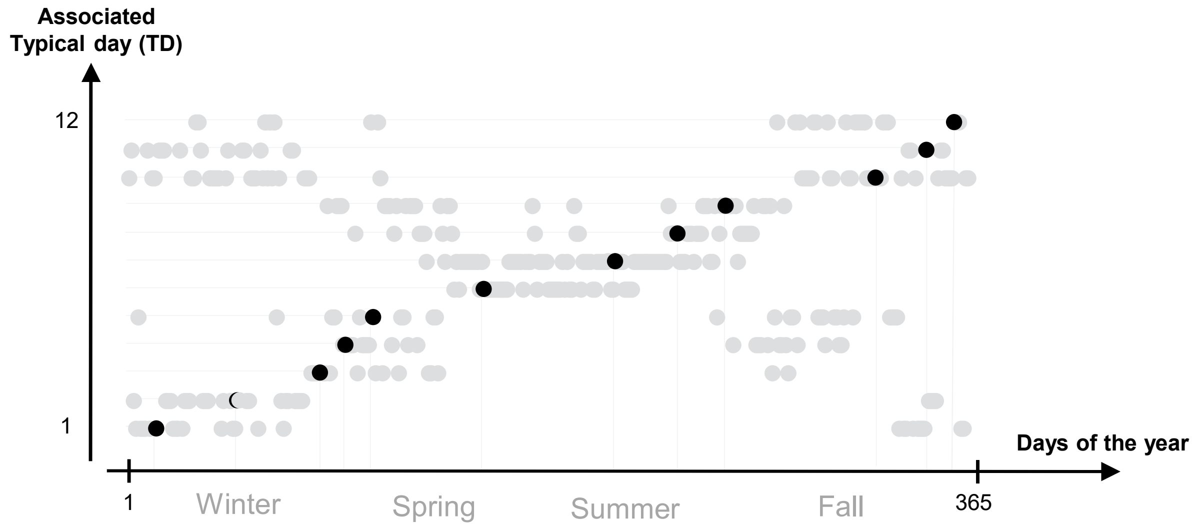


Figure 8: Association of days of the year (x-axis) to one of the twelve typical days (y-axis). Black points represent the selected typical day for each cluster (medoid). Grey points represent the day of the year.

The twelve typical days can be classified as follows:

- 5 winter days (TDs 1, 2, 10, 11 and 12) with high heat demand. There are nuances between them: TD-1 is a windy cloudy day, TD-2 and TD-10 are sunny unwindy days, with a very high heat demand for TD-2, TD-11 is a cloudy unwindy day and TD-12 is a sunny day with lower heat demand.
- 3 cold intra-season days (TDs 3, 4 and 5). TD-3 is a very sunny day with low wind, TD-4 is a cloudy unwindy day and TD-5 is a cloudy windy day.
- 2 hot intra-season days (TDs 8 and 9). TD-8 has a high hydro river production compare to TD-9 which uses industrial gas CHP to supply electricity during night.
- 2 warm summer days (TDs 6 and 7) with high hydro river production. TD-7 is a very sunny day.

Figure 8 illustrates that some intra season days are associated to typical winter or summer days and vice-versa: e.g, the 13th of July (day 194) was a cold summer day associated to TD-9, a hot intra season day. In summary, each TD has its specificity and brings some information to the system.

4.2 STEP 2: EnergyScope TD

In this section, we focus on the results when applying EnergyScope TD to the case study with the additional constraint of 50% of renewable primary energy. In particular, our goal is assessing how the model can handle the intermittency linked to the high share of renewable generation. In order to emphasize the impact of V2G, their availability is fixed to 80%. We first explain how the system is designed to reach the target of 50% RE share. Then, we show how the system operates to handle the high penetration of intermittent renewable energies (iRE). Finally, the role of storage is highlighted.

Reaching the 50% RE target

The Sankey diagram (Fig. 9) represents the entire energy conversion chain, from primary energy to the final energy consumption.

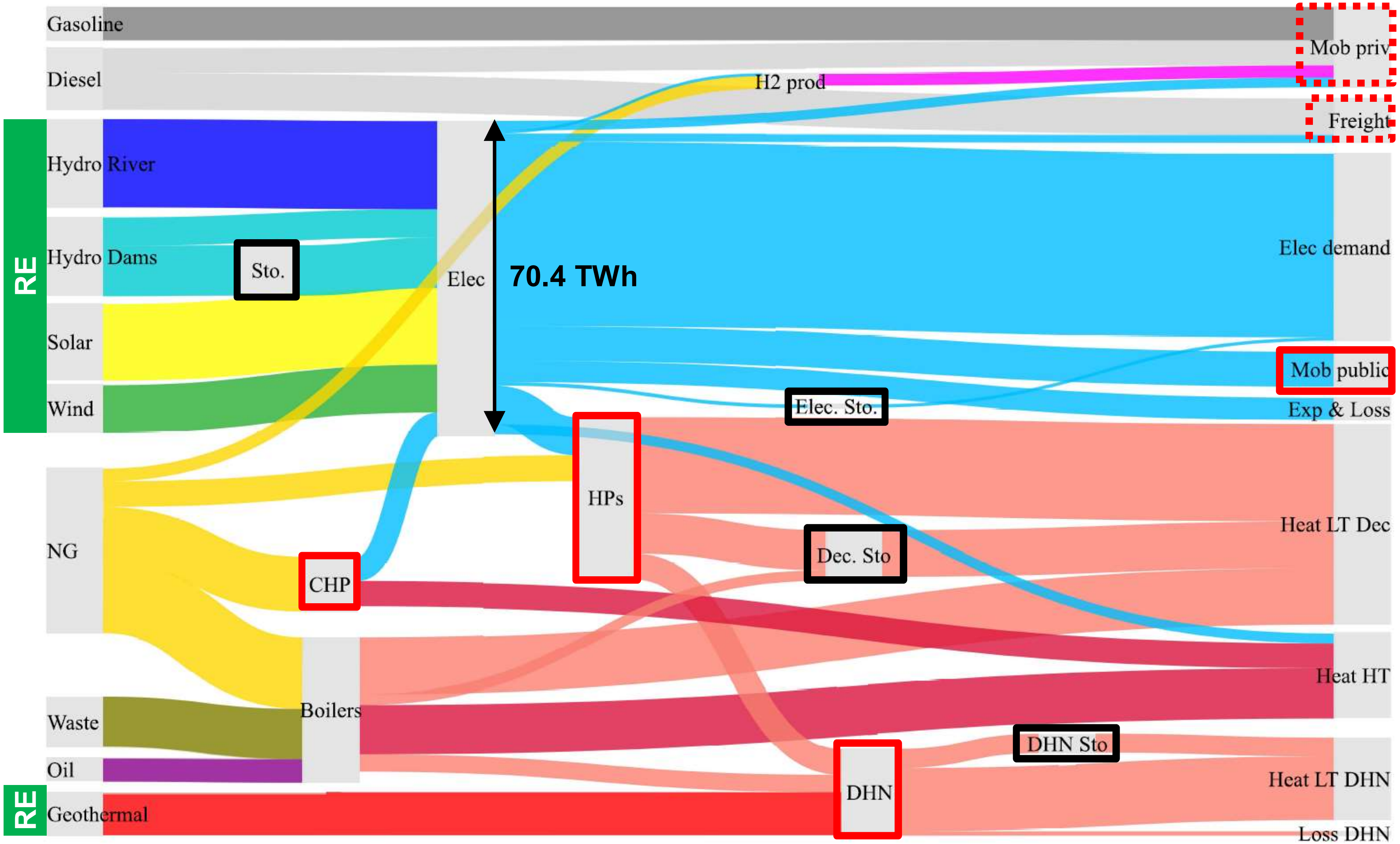


Figure 9: Energy flows in a scenario representing a 50% RE Switzerland in 2035. Primary energy (left part) is 50% RE (green). More efficient and storage technologies are framed in red and black, respectively. Dotted lines mean that the sector is partially efficient, such as Freight where only the electrical part (trains) is efficient. In this study, the only activated electricity storage option is pumped hydro storage (PHS).

The system reaches 150 TWh/y of primary energy consumption with a 50% share coming from RE (Electricity imports and waste are considered non-RE). The optimiser uses two levers to reach the RE share target. The first lever is to reduce primary energy supply by 12.3% compared to a scenario without RE constraint. This reduction is achieved by using more efficient technologies, such as CHPs, HPs, EVs and DHN technologies. The second lever is the increase of RE resources, out of which 37% are intermittent (wind and solar). To face this problem, storage capacities are deployed: PHS, centralised TS and decentralised TS. In parallel, hydro dams delay their production by storing the summer water inflow for winter electricity production. The total annual cost of the energy system is 14.33 billion Swiss Francs/y (Referring to 2015 Swiss francs), with the annualized capital expenditure (CAPEX) and maintenance of the system represents accounting for 76% of the total cost; the rest is the cost of resources which represents 89% of the GWP.

To summarise, the RE target is reached thanks to the partial electrification of heat and mobility, and to a higher penetration of efficient technologies and intermittent renewable energies (iRE). In this context, thermal storage is used as a buffer for the electricity grid, which reduces the need for electrical storage.

Handling RE intermittency

To understand how the system operates to handle the high share of iRE, Figure 10 shows, for each TDs, the hourly power flows in the electricity and low temperature heat layers. This time scale is necessary to understand how storage technologies address iRE.

The electricity production is dominated by renewable energies; it shows the intermittency of wind and solar power, the seasonality of hydro and the coupling of heat and power. From a seasonal perspective, solar and wind are complementary as highlighted in other studies [4, 5]. As a consequence of the high summer hydro and photovoltaic (PV) production, the excess of summer electricity is partially used for direct electric heating to supply industrial high temperature heat demand. During electricity scarcity periods, such as winter, industrial heat is supplied by NG CHPs which also provide electricity. From a daily perspective, the demand variations are significant, and derive mostly from the electricity required by the transportation end-use demand, characterized by a high penetration of public transportation (50%).

The intermittency of RE requires storage to absorb peaks and restore these excesses during the day or to store this energy for another period of the year. Hydro dams play a major role by storing 11123 GWh per year, whereas PHS and V2Gs store 716 and 642 GWh, respectively. During inter season days (such as TD-3), PHS shifts energy from day to day. Whereas, during summer days (such as TD-7), PHS stores these excesses for a longer period. EVs offer a double benefit for the power system: first, they can be used for smart charging, meaning that they can charge during excess of electricity production, such as PV peaks; second, EVs are used as V2Gs for daily cycles: 21% of the energy charged in the batteries is restored to the grid. As an example, during TD-7, the excess is stored in battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) and directly restored once PV production decreases. This result is made possible thanks to the large availability of V2G.

Coupling thermal storage with heat pumps makes the electricity demand for heating flexible. For example, we account for 1280 GWh/y of DHN heat stored coming from HPs, which is equivalent to 320 GWh/y of electricity stored (with a coefficient of performance (COP) of 4 for DHN HPs.). Similarly, 6400 GWh/y of heat produced with decentralised electrical HPs is stored in decentralised thermal storage, which is equivalent to 2140 GWh/y of electricity stored (with a COP of 3 for decentralised electrical HPs.).

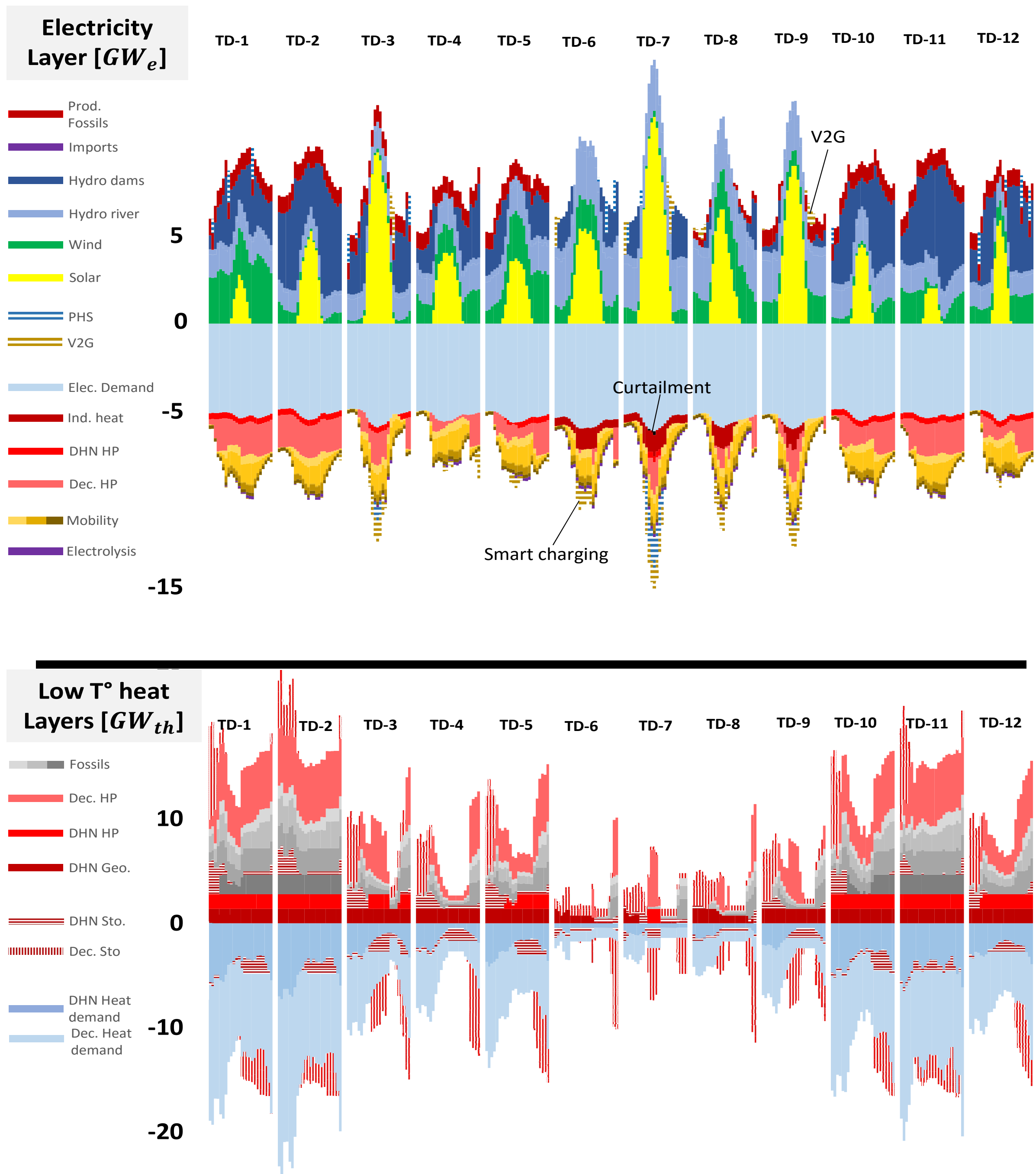


Figure 10: Power flows for the electricity layer (upper graph) and the low temperature heat layers (lower graph) shown separately for the 12 TDs. For both figures, only the active technologies are represented in the legend (left part) and the power supply (positive) has to compensate the power demand (negative). Stripes represent energy storage. Colour scales represent a group of technologies, such as for the grey scale oil boilers, gas boilers, gas HP...

The role of storage

Different storage technologies are deployed in the optimal solution. At a seasonal time scale, two technologies are installed: PHS and hydro dams. Figure 11 shows the energy stored during the year.

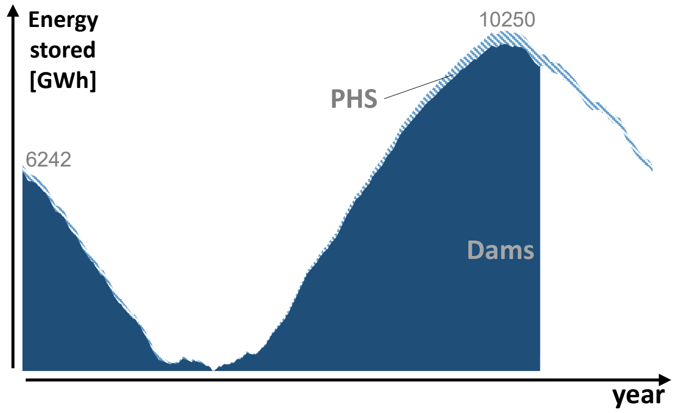


Figure 11: Hourly profile of stored energy for seasonal technologies related to the electricity layer.

As expected, seasonal storage is charged during summer and discharged during winter. Moreover, PHS is used as a seasonal storage, a behaviour which was first observed in a previous work focusing only on power system [4]. Over the year, hydro dams perform 1.12 cycles. PHS performs 1.94 cycles per year, as it is also used for daily applications (see Figure 10).

At a shorter time scale, thermal storage and vehicle-to-grid are installed. Figure 12 shows the energy stored in seasonal TS and daily TS (accounting for both decentralised TSs and centralised TS).

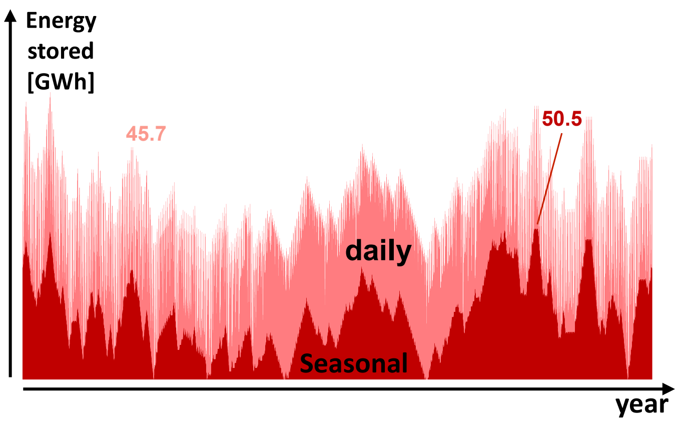


Figure 12: Hourly profile of stored energy for seasonal technologies related to heat layers. Thermal storage for seasonal and daily applications have a capacity of 50.5 and 45.7 GWh, respectively.

As illustrated in Figure 12, daily TS technologies perform almost every day a full cycle, while seasonal TS is mostly used for weekly to monthly applications. This shows that, even if the computation resorts to TDs, intra-days phenomena can be captured by the model.

Overall, by means of this example case study, we illustrated the potential of the EnergyScope TD model to optimise future energy systems with high shares of RE sources. The results appear consistent and highlight the benefits of electrification and, in particular, the integration of electrical heat pump with thermal storage systems. Moreover, the proposed formulation is able to capture daily, seasonal but also intra-days phenomena.

5 Discussion

In the paper, we presented EnergyScope Typical Days as a novel energy model and assessed its methodology and performance by applying it to a real-world energy system. Since there exists a wide variety of energy models, this section provides a perspective on the scope of EnergyScope TD and its advantages/limitations with respect to other models. This Section complements the general comparison already offered in Section 1 and Appendix A, detailing it based on the results of the application (Section 4.2).

5.1 Field of application

Each energy model has its specificities which make it more or less suitable for different applications. EnergyScope TD is designed for the strategic energy planning of urban and regional energy systems, facilitating the consideration of uncertainties and the integration of promising technologies. It has been developed with the following six objectives in mind: (i) to be representative of a multi-sector urban or regional energy system accounting for all the energy demand and carriers; (ii) to allow the implementation of energy storage at different time scales; (iii) to facilitate the integration of new branches or promising technologies into the energy system, such as the power to gas (PtG) or vehicle-to-grid (V2G); (iv) to allow high shares of intermittent renewable energies with an hourly time resolution and thus understand how the system (including storage technologies) deals with their intermittency; (v) to have an acceptable computational time for uncertainty applications and interactive *what-if* analyses [71]; (vi) to have a free and open-source code with a simple formulation to make it accessible to all and support education.

The results in Section 4 demonstrate how these objectives have been incorporated in the model development: (i) EnergyScope TD represents with the same level of detail the heating, mobility and electricity sectors. As presented in Figure 5, the model includes 8 end-use type, 24 layers which are energy carriers and 67 technologies. (ii) Out of these 67 technologies, 18 are storage technologies. As illustrated in Figures 11 and 12, 2 technologies (hydro dams and PHS) are used for seasonal storage, 1 technology (seasonal thermal storage) is used for weekly or monthly applications, 7 technologies (thermal storages and electric vehicles) are used for daily storage while the rest, such as batteries, are not used. (iii) The linear programming formulation presented in Section 2.3.2 facilitates the implementation of one or a set of technologies. As an example, both current and previous versions [25] have the same structure for the data even if EnergyScope TD includes additional storage technologies. (iv) In the results shown in Section 4.2, a share of 50% of renewable primary energy is imposed. Figure 9 shows how this RE is integrated in the system and Figure 10 represents, for each TDs, the hourly power flows in the electricity and low temperature heat layers. Section 4.2 details the system behaviour for the Swiss case and shows how the system can deal with iRE at an hourly resolution. (v) The proposed formulation is similar to the one of Moret, Bierlaire, and Maréchal [43] where an uncertainty analysis is performed. The computational time is around ninety seconds, which is acceptable for stochastic optimisation and global sensitivity analyses applications. (vi) EnergyScope TD is open-source[2]. The code can be run out-of-the-box with a free software (GLPK), using the data for the Swiss energy system as an example. We provide a full documentation, both in terms of formulation and data input, and a user guide. They are available in Supplementary Material.

5.2 Limitations

There are, however, applications for which the model is not - or, in some cases, not yet - designed for: (i) to define evolution pathways and investment strategies over multiple years; (ii) to have a high spatial resolution allowing to consider, for example, the national grid congestion or the limitation of electricity exportable from neighbouring countries, such as during a global lack of RE; (iii) to have a detailed formulation of a sector, such as analysing in details the power flow in the grid; (iv) to calculate the market equilibrium and deduct the hourly market price; (v) to define detailed operating strategies for a real-world system (e.g. a unit commitment problem). (vi) to analyse the energy system at a small scale, such as a single building;

As previously mentioned, some of these limitations (i-ii) could be overcome in future versions. As an example, this release of EnergyScope TD is not accurate for (i) planning an investment strategy over multiple years, as it looks only at a target future year. However, similarly to what Prina et al. [15] have done with EnergyPLAN, the EnergyScope TD framework can be extended to several years and integrate the investment strategy. There exist as well other models, such as OSeMOSYS [34] or EPLANoptTP [15], that offer longer time horizons covering decades, which might be necessary for strategic investments. As a drawback, OSeMOSYS simplifies the system operations, and EPLANoptTP uses a simulation tool (EnergyPLAN [23]) to optimise only PV and wind turbine investments. (ii) EnergyScope TD does not consider power limitations in the networks. However, its formulation could be extended to several countries connected to each other. Models, such as Plexos [22], already offer these formulations, such as in a study of West-Europe [72]. Other models, such as PyPSA [36, 37] or Dispa-SET [17], offer a spatial resolution of the power grid. As a drawback, these models focus solely on the power system.

The rest of the limitations (iii-vi) are not in line with EnergyScope TD objectives. (iii) EnergyScope TD is designed to equally represent sectors. Focusing more on one sector requires either an increase of the model complexity, and thus of the computational time, or a simplification of the other sectors. Other models, such as SciGRID [18, 73], propose a more detailed resolution of the grid or a more complex formulation of the power flow equations. As a drawback, they mostly focus on the power grid. (iv) *Market-equilibrium* models balance demand and supply to reach *equilibrium* in energy markets. These models are economic-oriented rather than technology-oriented. The main issue with this approach is the difficulty of forecasting the evolution of energy markets over long planning horizons. EnergyScope TD is a technical model where the demand is imposed and the model has to supply it while minimising the system cost. Investors might use *market-equilibrium* models, such as PLEXOS [22], to define future investment in a shorter time horizon (5 years); as a drawback, they usually are commercial. (v) Some energy models are made for very detailed and direct applications. As an example, an energy management system provides a reliable operation and a robust control solution to manage small energy systems (e.g. a thermostat in a house for heating). These models optimise the operation strategies under additional constraints, such as the risk of failure or the scheduled maintenance periods. As a drawback, they either have a long computational time, or focus on a very simple energy system with a quite short time horizon (a day). EnergyScope TD is made for strategic energy planning rather than robust operation and control. (vi) Focusing on an energy system at a smaller scale than an urban system requires to verify its reliable operability. As explained in (v), it is not the focus of EnergyScope TD.

6 Conclusions

In the context of the energy transition, energy planning models are needed to guide and support decision-makers at urban and regional level. Future low-carbon energy systems will be characterized by very high shares of intermittent renewables, as well as by a radical electrification of heat and mobility. Thus, new open-source models are needed, which can capture such dynamics, and optimise both the investment and the operation strategy of a real-world multi-sector energy systems in a computationally efficient way.

In the literature, a large variety of energy models exists, which we reviewed in detail (see Appendix A). In summary, none of them presents all these features and are ready-to-use.

Consequently, in this paper, we presented EnergyScope Typical Days (EnergyScope TD), a new open-source energy model for urban and regional energy systems planning[2]. In this work, we first introduced the energy model, focusing in particular on the methodology to define the typical days and on its linear programming formulation; then, after defining the case study, we verified the methodology consistency by applying it to the national energy system of Switzerland. In particular, the features of the model are illustrated by imposing a 50% renewable primary energy share for the year 2035. Finally, we discussed and defined the scope and foreseen applications of EnergyScope TD, and highlighted both its strengths and its limitations by critically comparing it with other energy models available in the literature.

Overall, our model is a suitable framework for assessing future energy scenarios in a target future year. In particular, it is able to assess cases with high penetration rates of renewable energies sources, need of storage, and high penetration of innovative and promising technologies. These features makes EnergyScope TD a new scientifically-based open-source model for energy planners in the context of the energy transition.

Future model development works will focus on the limitations of the model, such as the long term investment strategies or the spatial resolution. In addition, the model could be coupled with dispatch models, such as Dispa-SET or modules can be added to assess human health impacts for key pollutants (NOx, PM2.5, PM10).

A Review of existing energy models

This appendix presents a review of the different energy models proposed in the literature and identifies the ones which have the following features: freely available, with a monthly to hourly time resolution; and modelling - at least partially - mobility and heat supply besides the electricity sector. This review is built on previous work by Connolly et al. [13], Pfenninger, Hawkes, and Keirstead [26] and Zerrahn and Schill [31]. Also, data from the Open Energy Modelling Initiative [16] plaftorm are integrated in the analysis. This platform "*aims to share open models and open data, in order to advance knowledge and lead to better energy policies. Open up energy models improves quality, transparency, and credibility, leading to better research and policy advice.*" [16].

The models are compared based on the following criteria: (i-iii) Does the model include electricity, heat or mobility sector? (iv) is the model freely available? (v) Is the model open source? (vi) Does it optimise the operation strategy? (vii) Does it optimise the investment strategy? (viii) What is the time resolution? (ix) What is the computational time?

Table 6: Comparison models based on [13] and openmode-initiative [16]. Criteria are satisfied (✔), partially satisfied (√), unsatisfied (blank) or no data were found (-). Abbreviations: time resolution (res.), seconds (s), minutes (m), hours (h), months (mo), years (y).

Model	**Sectors**			**Open**		**Opti.**		**Time**	
	Elec.	**Heat**	**Mob.**	**Use**	**Sour.**	**oper.**	**inv.**	**res.**	**run**
Balmorel [13, 16, 74]	✔	√		✔	✔	✔	✔	h	m
BCHPS.T. [13, 75]				✔		✔		h	-
Calliope [16, 26, 27]	✔	√[7]	√[14]	✔	✔	✔	✔	h	m
COMPOSE [13, 28]	✔	✔	✔	✔		✔	✔	h	-
DESSTinEE [16, 29, 30]	✔	✔	✔	✔	✔			h	h
DIETER [16, 31]	✔	√	√	✔	✔	✔	✔	h	m
Dispa-SET [16, 17]	✔			✔	✔	✔		h	h
DynPP [16, 76]	✔	√[7]					✔	s	h
ELMOD [16, 77]	✔	√[7]		✔	✔	✔		h	m
EMINENT [13]	✔	✔		✔				y	-
EMLab-Generation [16, 78]	✔			✔	✔			y	h
EMMA [16, 79]	✔			✔	✔	✔	✔	h	m
EnergyNumbers-Bal. [16, 80]	✔			√[8]	✔			h	s
EnergyPLAN [13, 23]	✔	✔	✔	✔		√[9]		h	s
EnergyRt [16, 81]	✔	-	-	✔	✔	-	-	-	m
EnergyTrans.Mod. [16, 82]	✔	√[7]		✔	✔			y	s
ENPEP-BALANCE [13]	✔	✔	✔	✔				y	-
ESO-X [16, 83]	✔			✔	✔	✔	✔	h	m
Ficus [16, 84, 85]	✔	√[7]		✔	✔	✔	✔	m	h
GAMAMOD[10] [16, 86]				√[11]		✔	✔	-	m
Genesys [16, 87]	✔			√[8]	✔		✔	h	m

[7] CHPs technologies implemented
[8] Not directly downloadble.
[9] Based on an user defined decisions order.
[10] Natural Gas Market oriented
[11] Planned to open up in the future.

Model	Sectors			Open		Opti.		Time	
	Elec.	Heat	Mob.	Use	Sour.	oper.	inv.	res.	run
GridCal [16, 88]	✓			✓	✓	-	-	-	m
HOMER [13, 89]	✓	✓		✓		✓	✓	m	-
IKARUS [13]	✓	✓	✓	✓[12]			✓	y	-
Invert [13, 90]	✓	✓	✓	✓			✓	y	-
LEAP [13, 91]	✓	✓	✓	✓[12]				y	-
MEDEAS [16, 92]	✓	✓[7]		✓[8]	✓		-	y	h
MiniCAM [13, 93]	✓	✓	✓	✓[12]				y	-
MOCES [16, 94]	✓			[11]				s	m
MultiMod [16, 95, 96]	✓			[11]		-	-	y	h
NEMO [16, 97]	✓			✓	✓	✓		h	m
NEMS [13, 21, 25, 98]	✓	✓	✓	✓[12]				y	h
Oemof [16, 32, 33]	✓	✓	✓	✓	✓	✓	✓	h	m
OnSSET [16, 99, 100]	✓			✓	✓		✓	y	m
ORCED [13]	✓		✓	✓		✓	✓	h	-
OSeMOSYS [16, 34, 35]	✓	✓	✓	✓	✓	✓[13]	✓	d	m
PLEXOSOpenEU [16, 22]	✓			✓		✓		h	h
PowerMatcher [16, 101]	✓			✓	✓	-	-	-	m
PyPSA [16, 36, 37]	✓	✓[14]	✓[14]	✓	✓	✓	✓	h	m
Renpass [16, 102, 103]	✓			✓	✓	✓		h	h
RETScreen [13, 104]	✓	✓		✓			✓	mo	-
SciGRID [16, 18, 73]	✓			✓	✓			-	m
SimSES [16, 105, 106]	✓			✓	✓			m	h
SIREN [16, 107]	✓			✓	✓			h	m
SIVAEL [13]	✓	✓		✓				h	-
StELMOD [16, 108, 109]	✓			✓	✓	✓		h	m
STREAM [13, 19]	✓	✓	✓	✓[12]				h	-
Switch [16, 38, 39]	✓	✓[14]	✓[14]	✓	✓	✓	✓	h	h
Temoa [16, 110, 111]	✓	✓	✓	✓	✓		✓	y	m
TIMESEvora [16]	✓	✓[7]		[11]		✓[15]	✓[15]	mo	m
TIMES-PT [16]	✓	✓[7]		[11]		✓[15]	✓[15]	mo	m
TransiEnt [16, 112, 113]	✓	✓[7]		✓	✓			s	h
URBS [16, 40, 41]	✓	✓[14]	✓[14]	✓	✓	✓	✓	h	h

A.1 Energy model classification

Each energy model has its specificities and framework, which makes it suitable to answer different questions. As presented in the Introduction, the different modelling frameworks proposed in the literature have their advantages but feature one or more of the following limitations defined in this paper: (i) being limited to only one sector (usually the electricity sector); (ii) representing sectors with different level of details (usually by simplifying heating and mobility sectors); (iii) being commercial, i.e. not freely available nor open-source; (iv) not optimising both the investment and the hourly operation strategy.

[12] Free under conditions.
[13] Operation is usually not resolved on a hourly base.
[14] The model focuses on Power system.
[15] Not directly specified. However TIMES model usually optimises both operations and investments.

Multi-sector

From an historical perspective, energy system models have been focusing on separate sectors, avoiding interactions between sectors. For example, the gas sector was focusing on the supply of gas from resources to end users without considering technologies such as power to gas. Most of the energy models were and are still focusing on the power sector. This is a consequence of the difficulty to manage and balance the power grid.

Out of the 53 presented models, 18 are focusing on the power system without considering other sectors. A good example of these models is Dispa-SET [17], which is a dispatch optimisation model which focuses on the balancing and flexibility problems in the European grid.

Representing sectors with different level of details

More recently, multi-sectors models have been developed. These models usually focus on one sector and allow a partial implementation of the others. The two main issues that these models are facing are: (i) partial representation of sectors; (ii) incomplete representation of the energy system. As an example of (i), DIETER [31] represents the electricity sector and allows sector coupling through power to heat and electric vehicle [16]. However, the representation of these sectors is done only partially. As an example of (ii), ELMOD [77] focuses on the electricity and heat sectors without accounting for mobility.

Out of the 53 models, 10 of them offer a framework where the electricity, heat and mobility sectors can be implemented. A known example is EnergyPLAN[23], a simulation software that represents an energy system at a national scale.

Freely available and open source

Some energy models are oriented to commercial applications, such as operation and control or to support investor decisions. For example, a building which has both a boiler and a CHP requires an energy management system to optimise the use of the boiler and/or of the CHP. Energy models, such as PLEXOS[22], aim at supporting investors. These models usually model the market-equilibrium, which is necessary to compute the market price. This information is unavoidable to assess if an investment in the market is going to be profitable or not. Since these energy model can directly be used for commercial applications, they are often not open-source neither open-access.

Out of the 53 reviewed models, 39 are open access and 28 are both open access and open-source.

Not optimising both the investment and the operation strategy

As defined in the Introduction 1, models can either optimise or simulate. In a simulation the degrees of freedom are fixed *a priori* by the modeller, who defines a set of conditions which directly influence the results. Optimisation, instead, can reveal optimal configurations over a large number of available options and degrees of freedom, making it more suitable for analysing complex systems, where many combined alternatives need to be explored. As a drawback, optimization is computationally more expensive, which represents a fundamental barrier for uncertainty applications [25].

Depending on the application, a model can: (i) simulate both the investment and operation. As an example, EnergyPLAN [23] uses a merit order tree to define its operation strategy while its investments are imposed. The advantage of such model is its very short computational time (seconds) even if the system is complex. (ii) The model can optimise the investment and simulate the operation. Genesys [87] is an example. It optimises the investments with an evolutionary strategy while simulating the operation with a hierarchical management strategy [16]. The advantage of such model is to optimise the investment over multiple years while verifying its operability with a low computational time (minutes). (iii) The model can optimise the operation with fixed investments. A typical application of these models, such as Dispa-SET [17], is the power grid. The network exists and dispatchers want to optimise the flows in order to minimise the losses. (iv) The model can optimise both the investment and operation. As an example, the commercial software PLEXOS [22] is used by companies to define the best investment strategies while planning the optimal operation taking into account the risk of failure and the maintenance periods of technologies. The major drawback is the high computational time, hence these models usually cover only one sector.

A.2 Similar models

From Table 3, models which have the following features are reporter in the Introduction (Table 1): freely available; with a monthly to hourly time resolution; and modelling, at least partially, mobility and heat supply besides the electricity sector. They are: DESSTinEE, DIETER, COMPOSE, EnergyPLAN, OSeMOSYS, Oemof, Calliope, STREAM, Switch, PyPSA and URBS. These models are detailed in Section 1.

B Clustering

This section provides details about the different clustering algorithms compared in the paper. Moreover, additional details are provided about the performance of these methods applied to the case study.

B.1 Clustering methods

k-medoids

We used the MATLAB®-embedded clustering algorithm k-medoids. This implementation is based on the works by Gentle, Kaufman, and Rousseuw [58] and Park and Jun [59]. As results depend on the initial centroids randomly chosen by the algorithm, we use the "replicate" option, which sets the number of times to repeat the clustering, each time with a new set of initial centroids. This number is set to 50000, which is more or less equivalent to 1 hour of computation.

Domínguez-Muños method

This algorithm is presented in Domínguez-Muñoz et al. [57]. The full code is made available online[2] and its use is explained in the Supplementary Material.

Poncelet method

This algorithm is presented in [56]. However, this method does not compute the sequence of days. Hence, a post-processing is required to compute the sequence. This post processing computes for each day (d) of the year the closest typical day (TD) by minimising the euclidean distance, Eq 16[16].

$$\min_{td \in TD} \sqrt{\sum_{h \in H, i \in TIME\_SERIES} \omega(i) \cdot \Big(ts(i,h,td) - ts(i,h,d) \Big)^2} \tag{16}$$

[16]The nomenclature used for parameters and sets are later introduced.

Similarly to the k-medoids method, Poncelet's method tries every combination of TDs, which is again highly combinatorial. Hence, a variant called "Poncelet-HYB" is proposed, which resorts on samples of TDs.

B.2 Criteria

Typical days are selected based on five time series (ts which are part of the set $TIME\_SERIES$): power demand, heat demand, solar radiation, wind production and hydro dams production (these time series are provided in the Supplementary Material. Three of them are related to weather conditions; thus, we decide to impose a weight (ω) of 1 for each weather time series and 3 for the power and heat demands time series. As a consequence, power demand, heat demand and weather have the same weighting. The methods are compared for 4 and 12 typical days and based on the three following criteria: (i) computational cost; (ii) clustering error; (iii) duration curve error.

Additional sets and parameters

Criteria are defined based on duration curves and time series and requires additional sets and parameters. The time series are gathered in a parameter (ts). They are defined for every days of the year ($d \in D$) and for every hour of the day ($h \in H$). The time series used for criteria are gathered in a set ($TIME\_SERIES$). hence, the parameter *ts(i,h,td)* is called with three parameters a time serie part of set $TIME\_SERIES$, an hour ($h \in H$) and a day ($d \in d$).

Computational time

The computational cost is measured on a standard personal machine[17]. The k-medoids and Poncelet-HYB method are limited to 50000 replicates which is equivalent to around 1h of computational time. For the Poncelet method, a timeout is imposed at 1 hour, similarly to what is performed in their study [56]. No upper limit is required for the Domínguez-Muños method as it runs in less than 1h.

Clustering error

Eq. 17 defines the absolute clustering error (E_{cl}). For each typical day (td), a set of days (d) is associated: the set (TD_OF_DAY) relates days to typical days, e.g. $d \in TD\_OF\_DAY(td)$ gathers all the days (d) related to the typical day (td). Each typical day is related to a representative day (d_td) and are related by $d\_td \in DAY\_OF\_TD(td)$.Based on Eq. 18 which defines the reference clustering error ($E_{cl_{ref}}$), we define the relative error (ε_{cl}) as the ratio between the clustering error (E_{cl}) and the reference clustering error ($E_{cl_{ref}}$).

$$E_{cl} = \sqrt{\sum_{i \in TIME\_SERIES, t \in T | \{h,td\} \in T\_H\_TD(t) | d \in TD\_OF\_DAY(td) \& d\_td \in DAY\_Of\_TD} \omega(i) \cdot \Big(ts(i,h,d\_td) - ts(i,h,d)\Big)^2} \tag{17}$$

$$E_{cl,ref} = \sqrt{\sum_{i \in TIME\_SERIES, t \in T | \{h,td\} \in T\_H\_TD(t) | d\_td \in DAY\_OF\_TD} \omega(i) \cdot \Big(ts(i,h,d\_td) - \frac{1}{8760} \sum_{d2 \in D, h2 \in H} ts(i,h2,d2)\Big)^2} \tag{18}$$

Figure 13 represents the clustering error computation for one day of the year. The error is the normalized sum of the distances.

[17] Intel®Core^{TM} Quad i7-6600U CPU @2.60GHz, with a memory of 8 Go, and a 64-bit system.

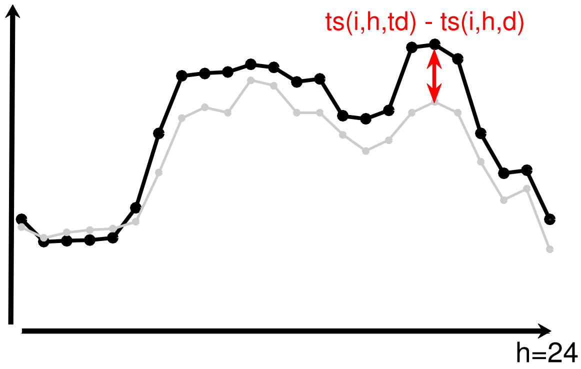


Figure 13: Illustration of a the clustering error for the electricity demand time serie (i=*Electricity demand*). The black curve represents the typical day 11, which is related to day 347. The Grey curve represents a day $d \in TD\_of\_day(11)$, in this case $d = 7$. The red arrow represents the distance between these two days at 7 pm ($h = 19$).

Duration curve error

A duration curve illustrates the variation of a certain load in a downward form such that the greatest load is plotted in the left and the smallest one in the right. In this case, the loads are the hourly capacity factors or the demand. Eq. 19 defines the absolute duration curve error (E_{dc}). For each time series ($i \in$ *TIME_SERIES*) and every time step ($t \in T$), we compare the real duration curve $dc_{ref}(i, T)$ with the approximated duration curve ($dc_{approx}(i, T)$) based on typical days. Based on Eq. 20 which defines the reference duration curve error ($E_{dc,ref}$), we define the relative error (ε_{cl}) as the ratio between the clustering error (E_{dc}) and the reference clustering error ($E_{dc,ref}$). The reference clustering error is computed as the error made compare to an averaged constant duration curve.

$$E_{dc} = \sqrt{\sum_{i \in TIME\_SERIES, t \in T} \omega(i) \cdot \Big(dc_{ref}(i,t) - dc_{approx}(i,t)\Big)^2} \tag{19}$$

$$E_{dc_{ref}} = \sqrt{\sum_{i \in TIME\_SERIES, t \in T} \omega(i) \cdot \Big(dc_{ref}(i,t) - \frac{1}{8760}\sum_{t2 \in T} dc_{ref}(i,t2)\Big)^2} \tag{20}$$

Figure 14 represents the clustering error computation for one day of the year.

B.3 Benchmark

Figure 15 resorts on 4 TDs and presents three approximated duration curves (power demand, heat demand and sun radiation) compared to the reference one. Figure 16 resorts on 12 TDs. The four clustering methods offer consistent results. Increasing the number of TDs decreases the space between the approximated duration curves and the real ones.

Tables 8 and 9 summarize the performance of the methods while resorting to 4 and 12 typical days respectively. The analysis reveals that Domínguez-Muños method offers the best results for each criteria.

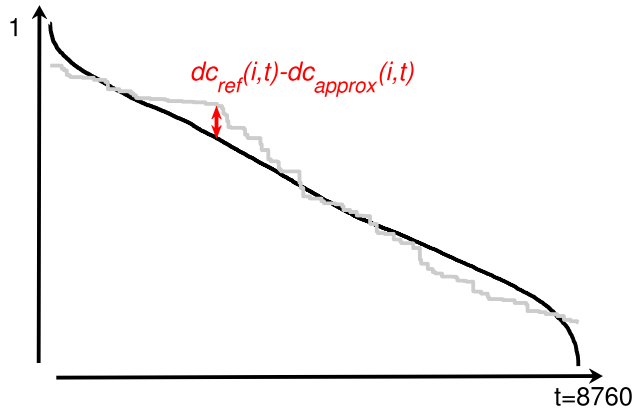


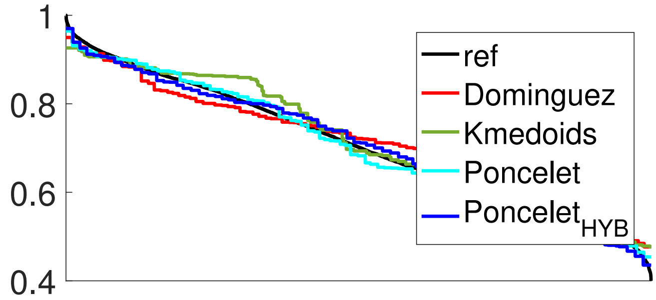
Figure 14: Illustration of a duration curve error for the electricity demand (i= *"Electricity demand"*). The black curve represents the real duration curve based on the 8760 h data. The grey curve represents the approximated duration curve while resorting to 4 TDs and the k-medoids method. The red arrow represents the distance between these two duration curves at a arbitrary hour (h= 2878).

Table 8: Performance of clustering methods to compute 4 typical days.

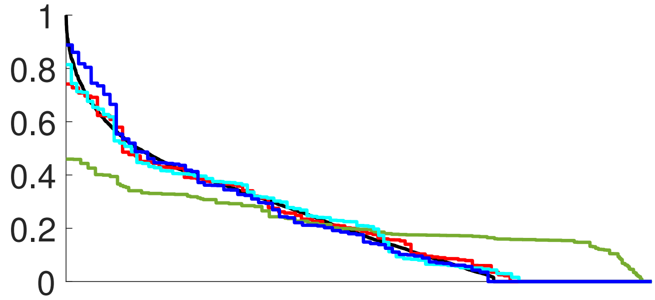
Criteria	Units	k-medoids	Domínguez-Muños	Poncelet	Poncelet HYB
Computational cost	[s]	1022	292	3600	3125
Clustering error ε_{cl}	[-]	25.9%	10.5%	12.2%	13.3%
Duration curve error ε_{dc}	[-]	49.7%	18.3%	20.4%	18.5%

Table 9: Performance of clustering methods to compute 12 typical days.

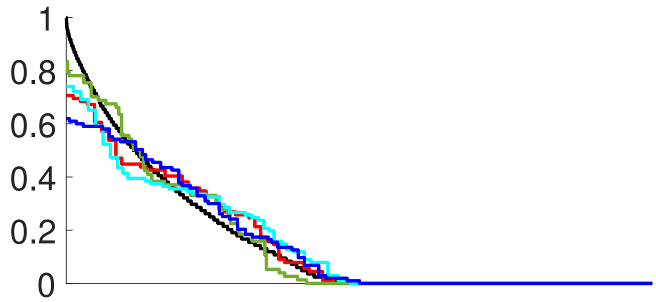
Criteria	Units	k-medoids	Domínguez-Muños	Poncelet	Poncelet HYB
Computational cost	[s]	3750	876	3600	3253
Clustering error ε_{cl}	[-]	24.4%	9.2%	11.6%	11.6%
Duration curve error ε_{dc}	[-]	19.1%	7.7%	12.5%	12.3%



(a) Power

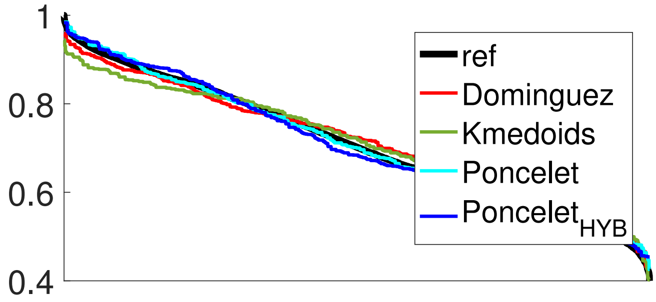


(b) Heat

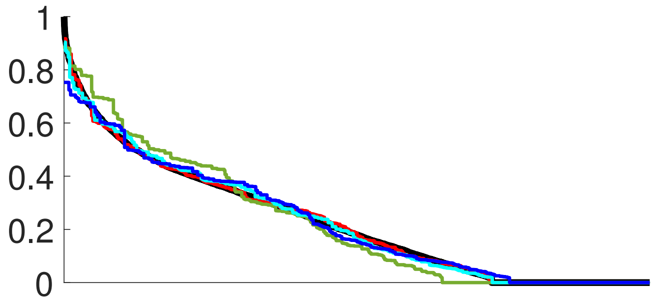


(c) Sun

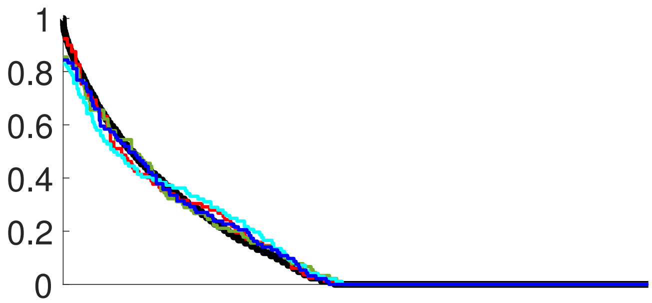
Figure 15: Approximation of the duration curves using different clustering methods and 4 typical days. Methods are consistent and similar, except for the k-medoids. Legend: Dominguez stands for the Domínguez-Muños method.



(a) Power



(b) Heat



(c) Sun

Figure 16: Approximation of the duration curves using different clustering methods and 12 typical days. Methods are consistent and perform better than when resorting to 4 TDs, as presented in Figure 15.

Acronyms

BEV battery electric vehicle.

CAPEX capital expenditure.

CCGT combined cycle gas turbine.

CHP combined heat and power.

CNG compressed natural gas.

COP coefficient of performance.

DHN district heating network.

EnergyScope TD EnergyScope Typical Days.

EUD end-use demand.

EUT end-use type.

EV electric vehicle.

FEC final energy consumption.

GHG greenhouse gas.

GWP global warming potential.

HP heat pump.

HW hot water.

IGCC integrated gasification combined cycle.

iRE intermittent renewable energies.

LCA life cycle assessment.

LIFO last in first out.

LNG liquified natural gas.

LP linear programming.

MILP mixed-integer linear programming.

NG natural gas.

Openmod Open Energy Modelling Initiative.

PHEV plug-in hybrid electric vehicle.

PHS pumped hydro storage.

PtG power to gas.

PtH power to heat.

PV photovoltaic.

RE renewable energies.

SH space heating.

TD typical day.

TS thermal storage.

V2G vehicle-to-grid.

References

[1] H. Lund and B. V. Mathiesen. "Energy system analysis of 100% renewable energy systems-The case of Denmark in years 2030 and 2050". In: *Energy* 34.5 (2009), pp. 524–531. ISSN: 03605442. DOI: 10.1016/j.energy.2008.04.003.

[2] S. Pfenninger and J. Keirstead. "Renewables, nuclear, or fossil fuels? Scenarios for Great Britain's power system considering costs, emissions and energy security". In: *Applied Energy* 152 (2015), pp. 83–93. ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.04.102.

[3] A. Van Stiphout, K. De Vos, and G. Deconinck. "Operational flexibility provided by storage in generation expansion planning with high shares of renewables". In: *International Conference on the European Energy Market, EEM* 2015-August (2015). ISSN: 21654093. DOI: 10.1109/EEM.2015.7216760.

[4] G. Limpens and H. Jeanmart. "Electricity storage needs for the energy transition: An EROI based analysis illustrated by the case of Belgium". In: *Energy* 152 (2018), pp. 960–973. ISSN: 03605442. DOI: 10.1016/j.energy.2018.03.180.

[5] D. Heide et al. "Seasonal optimal mix of wind and solar power in a future, highly renewable Europe". In: *Renewable Energy* 35.11 (2010), pp. 2483–2489. ISSN: 09601481. DOI: 10.1016/j.renene.2010.03.012.

[6] M. Z. Jacobson et al. "Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar for all purposes". In: *Proceedings of the National Academy of Sciences* 112.49 (2015), pp. 15060–15065. ISSN: 0027-8424. DOI: 10.1073/pnas.1510028112. URL: http://www.pnas.org/lookup/doi/10.1073/pnas.1510028112.

[7] M. Z. Jacobson et al. "100% Clean and Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World". In: *Joule* 1.1 (2017), pp. 108–121. ISSN: 25424351. DOI: 10.1016/j.joule.2017.07.005. URL: http://dx.doi.org/10.1016/j.joule.2017.07.005.

[8] D. Connolly et al. "Heat roadmap Europe: Combining district heating with heat savings to decarbonise the EU energy system". In: *Energy Policy* 65 (2014), pp. 475–489. ISSN: 03014215. DOI: 10.1016/j.enpol.2013.10.035. URL: http://dx.doi.org/10.1016/j.enpol.2013.10.035.

[9] B. V. Mathiesen et al. "Smart Energy Systems for coherent 100% renewable energy and transport solutions". In: *Applied Energy* 145 (2015), pp. 139–154. ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.01.075. arXiv: arXiv:1011.1669v3. URL: http://dx.doi.org/10.1016/j.apenergy.2015.01.075.

[10] A. A. Solomon, D. M. Kammen, and D. Callaway. "The role of large-scale energy storage design and dispatch in the power grid: A study of very high grid penetration of variable renewable resources". In: *Applied Energy* 134 (2014), pp. 75–89. ISSN: 03062619. DOI: 10.1016/j.apenergy.2014.07.095. URL: http://dx.doi.org/10.1016/j.apenergy.2014.07.095.

[11] G. Pleßmann et al. "Global energy storage demand for a 100% renewable electricity supply". In: *Energy Procedia* 46 (2014), pp. 22–31. ISSN: 18766102. DOI: 10.1016/j.egypro.2014.01.154.

[12] D. Connolly and B. V. Mathiesen. "Aalborg Universitet A technical and economic analysis of one potential pathway to a 100% renewable energy system". In: *International Journal of Sustainable Energy Planning and Management* 1 (2018), pp. 7–28. ISSN: 2246 - 2929. DOI: 10.5278/ijsepm.2014.1.2. URL: http://vbn.aau.dk/files/197397631/DC{_}BVM.pdf.

[13] D. Connolly et al. "A review of computer tools for analysing the integration of renewable energy into various energy systems". In: *Applied Energy* 87.4 (2010), pp. 1059–1082. ISSN: 03062619. DOI: 10.1016/j.apenergy.2009.09.026.

[14] S. Pfenninger et al. "Opening the black box of energy modelling: Strategies and lessons learned". In: *Energy Strategy Reviews* 19 (2018), pp. 63–71. ISSN: 2211467X. DOI: 10.1016/j.esr.2017.12.002. arXiv: 1707.08164.

[15] M. G. Prina et al. "Transition pathways optimization methodology through EnergyPLAN software for long-term energy planning". In: *Applied Energy* 235.August 2018 (2019), pp. 356–368. ISSN: 03062619. DOI: 10.1016/j.apenergy.2018.10.099. URL: https://doi.org/10.1016/j.apenergy.2018.10.099.

[16] *OpenMod-initiative*. URL: http://www.openmod-initiative.org/ (visited on 07/17/2018).

[17] S. Quoilin, I. Hidalgo Gonzalez, and A. Zucker. *JRC TECHNICAL REPORTS Modelling Future EU Power Systems Under High Shares of Renewables First Main Title Line First Line Second Main Title Line Second Line Third Main Title Line Third Line*. Tech. rep. European Union, 2017. DOI: 10.2760/25400. URL: https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/modelling-future-eu-power-systems-under-high-shares-renewables-dispa-set-21-open-source.

[18] DLR Institute of Networked Energy Systems. *SciGRID*. URL: http://git.scigrid.de/ (visited on 07/17/2018).

[19] Ea Energy Analyses. *The STREAM modelling tool - models*. 2016. URL: http://www.ea-energianalyse.dk/themes/stream{_}uk.html (visited on 07/17/2018).

[20] L. G. Fishbone and H. Abilock. "Markal, a linear-programming model for energy systems analysis: Technical description of the bnl version". In: *International Journal of Energy Research* 5.4 (1981), pp. 353–375. ISSN: 1099114X. DOI: 10.1002/er.4440050406.

[21] Energy Information Administration Office of Integrated Analysis and Forecasting. *The National Energy Modeling System (NEMS): An Overview 2009*. Tech. rep. October. 2009. URL: www.eia.doe.gov/oiaf/aeo/overview.

[22] University College Cork. *Plexos*. URL: https://energyexemplar.com/ (visited on 07/17/2018).

[23] H Lund. *EnergyPLAN Advanced Energy System Analysis Model*. 2007. URL: http://energy.plan.aau.dk (visited on 07/17/2018).

[24] R. A. Wurbs. "limited to predicting system performance for a user-specified set of variable values , optimization models automatically search for an " optimum " solu- Although optimization and simulation are two alternative modeling ap- proaches with different characte". In: *Journal of Water Resources Planning and Management* 119.4 (1993), pp. 455–472.

[25] S. Moret. "Strategic energy planning under uncertainty". PhD thesis. EPFL, 2017. DOI: 10.5075/EPFL-THESIS-7961. URL: https://infoscience.epfl.ch/record/231814?ln=fr.

[26] S. Pfenninger, A. Hawkes, and J. Keirstead. *Energy systems modeling for twenty-first century energy challenges*. 2014. DOI: 10.1016/j.rser.2014.02.003.

[27] S. Pfenninger. *Calliope: A multi-scale energy systems modelling framework*. URL: https://www.callio.pe/.

[28] A. University. *EnergyInteractive.NET*. URL: http://energyinteractive.net/ (visited on 07/17/2018).

[29] Imperial College London. *2050 Desstinee*. URL: https://sites.google.com/site/2050desstinee/ (visited on 07/17/2018).

[30] T. Bobmann and I. Staffell. "The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain". In: *Energy* 90 (2015), pp. 1317–1333. ISSN: 03605442. DOI: 10.1016/j.energy.2015.06.082. URL: http://dx.doi.org/10.1016/j.energy.2015.06.082.

[31] A. Zerrahn and W. P. Schill. "Long-run power storage requirements for high shares of renewables: review and a new model". In: *Renewable and Sustainable Energy Reviews* 79.November 2016 (2017), pp. 1518–1534. ISSN: 18790690. DOI: 10.1016/j.rser.2016.11.098. URL: http://dx.doi.org/10.1016/j.rser.2016.11.098.

[32] S. Hilpert et al. "The Open Energy Modelling Framework (oemof) - A new approach to facilitate open science in energy system modelling". In: *Energy Strategy Reviews* 22.July (2018), pp. 16–25. ISSN: 2211467X. DOI: 10.1016/j.esr.2018.07.001. URL: https://doi.org/10.1016/j.esr.2018.07.001.

[33] O. developer group. *oemof - open energy modelling framework (v0.2.2) (Version v0.2.2)*. 2018. URL: https://github.com/oemof/oemof/releases (visited on 07/17/2018).

[34] M. Howells et al. "OSeMOSYS: The Open Source Energy Modeling System. An introduction to its ethos, structure and development." In: *Energy Policy* 39.10 (2011), pp. 5850–5870. ISSN: 03014215. DOI: 10.1016/j.enpol.2011.06.033. URL: http://dx.doi.org/10.1016/j.enpol.2011.06.033.

[35] KTH Royal Institute of Technology. *OSeMOSYS (Open Source Energy Modelling System) OSeMOSYS*. URL: http://www.osemosys.org/ (visited on 07/17/2018).

[36] T. Brown, J. Hörsch, and D. Schlachtberger. "PyPSA: Python for Power System Analysis". In: (2017). DOI: 10.5334/jors.188. arXiv: 1707.09913. URL: http://arxiv.org/abs/1707.09913{\%}0Ahttp://dx.doi.org/10.5334/jors.188.

[37] T. Brown, J. Hörsch, and D. Schlachtberger. *PyPSA: Python for Power System Analysis*. 2017. DOI: 10.5334/jors.188. arXiv: 1707.09913. URL: http://arxiv.org/abs/1707.09913%0Ahttp://dx.doi.org/10.5334/jors.188 (visited on 07/17/2018).

[38] Univesity of Hawaii. *switch-model*. URL: https://github.com/switch-model/switch (visited on 04/25/2019).

[39] J. Johnston et al. "Switch 2.0: A Modern Platform for Planning High-Renewable Power Systems". In: (2018). arXiv: 1804.05481. URL: http://arxiv.org/abs/1804.05481.

[40] TUM EI ENS. *URBS*. URL: https://github.com/tum-ens/urbs (visited on 07/17/2018).

[41] J. Dorfner. "Open Source Modelling and Optimisation of Energy Infrastructure at Urban Scale". PhD thesis. Technische Universität München, 2016, p. 205.

[42] S. Moret et al. "Swiss-EnergyScope . ch : a Platform to Widely Spread Energy Literacy and Aid Decision-Making". In: *Chemical Engineering Transactions* 39.August (2014), pp. 877–882. ISSN: 22839216. DOI: 10.3303/CET1439147. URL: http://www.scopus.com/inward/record.url?eid=2-s2.0-84908089535{\&}partnerID=tZOtx3y1.

[43] S. Moret, M. Bierlaire, and F. Maréchal. "Strategic Energy Planning under Uncertainty: a Mixed-Integer Linear Programming Modeling Framework for Large-Scale Energy Systems". In: *Computer Aided Chemical Engineering*. Vol. 38. 2003. 2016, pp. 1899–1904. ISBN: 9780444634283. DOI: 10.1016/B978-0-444-63428-3.50321-0.

[44] S. Moret et al. "Characterization of input uncertainties in strategic energy planning models". In: *Applied Energy* 202 (2017), pp. 597–617. ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.05.106. URL: http://dx.doi.org/10.1016/j.apenergy.2017.05.106.

[45] V. Codina Gironès et al. "Strategic energy planning for large-scale energy systems: A modelling framework to aid decision-making". In: *Energy* 90.PA1 (2015), pp. 173–186. ISSN: 03605442. DOI: 10.1016/j.energy.2015.06.008.

[46] V. Codina Gironès. "Scenario modelling and optimisation of renewable energy integration for the energy transition". PhD thesis. EPFL, 2018.

[47] S. Moret et al. "Integration of deep geothermal energy and woody biomass conversion pathways in urban systems". In: *Energy Conversion and Management* 129 (2016), pp. 305–318. ISSN: 01968904. DOI: 10.1016/j.enconman.2016.09.079. URL: http://dx.doi.org/10.1016/j.enconman.2016.09.079.

[48] V. Codina Gironès et al. "On the Assessment of the CO2 Mitigation Potential of Woody Biomass". In: *Frontiers in Energy Research* 5.January (2018), pp. 1–18. DOI: 10.3389/fenrg.2017.00037.

[49] V. Codina Gironès et al. "Optimal use of biomass in large-scale energy systems: Insights for energy policy". In: *Energy* 137 (2017), pp. 789–797. ISSN: 03605442. DOI: 10.1016/j.energy.2017.05.027.

[50] S. Moret et al. "Decision support for strategic energy planning: A robust optimization framework". In: *European Journal of Operational Research* (2019). ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2019.06.015. URL: http://www.sciencedirect.com/science/article/pii/S0377221719304904.

[51] K. Poncelet et al. "Impact of the level of temporal and operational detail in energy-system planning models". In: *Applied Energy* 162 (2016), pp. 631–643. ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.10.100. URL: http://dx.doi.org/10.1016/j.apenergy.2015.10.100.

[52] P. Gabrielli et al. "Corrigendum to "Optimal design of multi-energy systems with seasonal storage" [Appl. Energy (2017)]". In: *Applied Energy* 212.June (2018), p. 720. ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.12.070. URL: http://dx.doi.org/10.1016/j.apenergy.2017.07.142.

[53] J. Després et al. "Storage as a flexibility option in power systems with high shares of variable renewable energy sources: a POLES-based analysis". In: *Energy Economics* 64 (2017), pp. 638–650. ISSN: 01409883. DOI: 10.1016/j.eneco.2016.03.006. URL: http://dx.doi.org/10.1016/j.eneco.2016.03.006.

[54] P. Nahmmacher et al. "Carpe Diem: A Novel Approach to Select Representative Days for Long-Term Power System Models with High Shares of Renewable Energy Sources". In: *Ssrn* (2014), pp. 1–28. ISSN: 1556-5068. DOI: 10.2139/ssrn.2537072. URL: http://www.ssrn.com/abstract=2537072.

[55] A. Pina, C. A. Silva, and P. Ferrão. “High-resolution modeling framework for planning electricity systems with high penetration of renewables”. In: *Applied Energy* 112 (2013), pp. 215–223. ISSN: 03062619. DOI: 10.1016/j.apenergy.2013.05.074. URL: http://dx.doi.org/10.1016/j.apenergy.2013.05.074.

[56] K. Poncelet et al. “Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems”. In: *IEEE Transactions on Power Systems* 32.3 (2017), pp. 1936–1948. ISSN: 08858950. DOI: 10.1109/TPWRS.2016.2596803.

[57] F. Domínguez-Muñoz et al. “Selection of typical demand days for CHP optimization”. In: *Energy and Buildings* 43.11 (2011), pp. 3036–3043. ISSN: 03787788. DOI: 10.1016/j.enbuild.2011.07.024.

[58] J. E. Gentle, L. Kaufman, and P. J. Rousseuw. *Finding Groups in Data: An Introduction to Cluster Analysis.* Vol. 47. 2. John Wiley & Sons, 2006, p. 788. DOI: 10.2307/2532178.

[59] H. S. Park and C. H. Jun. “A simple and fast algorithm for K-medoids clustering”. In: *Expert Systems with Applications* 36.2 PART 2 (2009), pp. 3336–3341. ISSN: 09574174. DOI: 10.1016/j.eswa.2008.01.039. URL: http://dx.doi.org/10.1016/j.eswa.2008.01.039.

[60] I. Panapakidis and G. Christoforidis. “Optimal Selection of Clustering Algorithm via Multi-Criteria Decision Analysis (MCDA) for Load Profiling Applications”. In: *Applied Sciences* 8.2 (2018), p. 237. ISSN: 20763417. DOI: 10.3390/app8020237.

[61] H. D. Vinod. “Integer Programming and the Theory of Grouping Author (s): Hrishikesh D . Vinod Source : Journal of the American Statistical Association , Vol . 64 , No . 326 (Jun ., 1969), pp . Published by : Taylor & Francis , Ltd . on behalf of the American Statis”. In: *Journal of the American Statistical Association* 64.326 (1969), pp. 506–519.

[62] European Commission - Eurostat. *Glossary: Final Energy Consumption.* (Visited on 12/14/2018).

[63] J. Hodges and J. Dewar. *Is it you or your model talking?: A framework for model validation.* Tech. rep. 1992, pp. 1–32. URL: http://www.rand.org/content/dam/rand/pubs/reports/2006/R4114.pdf.

[64] P. P. Craig, A. Gadgil, and J. G. Koomey. “ W HAT C AN H ISTORY T EACH U S ? A Retrospective Examination of Long-Term Energy Forecasts for the United States ”. In: *Annual Review of Energy and the Environment* 27.1 (2002), pp. 83–118. ISSN: 1056-3466. DOI: 10.1146/annurev.energy.27.122001.083425. arXiv: 1407.4895.

[65] Swiss Federal Office of Energy (SFOE). *Overall energy statistics 2011.* DE/FR. Tech. rep. 2012.

[66] Swiss Federal Office of Energy (SFOE). *Swiss electricity statistics 2011.* DE/FR. Tech. rep. Bern, Switzerland, 2012.

[67] Swiss Federal Office of Energy (SFOE). *Swiss electricity statistics 2012.* DE/FR. Tech. rep. Bern, Switzerland, 2013.

[68] Swiss Federal Office of Statistics (SFOS). *Statistique de la Suisse - Mobilité et transports 2013.* French. Tech. rep. Swiss Federal Office of Statistics (SFOS), 2013.

[69] Swiss Federal Office of Energy (SFOE). *Thermische Stromproduktion inklusive Wärmekraftkopplung (WKK) in der Schweiz - Ausgabe 2011.* German. Tech. rep. Nov. 2012.

[70] d. l.e.d.l.c. D. Département federal de l'environnement des transports. *Emissions d'apres la lio sur le CO2 et d'apres le protocole de Kyoto.* Tech. rep. 2005.

[71] S. Cajot et al. "Interactive optimization for the planning of urban systems". In: *Energy Procedia* 122 (2017), pp. 445–450. ISSN: 18766102. DOI: 10.1016/j.egypro.2017.07.383.

[72] A. S. Brouwer et al. "Least-cost options for integrating intermittent renewables in low-carbon power systems". In: *Applied Energy* 161 (2016), pp. 48–74. ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.09.090.

[73] D. Jung and S. Kettemann. "Long-range response in ac electricity grids". In: *Physical Review E* 94.1 (2016), pp. 1–11. ISSN: 24700053. DOI: 10.1103/PhysRevE.94.012307.

[74] H Ravn. *Balmorel*. URL: http://www.balmorel.com/ (visited on 07/17/2018).

[75] O. R. N. Laboratory. *Whole-Building and Community Integration Program*. URL: http://www.coolingheatingpower.org/ (visited on 07/17/2018).

[76] M. Hübel et al. "Modelling and simulation of a coal-fired power plant for start-up optimisation". In: *Applied Energy* 208.October (2017), pp. 319–331. ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.10.033.

[77] T. U. Berlin. *ELMOD*. URL: https://www.diw.de/de/diw{_}01.c.528493.de/forschung{_}beratung/nachhaltigkeit/umwelt/verkehr/energie/modelle/elmod.htmlWebsite/Documentation (visited on 07/17/2018).

[78] T. U. Delft and T. U. Delft. *EMLab Energy Modelling Laboratory Introduction*. 2015. URL: http://emlab.tudelft.nl/ (visited on 07/17/2018).

[79] L. Hirth. *The European Electricity Market Model EMMA Model documentation*. 2017. URL: https://neon-energie.de/emma-documentation.pdf.

[80] UCL Energy Institute. *EnergyNumbers-Balancing*. URL: http://energynumbers.info/balancing (visited on 07/17/2018).

[81] O. Lugovoy. *energyRT*. URL: https://olugovoy.github.io/energyRt/ (visited on 07/17/2018).

[82] Quintel. *Energy Transition Model documentation: Storage*. 2014. URL: https://github.com/quintel/documentation/blob/795b562baf75d54f044e79dab57889a44eb84a1e/general/storage.md (visited on 07/17/2018).

[83] C. F. Heuberger et al. "Power capacity expansion planning considering endogenous technology cost learning". In: *Applied Energy* 204.March (2017), pp. 831–845. ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.07.075.

[84] D. Atabay. "An open-source model for optimal design and operation of industrial energy systems". In: *Energy* 121 (2017), pp. 803–821. ISSN: 03605442. DOI: 10.1016/j.energy.2017.01.030. URL: http://dx.doi.org/10.1016/j.energy.2017.01.030.

[85] D. Atabay. *A (mixed integer) linear optimisation model for local energy systems*. URL: https://github.com/yabata/ficus (visited on 07/17/2018).

[86] Technische Universitat Dresden. *GAMAMOD*. URL: https://tu-dresden.de/bu/wirtschaft/ee2/forschung/modelle/gamamod?set_language=en.

[87] RWTH Aachen University. *Genesys - Energy system pathway optimisation*. URL: http://www.genesys.rwth-aachen.de/wordpress/ (visited on 07/17/2018).

[88] M. L. Santiago Peñate Vera. *GridCal*. URL: https://github.com/SanPen/GridCal.

[89] NREL. *HOMER Energy website*. 2015. URL: https://users.homerenergy.com (visited on 2018).

[90] Vienna University of Technology. *Invert.* URL: http://www.invert.at/ (visited on 07/17/2018).

[91] COMMEND. *Community for Energy, Environment and Development.* 2015. URL: https://www.energycommunity.org/default.asp (visited on 07/17/2018).

[92] T. Ahmed. *Modeling the Renewable Energy Transition in Canada.* 2016. DOI: 10.1007/978-3-319-31505-8. URL: http://link.springer.com/10.1007/978-3-319-31505-8 (visited on 07/17/2018).

[93] Pacific Northwest National laboratory. *MiniCAM.* URL: http://www.globalchange.umd.edu/ (visited on 07/17/2018).

[94] L. Exel, F. Felgner, and G. Frey. "Multi-domain modeling of distributed energy systems-The MOCES approach". In: *2015 IEEE International Conference on Smart Grid Communications, SmartGridComm 2015* (2016), pp. 774–779. DOI: 10.1109/SmartGridComm.2015.7436395.

[95] D. Huppmann and R. Egging. "Market power, fuel substitution and infrastructure - A large-scale equilibrium model of global energy markets". In: *Energy* 75 (2014), pp. 483–500. ISSN: 03605442. DOI: 10.1016/j.energy.2014.08.004. URL: http://dx.doi.org/10.1016/j.energy.2014.08.004.

[96] R. E. Daniel Huppmann. *The energy system and resource market model "MultiMod".* URL: https://www.diw.de/en/diw_01.c.510381.en/research_advice/research_projects/project_homepages/resources/multimod/multimod.html (visited on 07/17/2018).

[97] S. Fan, S. Member, and R. J. Hyndman. *National Electricity Market.* 2012. URL: https://github.com/bje-/NEMO (visited on 07/17/2018).

[98] E. I. Administration. *The National Energy Modeling System.* 2015. DOI: 10.17226/1997. URL: https://www.eia.gov/analysis/pdfpages/m068index.php (visited on 07/17/2018).

[99] A. de Roo et al. "Lighting the World: the first application of an open source, spatial electrification tool (OnSSET) on Sub-Saharan Africa". In: *Environmental Research Letters* 12.8 (2017), p. 085003. DOI: 10.1088/1748-9326/aa7b29.

[100] KTH Royal Institute of Technology. *OpeN Source Spatial Electrification Toolkit (ONSSET).* 2017. URL: https://www.kth.se/en/itm/inst/energiteknik/forskning/desa/projects/sustainable-energy-f/open-source-spatial-electrification-toolkit-onsset-1.663655 (visited on 07/17/2018).

[101] Flexiblepower Alliance Network. *PowerMatcher.* URL: https://github.com/flexiblepower/powermatcher/releases.

[102] F. Wiese. *renpass - Renewable Energy Pathways Simulation System.* 2013. URL: https://github.com/fraukewiese/renpass (visited on 07/17/2018).

[103] F. Wiese et al. "An open source energy system simulation model as an instrument for public participation in the development of strategies for a sustainable future". In: *Wiley Interdisciplinary Reviews: Energy and Environment* 3.5 (2014), pp. 490–504. ISSN: 2041840X. DOI: 10.1002/wene.109.

[104] B. Columbia and S. Black. *Natural Resources Canada.* 2014. DOI: https://www.nrcan.gc.ca/home. (Visited on 07/17/2018).

[105] M. Naumann et al. "SimSES: Software for techno-economic Simulation of Stationary Energy Storage Systems". In: *International ETG Congress* (2017), pp. 442–447.

[106] Technical University of Munich. *Simulation of stationary energy storage systems.* URL: https://bitbucket.org/Team{_}SES/opensimses (visited on 07/17/2018).

[107] Sustainable Energy Now Inc. *SEN Integrated Renewable Energy Network Toolkit.* URL: https://github.com/ozsolarwind/siren (visited on 07/17/2018).

[108] J. Abrell and F. Kunz. "Integrating Intermittent Renewable Wind Generation - A Stochastic Multi-Market Electricity Model for the European Electricity Market". In: *Networks and Spatial Economics* 15.1 (2015), pp. 117–147. ISSN: 15729427. DOI: 10.1007/s11067-014-9272-4.

[109] DIW Berlin. *Stochastic Multi-Market Electricity Model.* URL: https://github.com/frkunz/stELMOD (visited on 07/17/2018).

[110] K. Hunter, S. Sreepathi, and J. F. DeCarolis. "Modeling for insight using Tools for Energy Model Optimization and Analysis (Temoa)". In: *Energy Economics* 40 (2013), pp. 339–349. ISSN: 01409883. DOI: 10.1016/j.eneco.2013.07.014. URL: http://dx.doi.org/10.1016/j.eneco.2013.07.014.

[111] The Temoa Project. *Tools for Energy Model Optimization and Analysis.* 2018. URL: https://github.com/TemoaProject/temoa (visited on 07/17/2018).

[112] L. Andresen et al. "Status of the TransiEnt Library: Transient Simulation of Coupled Energy Networks with High Share of Renewable Energy". In: *Proceedings of the 11th International Modelica Conference, Versailles, France, September 21-23, 2015.* Vol. 118. 2015, pp. 695–705. DOI: 10.3384/ecp15118695.

[113] Hamburg University of Technology. *TransiEnt.* URL: https://www.tuhh.de/transient-ee/en/download.html (visited on 07/17/2018).