universität innsbruck

Fakultät für Technische Wissenschaften

Enhanced multi-energy hub concept - integration of industrial processes in a local energy system

Dipl.-Ing. Markus Groissböck, BA

Innsbruck, Juni 2021

Dissertation

eingereicht an der Leopold-Franzens-Universität Innsbruck, Fakultät für Technische Wissenschaften zur Erlangung des akademischen Grades

Doktor der Technischen Wissenschaften

Erster Beurteiler:	Univ.-Prof. Dr. techn. Wolfgang Streicher, Universität Innsbruck, Institut für Konstruktion und Materialwissenschaften, Arbeitsbereich Energieeffizientes Bauen
Zweiter Beurteiler:	Ass.-Prof. Dr. techn. Rui Castro, Universität Lissabon, Instituto Superior Técnico (IST), Abteilung Elektrotechnik und Informationstechnik, Arbeitsbereich Energiesysteme

Hauptbetreuer:	Univ.-Prof. Dr. techn. Wolfgang Streicher, Universität Innsbruck, Institut für Konstruktion und Materialwissenschaften, Arbeitsbereich Energieeffizientes Bauen

Acknowledgments

First, I would like to thank my supervisor Wolfgang for giving me the opportunity to pursue a PhD in Energy Efficient Buildings/Systems and his invaluable advice and continuous support during my studies. I am extremely grateful for the many constructive discussions, for his always positive and encouraging feedback and for giving me the space to structure my research as well as my schedule.

Secondly, I would like to thank Rui Castro from the Universidade de Lisboa, Instituto Superior Técnico (IST), for being my second examiner and supporting me on this journey: muito obrigado.

Furthermore, I would also like to thank Alexandre (my co-author), and the entire team at the Unit of Energy Efficient Building for stimulating discussions on (and off) the topic of my thesis as well as for their support and encouragement throughout my studies.

Finally, I would also like to thank my family and friends for their support they have shown me through this research and their understanding of working long hours, weekends, and holidays on this very special project.

Kurzfassung

Der Grüne Deal der Europäischen Union sucht Wege für unterschiedliche und untereinander verknüpfte Energiesysteme. Elektrischer Strom wird als die wichtigste Form von Energie der Zukunft gesehen und dessen Verfügbarkeit muss daher immer gegeben sein. Ein nachhaltiges und menschen-freundliches Klima basiert auf der Verringerung von Emissionen (im Speziellen von Kohlendioxid, CO_2). Es ist allgemein bekannt und weitgehend akzeptiert, dass Erneuerbare Energien und Energie-Effizienz-Verbesserungen beide Wünsche unterstützen können. Deshalb ist der Zweck dieser Arbeit beide Aspekte zu verbinden und zu evaluieren wie bestehende Open-Source Energie-System-Design (ESD)-Tools herangezogen werden können um den Energiebedarf von Industrieparks und Städten optimal zu planen.

Open-Source ESD-Tools werden immer besser, können in echten Anwendungen außerhalb von Forschung verwendet werden und müssen sich vielfach nicht mehr hinter kommerziellen Alternativen verstecken.

Die Bewertung von verschiedenen Europäischen Staaten in Bezug auf deren Erneuerbaren Energien (mit Fokus auf Solar PV und Wind) Potenzial zeigen, dass die Qualität dieser Erneuerbaren weniger Einfluss auf die optimale Ausbauplanung haben als die vorgegebenen energiepolitischen Rahmenbedingungen.

Ein tiefgreifender Ausbau an variablen Erneuerbaren Energien zeigt die solide Möglichkeit CO_2-Emissionen zu reduzieren und schafft es ohne Berücksichtigung gewaltiger Mengen an Energiespeichertechnologien nicht konventionelle Kraftwerke komplett zu ersetzen, ohne dabei die Versorgungssicherheit zu gefährden.

Zahlreiche Open-Source Frameworks sind verfügbar, um es Forschern zu erlauben sich auf die tatsächliche Forschungsfrage zu fokussieren und sich nicht mit der Programmierung von ESD-Tools herumzuschlagen. Innerhalb dieses Projektes wurden die Open-Source-Pakete Time Series Aggregation Module (tsam) und Framework for Integrated Energy System Assessment (FINE) intensiv genutzt. Innerhalb dieser Arbeit

wurde tsam um eigene Methoden zur Zeitreihen-Gruppierung erweitert. Außerdem wurde FINE durch einen Nachverarbeitungsschritt erweitert, um die Verfügbarkeit des Energiesystems zu berücksichtigen. Zusätzlich wurden TESpy und aristopy verwendet um thermische Systeme wie z.B. Wärmepumpen und Solarthermie-Systeme exakter abbilden zu können.

Abstract

The European Union's Green Deal asks for a diverse and more interconnected energy system. Electric power will be the most important type of energy in the future and therefore needs to be available at any time. A sustainable and human-friendly climate requires decreasing emissions (especially of carbon dioxide, CO_2). As well-known and widely accepted, only the use of renewable energy sources and energy efficiency improvement can support both desires. Therefore, this thesis aims to combine both aspects and examines how existing open-source energy system design (ESD) tools can be used to plan the energy delivery for industrial parks and cities in an optimal way.

Open-source ESD tools are mature enough to be used in real-world applications and do not have to hide behind commercial applications anymore.

The assessment of different European countries regarding the quality of their variable renewable energy (with a focus on Solar PV and Wind) showed that the quality of renewables is less important than the overall energy policy to follow.

Intensive expansion of variable renewables energy shows massive possibilities to reduce CO_2 emissions but clearly fails to result in significant conventional power generation replacement from a security of supply perspective without the introduction of massive energy storage technologies.

Many open-source frameworks are available to help researchers to focus on their research question instead of writing a new ESD tool. Within this project, the open-source packages Time Series Aggregation Module (tsam) and Framework for Integrated Energy System Assessment (FINE) have been used intensively. Within this study tsam has been expanded with own time series clustering methods. FINE was enhancements through a post-processing algorithm to assess the reliability of energy systems. Additionally, TESpy and aristopy have been used to assess thermal systems such as heat pump and solar thermal systems.

Contents

List of Figures ix
List of Tables x
1 Introduction 1
1.1 Motivation 2
1.2 Publications 4
1.3 Thesis structure 5
2 Literature review 7
2.1 Energy hubs 7
2.2 Energy system modeling 9
2.3 Open source 12
3 Open-source energy system design tools 15
3.1 Methodology 15
3.2 Results 16
4 Importance of renewable sources 19
4.1 Methodology 19
4.2 Results 21
5 Renewables impact on security of supply 24
5.1 Methodology 24
5.2 Results 26
6 Proposed open-source framework 28
6.1 Methodology 28
6.2 Results 30
7 Updated ESD tool assessment 33
7.1 Enhancements with little coding 35

7.2 Enhancements with significant coding ... 37
8 Input data assessment ... 40
8.1 Ambient condition ... 41
8.2 Energy demand ... 41
8.3 Renewable generation ... 42
8.4 Cost & prices ... 44
Power prices ... 44
Energy conversion technologies ... 44
8.5 Time series aggregation ... 47
9 Conclusion and further research ... 49
9.1 Conclusion ... 50
9.2 Further research ... 52
Bibliography ... 53
Appendix - Reprints ... 60
Paper 1 ... 61
Paper 2 ... 75
Paper 3 ... 87
Paper 4 ... 100

List of Figures

Figure 1: Aim of the European Green Deal [2] 1
Figure 2: Generations of district heating/cooling systems [4] 2
Figure 3: Exemplary and simple energy hub [7] 3
Figure 4: Distinct steps within the open-source discussion [68] 13
Figure 5: Simple open license selection [60] 14
Figure 6: Ranking the different evaluations [62] 18
Figure 7: Average capacity factors of PV and Wind [63] 20
Figure 8: Methodology [63] 21
Figure 9: Overall simulation results [63] 22
Figure 10: Methodology [67] 25
Figure 11: RM vs. EENS with different RES additions and different system sizes [67] . 26
Figure 12: Proposed methodology and selection of open-source data and tools [1] 29
Figure 13: Framework for Integrated Energy System Assessment (FINE) [40] 35
Figure 14: Implemented reliability methodology 38
Figure 15: Unordered and ordered temperature profiles [55] 41
Figure 16: Unordered and ordered electricity demands [55] 42
Figure 17: Unordered and ordered Solar PV generation [66] 42
Figure 18: Unordered and ordered Wind generation [66] 43
Figure 19: Ordered profiles with 100% and 200% renewables (based on [66]) 43
Figure 20: Ordered power exchange prices [55] 44
Figure 21: LCOE sensitivity 46
Figure 22: Modified screening curves with 200% renewables 47
Figure 23: Economy of scale sensitivity 47
Figure 24: MAE accuracy of TSA 48
Figure 25: Overall accuracy of TSA 48
Figure 26: Algorithm independent overall accuracy of TSA 52

List of Tables

Table 1: Link research questions with thesis chapters 4
Table 2: List of peer-reviewed publications 5
Table 3: List of conference presentations 5
Table 4: Classification of previous research [5] 11
Table 5: Examples of open-source initiatives [68] 14
Table 6: Assessed tools [62] 16
Table 7: Assessed functions and their interpretation [62] 17
Table 8: Assessed optimal RES expansion paths [63] 19
Table 9: Selected country list and considered rationale [63] 20
Table 10: Optimal RES paths as objective function of aim [63] 23
Table 11: Selective existing framework comparison [1] 30
Table 12: Proposal of selected open-source initiative components [1] 31
Table 13: Details for selected ESD tools 33
Table 14: Exemplary adjustment functions [73] [74] 36
Table 15: Own RC_BuildingSimulator extensions 37
Table 16: Own tsam extensions 37
Table 17: Own FINE extensions 37
Table 18: High-level uncertainty assessment of input data 40
Table 19: Technology overview considered in LCOE sensitivity [74] 45
Table 20: TSA to day of the week mapping 48
Table 21: Summary of most important parameters 51
Table 22: Publications 60

1 Introduction [1]

The European Union's (EU) Green Deal is one of the six priorities of the European Commission between 2019 and 2024 [2]. This Green Deal aims to lead the EU into a sustainable and net-zero greenhouse gas emission society by the latest 2050. Figure 1 shows how the Green Deal aims to change the European energy landscape from a predominantly linear and non-sustainable into a sustainable, fully integrated, and circular ecosystem. The most important principles are to electrify all end-use sectors as much as they can be electrified and using clean biofuels or e-fuels for the sectors that cannot be electrified economically or at all (such as heavy industry and long-distance transportation). On top of this, energy efficiency and sufficiency are two other very critical components of a sustainable future.

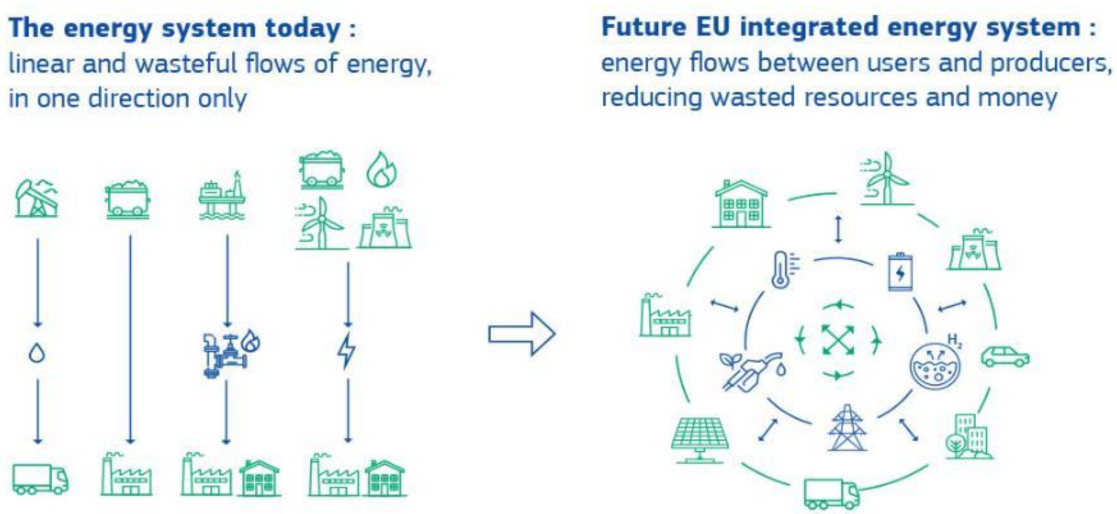


Figure 1: Aim of the European Green Deal [2]

Industrial energy demand makes about 1/3 of the total primary energy consumption within the European Union [3]. Most of this energy demand is used in continuous (all year long) process applications (mainly heating). Therefore, it provides a unique opportunity to be linked with cities, municipalities, or other energy-demanding sectors such as healthcare to fulfill their heat (or cold) requirements. Historically, (1st generation)

[1] Parts of this chapter has been taken out of Groissböck (2021) [1]

district heating systems were operating with steam (~200°C, >15 bar) as heat transfer media (see Figure 2) [4]. Since the 1930th, pressurized hot water (~100°C) has become the dominant heat transfer media for district heating systems. The latest development (4th generation) aims to use water temperature even below 50°C (known as ultra-low temperature district heat) and aims to utilize all kinds of energy sources. Examples of alternative energy sources are geothermal sources, low and high-temperature heat pumps, data center exhaust air, and excess heat from industrial processes.

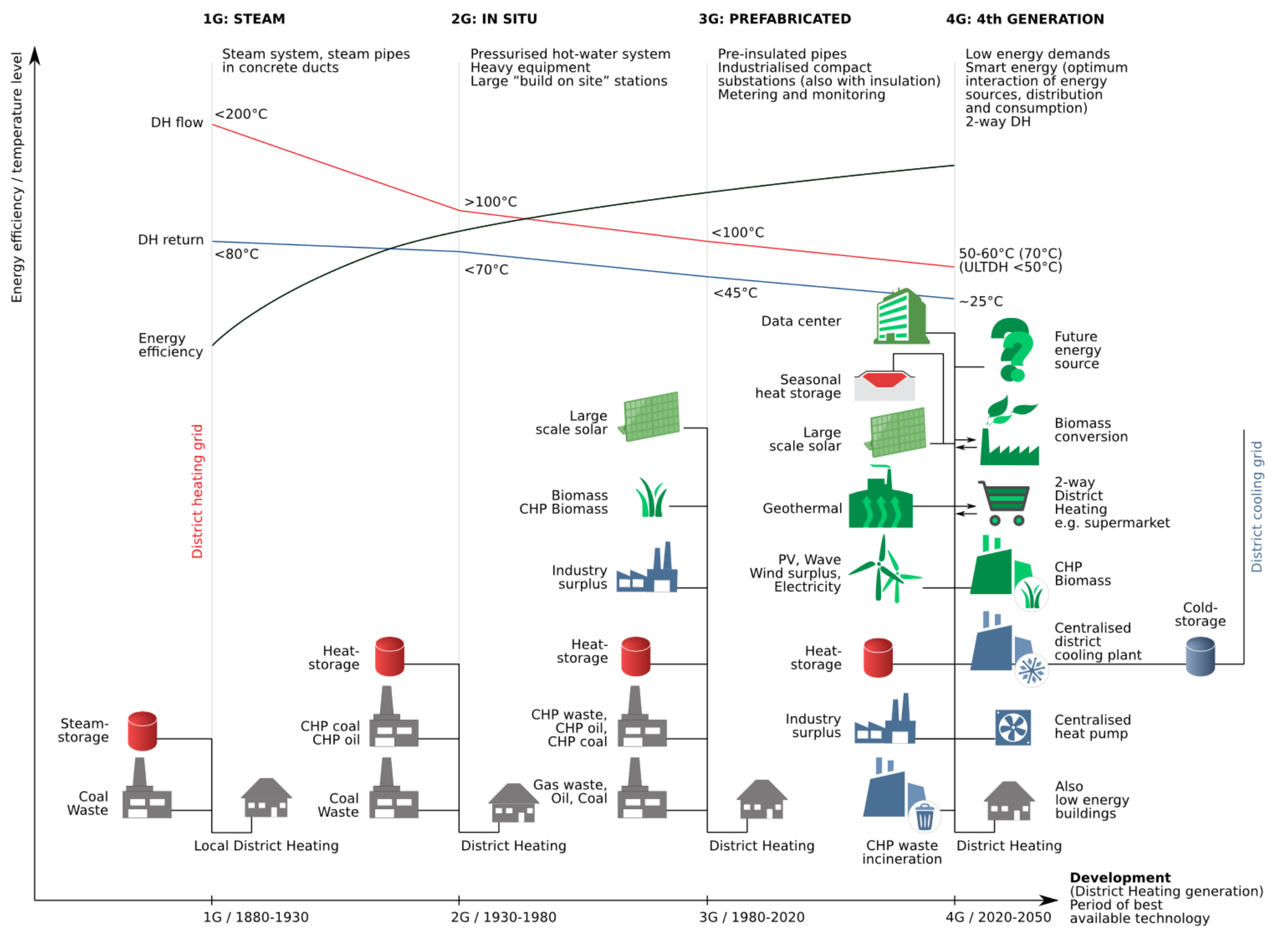


Figure 2: Generations of district heating/cooling systems [4]

Scholars such as Buffa et al. (2019) discuss the definition of the 5th generation of district heating and cooling (DHC) in detail. DHC aims to operate at temperature levels of about 5-35°C and considers concepts such as single and double-stage heat pumps to increase the DHC water temperature to desired temperature levels at the customer site [5].

1.1 Motivation

The vision of the EU and its Member States could and should be an aspiration for municipalities, districts, and industrial parks. Such interconnected systems have to deal with multiple energy carriers while today's state-of-the-art planning is still based on individual energy carriers as some organizations plan for power and others plan for heating. Some organizations plan for power generation, others plan for its transmission, and others for its distribution. Recently, multi-modal energy system design (ESD) has gained increased interest from science as well as from public and private organizations to enable integrated planning of different energy carriers [6]. Linking different energy-producing and consuming organizations within municipality boundaries needs more integrated planning of all energy carriers necessary and available.

The energy hub concept offers this linkage of multiple energy carriers. It supports increasing energy efficiency as well as decreasing greenhouse gas (GHG) emissions simultaneously. An energy hub is based on the interconnector concept where heating, natural gas (in future renewable biogas and/or gas from power-to-gas processes), and electricity are distributed within one physical multi-energy pipeline [7]. Each energy hub can use multiple energy carriers depending on its individual demand profiles, economics, and security of supply considerations, as shown in Figure 3.

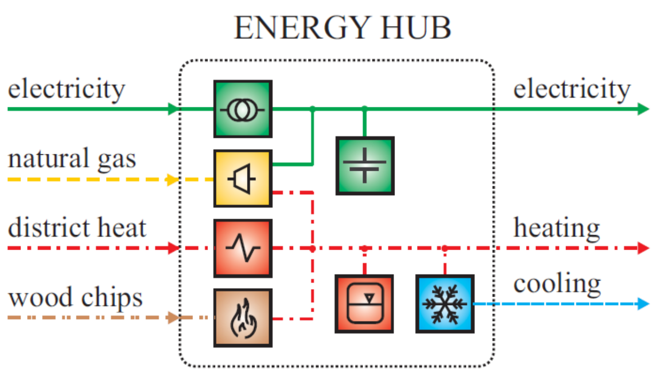


Figure 3: Exemplary and simple energy hub [7]

The sample energy hub contains typical elements: electrical transformer, gas engine or turbine, heat exchanger, battery storage, hot water storage, and absorption chiller [8]. Energy hubs could be extended by considering additional input streams (e.g., water, hydrogen, and carbon dioxide - CO_2) as well as additional output streams representing ‘power-to-X’ options (e.g., synthetic methane, methanol, and ammonia). From a mathematical modeling perspective, energy hubs are units (locations) where multiple forms of energy can be either converted (e.g., wood chips to heat), conditioned (e.g., electricity use in appliances), or stored (e.g., battery storage) for later use. All this transformation and processing comes with conversion and storage losses. It creates a place where all available and possible future energy carriers can have interactions to minimize the overall system cost.

While an energy hub has some inputs (such as electricity, natural gas, and district heating), it has to fulfill the energy demand within the energy hub (such as power demand, heating or cooling loads, compressed air demand, or steam requirements). It also can be used to forward any or all of the energy carriers to its neighbor energy hubs through different kinds of transportation (such as power lines, natural gas, district heating pipelines, or trucking). Within the energy hub, energy conditioning can happen through, e.g., combined heat and power technologies, compressors, or heat exchangers.

The energy hub concept can be used for single customers and industrial complexes. Industrial parks could be implemented as an energy hub as well, where demand from several commercial buildings, attached district heating/cooling networks, offices, and industrial demand is combined in one energy hub. To reflect multiple locations accordingly, the consideration of electricity transmission and distribution (active and reactive power) as well as water and gas pipelines (mass flow and pressure) is necessary [9].

The aspect of different temperature levels of heat (such as low/high-temperature heat or cold energy) has not been intensively considered in multi-energy systems (coupled electricity and heat management). Therefore, this project aims to provide a collection of tools allowing an improved linkage of multiple temperature levels of heat/cold as well as assessing the impact of ambient conditions on considered energy conversion technologies. Adding these technical details will allow the framework to be used in real-world applications to conduct pre-feasibility studies of superstructure problems for industrial parks linking energy-intensive customers with offices or municipalities' energy requirements.

The fact that variable renewable energy sources (RES) have seen significant cost reductions in recent years (especially for Solar photovoltaic (PV) and Wind) [8], ESD tools are forced to assess more interconnected systems with multiple energy carriers and energy conditions. Therefore, the study seeks to answer the research questions listed in Table 1.

Table 1: Link research questions with thesis chapters

Chapter	Research question
3	How mature are open-source energy system design tools compared with commercial alternatives?
4	How much impact has the quality of renewables on the decision for an optimal renewable expansion path?
5	How many conventional generators are still required for a reliable energy system with very high shares of renewables?
6	How to combine existing open-source tools for a thoughtful integration of industrial processes into a local energy system?
7	How to incorporate security of supply in ESD assessments?
8	How sensitive are key input parameters within an ESD assessment?

1.2 Publications

Table 2 lists all peer-reviewed publications, while Table 3 lists the presentations at conferences during the course of this study. Paper P1 defined 81 features and assessed 31 mostly open-source tools regarding their maturity. Paper P2 assessed the importance of renewable profiles for six selected European countries in terms of the impact on an optimal expansion plan. Paper P3 evaluated the renewable profiles of the same six European countries and the impact on the overall security of supply while considering different sizes of energy systems (e.g., industrial parks, cities, regions, countries). Paper P4 assessed recently shared open-source models with a focus on urban areas (including industrial parks) for their fit towards a new model capable to cover the entire project extent from project start (having no data) until the end of the project (having all data, optimization results, visualization). The first conference (C1) represented an initial step in producing paper P3, and the second conference (C2) served as the basis for P4.

Table 2: List of peer-reviewed publications

	Reference	**Open Access**
P1	Groissböck M. (2019) Are open-source energy system optimization tools mature enough for serious use? *Renewable and Sustainable Energy Reviews*, 102, 234-248, DOI: 10.1016/j.rser.2018.11.020.	No
P2	Groissböck M. (2020) Impact of spatial renewable resource quality on optimum renewable expansion, *Renewable Energy*, 160, 1396-1407, DOI: 10.1016/j.renene.2020.07.041.	Yes
P3	Groissböck M. & Gusmão A. (2020) Impact of renewable resource quality on security of supply with high shares of renewable energies, *Applied Energy*, 277, 115567, DOI: 10.1016/j.apenergy.2020.115567.	Yes
P4	Groissböck M. (2021) Energy hub optimization framework based on open-source software & data - review of frameworks and a concept for districts & industrial parks, *International Journal of Sustainable Energy Planning and Management*, 31, 109-120, DOI: 10.5278/ijsepm.6432.	Yes

Table 3: List of conference presentations

	Reference
C1	Groissböck M. & Gusmão A. (2019, April 12) Reliability constrained generation expansion planning: Case study for different system sizes and characteristic renewable profiles, *ENERDAY 2019*, Dresden, Germany.
C2	Groissböck M. (2020, October 6-7) Energy hub optimization framework based on open-source: review of frameworks and concept for districts & industrial complexes, *Smart-Energy-Systems 2020*, Aalborg, Denmark.

1.3 Thesis structure

The remainder of this thesis is structured as followed:

Chapter 2 starts with a literature review related to energy hubs, energy system design (ESD), and open-source movements within ESD.

Chapter 3 to Chapter 6 summarize the published papers and focuses on the basic principles and the main findings of the published and accepted papers. A detailed methodology description and more background information are available in the individual paper.

Chapter 3 gives an overview of available open-source ESD models and how to assess them for unbiased selection and usage. Comparing the 31 selected open-source tools with several commercial closed-source tools based on 81 features, it can be seen that open-source tools are getting closer to the functionality of closed-source tools. Within an operational focus pyPSA even takes over the commercial closed source tools.

Chapter 4 provides an overview of the importance of renewable energy sources related to generation expansion planning towards full decarbonization for local and industrial energy systems. Based on the analyzed renewable profiles it can be argued that the impact of RES quality is minor and is more dictated by the overarching objective function (e.g., economics, target residential contribution, maximize excess electricity).

Chapter 5 assesses the impact of renewable energy source expansion planning on the system security of supply for different sizes of energy systems with a particular focus on small energy systems potentially representing industrial customers. A too high assumption on reserve margin would increase the required conventional generation capacity unnecessarily. Using loss of load hours (LOLH) as the single metric for power system planning, the expected energy not served (EENS) will increase with growing renewable capacity installed. On the other side, a stringent and constant assumption of EENS would be too constraining for power system planning.

Chapter 6 sketches a proposal of how a holistic energy system framework could look based on available open-source packages and snippets allowing joined assessment of industrial and local energy systems. The proposed open-source framework is based on the principle of maximizing the reuse of existing data, software snippets, and packages. Added features include a scenery model to incorporate shadowing and elevation effects on conventional power generation technologies. By doing so, the utilization of limited resources could be improved significantly.

Chapter 7 summarizes an updated ESD model assessment and shows some modeling enhancements where some of them are based on combining different Python packages while others are based on my programming efforts. Individual extensions include the economy of scale for cost and performance as required. Also, additional clustering techniques have been added. The most significant enhancement has been the incorporation of a system reliability assessment by using LOLH and the capacity outage probability table (COPT). Combined with the possibility of limiting the largest unit size to be added, also short-term impact such as inertia can be considered in a simple and preliminary way to ensure a reliable power system even with high shares of renewable energy.

Chapter 8 shows an assessment of the importance of individual parameters within ESD modeling projects. The single most important parameters for expensive technologies are financing cost, investment cost, and technology lifetime. For low-cost technologies, the most important parameters are utilization, investment cost, energy conversion rates, and variable operating and maintenance cost.

Finally, Chapter 9 provides the key findings and draws conclusions derived from results shown and discussed in the previous chapters.

2 Literature review [2]

This chapter is divided into three parts: part one describes the energy hub in more detail, part two describes today’s move towards more open research, and part three describes the complex discipline of ESD.

With the movement to more interconnected energy systems, the complexity of the energy systems is rising and, therefore, the need for cooperation [10]. This broader call for cooperation comes hand in hand with the call for sharing assumptions and results, especially from publicly funded projects, to increase transparency in money use, research methods, and research outcomes. This is one of the reasons why open-source energy system modeling is gaining momentum. Traditionally energy planning started with planning for power, oil, and gas infrastructure. Planning for power system infrastructure was done with reference cases where expected maximum and minimum demand as well as expected maximum and minimum contribution of variable renewable power generation was predicted.

With the development of increasingly powerful computers, the process industry started optimizing their energy landscape with powerful optimization models. This also marked the start of operations research within the energy sector. The first optimization models used hourly or sub-hourly demand profiles and implemented the power flow (PF) in a linearized direct current (DC) version. As such, megawatt (MW) and megawatt-hours (MWh) were the units of choice for modeling. Such simplifications have been considered for other parts of the energy system.

2.1 Energy hubs

Since the first publication in 2004, different departments at the ETH Zurich (German abbreviation for Eidgenössische Technische Hochschule) have adjusted and improved the energy hub concept. The 'Group for Sustainability and Technology' studies how to ideally add the energy hub concept into existing energy markets and how to increase locally produced energy [10]. Considerable efforts in understanding the setup and impact of energy hubs within buildings and within the district level have been accomplished. The 'Energy Science Center' examines questions around minimizing greenhouse gas emissions, including the use of the energy hub concept at the neighborhood scale [11].

[2] This chapter has been taken out of Groissböck (2021) [9]

They consider details such as how to deal with load variability and the impact on system stability and aim to reduce the daily load imbalances within the energy hub. Also, social barriers and suggestions on how to overcome them were considered. The 'Separation Processes Laboratory' combines the possibilities of energy storage and demand-side management to increase energy efficiency through onsite co- and tri-generation (CHP, CCHP). The focus of this lab is to include detailed thermodynamics from a building's perspective. The 'Research Center for Energy Networks' has created software packages (middleware) to ideally schedule and manage existing equipment within technical limitations considering personal behavior and personal settings. The focus of this research group is on the communication of advanced measurement devices, and central and decentralized communication systems based on adequate software protocols. The overall goal is to optimize current equipment operation to minimize carbon emissions and maximize energy efficiency [12]. The overall target of ETH Zurich is to increase social acceptance. Currently, none of their referenced work is considering industrial loads with different temperature requirements of heat, cold, or steam.

EU-funded projects such as EFENIS (Efficient Energy Integrated Solutions for Manufacturing Industries) [13], EINSTEIN (Expert-system for an INtelligent Supply of Thermal Energy in INdustry and other large-scale applications) [14], ENEPLAN (ENergy Efficient Process pLAnning system) [15], EnRiMa (Energy Efficiency and Risk Management in Public Buildings) [16], and EPICHUB (Energy Positive Neighbourhoods Infrastructure Middleware based on Energy-Hub Concept) [17] worked on integrated software solutions to prove the overall concept within case studies to highlight the benefits of the superstructure in different sizes of industry. Nevertheless, none of them added the necessary non-linear technical constraints to mimic hourly or sub-hourly technical behavior.

Lately, several universities have been attracted by the energy hub concept. The Technical University (TU) Munich introduced an open-source optimization framework based on Python and Pyomo and is, therefore, able to use different solvers [18]. For performance reasons, the framework allows users to turn off features such as minimum required new capacity to build, simultaneous charge and discharge of storage, and part-load behavior to minimize computational requirements. While part-load behavior is able to be represented from an energy input and energy output perspective, the impact of ambient conditions on efficiency and power output has been ignored. The RWTH (German abbreviation of Rheinisch-Westfälische Technische Hochschule) Aachen works in decentralized energy supply systems (DESS) optimization [19] [20]. Retrofits and green field projects can be assessed with their approach. Robust optimization was chosen to ensure security of energy supply within the DESS. All technical system constraints are given in linear form. District heating, water supply, liquid fuel supply, and non-linear technical constraints have not been considered. The TU Vienna also focused on district heating systems (DHS) [21] [22].

Talebi et al. (2016) discussed possible modeling approaches based on hydraulic and thermal equilibrium, which are used within DHS simulation and optimization [23]. Lambert et al. (2016) created a framework for decision-makers to help them answer the questions "if" and "when" a DHS shall be expanded [24]. Dorfner (2016) incorporated other details such as building stock information [25], while Fritz (2016) added gas network considerations [22]. Bothe (2016) added hydraulic and thermodynamics considerations into this framework [21]. While thermodynamic and hydraulic details of DHS have been incorporated, no interaction between different conversion and storage technologies have been considered. Also, only some load steps a year have been used in their optimization framework. A small number of considered timesteps is not appropriate for reflecting the variability of Solar PV and Wind.

All previously mentioned optimization concepts use a mixed-integer linear programming (MILP) approach for solving their optimization problems. Zhou et al. (2017) handle the optimization within a mixed-integer quadratic programming (MIQP) formulation to assess co-expansion and operation optimization planning of electricity and gas [26]. Reliability is considered for each energy type (electricity, cooling, and heating load) via a simple value of lost load (VOLL). While the use of MIQP can eliminate the risk of diverging and sub-optimality, the solution process is much slower. In this case, it relies on processing a predefined link for technologies and is, therefore, not able to be used in green field projects, in which the most economic configuration and setup is not known. In addition, operational aspects of the natural gas system, such as compressor operation, are not considered.

Today, the energy hub concept is focusing on piped energy as district heat, gas, and electricity, while non-energy carriers (e.g., water) and non-pipeline energy supply is not considered. Storage is considered for final energy sources but not for primary sources. Within energy hubs, the daily demand patterns are optimized. However, none of the available publications incorporated correction functions for adjustment based on ambient conditions and part-load. More flexible tools capable of considering improved thermodynamics, hydraulics, or correction curves (e.g., impact on efficiency and power output on generation technologies) are required to answer questions around Net Zero Energy (NZE) and the use of high quantities of RES [27]. Part-load considerations might gain importance as the share of RES increases within the electricity transmission and distribution system resulting in more spinning reserve and up and down ramping flexibility.

2.2 Energy system modeling

Bruckner (1997) focused on overall energy efficiency improvements through the optimal configuration of available energy technologies [28]. Biberacher (2004) concentrated on the implementation of geographical information systems (GIS) into the optimization model to optimize long-term energy fulfillment on a national scale [29]. Both did not include a detailed energy model assessment in their work. Geidl (2007) focused purely on the modeling aspect of energy hubs, as his work was the first of its kind considering multiple forms of energy jointly within one expansion planning and operation application [30].

Connolly et al. (2010) listed 68 tools and investigated 37 out of them to validate if they can be used for renewable energy integration assessments [31]. While there were no typical applications identified, a screening for the use of the individual tools was examined. The ‘ideal’ tool depends on the final use case: e.g., building or energy system analysis, energy-sectors, technologies, and time parameters the tool is able to deal with. Nevertheless, the paper claims to provide ‘the information necessary to direct the decision-maker towards a suitable energy tool for an analysis that must be completed' [31:1059].

Mendes et al. (2011) focused on energy modeling assessments with a special interest in communities and districts [32]. The analysis was based on a survey of available bottom-up energy models for optimal planning of integrated community energy systems (including HOMER, DER-CAM, EAM, MARKAL/TIMES, RETScreen, and R2RES). After describing and examining these tools, a SWOT (strengths, weaknesses, opportunities, and threats) analysis was conducted. A detailed overview of approaches on how to optimize problems in energy distribution networks (such as simulated annealing, genetic algorithms, tabu search, and particle swarm optimization) was also presented. The overall finding was that DER-CAM is an appropriate energy model for optimized energy provisioning for communities.

Mancarella (2014) provided a detailed overview of existing concepts and evaluation models within the multi-energy system (MES) community [33]. Based on this work, MES aims to increase the final energy conversion by optimizing the split into centralized and decentralized energy conversion technologies. As such the overall energy system flexibility is increase. MES is characterized by its spatial, multi-service, multi-energy, and network perspective. It is an ideal concept for integrating different energy sectors (nowadays known as 'sector coupling' or 'integrated energy systems'), which traditionally have been treated in isolation. A brief discussion of the features of MES tools also considered a small number of tools. The study aimed to show the state-of-the-art of MES concepts and models but did not conduct a detailed assessment.

Dorfner (2017) provided a very brief overview of optimization tools based on an assessment conducted by Keirstead et al. (2012) [25] [34]. The only tools discussed are MARKAL, TIMES, and MESSAGE, as the study's objective was to provide open-source tools (via the source code sharing platform github.com) to support the idea of maintainability of models, reproducibility of case studies, and co-optimization of heat and electricity carriers. Keirstead et al. (2012) reviewed 219 papers and identified five key areas of practice: 'technology design, building design, urban climate, systems design, and policy assessment' [34:3847]. A great future for urban energy system modeling is predicted if the challenges of model complexity and data uncertainty can be resolved.

Thiem (2017) looked briefly into existing tools such as Balmorel, DER-CAM, EnergyPLAN, energyPRO, HOMER, MARKAL&TIMES, MGEOS, RETScreen, TOP-Energy, TRNSYS, and urbs [5]. After a brief discussion of these tools, the focus of the remaining literature review focused on six groups of applications (see Table 4). The groups have been created based on existing energy model reviews and the scope of optimization tools (such as spatial dimension, covered model details, and type of optimization problem) but no detailed screen analysis have been done. The focus of his research lies within group 5 to design multi-modal energy systems under consideration of part-load efficiencies.

Table 4: Classification of previous research [5]

<table>
<tr><th></th><th>Description</th><th colspan="2">Type optimization problem</th></tr>
<tr><td>1</td><td>Large-scale grid studies relying on simplified models</td><td rowspan="3">LP</td><td></td></tr>
<tr><td>2</td><td>Simple tools for quick assessments of small-scale energy systems</td><td></td></tr>
<tr><td>3</td><td>City district ESD studies with simplified models</td><td rowspan="3">MILP</td></tr>
<tr><td>4</td><td>On-site energy system studies with additional features</td><td></td></tr>
<tr><td>5</td><td>Mixed-integer linear programming with part-load efficiencies</td><td></td></tr>
<tr><td>6</td><td>Mixed-integer nonlinear programming with complex models</td><td></td><td>MINLP</td></tr>
</table>

Abbreviations: LP – Linear Programming; MILP – Mixed-Integer LP; MINLP – Mixed-Integer Nonlinear LP.

Paletto et al. (2019) integrated life cycle assessment (LCA) components into the discussion which allows adding factors that are not economically per se in a first instance [35]. This can be, e.g., plant emissions such as CO_2, CO, NOx, SOx, and PM10 (particulate matter with size ≤ 10 micrometers). Also, materials needed to build the plants can be added in such an approach allowing to consider, e.g., concrete, sand or working hours.

Prina et al. (2019) provided a novel classification schemes for bottom-up energy system modeling tools [36]. They identified two main categories and challenges: resolution and transparency. Hereby, resolution is further divided into time resolution, space resolution, techno-economic detail, and details around sector coupling. In addition, their proposed matrix of low, medium, and high level of resolution shows that no tool has been benchmarked as ‘high’ in any category. The closest to reach this is the open-source optimization tool pyPSA, followed by the commercial tool PLEXOS. The only category where pyPSA has received a rating of ‘medium’ is within the category ‘sector coupling’. It is not transparent why optimization tools such as oemof, Calliope, and ficus have been rated ‘high’ in this category. As to the best knowledge of the author, the tools have very similar or almost the same capabilities in this regard. Another top-ranked tool is the LUT model, which unfortunately is not available for the public. The simulation tool EnergyPLAN is also mentioned in this paper. It is a freeware but not open source. Therefore, only freely available and open-source models such as pyPSA, oemof, Calliope, and ficus have been considered in this work going forward.

Ridha et al. (2020) assessed surveys collected during the MODEX (Model Experiments) project in which the Forschungszentrum Jülich (FZ Jülich) asked modelers to provide their views on a questionnaire [37]. The survey data was analyzed based on the criteria of mathematical complexity (e.g., LP, MILP, MINLP, stochastic), temporal complexity (e.g., temporal resolution and horizon of planning), spatial complexity (e.g., geographical resolution and horizon), and system complexity (e.g., modeled scope). The focus of their work was to assess how complexity can be reduced through clustering, the use of less techno-economic details, or the use of less information about the individual sectors. Therefore, the common practice is that energy system modeling tools focus on their area of interest and ignore other aspects to decrease the complexity of the overall problem to a level on which available optimization solvers can deliver results in a reasonable time.

A joined activity between FZ Jülich and RWTH Aachen led to an open-source energy system model called Framework for Integrated Energy System Assessment

(FINE) [38] [39][3]. It focuses on TSA and how it impacts long-term planning until 2050 for Germany. The TSA was done with the Python package tsam [40] [41].

Up to now, most of the available open-source energy system models are based on LP or MILP formulations. A very interesting development here is the first release of aristopy, an open-source model which can solve even MINLP problems [42] [43]. The developers aimed for easy extendibility. Therefore, enhancements within the problem setup can be realized without advanced Python programming skills. Another new development is the open-source model Open Platform for Energy Networks (OPEN), which allows a non-linear optimization and simulation of smart local energy systems focusing on renewable energy and electric vehicle fast-charging applications [44].

2.3 Open source

Open source has a long history within information technology, in which several leading software packages have been made available to the public (e.g., Apache - web server, Netscape - browser, MySQL - database, Linux - operating system) [45]. Unfortunately, in research and development (R&D) as well as in some companies, there are serious ethical, security, and commercial concerns that open source is a threat [46]. The fear relates to unwanted exposure from, e.g., flawed source code, data, or analysis. Another assumption is that time-consuming activities (such as programming, verifying results, or writing documentation) are competitive advantages. Perhaps it is only natural that sometimes the institutional and personal inertia stops organizations and people from following open-source principles. But what are some of these open-source principles? First, adding transparency to the source code and allowing peer review increases the quality of the software package, which then can also be used by other organizations instead of writing the same piece of functionality again. A peer-review process can also lead to increased collaboration. With a focus on R&D, this implies that sharing data, models, and results increases productivity through burden-sharing. As a result, the focus can be set on doing something new and helpful for society instead of repeating necessary, important but sometimes monotonic tasks. Of importance within the R&D community is that only results, which are seen and challenged from other parts of the community, are useful to R&D and the overall society. Everything else can be considered self-adulation. An ethical argument is that if R&D is funded by public money, the results should be publicly available as well. Open access to data, source code, energy system models, and results are crucial for a balanced social and political debate. On top of this, R&D has to support society and governments to model for insights guiding policymakers instead of raising the numbers of publications [47].

Fostering open source to get more transparency and repeatability of analysis was written by DeCarolis et al. (2012) [48]. One of the main findings was that a thorough review of results and conclusions is currently impossible. A multi-national research team around Howells, in which DeCarolis was part of, developed the first open-source energy modeling tool, OSeMOSYS (Open Source Energy Modeling System) [49]. One of the key features of OSeMOSYS's implementation is the mathematical formulation in plain English, meaning that the mathematical formulation is the documentation as well. The

[3] The use of two references next to Python packages refers to a publication and the according source code.

formulation has less than five pages of documentation and an easily accessible code. A research team around DeCarolis started the development of another open-source energy modeling tool, Temoa (Tools for Energy Model Optimization and Analysis) [50]. The design of this tool aims for more tractable uncertainty analysis and utilization of multi-core high-performance computing to perform rigorous uncertainty investigation. Pfenninger et al. (2017) highlighted that energy models and data are an important part of energy policy assessments [51]. They also found that opening up R&D, including models and data, would show immense benefits for all participating parties inside and outside of R&D. Hülk et al. (2018) represent one of the latest open-source energy modeling approaches: oemof (Open Energy Modeling Framework - A modular open-source framework to model energy supply systems) [52]. This initiative aims to provide flexible and generic components to model cross-sectoral (e.g., heat, power, or mobility) and multi-regional open, modular, and transparent models allowing everyone to contribute. Publications stemming from this initiative became the steppingstone for an overall open R&D community, in which raw data, model formulation, energy model choice, raw results, interpretation, and dissemination are shared transparently with interested people.

Figure 4 shows how an overall open-source energy system modeling project might be divided into several distinct process steps in which individual R&D communities and projects contribute to one or several of these process steps. An often-ignored step is the numerical solver, as the R&D community assumes access to commercial solvers; some of them are free or very affordable for academics.

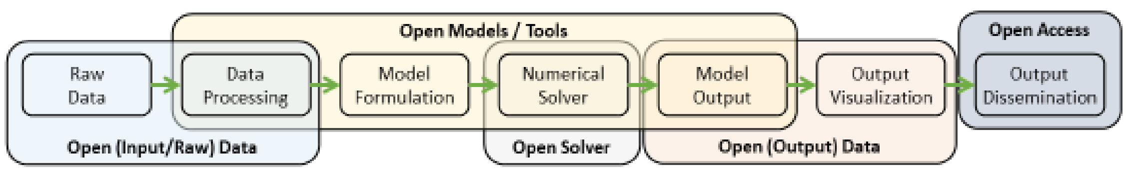


Figure 4: Distinct steps within the open-source discussion [68]

Table 5 shows some of the exemplary open-source related initiatives, which have been launched several years ago and in which process steps they are active. The table shows five of the numerous evolving initiatives and platforms and compares them with the overall aim of this work. The grey cells indicate an area in which the individual initiative and platform is active. While some of them cover a wide range of the process, others are focused on one of the required process steps. The suggested framework aims to support the entire process with limited efforts by developers using existing software and data.

Open and transparent R&D should be incentivized. Closer cooperation between national and international R&D bodies is necessary to reduce parallel efforts and duplication of work. Therefore, a very important step for implementation of open R&D has been initiated in July 2019: The Open Data Directive (EU) 2019/1024 of the European Parliament and of the Council of 20 June 2019 on open data and the re-use of public sector information [58]. This directive has to be implemented in all Member States until July 2021.

Table 5: Examples of open-source initiatives [68]

Examples	Raw Data	Data Processing	Model Formulation	Numerical Solver	Model Output	Output Visualization	Output Dissemination
Open Energy Modeling Initiative [53]							
Energy Modeling Platform Europe [54]							
Open Power System Data [55]							
Computational Infrastructure for Operations Research [56]							
Open Street Map [57]							
Suggested framework – link to existing work	API	Python	Pyomo	NEOS			OA journals, arXiv, …

Abbreviations: API - application programming interface; NEOS - Network-Enabled Optimization System.

A final remark related to open source is that licensing plays a part that must not be underestimated as it defines what the user can do with the shared source code, data, or models. Morrison (2018) provides a very detailed overview of available licenses used in the space of open source and open data [59]. The use of one of the licenses from the GPL family results in the highest copyleft, while ISC, MIT, BSD, and Apache-based licenses are very permissive, granting the user a wide range of activities, including the use of the code and/or data in their commercial products.

Open-source modeling, data, and publication is gaining momentum. Therefore, it is critical to have a comprehensive understanding of the licensing options. Figure 5 supports the decision making about which license to use for different aims such as sharing data, sharing software, or sharing presentations/reports [60]. The MIT license provides the most flexibility for developers as they are allowed to do almost everything. The GPL license, as a comparison, forces developers to share their work under the same license. A more detailed analysis of open-source licenses is available in [61].

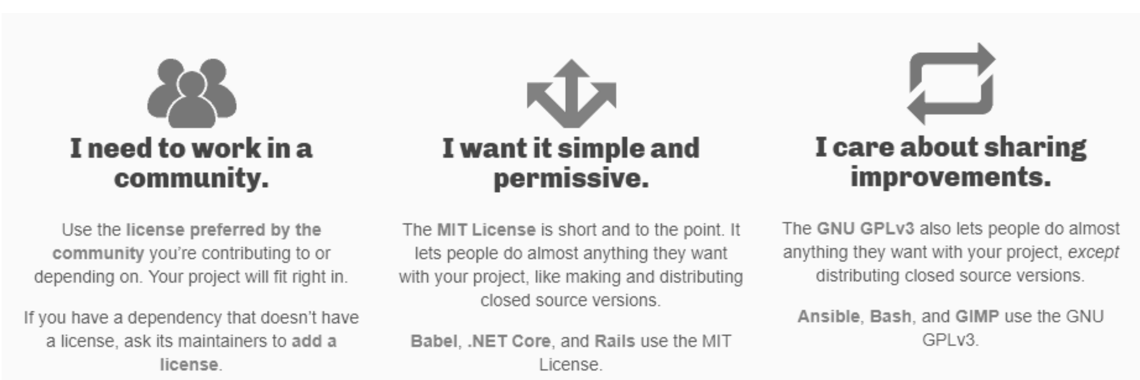


Figure 5: Simple open license selection [60]

3 Open-source energy system design tools [4]

The following paragraph represents the abstract of the 1st paper [62]:

“Historically, energy system tools were predominantly proprietary and not shared with others. In recent years, there has been an increase in developing open-source tools by international research and development organizations. More than half of the open energy modeling (openmod) initiative listed tools that are based on the freely available scripting language Python. Previous comparisons of energy and power system modeling tools focused on comparisons such as which tool category (e.g., optimization, simulation) or energy demand (e.g., electricity, cooling, and heating) can be considered. Until now, the assessment of incorporated functions such as unit commitment (UC) or optimum power flow (OPF) has been ignored. Therefore, this work assesses 31 mostly open-source tools based on 81 functions for their maturity. The result shows that available open-source tools such as Switch, TEMOA, OSeMOSYS, and pyPSA are mature enough based on a function comparison with commercial or proprietary tools for serious use. Nevertheless, future commercial, as well as open-source energy system analysis tools, have to consider more functions such as the impact of ambient air conditions and part-load behavior to allow better assessments of including high shares of renewable energy sources and other flexibility measures in existing and new energy systems.”

3.1 Methodology

The assessed 31 tools are listed in Table 6. For consistency, the selection of the assessed tools has not changed while the information within the table was updated to reflect today’s status. Important to note is that the shown table would be considerably different if the assessment would be repeated today as, within about five years, the number of new tools has increased significantly. A more up-to-date list can be found on the initiative openmod platform [49].

[4] This chapter has been taken out of Groissböck (2019) [62]

Table 6: Assessed tools [62]

Tool	Programming/ Scripting Language	First Release	Last Update	Age (years)	Lasst Update (months)	Commits	Branches	Release	Contributors	License	Web Address (URL)
Balmorel	GAMS	01.2001	12.2019	21	16	65	43	3	2	ISC	https://github.com/balmorelcommunity/Balmorel/
Calliope	Python	12.2013	03.2021	7	0	1047	17	26	11	Apache 2.0	https://github.com/calliope-project/calliope
DER-CAM	GAMS	10.2004	08.2017	17	45	n/a	n/a	n/a	n/a	n/a	https://building-microgrid.lbl.gov/projects/der-cam
dhmin	Python	12.2014	09.2017	6	43	13	1	n/a	1	GPL 3.0	https://github.com/tum-ens/dhmin
DIETER	GAMS	06.2015	10.2020	6	6	n/a	n/a	n/a	n/a	MIT	http://www.diw.de/dieter
Dispa-SET	GAMS	01.2015	04.2020	6	12	466	10	5	9	EUPL 1.2	https://github.com/energy-modelling-toolkit/Dispa-SET
ELMOD(st)	GAMS	01.2015	07.2017	6	45	11	n/a	1	n/a	MIT	https://github.com/frkunz/stELMOD
EMMA	GAMS	01.2013	05.2014	8	83	n/a	n/a	n/a	n/a	CC BY-SA 3.0	https://neon-energie.de/emma/
EnergyPlan	Executable	01.2000	11.2017	22	41	n/a	n/a	n/a	n/a	Freeware	http://www.energyplan.eu/
EnergyRt	R & GAMS	07.2016	03.2021	5	0	1276	6	11	4	AGPL 3.0	https://github.com/olugovoy/energyRt
ficus	Python	12.2015	01.2018	5	39	160	1	1	1	GPL 3.0	https://github.com/yabata/ficus
HOMER	Executable	03.2004	12.2020	17	4	n/a	n/a	n/a	n/a	Commercial	https://www.homerenergy.com
MATPOWER	Matlab/Octave	09.1997	03.2021	24	0	2150	7	25	8	3-clause BSD	https://github.com/MATPOWER/matpower
minpower	Python	08.2012	06.2016	9	59	855	10	41	1	MIT	https://github.com/adamgreenhall/minpower
MOST	Matlab/Octave	06.2016	12.2020	5	4	177	3	6	n/a	3-clause BSD	https://github.com/MATPOWER/most
NEMO	Python	01.2011	04.2021	10	0	1170	3	1	n/a	GPL 3.0	https://github.com/bje-/NEMO
oemof	Python	11.2015	02.2021	5	1	77	4	1	9	MIT	https://github.com/oemof/oemof
OSeMOSYS	Python	01.2011	01.2020	10	14	322	3	n/a	n/a	Apache 2.0	https://github.com/KTH-dESA/OSeMOSYS
pandapower	Python	11.2016	02.2021	4	2	5103	11	16	n/a	BSD	https://github.com/lthurner/pandapower
ProView	Executable	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	Commercial	https://www.hitachiabb-powergrids.com/offering/product-and-system/
psst	Python	01.2007	11.2020	14	4	36	7	n/a	7	MIT	https://github.com/power-system-simulation-toolbox/psst
PyOnSSET	Python	12.2016	11.2019	4	16	431	5	n/a	6	MIT	https://github.com/KTH-dESA/PyOnSSET
pypower	Python	07.2011	03.2021	10	0	336	7	22	13	BSD	https://github.com/rwl/PYPOWER
pyPSA	Python	01.2016	03.2021	5	0	1008	15	28	20	GPL 3.0	https://github.com/PyPSA/PyPSA
Renpass	R & GAMS	03.2017	03.2017	4	49	11	1	n/a	n/a	GPL 3.0	https://github.com/fraukewiese/renpass
RETScreen	Executable	12.1997	09.2016	24	55	n/a	n/a	n/a	n/a	Freeware	http://www.RETScreen.net
rivus	Python	11.2014	10.2017	7	42	251	1	n/a	3	GPL 3.0	https://github.com/tum-ens/rivus
Switch	Python	06.2015	03.2021	6	1	579	29	10	8	Apache 2.0	https://github.com/switch-model/switch
TEMOA	Python	05.2012	03.2021	9	0	825	21	9	n/a	GPL 2.0	https://github.com/TemoaProject/temoa
TIMES	GAMS	01.2014	07.2016	7	58	n/a	n/a	n/a	n/a	n/a	https://iea-etsap.org/index.php/etsap-tools/
urbs	Python	09.2014	03.2021	7	1	810	7	10	19	GPL 3.0	https://github.com/tum-ens/urbs

Remark: n/a,if no information is available — Last update: 02.04.2021

For tools that are not available via github.com or other code-sharing sites, it is not very easy to verify information such as the last update. Other packages have been restructured (e.g., oemof) and therefore show lower contribution as in the originally published comparison table in P1.

Table 7 shows the list of features or functions assessed throughout the mentioned 31 tools. The function screening has been from a short-term (operational) perspective as well as a long-term (planning) perspective.

3.2 Results

Figure 6 shows the assessment result for the selected tools for the short-term and long-term focus. Based on the author's ratings of the importance of the individual features, the difference between short- and long-term ranks is insignificant. This implies that models covering many details from an operational perspective also deal with a significant amount of planning details to balance the detailed coverage.

Important to note is that the detailed tool assessment has not been updated and therefore reflects the status about 3 years ago. In the meantime, a lot of tools have advanced significantly. urbs, pyPSA, and oemof are some of them.

Table 7: Assessed functions and their interpretation [62]

Function No.	Function	Evaluate ...
1 - 2	hourly time steps; variable time steps	if defining how many time-steps a day can be considered, and if different durations can be managed as well. Note: half-point for variable time step if only one duration can be defined;
3	copperplate approach	if transmission and distribution of energy is not considered;
4 - 5	direct current (DC); alternating current (AC)	which kind of electricity flow is considered;
5 - 8	power flow (PF); optimal PF (OPF); security-constrained (SCOPF)	if detailed (e.g., active and reactive PF considerations) are possible; and if security related PF constraints (e.g., transmission failure) are considered;
9 – 10	unit commitment (UC); security-constrained UC (SCUC)	if power and/or heat generating units are available within a multi-period time horizon; and if security related UC constraints (e.g., availability) are considered;
11 - 17	ramp up & down constraints; minimum up- & down-time; starts per day, minimum stable load; must run; startup & shutdown costs; cold & hot startup costs	which of the UC and SCUC details are considered; if startup cost is considered with addition fuel, half-point a point is added;
18 - 19	economic dispatch (ED); security-constrained ED (SCED)	if least-cost solution incorporating power output is considered; and if security related ED constraints (e.g., transmission failure) are considered;
20 - 23	non-electrical distribution (constraints), gaseous distribution (constraints), liquid distribution (constraints), thermal distribution (constraints)	which operational constraint is considered in some detail (e.g., voltage in electricity, pressure in gaseous, velocity in liquid, or temperature in thermal distribution systems); if operational details are ignored, and if non-electrical distribution can be used for any kind of service;
24 - 28	district heating/cooling demand; (drink) water demand; hot water demand; steam demand; other demand	which final demand can be included;
29	simulation (min. total costs)	if simulation is done instead of optimization;
30 – 38	obj. function: min. total costs; min. investment costs; min. operational costs; min. losses, max. profit; partial equilibrium; min. customer rates; max. efficiency; min. emissions	which objective function and combinations of it can be selected;
39	demand elasticity	if energy demand is impacted by price changes;
40	locational marginal price (LMP)	if within zonal energy prices the locational marginal price (LMP) is considered:
41 - 43	model foresight (perfect, flexible, or rolling horizon)	which kind of model foresight is considered;
44 - 46	size as integer/real variable; pre-defined unit size; cost based on economy of scale	if capacity additions are based on integer/real numbers or pre-defined sizes of technologies; in the case of integer/real sizes if economy of scale can be applied;
47 - 48	emission costs; emissions constraints	if emissions such as carbon dioxide CO_2 or water consumption can be associated with external costs and constrained;
49 – 51	multi-area system; multi-year investment; multi-year operation	if multi-area and multi-year assessments can be done;
52 – 53	year-varying CapEx & OpEx (CUR); year-varying fuel & emission (CUR)	if costs like capital expenditures (CapEx), operational expenditures (OpEx), fuel costs, and emissions costs/penalties can be different from year to year;
54 - 55	budget constraints (CUR); fuel constraints (CUR)	if upper and lower limits for budget and fuel consumption can be defined;
56	retirement of existing assets	if existing assets can be retired if found not economical;
57	fuel switch/dual fuel	if assets can be operated with different types of energy or fuels;
58 - 59	part-load impacts; ambient temperature impact	if technical performance (e.g., efficiency and output) change based on ambient conditions or if part-load can be considered;
60	technology degradation/aging	if technology age is incorporated into technical performance; if the yearly available capacity can be adjusted, the reduced available capacity is a half-point;
61 - 62	generic storage; detailed storage (SOC, DoD)	if storage can be considered in its simplest way (without e.g., state of charge, SOC) or if SOC and depth of discharge (DoD) is considered; if storage is modeled with a constant loss factor, it is a half-point;
63	component dispatch	if energy conversion can be represented in components and not in whole plants only;
64 - 67	energy conversion is implemented as: 1 in, 1 out: n in, 1 out: 1 in, m out; or n in, and m out	which energy conversion can be considered;
68 - 69	availability/forced outage; maintenance planning	if resource availability is considered, and if a maintenance schedule can be created;
70 - 71	energy purchase (fixed, variable pricing), energy sales (e.g., FiT)	if fixed and consumption-based prices can be considered, and if feed-in-tariff (FiT) based energy sales can be considered;
72 - 73	deferable demand; curtailment	if demand can be delayed, and if generation like photovoltaic or wind can be curtailed;
74 - 75	reserve margin; primary/secondary reserves	if minimum/maximum reserve margin can be defined, and if primary and secondary reserve (sometimes considered also as spinning reserve) is considered;
76 - 78	reliability indicators; risk level (appetite); probability/uncertainty	if reliability indicators such as loss of load expectation (LOLE) or expected energy not served (EENS); if different risk levels can be considered; and if uncertainty in profiles can be considered;
79	GIS representation	if there are GIS related functions incorporated;
80 - 81	documentation; example(s) available	if clear and clean documentation containing examples is available.

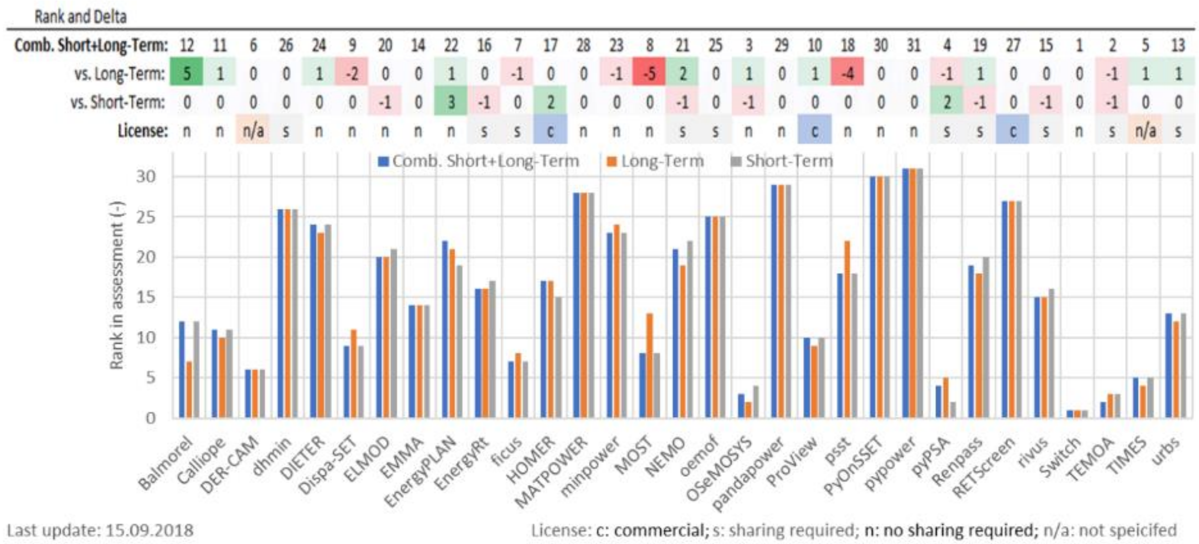


Figure 6: Ranking the different evaluations [62]

Switch, OSeMOSYS, and TEMOA show a strong focus on medium and long-term expansion planning, while pyPSA is more focused on short and medium-term operations. The strength of TEMOA, Switch, and OSeMOSYS is to consider details such as multi-year investment, year-varying capital and operational costs, and budget and emission constraints. pyPSA, on the other side, includes more details in a short-term unit commitment like optimal power flow, feasible ramp rates, minimum up- and down-time, as well as start-up costs.

The following items list indicates some technical functions which are not covered:

- distinction between hot and cold start-ups,
- use of advanced or alternative objective functions (e.g., multi-objective target function, maximize profit),
- technical parameters change as a result of part-load operation (e.g., efficiency),
- technical parameters change based on ambient conditions (e.g., power output),
- detailed storage model (e.g., charge cycles),
- maintenance planning, and
- security of energy supply (e.g., n-x reliability).

Comparing the selected open-source tools with the selected commercial closed-source tools, it can be seen that open-source tools are getting closer to the functionality of closed-source tools. Within the operational assessment, pyPSA even takes over the commercial closed source tools. As shown by projects such as the United Nations Atlantis, Integrated Systems Analysis of Energy, open-source tools like OSeMOSYS are also seen as mature enough to be used for regional power system planning. Despite significant contributions to date, there remain a number of key challenges, e.g., incorporating very high shares of variable renewables, considering simultaneous generation expansion and transmission planning, and considering uncertainty in operation of MES.

4 Importance of renewable sources [5]

The following paragraph represents the abstract of the 2nd paper [63]:

"Renewable energy sources (RES) are becoming more and more cost-competitive globally. Generally, optimization methods are used to identify the most economic setup of individual power systems. In such cases, only the final state of the power system is of interest. This study contributes to the discussion on how to reach a 100% RES-driven power system by assessing the importance of RES quality in selected European countries and identifies optimal strategies based on different objective functions (e.g., lowest capex requirement, lowest or largest curtailment). In a scenario in which economics is the only driver for optimal RES expansion, the 'min. LCOE' path with a strong focus on Wind would be used. If residential users are targeted to contribute as much as possible, the 'max. capacity' case with a Solar PV-Wind ratio of 0.65±0.35 would be selected. If the overall aim is to produce maximal excess electricity to be used in other sectors, the 'max. curtailment' or 'max. zero load' cases should be considered where mainly Solar PV would be the technology of choice."

4.1 Methodology

This study assesses the optimal RES expansion by comparing different optimal RES expansion paths. To overcome the limitations of Burger (2019) [64] and Kreifels et al. (2014) [65], the author developed the optimal RES expansion paths shown in Table 8.

Table 8: Assessed optimal RES expansion paths [63]

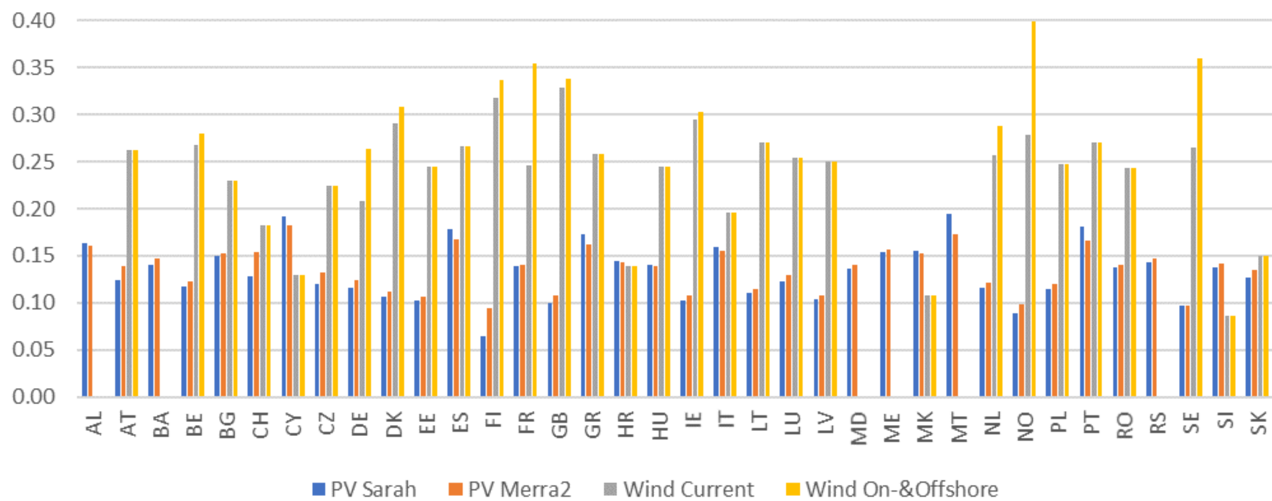
Optimal RES expansion path	Minimize	Maximize
RES capacity with specific curtailment rate	X	X
Curtailment	X	X
Levelized cost of electricity (LCOE)	X	
Zero net load hours	X	X

A case such as 'minimize capacity' is not necessary as the power contribution from Wind is almost always higher than from Solar PV. This study uses pure power-related key performance indicators (KPIs) such as curtailment and LCOE for the assessment.

[5] This chapter has been taken out of Groissböck (2020) [63]

Other KPIs such as security of supply, national manufacturing, and aspects of local content are ignored. This study focuses on mixed Solar PV-Wind expansion as this is currently seen as the technologies of choice with lower constraints compared to Hydropower or Biomass.

Historically measured hourly time series for load are based on open-power-system-data.org [55] while RES profiles are from renewables.ninja [66]. Both sources provide hourly profile data as publicly available data and focus on representative renewable and power demand profiles for the available countries. The country representing profiles are smoother than they would be in reality for an individual project. Figure 7 shows the average capacity factors for Solar PV and Wind for the entire data set of the covered 36 countries.



Data: www.renewables.ninja

Figure 7: Average capacity factors of PV and Wind [63]

Table 9 shows the considered combination (very good, very bad) of Solar PV and Wind quality within this work. Based on the available public data and defined conditions, the following countries have been identified as suited candidates to represent the RES quality conditions. RES quality is used in this work as a synonym for the RES capacity factor shown in Figure 7). Austria (AT), as host of the university, and Germany (DE), as the main force behind renewable developments in Europe, have been added to the list.

Table 9: Selected country list and considered rationale [63]

Wind quality	Solar PV quality	Country name	Country code
– –	– –	Cyprus	CY
– –	+ +	Czech Republic	CZ
+ +	– –	Norway	NO
+ +	+ +	Portugal	PT
o	o	Austria	AT
o	o	Germany	DE

Remark: ++: very good; – –: very bad; o: average.

Figure 8 shows the overall program logic which has been implemented in the programming language Julia. Step 1 is to select the first country to assess (in alphabetical order, it starts with AT). Based on the available data set, Step 2 selects the first available year (e.g., 2006). Steps 3 and 4 are initializing Solar PV and Wind capacity additions with 0% (of peak demand) to calculate the initial situation without RES in Step 5. Subsequently, and as long as not reaching the maximum of 200% (of peak demand), 0.5% is added for Solar PV and Wind. Within this work it is assumed that the technical potential for Solar PV and Wind of each country is always at least 200% of peak demand. Finally, if 200% of Solar PV and Wind have been considered in the calculations, Step 6 initiates the next available year to be considered (up to, e.g., 2016). As already indicated above, this study used the available data where entire years have been available at once to avoid data (weather, RES power generation, and power demand) contortions through individual (outlier) years. After finalizing all years, Step 7 initiates the next country for assessment. If all countries have been calculated, the simulation of all scenarios is finished.

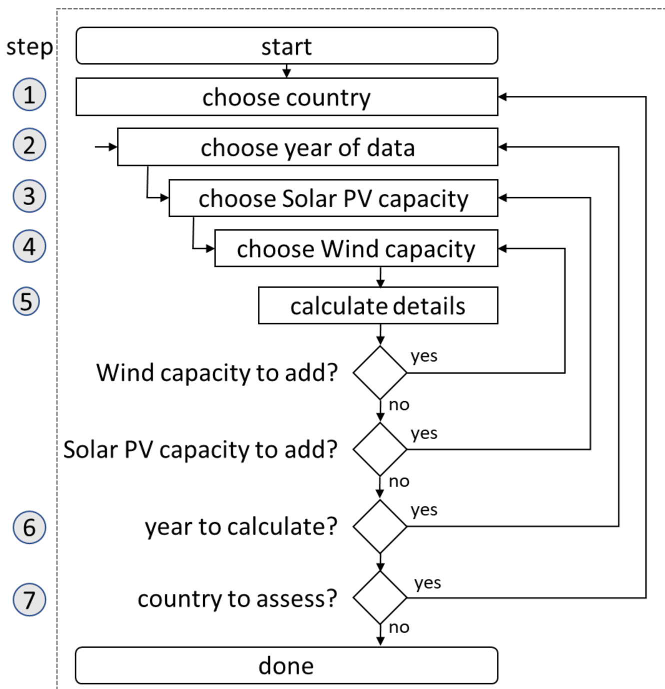


Figure 8: Methodology [63]

4.2 Results

The analysis is based on the average unbiased results, as shown in Figure 9, knowing that individual years will deviate from them. The horizontal axis shows the Solar PV share, and the vertical axis shows the Wind share (both in percent of peak demand, up to 200%). The sub-graph titled 'max. capacity' represents the 'RES capacity with specific curtailment' case. The sub-graphs 'min. curtailment' and 'max. curtailment' represent the minimize and maximize curtailment cases. The sub-graph 'min. LCOE' represents the minimize LCOE case. And finally, the 'min. zero load' and 'max. zero load' sub-graphs show the results for the minimize and maximize zero net load hour cases.

The small zigzag movements within the individual plots are the result of the RES matrix (200% x 200% of peak demand) considered in this study, in which a RES expansion step of 0.5% has been selected. It also shows non-steady results in some cases. In all sub-graphs, the dotted lines indicate a ratio of 3, 0.65, and 1 of installed Wind vs. Solar PV. Within the left top sub-figure, the optimal RES path from Kreifels et al. (2014) was added for comparison.

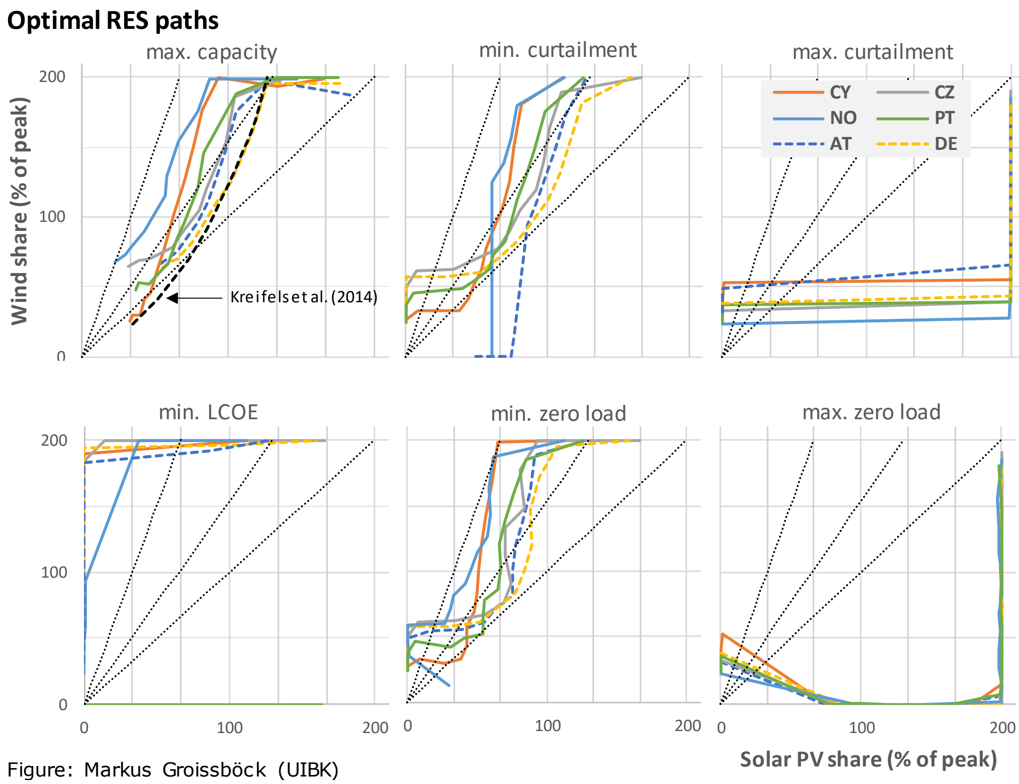


Figure 9: Overall simulation results [63]

Compared to the previous 'max. capacity' case, the 'min. curtailment' case has slightly higher Solar PV contributions until the curves reach the 200% Wind capacity. The reason for this is the better fit of Solar PV to the daily demand profiles. The optimal RES path based on 'min. zero load' has less Solar PV contribution as the previously mentioned cases. The 'min. LCOE' case is in all circumstances dominated by almost exclusive Wind expansions. For the Norwegian case, ~50% of Solar PV would be added before the Wind capacity reaches more than 180%. An interesting finding for the Portuguese (PT) case is that Solar PV would be preferred over Wind with the assumed RES cost and generation profiles. This is not reflected at all in the current RES policy, which focused historically on adding Wind and moves now more towards Solar PV. To support sector coupling through excess RES electricity, the cases 'max. curtailment' and 'max. zero load' should be considered. In both cases, up to 50% Wind would be added before the RES expansion would be solely based on Solar PV. Adding the 50% of Wind capacity would cover most of the night and cold season demand so that adding Solar PV afterward can be used for other purposes such as sector coupling.

Budischak et al. (2013) found that RES capacity of about 300% of peak demand and a significant amount of storage is needed to reach >90% RES contribution within the PJM market. The results of this study suggest that RES capacity of about 200% is already able to fulfill 90-122% of the energy demand in the assessed countries.

Figure 9 shows overlapping curve shapes while also indicating differences in how the optimal RES expansion path could be realized based on local conditions. It can be concluded that the shapes for 'max. capacity ', 'min. curtailment', and 'min. zero load' show similar evolutionary paths. Also, the paths for 'max. curtailment' and 'max. zero load' show similar shapes. It can be argued that the impact of RES quality is minor and is more dictated by the overarching objective function (see Table 10). If economics were the only driver, the cost of power generation ('min. LCOE') path with a strong focus on Wind would be the guide for RES expansion planning. If residential users are targeted to contribute as much as possible to the RES expansion, the cases 'max. curtailment' and 'max. zero load') should be selected. If the overall aim is to produce excess electricity to be used in other sectors, one of the sector-coupling approaches ('max. curtailment', 'max. zero load') should be selected where Solar PV would be the technology of choice.

Table 10: Optimal RES paths as objective function of aim [63]

Objective function: **Overall aim:**	**Max. capacity**	**Min. curtail-ment**	**Max. curtail-ment**	**Min. LCOE**	**Min. zero load**	**Max. zero load**
Opt. RES power	X	X			X	
Focus Solar PV			X			X
Focus Wind	X	X		X	X	
Least power cost				X		
Sector coupling			X			X

5 Renewables impact on security of supply [6]

The following paragraph represents the abstract of the 3rd paper [67]:

“Globally, renewable energy sources (RES) are getting more and more competitive even without subsidies. In general, optimization methods are used to identify the most economic setup of individual power systems. This study contributes to the discussion on how much reserve capacity a power system should have to ensure reliable electricity supply in assessing the explicit and probabilistic system reliability metric LOLH as well as EENS within a dynamic programming approach. Multi-year RES profiles from different locations are used to identify the minimum reserve margin (RM) requirements using LOLH and EENS as planning criteria. The findings indicate that using RM as the only reliability constraint within optimization is not appropriate: a too high assumption on RM would increase the required conventional generation capacity unnecessarily, and a too low assumption would risk reliable power supply. Using LOLH as the single metric for reliable power system planning, the EENS would grow with increasing RES contribution. This is the result due to the concept of LOLH as the amount of electricity not supplied is not part of the metric; only the hours of power undersupply are. On the other hand, a constant assumption of EENS is misleading, and the concept of EENS does not consider the number of hours the power service can’t be fulfilled. Therefore, the recommendation is to use LOLH and EENS simultaneously in a single optimization framework, as shown within this study.”

5.1 Methodology

This study assesses the security of supply through a dynamic programming approach, in which the RM and EENS are results to fulfill the predefined reliability level expressed in LOLH. To support medium- and long-term aspects of generation expansion planning (GEP), the assessment includes:

- multiple years of data,
- normalized demand profiles,
- different quality of renewables based on historical renewable profiles (as described in Chapter 4),
- variations of RES capacity (0 and 200% of peak demand),

[6] This chapter has been taken out of Groissböck & Gusmão (2020) [67]

- different levels of system reliability (in LOLH, between 0 and 10), and
- different system sizes (10 to 100,000 MW system sizes).

The overall program logic shown in Figure 10 has been implemented in the programming language Julia. Step 1 is to select the first system reliability target to assess (LOLH, measured in hours/year, starting from 0). Based on the available data set, Step 2 selects the first option to evaluate (e.g., no RES with a load multiplier of 0.01). Step 3 and 4 are initializing the number of units to be considered (starting with 0) and the maximum allowed capacity multiplier (starting with 15) to calculate the initial situation without RES in Step 5. Subsequently, and as long as being above the targeted system reliability, the capacity multiplier is decreased. If the required system reliability is reached, a simplified economic dispatch is done, and the result is saved (Step 6). As soon as the cost of the total system is increasing, the processing of the current option is finished. If there is an additional option to assess (LOLH ≤ 10), the program continues with the next option (in Step 3, increase LOLH by 1). Otherwise, the simulation is finished after all assessable options are calculated.

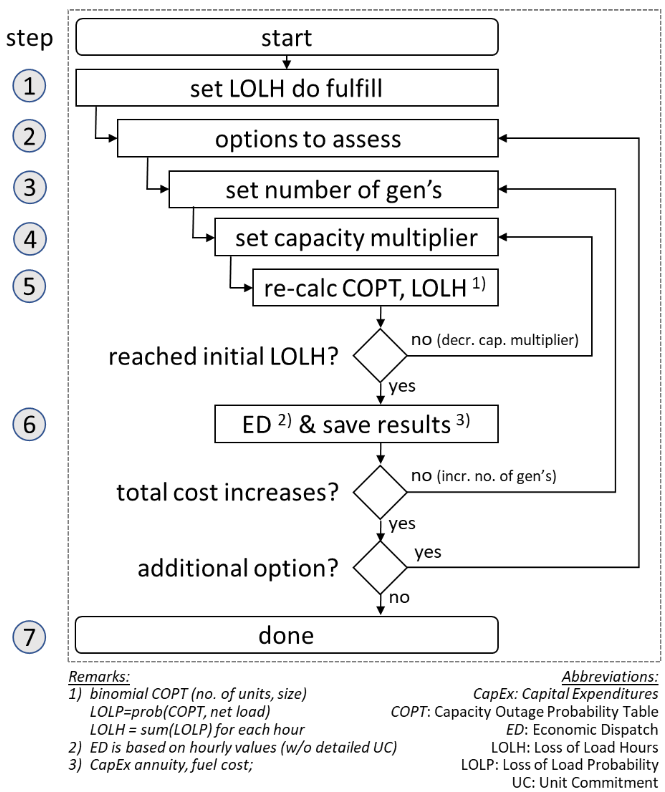
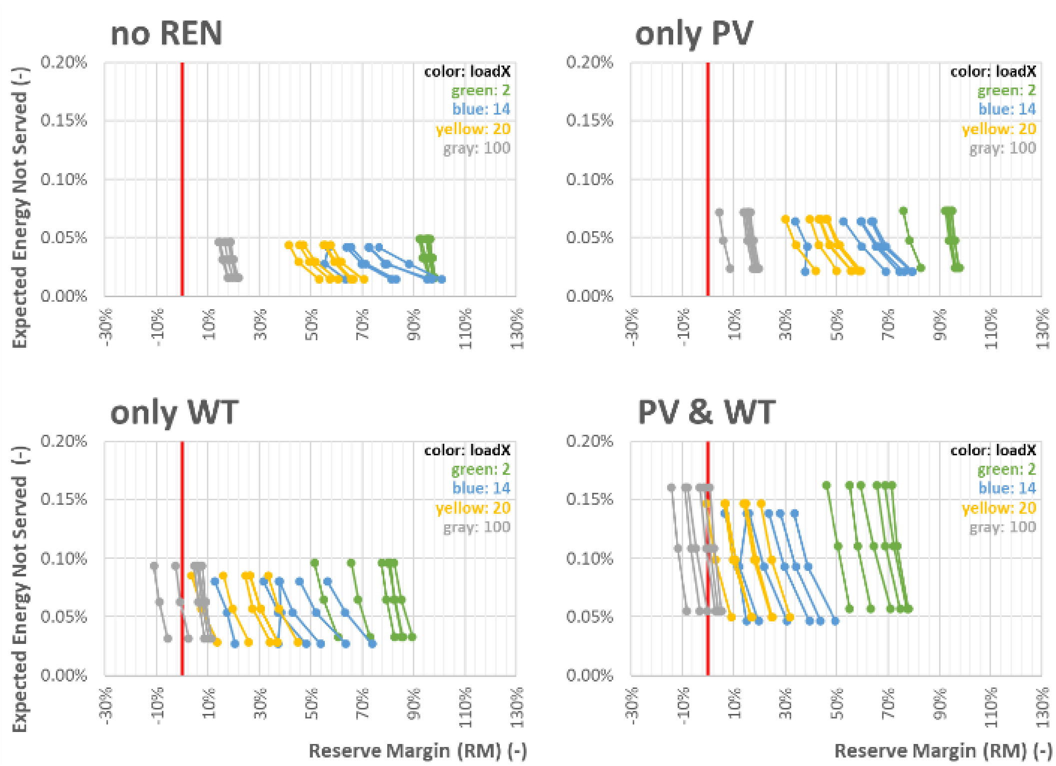


Figure 10: Methodology [67]

Economy of scale for specific costs and power generation efficiency are considered. The maximum allowed sizes for the considered conventional technologies are 80, 593, 1200, and 1740 MW for ICE, GT, ST, and CC, respectively. The forced outage rate (FOR) of the conventional generators is assumed to be 10%, including the required maintenance cycles and the start-up reliability.

5.2 Results

Figure 11 shows the results of four selected demand cases (load multiplier of 2, 14, 20, and 100) without differentiating the countries for required system reliability (measured in LOLH, hours/year) between 1 and 3. The red line indicates no (0%) reserve margin (RM). Each group of colors represents one of the mentioned demand cases (country profiles). The visualization clearly shows that there is no recognizable pattern within the different demand cases and RES/country qualities. Adding more RES into the power generation mix increases EENS as the residual demand profiles become more and more step-like (instead of the usual smooth sinus-like demand duration curve) and decrease RM slightly. Considering multi-year data of demand and RES profiles does not decrease the RM as much as indicated by other studies (between 7 and 29% with up to 30% RES contribution based on annual energy demand) based on a single year of data. The difficulty lies in predicting the amount of RM decrease for long-term GEP. As there is no pattern visible, the only recommendation at this point can be to assess LOLH and EENS for each GEP activity (characterized by, e.g., system size, RES quality, RES penetration) individually.



Remark: The colors indicate different system size multipliers (basis: 10 MW; green: x2, blue: x14, yellow: x20, gray: x100)

Figure 11: RM vs. EENS with different RES additions and different system sizes [67]

The results highlight the complicated situation regarding assumptions around reserve margin (RM) and expected energy not served (EENS). In this study, Cyprus and Portugal are the countries with the best Solar PV quality, but their change in reserve margin with PV additions is very different. Cyprus results show the highest change, while the Portugal results show the second-lowest change. Similarly, in the ‘only WT’ cases, Norway and Portugal are the countries with the best Wind quality, but also their change in reserve margin is very different with Wind additions. Norway shows the highest decrease in reserve margin, while Portugal displays a change which is about on average with the other countries studied. One of the main reasons for this is that Norway has a peakier demand but a flatter Wind profile than Portugal. The changes in reserve margin are on average: 9%, 29%, and 43% for the cases ‘only PV’, ‘only WT’, and ‘PV&WT’, respectively.

Looking into the changes in EENS also highlights a difficult picture: a) within the ‘only PV’ cases, the change in EENS is between 0.005% and 0.010%, b) within the ‘only WT’ cases, the change is between 0.010% and 0.028%, and c) within the ‘PV & WT’ cases, the change is between 0.023% and 0.060%. The only pattern identifiable is that high-quality RES results in higher EENS. In the absence of a very large amount of storage capacities, the net load becomes more and more step-like (instead of the usual smooth sinus-like curve). Storage is and will be a fundamental component for power systems with very high shares of RES. But as a very high decentralized storage penetration is not expected in the near future it has been excluded in this assessment.

Therefore, using reserve margin as an assumption for optimization is not appropriate. A too high assumption on reserve margin would increase the required conventional generation capacity unnecessarily. Using LOLH as the single metric for power system planning, the EENS will increase with growing renewable capacity installed. This is because LOLH does not cover the amount of unsupplied electricity. LOLH only accounts for the hours power can’t be fulfilled entirely. On the other side, a stringent and constant assumption of EENS would be too constraining for GEP. Therefore, the recommendation is to use LOLH and EENS simultaneously to incorporate a proper reserve margin in a single optimization framework as done within this study.

6 Proposed open-source framework [7]

The following paragraph represents the abstract of the 4th paper [1]:

“Multi-model energy systems are gaining importance in a world where different types of energy, such as electricity, natural gas, hydrogen, and hot water, are used to create more complex but also more economic energy systems to support defossilization. While the research community is using open source for a long time, collaborative work on open-source tools is not yet the norm within the research community. To increase the open source and sharing efforts between research organizations, governments are driving publicly funded projects to share their outcomes. Today, no open-source modeling framework exists that can assess different optimization tools. The proposed open-source framework is based on the principle of maximizing the reuse of existing data, software snippets and packages, and adds individual code only as necessary. An intensive software package screening identified six suitable open-source tools to be partly incorporated into the proposed open-source framework. The best tools of individual contributors have been combined and further improved by adding supplementary features such as a scenery model to incorporate shadowing and elevation effects on conventional and renewable power generation technologies. Going forward, this approach allows expanding research into urban air assessment in which traffic and energy emissions can be assessed jointly.”

6.1 Methodology

The initial step of this research was to assess existing open-source software tools and better understand their strengths and weaknesses (paper P1). A thorough screening of 31 energy modeling tools was based on characterizing them into 12 applications and 81 functions. The applications cover the geographical scope or use of the tool (house, industry, district, city, region, or country), types of considered energy (electricity, heat, or natural gas), and whether it is an open-source tool as well as an optimization or a simulation tool. The screening of the functions cover aspects such as hourly or variable time steps, altermatic or direct current modeling of power transmission, (security-constrained) unit commitment details, and (security-constrained) economic dispatch. The conclusion from this initial work was that – compared to commercially available tools - open-source energy system modeling tools are ready for serious use. Possible

[7] This chapter has been taken out of Groissböck (2021) [1]

enhancements could be considering the impact of ambient air conditions, part-load behavior, and redundancy aspects. The top-scoring tools (Switch Model 2.0, Temoa, OSeMOSYS, and pyPSA) and about 50% of the assessed tools were based on the programming language Python. As a result, further assessments represented in this work focus on Python-based tools solely.

The second step of the research involved the assessment of additional tools, software packages, and software snippets to identify what the open-source community has done already and what can be used as a basis for this work. A summary of the assessed Python packages and snippets is available online at Zenodo [68]. As usually for engineering tasks, the difficulty lies in the details: the number of Python-based packages are almost countless. By the end of March 2021, more than 295,000 packages have been registered at pypi.org, neglecting thousands of additional software snippets and tools shared via github.com, gitlab.com, or other code sharing platforms with millions of registered repositories and active developers. This shows one of the biggest downsides of open-source package writing: there is no or very limited coordination between the countless number of packages. Duplication of work also happens in the open-source community. It is very difficult to keep track of all the frequent changes as well as new developments. Also, relying on some of these packages means that if there is a (major) redesign of the package, one has to adjust accordingly.

The here proposed open-source framework divides the required process steps between having no data at the top of the process (see the box on the left in Figure 12) and having all data, results, and visualization in eleven steps (indicated by superscript numbers within the workflow). The box on the right in Figure 12 shows a selection of assessed tools and data, which have been found useful in the proposed framework. The text in bold marked with a times sign (*) shows where enhancement by the author is considered or has been incorporated already.

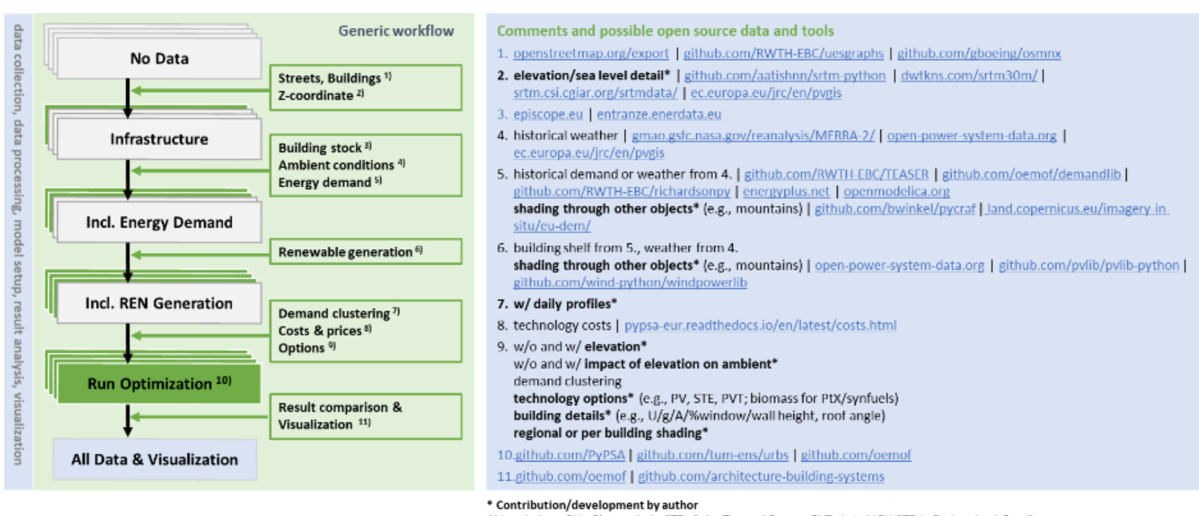


Figure 12: Proposed methodology and selection of open-source data and tools [1]

6.2 Results

The preliminary assessment highlights six open-source-oriented R&D contributors where parts of their tools might be incorporated into the suggested framework (see Table 11). The identified contributors developed several individual tools such as GIS-related data collection, building stock-related load curves, or optimization tools. Usually, all of these individual tools have been made available by the framework contributors to support city or national ESD. The cells shown in dark grey indicate areas where the individual tools have no or very little contribution to the predefined eleven process steps. Light grey cells indicate a partial contribution. Typical for such assessments, it always depends on the conducted analysis by the author and, therefore, might not reflect the opinion of the open-source framework owners and maintainers.

Table 11: Selective existing framework comparison [1]

	Focus: 1)	≥ State	≤ City	≥ State	≥ State	≤ City	≤ City
	github.com/	FZJ-IEK3-VSA	RWTH-EBC	oemof	pyPSA	tum-ens	architecture-building-systems
1	Streets, buildings,	n/a	n/a	n/a	n/a	n/a	CEA
	Land use,	n/a	n/a	n/a	n/a	pyGRETA	CEA
	District heating,	n/a	n/a	n/a	n/a	n/a	CEA
	Power,	n/a	n/a	n/a	bdw/GridKit	n/a	CEA
	Gas, oil, biomass	n/a	n/a	n/a	n/a	n/a	n/a
2	Z-coordinate	n/a	n/a	n/a	n/a	n/a	CEA
3	Building stock	tsib (for EU)	TEASER (for EU)	tabular (for EU)	n/a	n/a	CEA (for CH)
4	Hist. ambient conditions	tsib (TRY, TMY, ISO 12831)	pyCity (TRY, TMY)	feedinlib.era5	n/a	n/a	E+ weather files (epw)
5	Energy demand	tsib, tsorb:occupation	pyCity:occupancy, TEASER, AixLib, IBPSA	demandlib	n/a	n/a	CEA
6	Renewable profile	RESKit, windtools	pyCity	feedinlib	Atlite	pyGRETA	CEA
7	Demand Clustering	tsam	pyCity	solph	pyPSA	pyCLARA	n/a
8	Prices, technologies	n/a	n/a	n/a	technology-data	n/a	CEA
9	Optimization	FINE	pyCity	solph	pyPSA	pyPRIMA	CEA
	Solvers (solver abstraction)	any local (pyomo)	tbd	any local (pyomo)	any local (pyomo)	any local (pyomo)	Gurobi, Genetic Algorithm
10	Visualization, result comparison	n/a	n/a	OEDB	n/a	n/a	n/a
	Design for addition	n/a	n/a	yes	yes	n/a	n/a
	Additional features			• visio • oemof.db	• nomopyomo (cbc, gurobi)		• Web-GUI
	Contributors:	FZ Jülich	EBC	RLI, FHF	KIT, FIAS	TU Munich	ETH Zurich

1) Focus options: Households, District, City, State, Region, Country, Continent, World
Abbreviations: EBC: RWTH Aachen, E.ON EBC, RLI: Reiner Lemoine Institute, FHF: FH-Flensburg, KIT: Karlsruhe Institute of Technology, FIAS: Frankfurt Institute for Advanced Studies.

Regarding the previously mentioned disregard of the GIS z-coordinate, the City Energy Analyst (CEA) tool shown in the last column on the right considers this detail for line and pipeline calculations but not for elevation adjustments of, e.g., efficiency of conventional power generation technologies. As known, individual tools set different focuses. For example, pyPSA's focus is spatial nature, therefore spatial clustering is considered accordingly. Other frameworks, such as the one from FZJ-IEK3-VSA, are focused on time-series aggregation and clustering. Within the proposed framework, both options shall be available to assess the importance of the individual clustering option.

Obviously only European R&D organizations are listed based on the conducted analysis, the proposed framework aims to incorporate particular features from the assessed contributors into a new open-source framework (see Table 12). The table specifies which process step has been taken from which contributor and the according tool to use. For example, step1, the street and building data can be initialized by using the osmnx package. Step 3, as another example, will use the packages tsib, TEASER, and tabular. While a lot of it has been already implemented, severe actions are still required to finish the framework in a first shareable and stable release. Once available in a shareable and stable release, it will be made available via Zenodo [18]. As indicated during the introduction, the goal is to have a single framework in which several energy optimization tools can be assessed against each other to verify the resulting quality of the individual tools as well as support the decision-making on which one to use for which purpose.

Table 12: Proposal of selected open-source initiative components [1]

Framework / **Process step**	**FZJ-IEK3-VSA**	**RWTH-EBC**	**oemof**	**pyPSA**	**tum-ens**	**architecture-building**	**new features**
1 – Streets, land use, building shapes							osmnx
2 – Z-coordinate							pycraf, tkrajina/srtm.py
3 – Building stock	tsib	TEASER	Tabular				
4 – Ambient conditions							OPSD/ weather_data
5 – Energy demand		pyCity: occupancy, TEASER				CEA	
6 – Renewable profile			feedinlib				Pvlib, windlib, Solar3DCity
7 – Demand clustering	tsam						
8 – Cost & prices, technologies, …				technology-data			economy of scale
9 – Options							sensitivity analysis
10 – Optimization					pyPRIMA		Solver: NEOS
10 – Visualization			OEDB				
Additional features							pyPSA: market, reserve margin

Hundreds of thousands of repositories are available on code sharing platforms, and the number is growing daily. The proposed open-source framework in this work is based on the principle of maximizing the reuse of existing data, software snippets, and packages. The addition of individual code to the framework occurs only as much as ultimately necessary. After careful screening of additional software packages, six favorite open-source frameworks have been identified; the best parts of each of these frameworks are combined into a single open-source framework (see Table 11). Table 11 might give the impression of six complete frameworks that already exist. However, this is not the case. The listed six contributors have some individual tools, which they use in their daily work. Nevertheless, a comprehensive framework does not exist yet; at least none that fulfills the proposed eleven steps (from having no data towards having all data, results, and visualization).

To further improve the energy system framework for the purpose of this research, some more features were added (see Table 12). Those features include a scenery model to incorporate shadowing and elevation effects on conventional power generation technologies. By doing so, the utilization of limited resources could be improved significantly. Going forward, this approach allows for further research, for example, with a focus on city air assessment in which traffic and energy emissions can be assessed jointly with urban climate effects (e.g., heat islands or cold streams through rivers).

The framework test and verification process are still ongoing and will be applied in a demonstration village to ensure proper quality and stability. The framework test aims to ensure the quality of the new framework. Afterward, the framework will be made accessible on Zenodo [68]. Other framework enhancements and evaluations are still ongoing. In the near future, additional energy system models, such as FlexiGIS [69], will be analyzed whether it provides a useful option for consideration. Another aspect to consider is a standardized database schema for saving GIS-related information. Therefore, the current 3D City DB schema will be assessed for its potential fit.

It is positive that more and more tools within the energy system modeling area are shared and made available for the interested R&D community. Unfortunately, cooperation between different R&D organizations still is limited to some exceptions. It would be appreciated to see more multi-national R&D efforts working on open-source energy system modeling tools such as the Spine project. In this project, organizations from Finland, Ireland, Belgium, and Sweden cooperate with one from the US.

7 Updated ESD tool assessment

The first paper within this research project assessed 31 tools and identified Switch, TEMOA, OSeMOSYS, and pyPSA as the most advanced [62]. The advancement of the assessed tools was measured, fulfilling 81 predefined features. Based on this work and expanded by some new tools, the final focus of ESD tools is shown in Table 13. Compared to the previous assessment, the tools FINE [70] [39] and aristopy [42] [43] have been added.

Table 13: Details for selected ESD tools

	ESD Repository github.com/	**Last changes**	**Number of contributors**	**Latest release**	**Open-Source License**	**Main Contributors**
calliope	calliope-project/ calliope	31.03.2021	11	0.6.6-post1	Apache 2	ETH Zurich, Univ of Cambridge
oemof	oemof/ oemof-solph	18.03.2021	33	0.4.1	MIT	RLI, FH Flensburg, Univ of Bremen
Switch 2.0	switch-model/ switch	09.03.2021	8	2.0.6	Apache 2	Univ of Hawaii, Univ of California, Pontificia Univ of Católica de Chile
pyPSA	PyPSA/ pyPSA	23.03.2021	20	0.17.1	GPL	KIT, FIAS
urbs	tum-ens/ urbs	01.03.2021	19	1.0.1	GPL	TU Munich
FINE	FZJ-IEK3-VSA/ FINE	05.01.2021	11	2.1.1	MIT	FZ Jülich, RWTH Aachen, FAU
aristopy	sbruche/ aristopy	24.11.2020	1	0.9.3	MIT	TU Berlin

Last update: 02.04.2021
Abbreviations: RLI - Reiner Lemoine Institute; FAU - Friedrich-Alexander-Universität Erlangen-Nürnberg; KIT - Karlsruher Institut für Technologie; FIAS - Frankfurt Institute for Advanced Studies.

The focus areas for the individual communities are very different. The OSeMOSYS project, for example, has a very strong focus on education and therefore offers the ESD tool in four different implementations to maximize reach: Pyomo, MathProg, PuLP, and GAMS. While almost all listed ecosystems have a package to create input time series for renewables, only oemof and FINE provide some demand profile generation packages. In regard to thermodynamic modeling, only oemof offers a package to consider heat exchange and heat transfer details in ESD modeling. FINE and oemof offer a package for TSA. Only OSeMOSYS provides a graphical user interface.

pyPSA is providing a technology database [71], several examples, an online service to run their ESD, and the ability to replace Pyomo – which is used in all mentioned ESD tools – within their development called nomopyomo. They created this development as the flexibility of Pyomo comes with time and memory-consuming disadvantages.

Two of the ESD tool communities (calliope, pyPSA) also experiment with implementations of their tools in the new programming language Julia [72]. The advantage of Julia is its ability to compile source code at the time of first usage and is then available in machine-executable assembly language.

The TUM-ENS is developing the package pyPRIMA, which allows the alignment of input data to feed multiple ESD models. Unfortunately, only TUM-ENS packages (urbs and EVRYS) are currently available out of the shelf.

All mentioned ESD tools are open source, and as such, the possibility to advance them is given by nature. On top of this source-focused expandability, the tools pyPSA and aristopy are designed in a way that additional constraints can be added without the need of reviewing the source code intensively. Of course, programming skills are necessary to add individual constraints.

Aristopy can be seen as one of the most flexible ESD tools available today and is able to deal even with non-linear relationships. pyPSA is the most advanced model in regard to the consideration of details around power flow in the currently assessed open-source tools. Nevertheless, there are several reasons why FINE has been selected within this work, as the in-depth representation of electricity and assessing non-linearities are not the focus of this study. The reasons are listed as follows:

- unit representation,
- time aggregation feature (so-called typical periods) independent of optimization task,
- time resolution adjustment (e.g., 1, 2, or 3-hour duration per timestep),
- definition of minimum load requirements for conversion technologies during the period of operation,
- emission constraints at certain levels,
- non-linear energy conversion rates,
- configurable demand-side management,
- minimum contribution of renewables (with variable definitions of what renewables are), and
- availability of an MS Excel®-based optimization workflow.

On top of the already listed features, FINE is also able to provide the following functionality, which is very important (for ESD studies connecting urban and industrial aspects):

- link technologies (e.g., if technology A is built, also B needs to be built),
- limited available space for several technologies (e.g., install technology C and/or D, but limited on space to E m²; or the use of an existing storage option for either gas or hot water),

- two-stage optimization (function optimizeTSAmultiStage), where the first stage is an optimization with a number of typical days and the second stage optimizes the entire period only considering the in stage one selected technologies, and
- multi-period myopic optimization (function optimizeSimpleMyopic) where several years (e.g., 30 years in 5 years steps) can be optimized to get a transformation path for a given energy system based on targeted GHG emission reduction.

Figure 13 shows a generic system and the available components in FINE [40]. A Source is any kind of energy input (e.g., renewable energy, fossil fuel, or water) into the system other as via a Transmission component. The Transmission component aims to exchange energy between locations. The Sink is any kind of energy demand to be fulfilled. Both - a Sink and a Source - could also be non-energy streams such as CO_2 or water. Therefore, it allows modeling any kind of energy system. The Storage component provides the ability to store energy for later use. And a Conversion component can convert one or multiple energy input streams into one or multiple other energy output streams. A Conversion also represents a heat exchanger with a possible state change of steam towards water or a compressor with its associated pressure increase. Even with the limited number of components, FINE is able to represent the most complex energy systems.

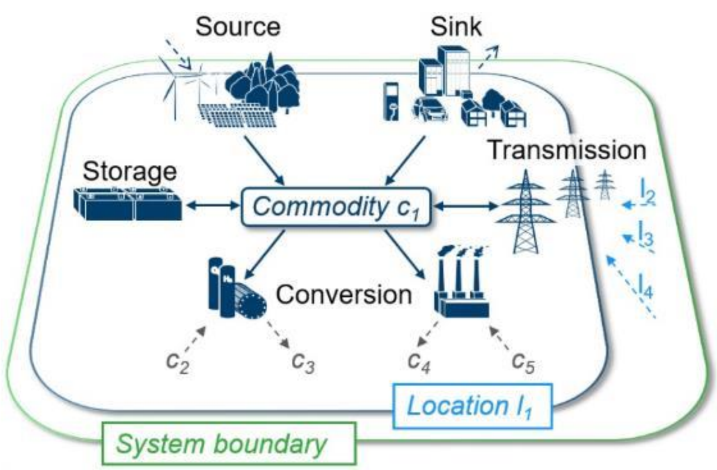


Figure 13: Framework for Integrated Energy System Assessment (FINE) [40]

7.1 Enhancements with little coding

Not each new requirement needs to be coded as a new feature in an ESD tool. Frequently available features can be used to implement new functionality with some modeling tricks. For national and generic assessments, considering the energy throughput (measured in MW_{th}) of a pipeline is accurate enough. However, it is not sufficient for a pre-feasibility assessment within a city boundary or in combination with an industrial park.

For example, the variable ‘operation Rate Max’ of the component Source primary use is to limit the variable renewable energy production. But it also can be used to reflect the following constraints:

- model the impact of ambient air temperature towards the power output (especially useful for gas turbines),
- model the ambient air temperature impact on the water supply temperature in district heating (DH) networks (e.g., summer: 0.25, winter peak: 1.0), or
- model the impact of ambient air temperature on the capacity of pipeline and consider the pipeline’s capability of supply storage capacity through temporary pressure adjustments.

As an example, Table 14 shows how such adjustments or correction functions can be used for time series adjustment as a result of varying ambient air temperature (e.g., gas turbine output and efficiency output; water supply temperature adjustments in district heating systems).

Table 14: Exemplary adjustment functions [73] [74]

Description	Equation	Source
Correction factor for efficiency (gross) of steam turbines	$1.0426 - 0.0028 \cdot \mathrm{t_{cw}}$	[73]
Correction factor for power output of gas turbines	$1.105 - 0.007 \cdot \mathrm{t_{amb}}$	[73]
Correction factor for efficiency (gross) of gas turbines	$1.033 - 0.0022 \cdot \mathrm{t_{amb}}$	[73]
Correction factor for water supply temperature (variable) *	$max\left(\begin{matrix} 0.25; \\ 0.25 - \frac{(t_{\mathrm{amb}} - 15)}{120} \cdot \frac{60}{35} \end{matrix}\right)$	[74]
Correction factor for water supply temperature (variable-constant) *	$min\left[\begin{matrix} \frac{11}{12}; \\ max\left(\begin{matrix} \frac{7}{12}; \\ \frac{7}{12} - \frac{(t_{\mathrm{amb}} - 10)}{60} \end{matrix}\right) \end{matrix}\right]$	[74]

<u>*Remark*</u>: t_{amb} – ambient air temperature; t_{cw} – cooling water temperature; * 120°C assumed as max. supply temperature.

Similarly, in the case of the district heating and/or cooling system, the correction curve can be combined with the knowledge of minimum and maximum water velocity during the heating period (min. 0.8 m/s; diameter nominal (DN) or nominal size < 150: max. 2.0 m/s; DN > 150: max. 3.0 m/s) [75]. If these details are combined, the minimum and maximum possible energy transfer can be estimated based on the selected operational regime.

Additional enhancements can be achieved by combining existing tools and scripts. The OPSD shares a script which allows to download MERRA2 weather data for each location globally. Based on this weather data, the Python package TESpy provides the possibility to calculate the solar gains for Solar Thermal systems [76] [77]. Profiles for Solar PV and Wind can be created by using alite. TESpy can also be used to calculate ambient condition impacted steady-state energy output and conversion efficiency for diverse technologies, including heat pumps, gas and steam turbines, combined heat and power plants, and solar collectors. The Python packages RC_BuildingSimulator [78] or

TEASER [79] can be used to estimate the hourly demand profiles for electricity, heating, and cooling within residential customers. Data for commercial or industrial customers are usually not available as open source.

The ESD tool FINE can deal with multi-modal and multi-node configurations out-of-the-box, considering some time-clustering techniques are also part of the framework. Individual extensions of FINE include the economy of scale for cost and performance as required. Also, additional clustering techniques have been added. The most significant enhancement has been the incorporation of a system reliability assessment by using LOLH and the capacity outage probability table (COPT). Combined with the possibility of limiting the largest unit size to be added, also short-term impact such as inertia can be considered in a simple and preliminary way to ensure a reliable power system even with high shares of renewable energy.

7.2 Enhancements with significant coding

During the course of this work, existing software packages have been expanded on individual occasions. The changes in the thermal building modeling tool RC_BuildingSimulator, tsam, and FINE are shown in Table 15, Table 16, and Table 17, respectively.

Table 15: Own RC_BuildingSimulator extensions

Function	Feature
solve_energy	• add solar air temperature
rcsim	• four separate window directions instead of one • heat transfer coefficient as function of wind speed

Table 16: Own tsam extensions

Class	Feature
KMedoidsUibk	• resolved bugfix with Gurobi in the original code (class k_medoids)
timeseriesaggregationUibk	• adjusted code, so that additional algorithms (Affinity, Mini-Batch K-Means, Birch, Spectral) can be assessed • added several own algorithms following the idea of having x days per period, where *x* can be 7, 5, 4, 3, 2, and 1, and *period* can be 1, 2, 3, 4, 6, 12 month(s)

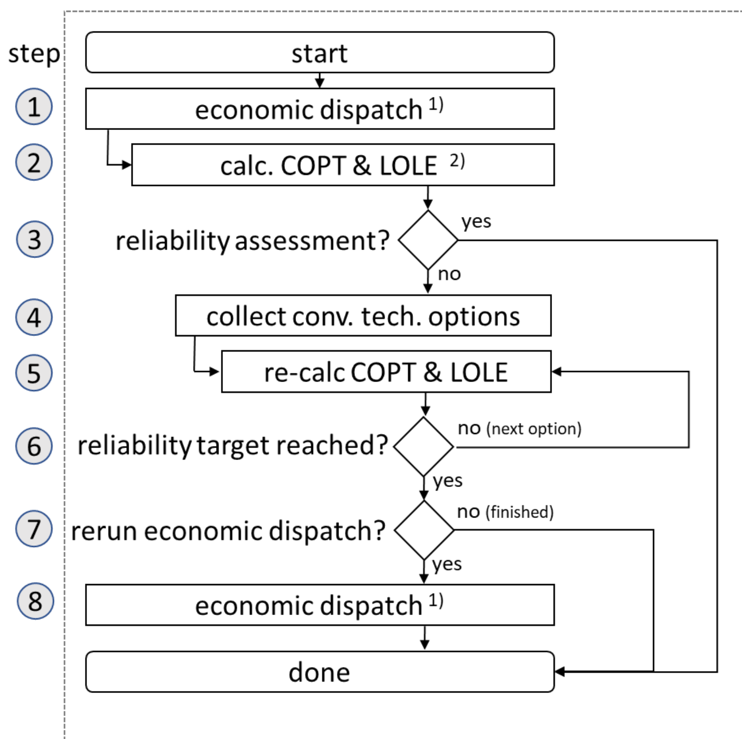
Table 17: Own FINE extensions

Class	Comment
energySystemModelUibk	• added option to use NEOS • added option switch between minimization and maximization depending on the requirements (e.g., min. cost, max. profit) • added solver using the GDPopt (nonlinear Generalized Disjunctive Programming) option • link to the new class TimeSeriesAggregationUibk within the tsam package
conversionDynamicPartLoadUibk	• created a new class and combined the features from conversionDynamic and conversionPartLoad for a more accurate representation of technical reality

Class	Comment
standardIOUibk	• adjusted code to link to the new class EnergySystemModelUibk
utilsUibk	• created helper functions for reporting (getOperationData, getCapacityData) • created functions for COPT-related calculations (calcCOPT_v1, calcCOPT_v2, calcCOPT_v3, calcKPIs, analyzeResult, readEnhancedStats)
optimizeTSAmultiStageUIBK	• adjusted multi-stage function to allow more flexibility in adjusting results from the first stage

FINE’s MS Excel®-based optimization workflow was enhanced to allow the assessment of sensitivities. The simple data management interface was enhanced to allow the creation of a technology overview as well as a Sankey diagrams. This was done using Graphviz [80].

As indicated in Table 17, one of the largest improvements of FINE was the implementation of a COPT-based reliability algorithm in the optimization process. The COPT-based reliability assessment is described in Figure 14.



Remark: *1) using FINE; 2) three COPT-calculation implementations, one using Octave®.*
Abbreviation: *COPT*: Capacity Outage Probability Table; *LOLE*: Loss of Load Expectation; ESM: Energy System Model; OS: open source; FINE: Python-based OS ESM optimization.

Figure 14: Implemented reliability methodology

After the initial economic dispatch of the modeled energy system (step (1)), the second step is to reliability metrics, even if they are not required later on. If reliability should be evaluated in detail (step (3)), the fourth step is to prepare a table with technology candidates to be considered for additions. All candidates have to be defined with a given size per unit. Candidates are already added as optimal solvers; only the non-engineering costs are considered for additional units. Otherwise, they cannot be considered as the size of the option is unknown. Starting with the cheapest option (based on its annuity), the first option is added into the existing COPT and the reliability metric is assessed. If in step (6) the reliability target is not met yet, the next option within the candidate list is evaluated together with the existing COPT. Once the reliability criteria are met, the system reruns the optimization and forces the selected candidate into the solution if the user wishes to do so. Available reliability metrics are LOLE, EUE, and EIR, respectively. The current reliability assessment implementation covers one type of energy only, which is defined within the analysis by the user.

There are different ways to consider energy storage in reliability assessments. Storage could be considered in dispatch, or within in the reliability calculations. Another possibility would be to do a system dispatch without and with energy storage and then assess the change in net load curves. In this implementation, energy storage is considered the same way as conventional technologies. Based on the initial optimization results, the size of the storage is known in power and energy. This result is used to calculate a conservative statistical availability by dividing the energy content (MWh) by the energy capacity (MW), which gives an indication of how long the storage can be used without re-charging. The discharge rate, the useful storage content, and the storage self-discharge rate are considered in this calculation.

8 Input data assessment

Within this case study, a high-level assessment regarding the importance of multiple parameters will be shown. To reflect most of the spectrum between physics (e.g., energy transfer) and economics (e.g., financing), the group of data based on Figure 12 is shown in Table 18. The column 'Y/N' indicates if uncertainty should be considered depending on the scope of assessment being either a whole city, a suburb, or an industrial park.

Table 18: High-level uncertainty assessment of input data

Assessment of	City, suburb		Industrial park	
Process step	Uncertainty consideration Yes/No		Uncertainty consideration Y/N	
Streets, buildings	No	GIS & LiDAR	No	GIS & LiDAR
Z-coordinate	No	GIS	No	GIS & LiDAR
Building stock	Yes	Statistical data	No	Questionnaire
Ambient condition	Yes	Historical data	Yes	Historical data
Energy demand	Yes	Statistical data	Yes	Statistical data
Renewable generation	Yes	Historical data	Yes	Historical data
Demand clustering	No	Statistics	No	Statistics
Costs & prices (e.g., technologies, fuel and power prices)	Yes	Unclear sizes and decision preferences	Yes	Predefined project scope and decision preferences, but unclear sizes
Options (e.g., combination of technologies)	Yes	Unclear technology preferences	No	Known technology preferences

Abbreviations: GIS – Geographical Information Systems; LiDAR – Light Detection and Ranging.

While for city-wide assessments uncertainty is almost everywhere, the assessment of a specific industrial park or city suburb might be able to eliminate some of the uncertainty regarding input data, and only the following process steps remain ambiguous:

- ambient conditions (mainly air temperature, cloudage),
- energy demand,
- renewable generation (incl. distance shadowing), and

- costs.

While paper P2 and P3 are dealing with six different countries, this assessment will be based on historical data for Austria (AT) only. Historically measured hourly time series for load are based on open-power-system-data.org [55] while RES profiles are from renewables.ninja [66]. Both sources provide hourly profile data as publicly available data and do focus on representative profiles for the available countries. Therefore, the country representing profiles are smoother than they would be in reality for an individual project.

8.1 Ambient condition

Figure 15 shows the average temperature profile for Austria for the years between 2015 and 2019. The average temperature was between 8.3 and 9.2 °C with a tendency to increase.

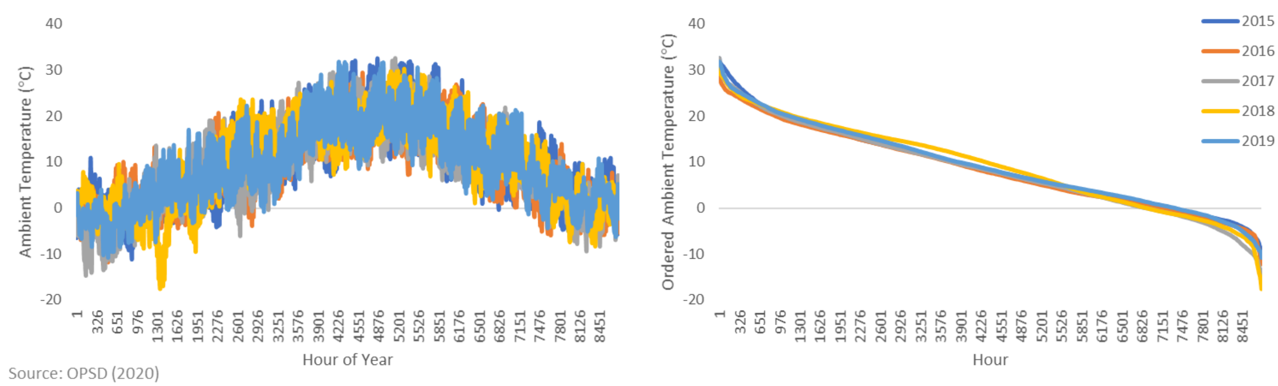


Figure 15: Unordered and ordered temperature profiles [55]

The generic need to consider ambient conditions in ESM activities is decreasing as the use of renewable energy is increasing. Nevertheless, as shown in Table 14, the requirement of correction curves still exists in a future energy system were, e.g., steam turbines are fired by biomass, gas turbines are fired by e-fuels, and local and district heating and/or cooling systems are incorporated.

Hourly energy profiles of renewables such as Solar PV, Solar Thermal, and Wind consider the ambient conditions already through modeling the individual components (e.g., solar module efficiency impact of ambient temperature).

8.2 Energy demand

Figure 16 shows the normalized power demand for Austria for the years between 2015 and 2019. The average utilization changed between 0.668 and 0.680, while the minimum demand shows a tendency to increase.

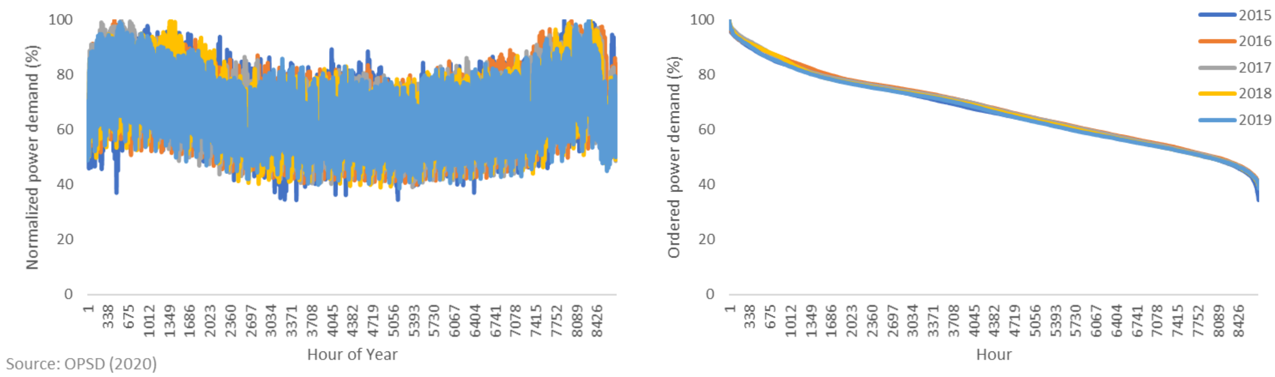


Figure 16: Unordered and ordered electricity demands [55]

Ignoring factors such as building mass, occupation change, change of room temperature settings, heating and cooling demand can be assumed to be a constant function of ambient air temperature. Therefore, the temperature curve in Figure 15 is a proxy for the heat and cold demand in residential buildings, offices, and commercial buildings. In industry, the majority of heat and cold demand usually comes from the processes operating more or less constantly throughout the year.

Neglecting population growth, efficiency improvements in white goods, electrification of processes, and increased penetration of e-mobility, the electricity demand is relatively stable and mainly depends on factors such as cloudage (e.g., lighting), room conditioning (e.g., electricity-driven HVAC, heater rod, heat pump), and house occupation (e.g., weekends, weekdays). As more and more processes (including private transportation) are becoming electrified, a change in the demand curve is expected.

8.3 Renewable generation

Figure 17 shows the average Solar PV generation profile for Austria for the years between 2015 and 2019. The average utilization changed between 0.137 and 0.143 (or 1201 and 1250 full load hours, FLH's) while the minimum demand shows a tendency to increase.

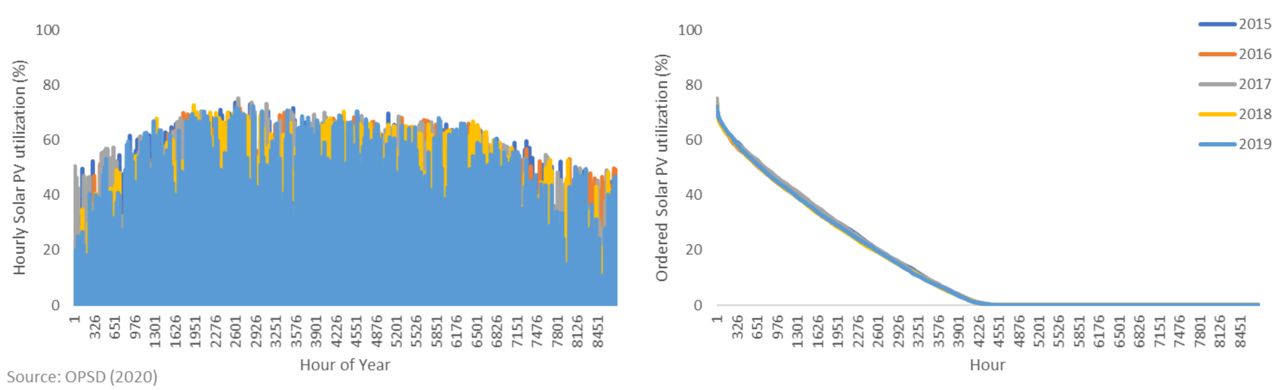


Figure 17: Unordered and ordered Solar PV generation [66]

While there is some uncertainty within hourly Solar PV production, the ordered annual utilization profiles are almost identical for the available 5 years of data.

Figure 18 shows the average Wind generation profile for Austria for the years between 2015 and 2019. The average utilization changed between 0.241 and 0.285 (or 2114 and 2493 FLH's).

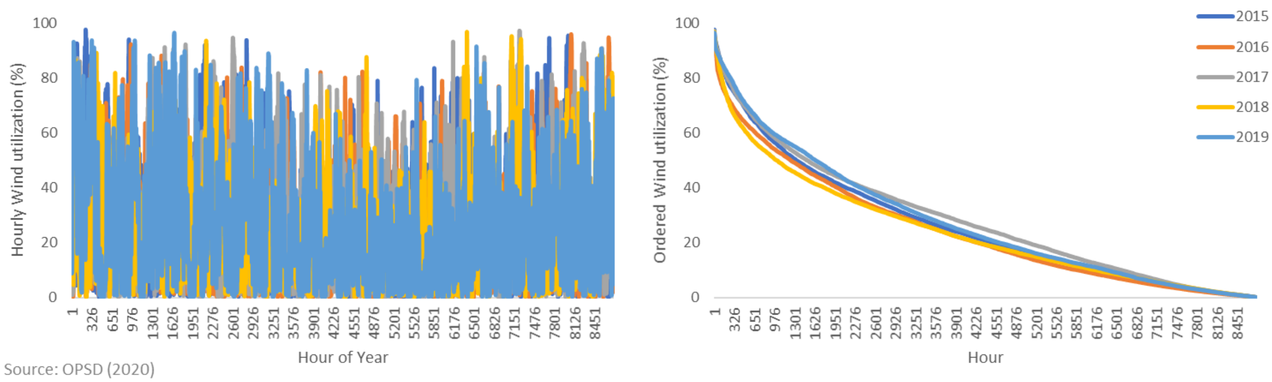


Figure 18: Unordered and ordered Wind generation [66]

There is significant uncertainty (unpredictability) within hourly Wind production. Even the ordered annual utilization profiles show significant variations. The Wind profiles for 2017 and 2018 are the most different ones and used to show their effect on the net-load curves with a renewable penetration by capacity of 100% and 200%, respectively (see Figure 19). Based on the findings in paper P2, a split of 40-60 is used for Solar PV and Wind within this comparison.

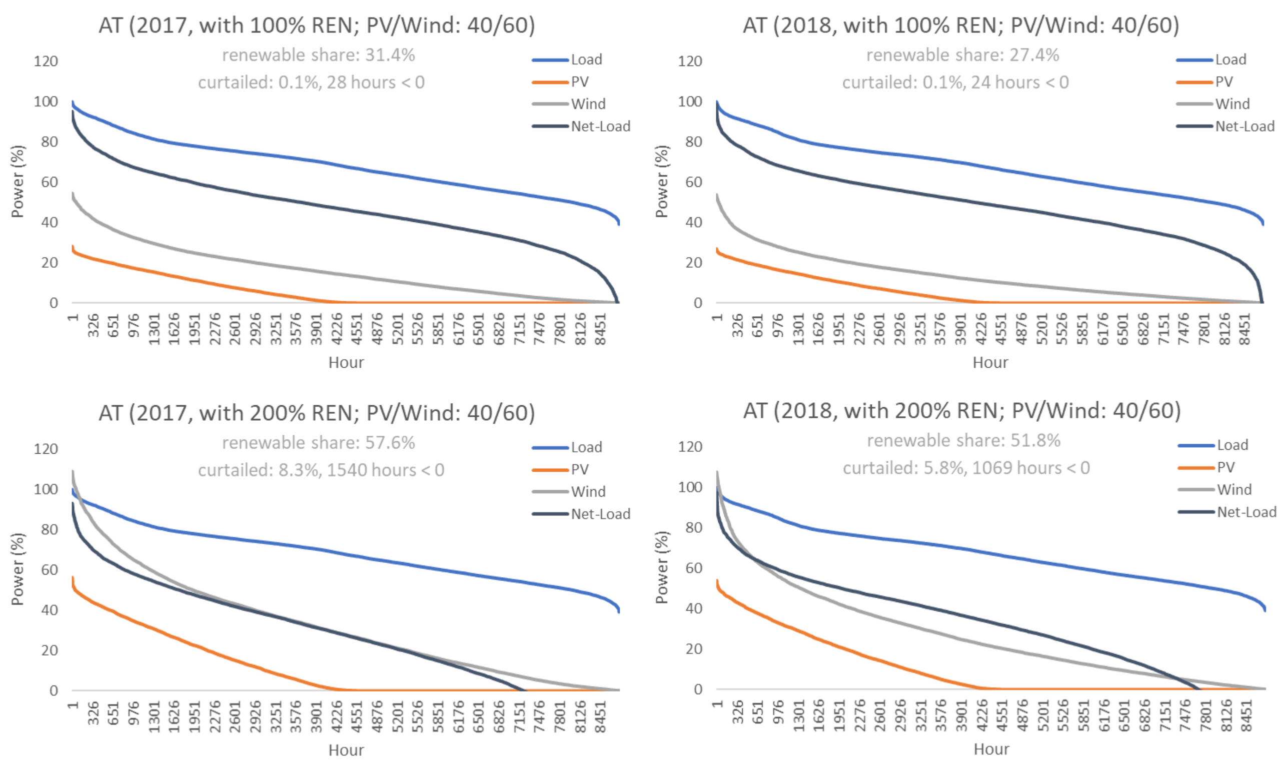


Figure 19: Ordered profiles with 100% and 200% renewables (based on [66])

8.4 Cost & prices

Power prices

Figure 20 shows the power exchange prices for Austria for the years between 2015 and 2018. Unfortunately, for 2019, the time series is not available. The average electricity price changed between 32 and 44 EUR/MWh.

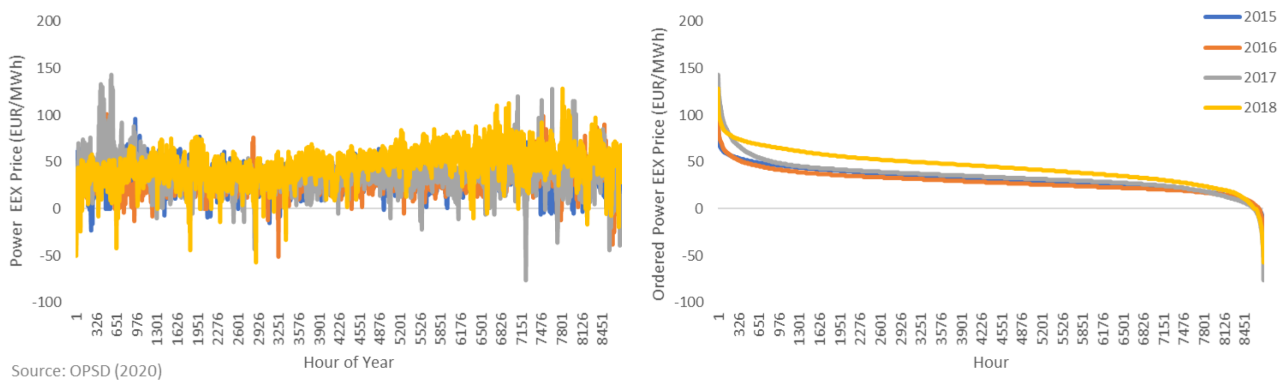


Figure 20: Ordered power exchange prices [55]

The general trend towards lower power EEX prices is in line with higher shares of renewables in the power generation mix. In most power systems, renewables are defined as 'must-run' power plants and therefore have to be dispatched before the conventional power plants. In other markets, renewables have to compete on their marginal costs in the day-ahead market. As a result, the ordered power EEX price curve shows a tendency to lower prices on the right side. But in hours of scarce renewable energy contribution, the order price curves also show a tendency to higher prices on the left side.

All in all, the impact of EEX prices is declining as future energy systems will be more and more design-focused based on allowed carbon dioxide emissions.

Energy conversion technologies

Table 19 shows technologies considered in the upcoming LCOE study with its technical and economic details expected in 2025 for large (>100 MW) projects [74].

Table 19: Technology overview considered in LCOE sensitivity [74]

	Description	**Capex** (€/kW)	**Lifetime** (a)	**FOM** (%/Capex)	**Fuel** (€/MWh)	**Eff.** (%)	**VOM** (€/MWh)
PV	Solar PV	453	27.5	1.8%	-	-	1
Wind	Wind	1,077	28.5	1.2%	-	-	1
SCGT	Simple Cycle GT	445	25.0	1.8%	6.0	0.40	45
CCGT	Combined Cycle GT	855	25.0	3.3%	6.0	0.57	43
ST	Steam Turbine	3,500	25.0	5.0%	1.0	0.38	100
PV1h	Solar PV with 1 hour BES	855	22.5	2.0%	-	1.00	2
Wind1h	Wind with 1 hour BES	1,479	22.5	1.5%	-	1.00	2
CSP8h	Concentrated Solar Power	3,500	20.0	1.8%	-	-	50
PtX	Power-to-Hydrogen	1,430	25.0	5.0%	4.0	0.65	20

Abbreviations: GT – Gas Turbine: BES – Battery Energy Storage; FOM – Fixed Operational & Maintenance costs; VOM – Variable O&M: Eff. – Efficiency (LHV); LHV – Lower Heating Value; PtX – Power to Anything.

The levelized cost of electricity (LCOE) estimates the price per MWh electricity produced required to meet a predefined level of return within the overall project lifetime. Within this work, a simplified LCOE approach is used, ignoring, e.g., tax, depreciation effects, and effects from technology aging [75]:

$$LCOE = \frac{n \cdot P_n \cdot (CRF + FOM) + P_p \cdot VOM}{P_p} \qquad \text{(Eq. 1)}$$

where *FOM* is the fixed annual operation and maintenance (O&M) costs (in % of capital expenditure), *VOM* the variable power generation costs (in EUR/kWh), P_p the useful annual RES power production (kWh/a), and CRF the capital recovery factor defined as:

$$CRF = \frac{i \cdot (1+i)^n}{(1+i)^n - 1} \qquad \text{(Eq. 2)}$$

where *i* is the interest rate (%) and *n* the number of years the annuity should be considered.

Figure 21 shows the LCOE sensitivity in a range of ±50%, focusing on the Austrian weather and renewable profiles. The charts in the first row show the sensitivity for varying the financing costs (with an initial assumption of 8% weighted average capital of cost, WACC), the capital expenditures (Capex), and the efficiency of conventional generation technologies (SCGT, CCGT, and ST). The charts in the bottom row show the sensitivity for varying the technology lifetime, the variable operating and maintenance (VOM) costs, and the utilization of the individual technology options.

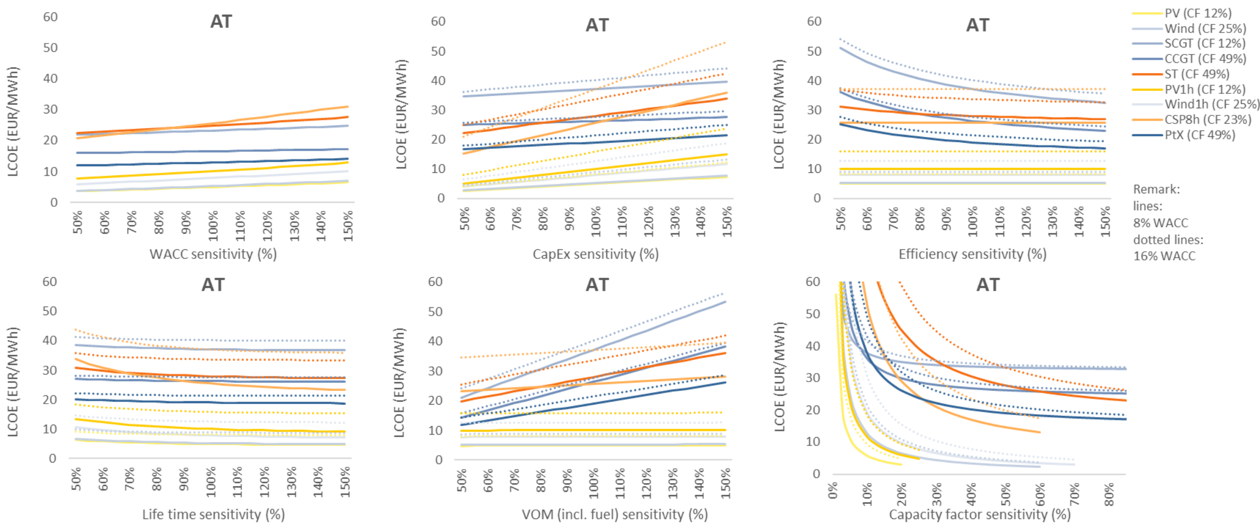


Figure 21: LCOE sensitivity

The impact of financing costs is most for technologies where investments are highest, e.g., CSP, Steam Turbines (ST), Solar PV with BES, Wind with BES (in descending order). The LCOE spread for CSP is 10 EUR/MWh, while the other mentioned technologies show a spread between 4 and 5 EUR/MWh.

The impact of capital expenditure is again highest for the technologies with the highest investment costs. This time the LCOE spread is between 21 and 8 to 12 EUR/MWh for CSP and the other mentioned technologies.

The impact of energy conversion efficiency is highest where the current efficiency is low and fuel cost is high. As such, SCGT and CCGT show an LCOE spread of 19 and 13 EUR/MWh, respectively. ST technology only shows a spread of 4 EUR/MWh as the assumed fuel (coal) is relatively cheap.

The impact of lifetime is again highest for technologies with the highest investment costs (CSP, followed by ST, Solar PV with BES, and Wind with BES). The LCOE spread is 10 and 4 EUR/MWh.

The impact of variable O&M costs (including fuel costs) is highest for technologies with low efficiencies and high fuel costs (SCGT, CCGT, ST, PtX, CSP). The spread for the conventional technologies (SCGT, CCGT, ST) is between 16 and 32 EUR/MWh, while PtX and CSP show a spread of 14 and 5 EUR/MWh, respectively.

The impact of utilization is tremendous for all technologies. As soon as technology usage is below a critical range, for example, 15%, power generation from this technology is decreasingly economical. In all such cases the operating hours within a year are too little for an economical operation. Utilization is also impacted by the shape of the demand. The peakier the demand, the more expensive it is to provide the demand during a usually limited period of time (e.g., <100 hours/a).

The net-load curves for the 200% renewable cases (from Figure 19) is used to show the impact on necessary power generation capacity using the modified screening curve method (see Figure 22) [76].

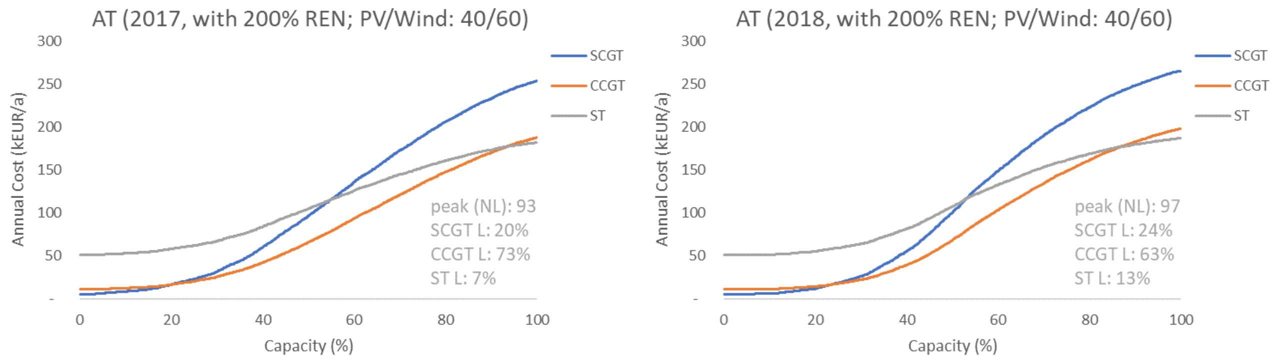


Figure 22: Modified screening curves with 200% renewables

Within the modified screening curve, each MW is assessed within the load curve, and the model considers start costs but no economy of scale. Therefore, Figure 23 shows the LCOE sensitivity focusing on the size of the equipment with the simplified screening curve (ignoring start-up costs). The left chart shows the expected power generation costs for the costs provided in [74] (solid lines), and adds economy of scale effects by multiplying the capital costs, the fixed costs, and the variable costs with 1.2 and dividing the efficiency with 1.2 (dotted lines). The left chart shows the differential between the initial data (solid lines in Figure 23) and the applied economy of scale adjustments (dotted lines in Figure 23).

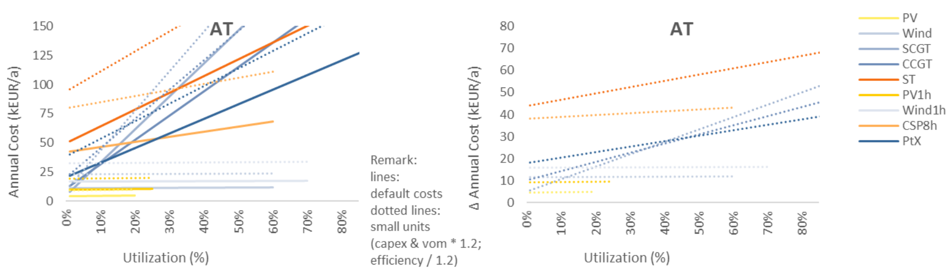


Figure 23: Economy of scale sensitivity

8.5 Time series aggregation

One of the biggest single issues within multi-modal ESD is using MILP considering time series for whole years. Problems incorporating 8760 hours a year frequently result in multiple days or weeks of optimization runtime, and there is no guarantee that either open-source or commercial solvers are able to find the optimal solution within a reasonable time. Therefore, using time series aggregation (TSA) is the biggest change (or at least hope) to find a solution within a reasonable time.

The open-source package tsam already comes with some clustering algorithms: averaging, k-means, k-medoids, and hierarchical; added algorithms are: 7days, 5days, 4days, 3days, 2days, 1days, affinity, birch, and spectral. The latter three are implemented through the Python package sklearn, while the others have been implemented by individual programming efforts. The method <x>day(s) incorporates the idea of averaging the hourly values of x days per <y> months. Figure 24 shows the accuracy measured in mean absolute error (MAE) for the mentioned aggregation methods.

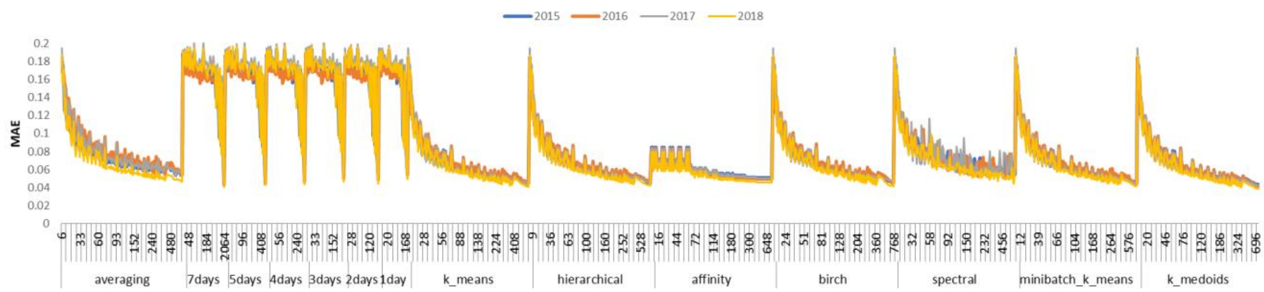


Figure 24: MAE accuracy of TSA

Table 20 shows how the days of the week are mapped to the representative days within a week.

Table 20: TSA to day of the week mapping

method	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
7days	1	2	3	4	5	6	7
5days	1	2	2	2	3	4	5
4days	1	1	1	1	2	3	4
3days	1	1	1	1	1	2	3
2days	1	1	1	1	1	2	2
1day	1	1	1	1	1	1	1

Within the used TSA package, all available algorithms are finally adjusted to fulfill the overall energy demand. Therefore, Figure 25 shows the impact on overall accuracy measured in mean absolute error (MAE), runtime (in logarithmic scale), and peak and base load of electricity (both in percent of real peak demand) for the assessed algorithms and different settings.

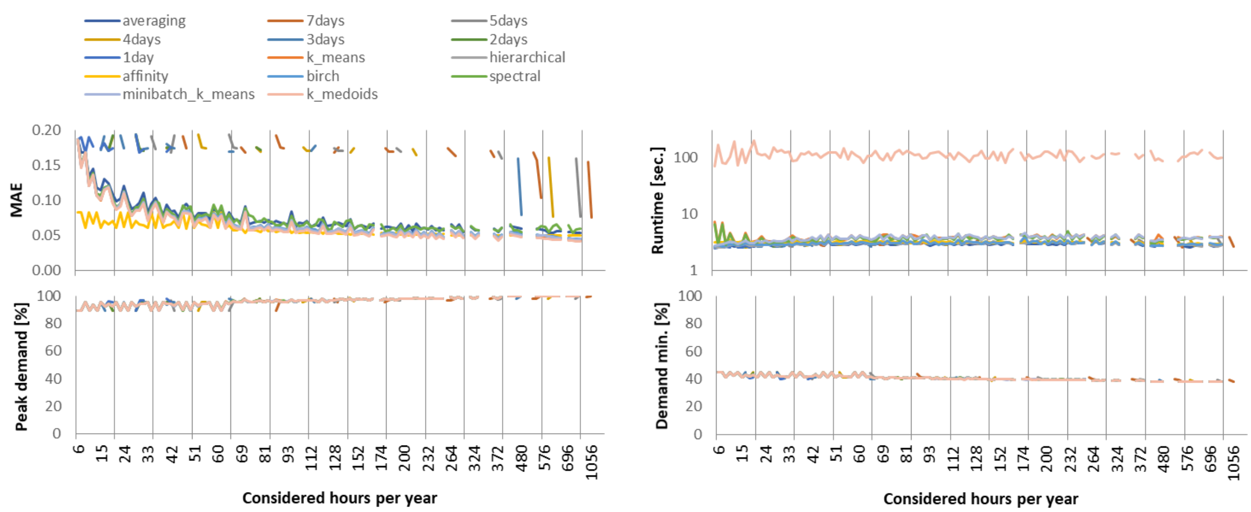


Figure 25: Overall accuracy of TSA

9 Conclusion and further research

The European Green Deal is one of the six priorities of the European Commission between 2019 and 2024 and aims to lead the EU into a sustainable and net-zero greenhouse gas emission society by the latest 2050. The Green Deal aims to change the European energy landscape from a predominantly linear and non-sustainable into a sustainable, fully integrated, and circular ecosystem. The most important principles are to electrify all end-use sectors as much as they can be electrified and use clean biofuels or e-fuels for the sectors that cannot be electrified economically or at all (such as heavy industry and long-distance transportation).

Industrial energy demand makes about 1/3 of the total primary energy consumption within the European Union. Most of this energy demand is used in continuous (all year long) process applications (mainly heating). Therefore, it provides a unique opportunity to be linked with cities, municipalities, or other energy-demanding sectors such as healthcare to fulfill their heat (or cold) requirements.

With the movement to more interconnected energy systems, the complexity of the energy systems is rising and, therefore, the need for cooperation. This broader call for cooperation comes hand in hand with the call for sharing assumptions and results from publicly funded projects to increase transparency in the use of money as well as in research methods and outcomes. This is one of the reasons why open-source energy system modeling is gaining momentum. Traditionally, energy planning started with planning for power as well as oil and gas infrastructure. Planning for power system infrastructure was done with reference cases where expected maximum and minimum demand as well as expected maximum and minimum contribution of variable renewable power generation was predicted.

Starting with more and more powerful computers, the process industry started optimizing its energy landscape with powerful optimization models. This also was the start of operations research within the energy sector. Open-source energy system models nowadays are used jointly with openly available data. This push towards open science allows the verification of each other's assumptions and results. This also helps to guide governments towards more transparent regulation regarding required decarbonization targets. Unfortunately, the available open-source energy system models are not able to assess security of supply accordingly, which is a must-have for the steadily increasing contribution of variable renewables. Unfortunately, variable renewables are not contributing during the dark dull. As a global large-scale storage is not economically available to deal with 48+ hours without a significant contribution of Solar PV and Wind, the use of conventional technologies is most likely required at least within the decades to come.

9.1 Conclusion

As shown within paper P1, the available open-source energy system models are developed very intensively. The feature comparison shows that several models are able to compete head-on-head with commercial alternatives or are even ahead in developing some special features. The biggest disadvantage of the open-source packages is their somehow uncoordinated development and the missing graphical user interface. Sometimes also the quality of documentation and examples has room for improvement. Nevertheless, the assessed tools show their maturity compared with selected closed-source alternatives, especially FINE, aristopy, Switch, TEMOA, OSeMOSYS, and pyPSA.

The assessment of optimal renewable expansion within selected countries with varying renewable quality in paper P2 shows that their quality does not impact the optimal expansion path. In a scenario in which economics is the only driver for optimal RES expansion, the 'min. LCOE' path with a strong focus on Wind should be considered. If residential users are targeted to contribute as much as possible, the 'max. capacity' case with a Solar PV-Wind ratio of 0.65±0.35 should be selected. If the overall aim is to produce maximal excess electricity to be used in other sectors, the 'max. curtailment' or 'max. zero load' cases should be considered where mainly Solar PV is the technology of choice. Therefore, more important is the overall (policy) goal.

For appropriate consideration of the security of supply within the significant renewable expansion aims, paper P3 has shown that using RM as the only reliability constraint within optimization is not appropriate as a too high assumption on RM would increase the required conventional generation capacity unnecessarily and a too low assumption would risk reliable power supply. Using LOLH as the single metric for reliable power system planning, the EENS would grow with increasing RES contribution. This is the result due to the concept of LOLH as the amount of electricity not supplied is not part of the metric; only the hours of power undersupply are. On the other hand, a constant assumption of EENS is misleading, and the concept of EENS does not consider the number of hours the power service cannot be fulfilled. Therefore, the recommendation is to use LOLH and EENS simultaneously in a single optimization framework, as shown within this work. Variable renewables are key to decrease the carbon dioxide emissions within the power and overall energy system. However, they are not able to contribute to the security of supply during dark dull periods without a very large amount of energy storage, which are currently not economically and technologically feasible on a national or even continental scale. Therefore, the security of supply has to be reached by using conventional technologies (turbines or engines) firing environmentally friendly fuels (e.g., biomass, biogas, hydrogen, or other e-fuels).

As shown in paper P4, several open-source frameworks exist and are enhanced with high speed. More coordination between universities and research agencies would make the open-source approach even more powerful. The ETH Zurich, for example, is developing a very powerful tool called City Energy Analyst (CEA), which even has a very promising web-based user interface. Another very promising approach is shown by aristopy, where non-linear equations can be considered on a smart TSA feature borrowed from the makers of FINE. It has been designed to allow adding mathematical constraints with very limited programming knowledge. Unfortunately, it does not have a user interface yet.

What most ESD studies do not consider accordingly is economy of scale. Economy of scale revers to the effect that an increase of size leads to a decrease in cost per energy unit and an increase of efficiency. They almost always assume that technology will be installed on a large enough scale so that the assumed cost will be suitable. Tools such as FINE are able to define the specific size of a technology option. It also allows the distinction between hardware and engineering costs.

While open-source tools have disadvantages, the biggest advantage of open-source tools is that they are relatively easy to customize. This makes it also easy to create adjusted optimization procedures aiming to shorten the overall optimization time without losing accuracy, e.g.:

- step 1: find optimal typical period configuration based on available input data,
- step 2: find optimal system design,
- step 3: find alternative near-optimal configurations (e.g., using integer cuts),
- step 4: check all available system design regarding their fit to security of supply,
- step 5: check the system design passing the security of supply assessment with alternative renewable and/or demand profiles,
- finally, sort results based on considered KPI’s (e.g., annual costs, CO_2 emissions, or security of supply).

Table 21 shows the summary of the input data assessment. It shows that the expensive equipment needs special care as it is most impacted by its assumption.

Table 21: Summary of most important parameters

	Expensive equipment	**Low utilization**	**Low conversion efficiency**	**High O&M**	**Mega- or Negawatt**
Financing cost	X				
Investment cost	X	X			
Energy conversion efficiency			X		
Technology lifetime	X				
Variable operating and maintenance cost			X	X	
Utilization	X				
Customer behavior					X

Abbreviations: O&M – operation & maintenance; Negawatt – negative watt (behavioral change reducing energy usage).

While TSA is a very powerful possibility to reduce the overall optimization time, its use should be assessed carefully. The algorithm Affinity might be a new candidate to support reducing the number of typical periods while having a significant lower MAE as the other assessed algorithms. Nevertheless, a too low number of representative periods end up in high MAE, too low peak demand, and too high base demand (see Figure 25 and Figure 26 for a TSA algorithm independent summary chart), which all in all has negative implications on the optimal technology selection.

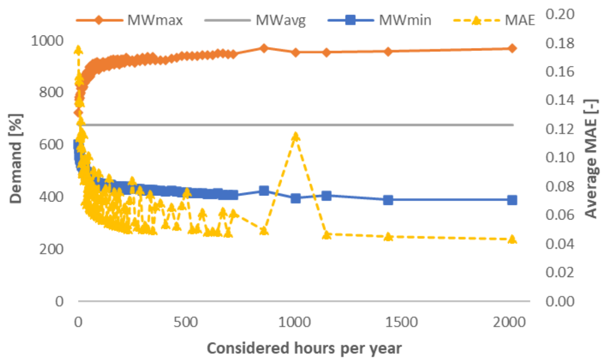


Figure 26: Algorithm independent overall accuracy of TSA

Assessing three to five years of varying renewable generation profiles is seen mandatory for a proper pre-feasibility study. While temperature impact on, e.g., power generation efficiency is an important detail to cover, pressure losses within pre-feasibility studies can be neglected. Especially for variable renewable integration, the typical periods have to consider as many periods as possible, and timesteps should not be longer than two hours. Naturally, the accuracy in operation has to be much higher as in long-term reflections where a lot of information are not known with certainty during the project planning phase. Non-linear technical details are not necessary for long-term considerations but might be valuable for technology dispatch considerations.

9.2 Further research

As indicated within the adjusted optimization procedure, the model to generate alternatives (MGA) approach can be very interesting to evaluate the solutions closest to the most economical one. This allows the assessment of the impact of technology alternatives within, e.g., 1% of optimal annuity, regarding additional performance indicators such as complexity or easiness of implementation in a brownfield environment.

As industrial sites and municipalities might move closer through sector coupling, the future ESD tools have to be able to deal with peak demand charges and multi-year optimization to better sketch the transition path of the assessed energy system. Also, inertia and grid forming aspects through conventional generators (e.g., turbines and engines) as well as synthetic inertia through electronics should be considered in future models.

While storage has been excluded in this work, future research might also consider different central and decentral storage options (e.g., batteries, thermal storage, or synthetic fuels) for hourly, daily, or seasonal shifts of energy.

One of the biggest issues with open-source software ESD tools is the lack of a common graphical user interface (GUI). Having such an enhancement would add dramatic value for further dissemination.

Bibliography

[1] Groissböck M. (2021) Energy hub optimization framework based on open-source software & data - review of frameworks and a concept for districts & industrial complexes, *International Journal of Sustainable Energy Planning and Management*, 31, 109-120, 10.5278/ijsepm.6432.

[2] EC (2020) EU strategy on energy system integration [online], *European Commission*. Available: https://ec.europa.eu/energy/topics/energy-system-integration/eu-strategy-energy-system-integration_en [accessed 14 September 2020].

[3] Eurostat (2020) Database [online], *European Commission*. Available: https://ec.europa.eu/eurostat/data/database [accessed 17 January 2021].

[4] Thorsen J.E., Lund H. & Mathiesen B.V. (2018) Progression of District Heating – 1st to 4th generation [online], *Aalborg University*. Available: https://vbn.aau.dk/en/publications/progression-of-district-heating-1st-to-4th-generation-3 [accessed 21 January 2021].

[5] Buffa S., Cozzini M., D'Antoni M., Baratieri M. & Fedrizzi R. (2019) 5th generation district heating and cooling systems: A review of existing cases in Europe, *Renewable and Sustainable Energy Reviews*, 104, 504-522, DOI: 10.1016/j.rser.2018.12.059.

[6] Thiem S. (2017) Multi-modal on-site energy systems Development and application of a superstructure-based optimization method for energy system design under consideration of part-load efficiencies, Doctoral Thesis, Department of Electrical and Computer Engineering, *Technical University Munich*, Germany.

[7] Frik R. & Favre-Perrod P. (2004) Proposal for a multifunctional energy bus and its interlink with generation and consumption, Diploma thesis, High Voltage Laboratory, *ETH Zurich*, Switzerland.

[8] Lazard (2020) Levelized Cost of Energy Analysis 14.0 [online], *Lazard Frères & Co. LLC*. Available: https://www.lazard.com/perspective/lcoe2020 [accessed 17 January 2021].

[9] Morvaj B., Evins R. & Carmeliet J. (2016) Optimization framework for distributed energy systems with integrated electrical grid constraints, *Applied Energy*, 171, 296-313, DOI: 10.1016/j.apenergy.2016.03.090.

[10] ETHZ (2021a) Energy Hubs [online], *ETHZ*. Available: http://www.sustec.ethz.ch/research/topics/technology/energy-hubs.html [accessed 17 January 2021].

[11] ETHZ (2021b) Integration of sustainable multi-energy-hub systems from the system control perspective (IMES-SC) [online], *ETHZ*. Available: https://www.fen.ethz.ch/projects/infrastructure-interdependencies/imes-sc.html [accessed 17 January 2021].

[12] ETHZ (2021c) Energy Positive Neighbourhoods Infrastructure Middleware based on Energy-Hub Concept [online], *ETHZ*. Available: https://www.fen.ethz.ch/projects/infrastructure-interdependencies/epic-hub.html [accessed 17 January 2021].

[13] EFENIS (2021) Efficient Energy Integrated Solutions for Manufacturing Industries [online], *European commission*. Available: https://cordis.europa.eu/project/id/296003/de [accessed 17 January 2021].

[14] Einstein (2021) Expert-system for an Intelligent Supply of Thermal Energy in Industry and other large-scale applications [online], *E4-Experts GmbH*. Available: https://www.einstein-energy.net/index.php/about-einstein/fundedprojects/einstein-ii [accessed 17 January 2021].

[15] ENEPLAN (2021) Energy Efficient Process pLAnning system [online], *European Commission*. Available: https://cordis.europa.eu/project/id/285461 [accessed 17 January 2021].

[16] EnRiMa (2021) Energy Efficiency and Risk Management in Public Buildings [online], *European Commission*. Available: https://cordis.europa.eu/project/id/260041 [accessed 17 January 2021].

[17] EPICHUB (2021) Energy Positive Neighbourhoods Infrastructure Middleware based on Energy-Hub Concept [online], *European Commission*. Available: https://cordis.europa.eu/project/id/600067 [accessed 17 January 2021].

[18] Atabay D. (2018) Comparison of optimization methods for model predictive control: An application to a compressed air energy storage system. Doctoral Thesis, Department of Electrical and Computer Engineering, *Technical University Munich*, Germany.

[19] Voll P., Klaffke C., Hennen M. & Bardow A. (2013) Automated superstructure-based synthesis and optimization of distributed energy supply systems, *Energy*, 50, 374-388, DOI: 10.1016/j.energy.2012.10.045.

[20] Majewski D., Lampe M., Voll P. & Bardow A. (2017) TRusT: A Two-stage Robustness Trade-off approach for the design of decentralized energy supply systems, *Energy*, 118, 590-599, DOI: 10.1016/j.energy.2016.10.065.

[21] Bothe D. (2016) Modellierung und Simulation von weit verzweigten, vermaschten Netzen für thermische Energie und Gas, Doctoral Thesis, *Technical University Vienna*, Austria.

[22] Fritz S. (2016) Economic assessment of the long-term development of buildings' heat demand and grid-bound supply - a case study for Vienna, Doctoral Thesis, *Technical University Vienna*, Austria.

[23] Talebi B., Mirzaei P.A., Bastani A. & Haghighat F. (2016) A Review of District Heating Systems: Modeling and Optimization, *Frontiers in Built Environment*, 2, 57-73, DOI: 10.3389/fbuil.2016.00022.

[24] Lambert R.S.C., Maier S., Shah N. & Polak J.W. (2016) Optimal phasing of district heating network investments using multi-stage stochastic programming, *International Journal of Sustainable Energy Planning and Management*, 09, 57-74, DOI: 10.5278/ijsepm.2016.9.5.

[25] Dorfner J.F. (2017) Open Source Modelling and Optimisation of Energy Infrastructure at Urban Scale, Doctoral Thesis, Department of Electrical and Computer Engineering, *Technical University Munich*, Germany.

[26] Zhou X., Guo C., Wang Y. & Li W. (2017) Optimal Expansion Co-Planning of Reconfigurable Electricity and Natural Gas Distribution Systems Incorporating Energy Hubs, *Energies*, 10, 124, DOI: 10.3390/en10010124.

[27] Strauss K. (2016) Kraftwerkstechnik zur Nutzung fossiler, nuklearer und regenerativer Energiequellen, 7th Edition, Berlin: Springer Vieweg.

[28] Bruckner T. (1997) Dynamische Energie- und Emissionsoptimierung regionaler Energiesysteme, Doctoral Thesis, Department of Theoretical Physics, *University of Würzburg*, Germany.

[29] Biberacher M. (2004) Modelling and optimisation of future energy systems using spatial and temporal methods, Doctoral Thesis, Institute for Physics, Experimental Plasma Physics, *University of Augsburg*, Germany.

[30] Geidl M. (2007) Integrated Modeling and Optimization of Multi-Carrier Energy Systems, Doctoral Thesis, Institute for Power Systems and High Voltage Laboratory, *ETH Zurich*, Switzerland.

[31] Connolly D., Lund H., Mathiesen B.V. & Leahy M. (2010) A review of computer tools for analysing the integration of renewable energy into various energy systems, *Applied Energy*, 87, 4, 1059-1082, DOI: 10.1016/j.apenergy.2009.09.026.

[32] Mendes G., Ioakimidis C. & Ferrão P. (2011) On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools, *Renewable and Sustainable Energy Reviews*, 15, 9, 4836-4854, DOI: 10.1016/j.rser.2011.07.067.

[33] Mancarella P. (2014) MES (multi-energy systems): An overview of concepts and evaluation models, *Energy*, 65, 1-17, DOI: 10.1016/j.energy.2013.10.041.

[34] Keirstead J., Jennings M. & Sivakumar A. (2012) A review of urban energy system models: Approaches, challenges and opportunities, *Renewable and Sustainable Energy Reviews*, 16, 6, 3847-3866, DOI: 10.1016/j.rser.2012.02.047.

[35] Paletto A., Bernardi S., Pieratti E., Teston F. & Romagnoli M. (2019) Assessment of environmental impact of biomass power plants to increase the social acceptance of renewable energy technologies, *Heliyon*, 5(7), e02070, DOI: 10.1016/j.heliyon.2019.e02070.

[36] Prina M.G., Manzolini G., Moser D., Nastasi B., & Sparber W. (2019) Classification and challenges of bottom-up energy system models - A review, *Renewable and Sustainable Energy Reviews*;129, 109917, DOI: 10.1016/j.rser.2020.109917.

[37] Ridha E., Nolting L. & Praktiknjo A. (2020) Complexity profiles: A large-scale review of energy system models in terms of complexity, *Energy Strategy Reviews*, 30, 100515, DOI: 10.1016/j.esr.2020.100515.

[38] Lopion P.M. (2020) Modellgestützte Analyse kosteneffizienter CO2-Reduktionsstrategien, RWTH Aachen, Doctoral Thesis, *Forschungszentrum Jülich*, Germany.

[39] FINE (2020) github.com [online]. Available: https://github.com/FZJ-IEK3-VSA/FINE [accessed 14 September 2020].

[40] Welder L., Ryberg D.S., Kotzur L., Grube T., Robinius M. & Stolten D. (2018) Spatio-temporal optimization of a future energy system for power-to-hydrogen applications in Germany, *Energy*, 158, 1130-1149, DOI: 10.1016/j.energy.2018.05.059.

[41] tsam (2020) github.com [online]. Available: https://github.com/FZJ-IEK3-VSA/tsam [accessed 14 September 2020].

[42] Bruche S. & Tsatsaronis G. (2019) A Multi-Stage Optimization Approach for Energy Supply Systems with Discrete Design Decisions, ASME 2019 International Mechanical Engineering Congress and Exposition *Proceedings of the ASME 2019 International Mechanical Engineering Congress and Exposition. Volume 6: Energy*. Salt Lake City, USA, DOI: 10.1115/IMECE2019-11519.

[43] aristopy (2020) github.com [online]. Available: https://github.com/sbruche/aristopy [accessed 14 September 2020].

[44] Morstyn T., Collett K.A.., Vijay A., Deakin M., Wheeler S., Bhagavathy S.M., Fele F. & McCulloch M.D. (2020) An Open-Source Platform for Developing Smart Local Energy System Applications, *Applied Energy*, 275, 115397, DOI: 10.1016/j.apenergy.2020.115397.

[45] Wikipedia, Open Source [online], Wikipedia. Available from https://de.wikipedia.org/wiki/Open_Source [accessed 19 January 2021].

[46] EU, SETIS Magazine November 2016 - Energy Systems Modelling [online], *European Commission*. Available from https://setis.ec.europa.eu/publications/setis-magazine/energy-systems-modeling [accessed 4 October 2020].

[47] Huntington H.G., Weyant J.P. & Sweeney J.L. (1982) Modeling for insights, not numbers: the experiences of the energy modeling forum, *Omega*, 10(5), 449-462, DOI: 10.1016/0305-0483(82)90002-0.

[48] DeCarolis J.F., Hunter K. & Sreepathi S. (2012) The case for repeatable analysis with energy economy optimization models, *Energy Economics*, 34(6), 1845-1853, DOI: 10.1016/j.eneco.2012.07.004.

[49] Howells M., Rogner H., Strachan N., Heaps C., Huntington H., Kypreos S., Hughes A., Silveira S., DeCarolis J.F., Bazillian M. & Roehrl A. (2011) OSeMOSYS: The Open Source Energy Modeling System: An introduction to its ethos, structure and development, *Energy Policy*, 39(10), 850-5870, DOI: 10.1016/j.enpol.2011.06.033.

[50] Temoa (2020) Tools for Energy Model Optimization and Analysis, github.com [online]. Available: https://github.com/TemoaProject [accessed 4 October 2020].

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

[52] Hülk L., Müller B., Glauer M., Förster E. & Schachler B. (2018) Transparency, reproducibility, and quality of energy system analyses - A process to improve scientific work, *Energy Strategy Reviews*, 22, 264-269, DOI: 10.1016/j.esr.2018.08.014.

[53] openmod (2020) Open Energy Modelling Initiative [online]. Available: https://www.openmod-initiative.org/manifesto.html [accessed 2 April 2021].

[54] EMP-E (2020) Energy Modelling Platform for Europe [online]. Available: http://www.energymodellingplatform.eu/ [accessed 24 September 2020].

[55] OPSD (2020) Open Power System Data - a free-of-charge data platform for power system modelling [online]. Available: https://open-power-system-data.org/ [accessed 24 September 2020].

[56] COIN-OR (2020) Computational Infrastructure for Operations Research [online]. Available: https://www.coin-or.org [accessed 24 September 2020].

[57] OSM (2020) Open Street Map [online]. Available: https://www.openstreetmap.org/ [accessed 24 September 2020].

[58] EU (2020) Directive (EU) 2019/1024 on open data and the re-use of public sector information [online], *European Commission*. Available from http://data.europa.eu/eli/dir/2019/1024/oj [accessed 4 October 2020].

[59] Morrison R. (2018) Energy system modeling: Public transparency, scientific reproducibility, and open development, *Energy Strategy Reviews*, 20, 49-63, DOI: 10.1016/j.esr.2017.12.010.

[60] Chosealicense (2021) Choose an open source license [online]. Available: https://choosealicense.com/ [accessed 29 January 2021].

[61] Mehmood R., SeeIyad Katib S. & Chlamtac, I. (2019) Smart Infrastructure and Applications: Foundations for Smarter Cities and Societies, Springer, Cham, Switzerland.

[62] Groissböck M. (2019) Are open source energy system optimization tools mature enough for serious use? *Renewable and Sustainable Energy Reviews*, 102, 234-248, DOI: 10.1016/j.rser.2018.11.020.

[63] Groissböck M. (2020) Impact of spatial renewable resource quality on optimum renewable expansion, *Renewable Energy*, 160, 1396-1407, DOI: 10.1016/j.renene.2020.07.041.

[64] Kreifels N., Mayer J.N., Burger B. & Wittwer C. (2014) Analysis of Photovoltaics and Wind Power in Future Renewable Energy Scenarios, *Energy Technology*, 2, 29-33, DOI: 10.1002/ente.20130090.

[65] Newell S., Carroll R., Kaluzhny A., Spees K., Carden K., Wintermantel N. & Krasny A. (2018) Estimation of the Market Equilibrium and Economically Optimal Reserve Margins for the ERCOT Region - 2018 Update [online], *The Brattle Group*. Available: http://www.ercot.com/content/wcm/lists/143980/10.12.2018_ERCOT_MERM_Report_Final_Draft.pdf [Accessed 5 May 2019].

[66] Pfenninger S. & Staffell I. (2016) Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data, *Energy*, 114, 1251-1265, DOI: 10.1016/j.energy.2016.08.060.

[67] Groissböck M. & Gusmão A. (2020) Impact of renewable resource quality on security of supply with high shares of renewable energies, *Applied Energy*, 277, 115567, DOI: 10.1016/j.apenergy.2020.115567.

[68] Groissböck M. (2021) Energy hub optimization framework bases on open source [online]. Available: DOI: 10.5281/zenodo.4459140 [accessed 23 January 2021].

[69] Alhamwi A., Medjroubi W., Vogt T. & Agert C. (2018) FlexiGIS: an open source GIS-based platform for the optimisation of flexibility options in urban energy systems, *Energy Procedia*, 152, 941-946, DOI: 10.1016/j.egypro.2018.09.097.

[70] Firouzi M. (2020) Finding the Right Data Qualities and Clustering Indicators for Time Series Aggregation in Energy Systems Models with High Shares of Renewables, Master thesis, School of Industrial and Information Engineering, *Politecnico di Milano*, Italy.

[71] PyPSA Technology Data (2021) github.com [online]. Available: https://github.com/PyPSA/technology-data [accessed 11 April 2021].

[72] Julia (2021) The Julia Programming Language, Version 1.5.3 [online], *The Julia Project*. Available: https://julialang.org/ [Accessed 3 February 2021].

[73] Konstantin P. & Konstantin M. (2018) The Power Supply Industry – Best Practice Manual for Power Generation and Transportation, Economics and Trade, Springer imprint, Cham.

[74] EnergieSchweiz (2020) Handbook on Planning of District Heating Networks, Swiss Federal Office of Energy [online]. Available: http://www.verenum.ch/Dokumente_QMFW.html [accessed 3 February 2021].

[75] Dötsch C., Taschenberger J. & Schönberg I. (1998) Leitfaden Nahwärme, Fraunhofer UMSICHT [online]. Available: http://publica.fraunhofer.de/dokumente/PX-52182.html [accessed 31 January 2021].

[76] Witte F. & Tuschi I. (2020) TESpy - Thermal Engineering Systems in Python, *Journal of Open Source Software*, 5(49), 2178, DOI: 10.21105/joss.02178.

[77] TESpy (2020) github.com [online]. Available: https://github.com/oemof/tespy [accessed 14 September 2020].

[78] RC_BuildingSimulator (2021) github.com [online]. Available: https://github.com/architecture-building-systems/RC_BuildingSimulator [accessed 11 April 2021].

[79] TEASER (2020) github.com [online]. Available: https://github.com/RWTH-EBC/TEASER [accessed 11 April 2021].

[80] Graphviz (2021) graphviz.org [online]. Available: https://graphviz.org/about/ [accessed 6 June 2021].

Appendix - Reprints

This chapter includes all published papers as reprints. The reference numbering as well as the figure and table numbering within the individual papers are independent from the references within this thesis. Table 22 shows the publications with all details.

Table 22: Publications

Pub. no	**Author(s)**		**Pub. year**	**Title**	***Journal*, vol., page, DOI**
	Groissböck M.	**Gusmão A.**			
1	X		2019	Are open source energy system optimization tools mature enough for serious use?	*Renewable and Sustainable Energy Reviews*, 102, 234-248, 10.1016/j.rser.2018.11.020
2	X		2020	Impact of spatial renewable resource quality on optimum renewable expansion	*Renewable Energy*, 160, 1396-1407, 10.1016/j.renene.2020.07.041
3	X	X	2020	Impact of renewable resource quality on security of supply with high shares of renewable energies	*Applied Energy*, 277, 115567, 10.1016/j.apenergy.2020.115567
4	X		2021	Energy hub optimization framework based on open-source software & data - review of frameworks and a concept for districts & industrial parks	*International Journal of Sustainable Energy Planning and Management, 31, 109-120,* 10.5278/ijsepm.6432

Paper 1

Renewable and Sustainable Energy Reviews 102 (2019) 234–248

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Are open source energy system optimization tools mature enough for serious use?

Markus Groissböck

University of Innsbruck, Institute for Construction and Materials Science, Innsbruck, Austria

ARTICLE INFO

Keywords:
Open source
Multi-energy system
Sector coupling
Optimization
Simulation

ABSTRACT

Historically, energy system tools were predominantly proprietary and not shared with others. In recent years, there has been an increase in developing open source tools by international research and development organizations. More than half of the open energy modeling (openmod) initiative listed tools are based on the freely available scripting language Python. Previous comparisons of energy and power system modeling tools focused on comparisons such as which tool category (e.g. optimization, simulation) or energy demand (e.g. electricity, cooling, and heating) can be considered. Until now, the assessment of incorporated functions such as unit commitment (UC) or optimum power flow (OPF) has been ignored. Therefore, this work assesses 31 mostly open source tools based on 81 functions for their maturity. The result shows that available open source tools such as Switch, TEMOA, OSeMOSYS, and pyPSA are mature enough based on a function comparison with commercial or proprietary tools for serious use. Nevertheless, future commercial, as well as open source energy system analysis tools, have to consider more functions such as the impact of ambient air conditions and part-load behavior to allow better assessments of including high shares or renewable energy sources and other flexibility measures in existing and new energy systems.

1. Introduction

Open source is defined as "open, publicly accessible software and data" [1, p. 149] and has received more and more attraction within energy system modeling in the last years [2]. In general, the concept of open source can be applied to tools, data, methodologies, results, and discussions as e.g. open access publications contributed to the open source approach [3]. One of the promises of open source tools includes significantly lower training and startup time requirements [4]. The purpose of most analyzed tools is to explore the future by considering the impact of today's decisions. Other expectations are to increase scientific quality, increase transparency and productivity, and improve collaboration between all contributing parties. In 2005, PSAT was one of the first free and open source software (FOSS) power system modeling tools founded by Dr. Federico Milano [5]. After limited community contribution, he decided to stop this open source project [6]. Some reasons have been identified for the limited interest: firstly, each organization strives to create something unique in order to successfully apply for funding to further improve proprietary methods and tools, and secondly, the topic power system simulation in itself is not able to attract enough interest as it is a very narrow research area. In 2013, Dr. Milano started a new power system modeling approach called Dome, entirely based on Python [7]. This time the programming language Python was chosen as it provides a freely available modern scripting language in which classes, as well as neat functions, can be incorporated accordingly. [8] provides a list of tools shared with the community. Based on this tool collection, about half of the listed tools produced in the last two years have been shared with the community. This can be seen as an indication of growing interest of research in free and publicly available software [8]. Many of these new tools are based on Python. If this movement towards open source energy and power system modeling tools creates more ideas and free code exchange as before has to be observed over time [9]. Each of the available tools has different purposes and main emphasis and therefore it is difficult to differentiate between them.

The existing literature reviews regarding energy system tool comparisons deal with details such as modeling language, modeling approach, considered planning horizon, and energy carriers. None of the authors of existing literature reviews assessed the detailed technical capability of the individual modeling tools. The contribution of this work to the state-of-the-art of energy and power system modeling is to propose 81 functions (such as unit commitment (UC), optimal power flow (OPF), minimum up/down time, starts a day, model foresight, reliability indicators, and risk appetite) and to analyze 31 energy modeling tools to allow an unbiased tool comparison and objective tool selection. By undertaking this research, it closes the gap among detailed

E-mail address: markus.groissboeck@student.uibk.ac.at.

https://doi.org/10.1016/j.rser.2018.11.020
Received 25 April 2018; Received in revised form 29 September 2018; Accepted 17 November 2018
Available online 19 December 2018
1364-0321/

assessments of available open source energy system modeling tools and shows that these models have reached a proper level of maturity for serious use whereas the level of maturity is measured in terms of functions considered. For open source multi-energy system (MES) tools the number of users cannot be assessed as there is no central registration required. The number of downloads could be used as an indicator but would not imply the actual use of a tool. A discussion of functions that haven't been seen in open source energy modeling tools yet is added to show the importance of those within an environment of increasing contribution of volatile energy resources (VER), storage, and other flexibility measures.

The structure of the remaining paper is as follows: Chapter II contains a literature review considering previous tool comparisons. Chapter III provides a discussion around the list of tools evaluated within this paper as well as a brief discussion on the considered functions. Chapter IV shows the detailed assessment as well as the results of the evaluation. Chapter V discusses the missing but important functions to narrow the gap between reality and the optimization results. Chapter VI and Chapter VII summarize the findings and conclusions and present possible future research ideas.

2. Literature review

Before the different available assessments are analyzed, it is important to highlight that terminology is an important consideration in this research. In general, the term 'model' refers to the published software tool or software package. It is also used as a short name for the mathematical formulation as well as for the result of the optimization or simulation. For the purpose of this publication, the term 'model' is used purely for the mathematical formulation. For the results of the optimization, the term 'scenario' is used. The term 'tools' refer to the source code in which the mathematical formulation is written in.

From a physics perspective, energy system simulations can consider either steady-state or transient details [10]. Transient modeling is considered if the detailed time-dependent process behavior is of interest. Steady-state modeling is considered if time-dependent derivations can be ignored. In such a case, the modeled components only have entry and exit parameters such as pressure, temperature, and mass flow expressed as state variables. If details along an energy transmission system, like a pipeline, should be covered, a steady-state 1D model can be incorporated. In general, steady-state models are used for system design, measurement validation, and part load estimations. Control systems and simulators have to use transient modeling in which also details as momentum is considered. For the purpose of this publication, short-term represents timesteps in the range of at least one minute. Therefore, transient details are not considered within this publication.

Comparing available and published energy simulation and optimization models has a long history and all publications have a different focus of assessment. [11] assesses six tools comparing whether they are a simulation, an optimization, an operational or investment tool. In their assessment, "Distributed Energy Resources Customer Adoption Model" (DER-CAM), EAM, "MARKet ALlocation model" (MARKAL), and "The Integrated MARKAL/EFOM System" (TIMES) are optimization tools while the remainder such as "Hybrid Optimization Model for Electric Renewables" (HOMER) and H_2RES are simulation tools. HOMER is able to consider sensitivities within the economic assessment. The DER-CAM has been used to assess the required subsidy levels with increasing carbon emission taxes. EAM is a tool similar to DER-CAM but is able to consider nonlinear technical constraints (nonlinear efficiency of conventional generation). MARKAL and TIMES are able to consider energy, economics, and the environment. "Renewable Energy Technology Screening" (RETScreen) is a planning tool which allows the comparison of different possible scenarios. [8] lists 31 tools published under open source licenses and is a collection of generic information such as covered sectors, modeling environment, time resolution, the license under which tools have been published as well as wether the model source is available for the public. [12] is a meta-study in which ten publications are considered to discuss to what kind of paradigm a model does belong. Four paradigms have been selected, "energy systems optimization models, energy systems simulation models, power systems and electricity market models, and qualitative and mixed-methods scenarios" [12, p. 76], to show four challenges energy system modeling faces. Those challenges are "resolving time and space, balancing uncertainty, transparency and reproducibility, developing methods to address the growing complexity of the energy system, and integrating human behavior and social risks and opportunities" [12, p. 80]. [13] assesses 24 tools in terms of usability within MES modeling on a district scale. The chosen criteria include different types of network (gas, electricity, and thermal) and renewable energy (photovoltaic, wind, and ground source). The different tools are focusing on different parts of the problem like detailed modeling of radiation, spatial resolution, or energy networks. Pure city or district energy modeling systems consider thermal loads in buildings in high accuracy. While for national considerations such accuracy is not feasible, industrial use cases might require such precision of modeling MES. [14] shows 13 tools and how they can be used in city-scale planning and optimization. The authors assess details such as training requirements, user-friendliness of the tool, objective function considered, modeling approach (operation, planning, and scenario), as well as considered energy resources and different sector demands. [15] provides a generic and high-level description of an energy hub in which different types of energy can be considered in parallel. Energy hub represents one possibility for a generic representation of MES [15–17]. Potential drivers for an increased importance of considering MES in city planning are high costs of energy as well as efficiency improvement to minimize greenhouse gas emissions which drive global warming. The authors define several criteria like spatial scope, temporal scale, uncertainty, security of supply, emission reduction, and economics as some of the most important indicators to be assessed with MES planning tools. As already identified by [14], the available tools vary significantly as the authors attempt to answer different kinds of questions and therefore require different levels of details to be considered or ignored. [18] identifies more than 100 publications focusing on energy hubs. Unfortunately, none of the screened tools have been identified as an open source tool.

A gap analysis within MES shows that different energy networks (e.g. electricity, water, district heating, and steam) should be considered in parallel [17]. This so-called sector coupling is seen as a crucial contributor to a sustainable energy system incorporating very high shares of volatile renewable energy resources such as PV and wind. Operational implications such as storage levels, spinning reserve, and uncertainty in forecasts have to be considered in the long run as more systems are interacting with each other [5]. [19] is a meta-study in which nearly 100 tools have been identified and 22 of them have been assessed in detail. The biggest challenge within the complexity of modeling MES is integrating decision transparency, proper human behavior, and accurate decision theory [19,20]. Most of the assessed tools are based on either linear programming (LP) or dynamic programming (DP). The advantage of DP is the ability to assess all results and assess the differences between them, while LP only provides the most optimum solution. Simulation models, on the other hand, are possible to generate solutions in which evolution and system behavior is incorporated [20]. This is a balancing act between performance and accuracy. In general, long-term expansion planning does search for cost-effective investments decision and does ignore some functions related to operation [4]. Opposed to this, short-term operational planning requires consideration of as many functions as possible to be meaningful. [21] assesses 34 tools for their fit to be used within district scale MES applications. A holistic comparison is provided which does not include functions or the method of implementation. [22] shows that functions around the electricity system are considered in details such as power flow in several optimization tools. It needs to be stressed that heating and cooling loads and networks are considered as energy balance only.

While high-level details such as required heat and available capacity are considered, more detailed constraints such as temperature and pressure are not. Incorporating details as temperature and pressure are required for accurate and detailed industrial and district level optimization approaches where multiple temperature levels of water can be available. Nevertheless, the individual publications analyzed do not consider functions such as mass flow rate, thermal conductance, heat losses, and pumping requirements decreasing result accuracy. All non-linear technical behaviors are approximated by piecewise linearized functions to be able to use faster linear solvers but ignore actual equipment behavior. None of the assessed tools has been shared with the community making it impossible to analyze them in detail. The 4th generation of district heating network (DHN) aims for use of low-temperature water between 30 and 70 °C as a heat carrier and is seen as a possibility for sector coupling where lower temperatures can be used to fulfill demand in residential buildings as their demand might decrease with rising building insulation [23].

It might be that one model does consider alternating current (AC) electricity supply while others consider direct current (DC). Historically, long-term planning models consider DC electricity systems while medium- and short-term planning models aim for a more accurate electricity system representation through AC electricity flow modeling. Another reason for selecting either AC or DC is which type of energy represents the majority of the demand and generation in the assessed system. For DHNs, it might be similar: some models consider the energy consumption only while others incorporate a detailed technical system where supply and return pipelines are modeled separately. Holistic models do not only consider energy (e.g. electricity, steam, and hot water), they also consider other required services such as drinking water through desalination or cooling/heating requirements. [24] shows how an MES is represented as energy hub. Two types of energy networks (electricity and district heating) are considered. Some energy hubs are used as energy source (borehole), energy conversion (buildings), or as transmission (routing). This shows the flexibility of the generic energy hub concept. Pumping requirements and thermal storage losses are considered in a linearized way and with a constant loss factor. [25] presents an integrated energy system in which operational non-linear functions are considered for operational optimizing a period of 24-h in 30 min steps. Simplified district heating is represented by one pipeline only where the amount of energy is considered. Supply and return pipeline, heat exchangers, mass flow, velocity of water supply, transmission delay, and pressure losses are considered. [26] presents a detailed analysis of how a DHN expansion is optimized to maximize net present value or minimize carbon dioxide emissions. Based on a predefined district heating pipeline layout, details such as hydraulics, velocity, pressure drop, friction factor, network losses, and pumping requirements are considered. Additional improvement possibilities by adding more hydraulic details are highlighted as well. A daily thermal energy storage (TES) is considered the most common form within DHN schemes. TES losses are considered with a linear loss factor approach ignoring varying ambient air conditions and stored energy within the TES. Economy of scale is considered by predefined sizes of technologies with different generation capacities, investment costs, and annual maintenance costs. For not specified reasons, only two units of each technology can be installed.

Within the research and development environment, HOMER and "System Advisor Model" (SAM) are frequently used tools for pre-feasibility assessments [27,28]. Both are simulation tools and used to assess predefined configurations with an input based on a representative year. Furthermore, they allow the user to perform a sensitivity analysis of economic or technical assumptions (e.g. fuel price and capital cost). Also, commercially available tools (e.g. SimTech's IPSEpro, Schneider Electric's SimSci, or Siemens' PSS® SINCAL) and freely available tools (e.g. ASCEND4) are simulation tools in which individual configurations can be verified, for example during acceptance tests [29–32]. In general, they do not combine investment and operational decisions. They are used to assess predefined configurations based on experience and state-of-the-art. These kinds of tools are used to perform "what-if-scenarios" while considering heat and mass balances for design and off-design circumstances as some MINLP publications show [33–35].

3. Tools and details overview

It is important to note that it is quite complex to analyze all models in a completely fair and adequate matter as the quality and availability of source code, documentation, examples, and publications are different and sometimes spread around in multiple documents and web pages. The assessment is based on the latest available tools and does not consider additional potential enhancements done by others than the original development team. It is understood that all free and publicly available tools can be adjusted to the user's requirements and can be changed to fulfill all proposed modeling details.

3.1. Tools

In 2009, ten Free and Open Source Software (FOSS) tools were assessed while only one of them was based on Python [36]. In 2017, the openmod initiative, an "initiative fostering Open Source and Open Data in energy modeling", lists 31 tools whereby 11 are based on Python [8]. The use of different programming and modeling environments makes it difficult to assess the technical feasibility as the setup of each programming and modeling environments is very time-consuming. Balmorel, DER-CAM, DIETER, ELMOD, and EMMA have been implemented in GAMS, which is a commercial modeling environment representing a financial burden for model validation [15,37]. DER-CAM does not share the GAMS code while all other models considered in this work do. Therefore, the shared models can be verified through any research organization and allow adjustments for specific needs. Tools like EnergyPlan and HOMER are distributed as an executable application, and therefore the source code is not available to be verified, adjusted, or enhanced [15]. RETScreen bases its assessment on monthly data and therefore the integration of VER, such as photovoltaic (PV) and wind, as well as storage cannot be considered in required hourly or even sub-hourly details. HOMER depends on Windows as an operating system, while Python can be used on different operating systems. The use of Python does not restrict the research community on one operating system. HOMER and RETScreen do not consider network constraints as they assume a well-interconnected system, which sometimes is referred to as copperplate design. Some models only consider one year of operation and assume that this is a representative year; especially in the light of climate variability, this is a challengeable assumption. The majority of tools assessed within this paper are based on Pyomo, which is a "Python-based, open source optimization modeling language with a diverse set of optimization capabilities for formulating, solving, and analyzing optimization models" [38]. Pyomo is a generic modeling language, which has interfaces to multiple solvers in order to allow solving linear, non-linear, quadratic, mixed-integer, and stochastic problems. This allows the use of different solvers, free solvers such as GLPK or commercial solvers such as CPLEX, without changing the code. The use of the open source programming language Python does distinguish Pyomo from modeling languages including GAMS, AMPL, or AIMMS as it represents a 100% open source approach which is not based on any proprietary or closed tools. This allows unlimited sharing of developments and unlimited verification of models. Using Python and Pyomo as modeling language allows easy exchange of functions, functionality, and ideas between the different modeling approaches based on Pyomo. [8] provides an initial list of assessed tools. Only optimization models have been incorporated in this work. To enrich the discussion about available functions, also other tools have been added. MATPOWER and MOST have been added as they represent the state-of-the-art open source implementation of a power system planning tool [39]. Pandapower has been added to the assessed tools as it does calculate mixed AC-DC optimal power flows (OPF) as well it can be used to convert electricity models between MATPOWER and PSS*E [40]. DER-CAM has been added as it represents an enhanced model where several required details for proper operational and planning tools are considered [22,41]. Table 1 represents the short-listed and assessed 31 energy models in alphabetic order. On top of the mentioned open source tools leading closed source or proprietary tools such as ProView and TIMES have been added for a broader function comparison.

The column 'first release' indicates the month and year when the assessed model was distributed the first time. While it is relatively simple to get information about the first release of a version, it is quite difficult to get the latest date of modification. GitHub is an open and free accessible platform where everyone can store his/her open source projects. Otherwise, some monthly fees have to be paid for hosting closed project development. GitHub not only records the latest changes in the code but also indicates changes in documentation and non-code related files. Therefore, the column 'last update' has to be considered with care. The median project age is around 4 years and the last change happened within the last months. Within the last 30 days of writing, 8 tools have seen updates. The oldest tools within the assessed are MATPOWER, RETScreen, EnergyPlan, Balmorel, ELMOD, HOMER, and DER-CAM, being between 14 and 21 years old. One of the tools has been created in 2017, six in 2016, five in 2015, and four in 2014, respectively. The next columns ('commits', 'branches', 'releases', and 'contributors') reflect data from GitHub and indicate how actively the projects are worked on. GitHub manages the individual project as a repository of files and directories. A 'commit' represents an update of the project repository. GitHub does create by default a branch master. A 'branch' represents a pointer to a specific commit (collection of files and directories), which allows the developer to manage his/her changes in and additions to the versions. The online Pro Git book is recommended for more details about GitHub and the used terminology [42]. It has to be mentioned that GitHub was founded in 2008 and therefore not all activities during the entire project lifetime can be captured in the shown statistics in some cases. Oemof, which is the abbreviation for "Open Energy Modeling Framework", shows the highest numbers of commits and branches. Minpower shows the highest number of releases and pandapower has the highest numbers of contributors. Important to mention is that neither a high number of commits, branches, releases, or contributors imply high quality or very good usability of a tool. It does not imply the success of a tool at all. It also does not imply high distribution or diffusion. However, a high number of contributors at least indicates that a significant number of people contributed to a model and might give an indication of the usability of a tool. The column 'license' shows under which license the tools have been published. All of the listed non-commercial tools allow the use in commercial and private environments, allow modification, and also allow distribution. None of the authors take any liability or warranty. The licenses marked in grey (GPL 2.0 and GPL 3.0) do require sharing new code with the community, while the not highlighted licenses (Apache 2.0, EUPL 1.1, and BSD) do not require sharing new developments. The tools DER-CAM and TIMES do not specify the license they are using and therefore for them 'n/a' is shown in the table in light orange. The column 'web address (URL)' shows the address under which the project can be downloaded from. The cells in grey indicate that the links are not hosted on GitHub, a source code deployment platform.

Table 2 shows the use cases for which the tools have been designed and developed for. While all of them are considering electricity demand only, some of them are able to consider heat or other kinds of energy. About half of the tools consider just electricity demand. The majority of the tools were designed for use in large systems such as countries, regions, or even continents. The remaining tools were designed medium and small-scale applications. Only a few of them are designed to be completely flexible in considered technologies and abstraction level of technologies (such as entire power plant vs. being able to model pumps and turbines separately). The columns in light grey identify the tools where the source is not available for a detailed analysis.

3.2. Functions

Table 3 provides information on the functions including the reasons for individual functions being considered. The list represents all details covered in one of the assessed publications and MES tools [4,6,8,11,12,14,15,17,19,20,37,39,43–49]. Furthermore, other functions have been added based on the following publications [18,22,26,33–35,49–59].

It is understood that this list is never final as many functions could be divided into several more options. For example, OPF could be split into the way OPF is implemented (polar power-voltage formulation, rectangular power voltage formulation, current injection (IV) formulation, or rectangular IV formulation). Other examples would be probability, uncertainty, and physical detail considered in energy logistics. Several additional functions within probability and uncertainty might be scenario tree creation and scenario tree reduction. Within the considered physical details transient, steady-state 0D, and steady-state 1D would be additional functions to be added. Nevertheless, the focus of this work is assessing the functions around ED and UC.

4. Results

After examining the modeling tools and functions, Table 4 shows the evaluation of those selected tools and functions. Each technical function can be evaluated with three possible values: 'x' represents full consideration (full point), ' (x)' represents partly or weak implementation (half-point), and empty cell represents no implementation possible (zero points). It is understood that individual functions such as the availability and quality of documentation and examples can increase the usability of a tool significantly. Depending on the research focus (short-term or long-term) also functions such as variable time steps, security-constrained OPF, and security constrained UC might be weighted differently. This work uses a data-driven approach to calculate the weighting. The considered weighting is between 0 and 1 and is calculated as the ratio of usage of a feature (between 0 and 31) divided by the number of tools assessed (31). By doing so, the features with high penetration are treated as more important than others. To differentiate the use of short-term and long-term model use, the two leftmost columns have been added to allow the assessment accordingly. Based on the author's experience and judgment, 72 out of 81 functions are utilized to assess short-term focused tools and 69 of 81 functions are used to assess long-term focused tools, respectively.

Fig. 1 shows the results after ranking the evaluated tools based on the 81 discussed functions using the combined overall weighting where all functions are weighted equally with one point. Given the available public information, modeling tools focusing on MES are shown at the high end of the scale. The commercial tools (ProView and TIMES) are ranked 5th and 10th and are evaluated with 72% and 63% of the assessed functionality. The open source tools SWITCH, TEMOA, OSeMOSYS, and pyPSA are ranked before and are able to fulfill between 76% and 74% of the assessed functions. DER-CAM, ficus, MOST, and Dispa-SET rank next with between 67% and 63% of the assessed points, respectively. Modeling tools focusing on power or district heating only are ranked at the low end of the scale (see MATPOWER, pandapower, PyOnSSET, and pypower) (Figs. 2 and 3).

While Fig. 1 shows the overall ranking for the combined weighting, Figs. 2 and 3 show the results using the long-term and short-term weighting (for reference see the leftmost columns in Table 4), respectively.

Table 1
Assessed tools.

Tool	Programming/ Scripting Language	First Release	Last Update	Age (years)	Lasst Update (months)	Commits	Branches	Release	Contributors	License	Web Address (URL)
Balmorel	GAMS	01.2001	02.2012	18	82	n/a	n/a	n/a	n/a	ISC	http://balmorel.com/index.php/downloadmodel
Calliope	Python	12.2013	09.2018	5	2	899	11	21	5	Apache 2.0	https://github.com/calliope-project/calliope
DER-CAM	GAMS	10.2004	08.2017	14	16	n/a	n/a	n/a	n/a	n/a	https://building-microgrid.lbl.gov/projects/der-cam
dhmin	Python	12.2014	09.2017	4	14	13	1	0	1	GPL 3.0	https://github.com/tum-ens/dhmin
DIETER	GAMS	06.2015	02.2017	3	21	n/a	n/a	n/a	n/a	MIT	http://www.diw.de/dieter
Dispa-SET	GAMS	01.2015	09.2018	4	2	129	8	3	6	EUPL 1.1	https://github.com/energy-modeling-toolkit/Dispa-SET
ELMOD	GAMS	01.2004	07.2017	15	16	n/a	n/a	n/a	n/a	MIT	http://www.diw.de/elmod-de
EMMA	GAMS	01.2013	05.2014	6	55	n/a	n/a	n/a	n/a	CC BY-SA 3.0	https://neon-energie.de/emma/
EnergyPlan	Executable	01.2000	11.2017	19	12	n/a	n/a	n/a	n/a	Freeware	http://www.energyplan.eu/
EnergyRt	R & GAMS	07.2016	02.2018	2	9	330	3	7	2	AGPL 3.0	https://github.com/olugovoy/energyRt
ficus	Python	12.2015	01.2018	3	10	160	1	1	1	GPL 3.0	https://github.com/yabata/ficus
HOMER	Executable	03.2004	09.2014	15	51	n/a	n/a	n/a	n/a	Commercial	https://www.homerenergy.com
MATPOWER	Matlab/Octave	09.1997	09.2018	21	2	1819	3	36	3	3-clause BSD	https://github.com/MATPOWER/matpower
minpower	Python	08.2012	06.2016	6	30	855	10	41	1	MIT	https://github.com/adamgreenhall/minpower
MOST	Matlab/Octave	06.2016	05.2018	3	6	116	2	3	1	3-clause BSD	https://github.com/MATPOWER/most
NEMO	Python	01.2011	08.2018	8	3	1029	1	0	1	GPL 3.0	https://github.com/bje-/NEMO
oemof	Python	11.2015	09.2018	3	3	4191	38	20	22	GPL 3.0	https://github.com/oemof/oemof
OSeMOSYS	Python	01.2011	03.2018	8	8	131	3	0	5	Apache 2.0	https://github.com/KTH-dESA/OSeMOSYS
pandapower	Python	11.2016	09.2018	2	2	2210	3	11	22	BSD	https://github.com/lthurner/pandapower
ProView	Executable	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	Commercial	https://new.abb.com/enterprise-software
psst	Python	09.2016	10.2017	2	14	106	2	0	2	MIT	https://github.com/power-system-simulation-toolbox/psst
PyOnSSET	Python	12.2016	09.2018	2	3	363	2	0	4	MIT	https://github.com/KTH-dESA/PyOnSSET
pypower	Python	07.2011	06.2018	7	5	266	6	11	12	BSD	https://github.com/rwl/PYPOWER
pyPSA	Python	01.2016	09.2018	3	3	625	8	20	9	GPL 3.0	https://github.com/PyPSA/PyPSA
Renpass	R & GAMS	03.2017	03.2017	2	21	11	1	0	1	GPL 3.0	https://github.com/fraukewiese/renpass
RETScreen	Executable	12.1997	12.2005	21	158	n/a	n/a	n/a	n/a	Commercial	http://www.RETScreen.net
rivus	Python	11.2014	10.2017	4	14	251	1	0	3	GPL 3.0	https://github.com/tum-ens/rivus
Switch	Python	06.2015	08.2018	3	4	456	12	3	8	Apache 2.0	https://github.com/switch-model/switch
TEMOA	Python	05.2012	08.2018	7	4	645	12	5	6	GPL 2.0	https://github.com/TemoaProject/temoa
TIMES	GAMS	01.2014	07.2016	5	29	n/a	n/a	n/a	n/a	n/a	https://iea-etsap.org/index.php/etsap-tools/
urbs	Python	09.2014	03.2018	4	9	560	1	8	14	GPL 3.0	https://github.com/tum-ens/urbs

Remark: n/a,if no information is available. Update: 15.09.2018

M. Groissböck

Renewable and Sustainable Energy Reviews 102 (2019) 234–248

Table 2
Applications.

Application No.	Tool Application	Balmorel	Calliope	DER-CAM	dhmin	DIETER	Dispa-SET	ELMOD	EMMA	EnergyPLAN	EnergyRt	ficus	HOMER	MATPOWER	minpower	MOST
1	**House/Industry**			x								x	x	x		
2	**District**		x	x	x							x		x	x	
3	**City**		x							x						
4	**Country / Region**	x				x	x	x	x	x	x					x
5	**Electricity**	x	x	x		x	x	x	x	x	x	x	x	x	x	x
6	**Heating**	x	x	x	x					x		x	(x)			
7	**Natural Gas**	x	x	x						x		x				
8	**High-Level Systems**	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
9	**Complex Individual Units**		(x)									(x)	(x)	(x)		
10	**Open Source**	x	x		x	x	x	x	x	(x)	x	x		x	x	x
11	**Optimization**	x	x	x	x	x	x	x	x		x	x		x	x	x
12	**Simulation**									x			x			
	Legend: x: considered; (x): partially considered; empty: not considered												Update: 15.09.2018			

Application No.	NEMO	oemof	OSeMOSYS	pandapower	ProView	psst	PyOnSSET	pypower	pyPSA	Renpass	RETScreen	rivus	Switch	TEMOA	TIMES	urbs
1				x				x			x					
2		x		x				x			x	x				
3		x		x							x	x				
4	x	x	x		x	x	x		x	x			x	x	x	x
5	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
6		x	x						x	x		x		x	x	x
7		x	x						x	x		x		x	x	x
8	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
9			(x)					(x)		(x)		(x)	(x)	(x)		(x)
10	x	x	x	x		x	x	x	x	x	(x)	x	x	x		x
11	x	x	x	x		x		x	x	x		x	x	x	x	x
12					x		x				x					
	Update: 15.09.2018															

Table 3
Assessed functions and their interpretation.

Function No.	Function	Evaluate ...
1–2	hourly time steps; variable time steps	if defining how many time-steps a day can be considered, and if different durations can be managed as well. Note: half-point for variable time step if only one duration can be defined;
3	copperplate approach	if transmission and distribution of energy is not considered;
4–5	direct current (DC); alternating current (AC)	which kind of electricity flow is considered;
5–8	power flow (PF); optimal PF (OPF); security-constrained (SCOPF)	if detailed (e.g. active and reactive PF considerations) are possible; and if security related PF constraints (e.g. transmission failure) are considered;
9–10	unit commitment (UC); security-constrained UC (SCUC)	if power and/or heat generating units are available within a multi-period time horizon; and if security related UC constraints (e.g. availability) are considered;
11–17	ramp up & down constraints; minimum up- & down-time; starts per day, minimum stable load; must run; startup & shutdown costs; cold & hot startup costs	which of the UC and SCUC details are considered; if startup cost is considered with addition fuel, half-point a point is added;
18–19	economic dispatch (ED); security-constrained ED (SCED)	if least-cost solution incorporating power output is considered; and if security related ED constraints (e.g. transmission failure) are considered;
20–23	non-electrical distribution (constraints), gaseous distribution (constraints), liquid distribution (constraints), thermal distribution (constraints)	which operational constraint is considered in some detail (e.g. voltage in electricity, pressure in gaseous, velocity in liquid, or temperature in thermal distribution systems); if operational details are ignored, and if non-electrical distribution can be used for any kind of service;
24–28	district heating/cooling demand; (drink) water demand; hot water demand; steam demand; other demand	which final demand can be included;
29	simulation (min. total costs)	if simulation is done instead of optimization;
30–38	obj. function: min. total costs; min. investment costs; min. operational costs; min. losses, max. profit; partial equilibrium; min. customer rates; max. efficiency; min. emissions	which objective function and combinations of it can be selected;
39	demand elasticity	if energy demand is impacted by price changes;
40	locational marginal price (LMP)	if within zonal energy prices the locational marginal price (LMP) is considered:
41–43	model foresight (perfect, flexible, or rolling horizon)	which kind of model foresight is considered;
44–46	size as integer/real variable; pre-defined unit size; cost based on economy of scale	if capacity additions are based on integer/real numbers or pre-defined sizes of technologies; in the case of integer/real sizes if economy of scale can be applied;
47–48	emission costs; emissions constraints	if emissions such as carbon dioxide CO_2 or water consumption can be associated with external costs and constrained;
49–51	multi-area system; multi-year investment; multi-year operation	if multi-area and multi-year assessments can be done;
52–53	year-varying CapEx & OpEx (CUR); year-varying fuel & emission (CUR)	if costs like capital expenditures (CapEx), operational expenditures (OpEx), fuel costs, and emissions costs/penalties can be different from year to year;
54–55	budget constraints (CUR); fuel constraints (CUR)	if upper and lower limits for budget and fuel consumption can be defined;
56	retirement of existing assets	if existing assets can be retired if found not economical;
57	fuel switch/dual fuel	if assets can be operated with different types of energy or fuels;
58–59	part-load impacts; ambient temperature impact	if technical performance (e.g. efficiency and output) change based on ambient conditions or if part-load can be considered;
60	technology degradation/aging	if technology age is incorporated into technical performance; if the yearly available capacity can be adjusted, the reduced available capacity is a half-point;
61–62	generic storage; detailed storage (SOC, DoD)	if storage can be considered in its simplest way (without e.g. state of charge, SOC) or if SOC and depth of discharge (DoD) is considered; if storage is modeled with a constant loss factor, it is a half-point;
63	component dispatch	if energy conversion can be represented in components and not in whole plants only;
64–67	energy conversion is implemented as: 1 in, 1 out: n in, 1 out: 1 in, m out; or n in, and m out	which energy conversion can be considered;
68–69	availability/forced outage; maintenance planning	if resource availability is considered, and if a maintenance schedule can be created;
70–71	energy purchase (fixed, variable pricing), energy sales (e.g. FIT)	if fixed and consumption-based prices can be considered, and if feed-in-tariff (FiT) based energy sales can be considered;
72–73	deferable demand; curtailment	if demand can be delayed, and if generation like photovoltaic or wind can be curtailed;
74 –75	reserve margin; primary/secondary reserves	if minimum/maximum reserve margin can be defined, and if primary and secondary reserve (sometimes considered also as spinning reserve) is considered;
76–78	reliability indicators; risk level (appetite); probability/uncertainty	if reliability indicators such as loss of load expectation (LOLE) or expected energy not served (EENS); if different risk levels can be considered; and if uncertainty in profiles can be considered;
79	GIS representation	if there are GIS related functions incorporated;
80–81	documentation; example(s) available	if clear and clean documentation containing examples is available.

5. Discussion

5.1. Ranking

As shown in the Figures above, none of the publicly available and assessed models are able to consider all listed functions. The best open source tool is able to fulfill 44% of the evaluated technical functions. The assessed functions (long-term, short-term, and a combination of both) do not change the rank of the tools significantly (see Fig. 4). Within the long-term assessment, the tools Balmorel and NEMO are able to improve most with a boost of 5 and 2 ranks while MOST and psst are losing 5 or 4 ranks, respectively. Within the short-term focused models, EnergyPLAN, pyPSA, and HOMER do improve by 3 or 2 ranks, respectively (see Fig. 4).

Fig. 4 shows that the most significant change in ranking is ± 5. In 37 (58%) of the cases the change in rank is zero and in 13 (20%) or 14 (22%) of the cases the change in rank is positive or negative, respectively. Ranking of the assessed tools is not impacted by the selected

Renewable and Sustainable Energy Reviews 102 (2019) 234–248

Table 4
Assessed tools and their scores for the mentioned functions.

Function No.	Tool / Function	Balmorel	Calliope	DER-CAM	dhmin	DIETER	Dispa-SET	ELMOD	EMMA	EnergyPLAN	EnergyRt	ficus	HOMER	MATPOWER	minpower	MOST	NEMO
1	hourly time steps	(x)	x	x		x	x	x	x	x	(x)	x	x		x	x	x
2	variable time steps	(x)		(x)	x						x	(x)			(x)	(x)	
3	copperplate approach									x			x				
4	direct current (DC)	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x
5	alternating current (AC)			x										x			
6	power flow (PF)			x										x		x	
7	optimal PF (OPF)			x										x		x	
8	security-constrained OPF															x	
9	unit commitment (UC)		x				x		x			x			x	x	
10	security constrained UC (SCUC)						x								x	x	
11	ramp up & down constraints		x				x								x	x	
12	min. up & down time						x								x	x	
13	starts per day/period																
14	min. stable load						x		x			x	x		x	x	
15	must run						x		x			x			x	x	
16	startup & shutdown costs						x		(x)			(x)			x	x	
17	cold & hot startup costs																
18	economic dispatch (ED)	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x
19	security constrained ED			(x)			x								x	x	
20	non-elec. distribution (constraints)	x	x	x	x					x		x					
21	gaseous distribution (constraints)																
22	liquid distribution (constraints)																
23	thermal distribution (constraints)																
24	district heating/cooling demand	(x)	(x)	(x)	(x)					(x)		(x)	(x)				
25	(drink) water demand		(x)	(x)						(x)		(x)					
26	hot water demand	(x)	(x)	(x)						(x)		(x)	(x)				
27	steam demand		(x)							(x)		(x)					
28	other demand		(x)	(x)						(x)		(x)	(x)				
29	simulation (min. total costs)									x			x				
30	min. total costs		x	x	x	x	x		x		x	x					x
31	min. investment costs																
32	min. operational costs		x	x	x		x	x				x			x	x	
33	min. losses													x			
34	max. profit			x													
35	partial equilibrium	x															
36	min. customer rates																
37	max. efficiency																
38	min. emissions			x													
39	demand elasticity	x															
40	locational marginal price (LMP)							x					x			x	
41	perfect model foresight	x	x	x	x	x	x	x	x		x	x		x	x	x	x
42	flexible model foresight																
43	rolling horizon						x										
44	size as integer/real variable	x	x	x	x	x	x	x	x		x	x		x	x	x	x
45	pre-defined unit size			x						x			x				

(continued on next page)

Table 4 (*continued*)

Function No.	Tool / Function	Balmorel	Calliope	DER-CAM	dhmin	DIETER	Dispa-SET	ELMOD	EMMA	EnergyPLAN	EnergyRt	ficus	HOMER	MATPOWER	minpower	MOST	NEMO
46	cost based on economy of scale																
47	emission costs	x	(x)	x	(x)	x	(x)	(x)	x	x		(x)	x		(x)	(x)	x
48	emissions constraints	x					x			x			x				
49	multi area system	x	x	x	x		x	x	x		x	x		x		x	x
50	multi-year investment	x									x					x	
51	multi-year operation	x	x								x					x	
52	year varying capex & opex (CUR)										x						
53	year varying fuel & emission (CUR)																
54	budget constraints (CUR)	x								x							
55	fuel constraints	x								x			x				
56	retirement of existing assets										x						
57	fuel switch/dual fuel	(x)	(x)		(x)	(x)	(x)	(x)	(x)		(x)	(x)	x				(x)
58	part load impacts											x	x				
59	ambient temperature impact																
60	technology degradation/ aging																
61	generic storage	x	x	x		x	x	x	x	x	x	x	x			x	x
62	detailed storage (SOC, DoD)																
63	component dispatch		x									x					
64	1-1 energy conversion	x	x	x		x	x	x	x	x	x	x	x		x	x	x
65	n-1 energy conversion	x	x	x						x	x	x	x				
66	1-m energy conversion	x	x	x						x	x	x	x				
67	n-m energy conversion	x	x	x						x	x	x	x				
68	availability / forced outage	(x)					x	(x)	x		(x)						
69	maintenance planning																
70	energy purchase (fixed, variable pricing)			x						x			x				
71	energy sales (e.g. FiT)			x			x	x	x	x			x				
72	deferable demand					x							x			x	
73	generation curtailment	x		x		x	x	x	x				x		x	x	x
74	reserve margin	x	x														
75	primary/secondary reserves					x	x		x						x	x	
76	reliability indicators																
77	risk level (appetite)																
78	probability/uncertainty	x		x									(x)		x	x	
79	GIS representation				x							x					
80	documentation	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x
81	example(s) available	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

Function No.	oemof	OSeMOSYS	pandapower	ProView	psst	PyOnSSET	pypower	pyPSA	Renpass	RETScreen	rivus	Switch	TEMOA	TIMES	urbs	overall w.	long-term w.	short-term w.
1	x	x		x	x			x	x			x	x	x	x	1	0	1
2		x						(x)	(x)		x	x	x	x		1	1	1
3										x						1	1	1
4	x	x	x	x	x		x	x	x	x	x	x	x	x	x	1	1	1
5			x				x	x								1	1	1
6			x				x	x								1	1	1
7			x				x	x								1	0	1
8								x								1	1	1

(*continued on next page*)

Renewable and Sustainable Energy Reviews 102 (2019) 234–248

Table 4 (*continued*)

Function No.	oemof	OSeMOSYS	pandapower	ProView	psst	PyOnSSET	pypower	pyPSA	Renpass	RETScreen	rivus	Switch	TEMOA	TIMES	urbs	overall w.	long-term w.	short-term w.
9				x	x			x				x	x	x		1	1	1
10					x			x								1	1	1
11					x			x					x	x		1	0	1
12					x			x						x		1	0	1
13														x		1	0	1
14					x			x				x		x		1	1	1
15				x				x				x		x		1	1	1
16				x	x			x						x		1	0	1
17																1	0	1
18	x	x		x	x			x	x		x	x	x	x	x	1	1	1
19					x			x								1	1	1
20	x	x						x			x	x	x	x	x	1	1	1
21																1	1	1
22																1	1	1
23																1	1	1
24	(x)	(x)						(x)			(x)	(x)	(x)	(x)	(x)	1	1	1
25		(x)						(x)			(x)	(x)	(x)	(x)	(x)	1	1	1
26		(x)						(x)			(x)	(x)	(x)	(x)	(x)	1	1	1
27		(x)						(x)			(x)	(x)	(x)	(x)	(x)	1	1	1
28		(x)						(x)			(x)	(x)	(x)	(x)	(x)	1	1	1
29										x						1	1	1
30		x		x		x		x	x		x	x	x	x	x	1	1	1
31				x											x	1	1	1
32		x			x			x			x	x	x		x	1	1	1
33			x				x									1	1	1
34				x											x	1	1	1
35				x												1	1	1
36				x												1	1	0
37																1	1	1
38															x	1	1	1
39														x		1	1	1
40				x				(x)	(x)							1	0	1
41	x	x	x	x	x	x	x	x	x		x	x	x	x	x	1	1	1
42																1	0	1
43														x		1	0	1
44	x	x	x		x	x	x	x	x		x	x	x	x	x	1	1	0
45		x		x						x						1	1	0
46																1	1	0
47	(x)	x		x	(x)	(x)		(x)	x	x	(x)	x	x	x	(x)	1	1	1
48		x		x				x		x		x	x	x	x	1	1	1
49	x	x	x	x	x	x		x	x		x	x	(x)	x	x	1	1	1
50		x		x								x	x	x		1	1	1
51		x		x	x			x				x	x	x		1	1	1
52		x		x									x	x		1	1	0
53		x		x									x	x		1	1	0
54		x								x						1	1	1
55		x		x						x			x	x		1	1	1
56														x		1	1	0
57	(x)	(x)		x				(x)	(x)		(x)	(x)	(x)	x	(x)	1	1	1
58				x												1	0	1
59																1	1	1
60				x										x		1	1	1
61		x		x				x	x	x		x	x	x	x	1	1	1
62																1	1	1

(*continued on next page*)

Table 4 (continued)

Function No.	oemof	OSeMOSYS	pandapower	ProView	psst	PyOnSSET	pypower	pyPSA	Renpass	RETScreen	rivus	Switch	TEMOA	TIMES	urbs	overall w.	long-term w.	short-term w.
63		x						x			x	x	x		x	1	0	1
64	x	x		x	x			x	x	x	x	x	x	x	x	1	1	1
65		x									x	x	x		x	1	1	1
66		x						x			x	x	x	x	x	1	1	1
67		x									x	x	x		x	1	1	1
68		x		x				(x)	(x)			(x)	x			1	1	1
69				(x)												1	1	1
70				x						x						1	1	1
71				x						x						1	1	1
72				x								x				1	1	1
73		x		x				x	x			x	x			1	1	1
74		x		x								x	x	x		1	1	0
75		x		x	x							x	x			1	1	1
76				x												1	1	0
77														x		1	1	1
78				x						(x)		x	x	x		1	1	1
79	x					x		x			x				x	1	1	1
80	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	1	1	1
81	x	x	x		x	x	x	x	x	x	x	x	x	x	x	1	1	1

Legend: x: considered; (x): partially considered; empty: not considered Update: 15.09.2018
Abbreviations: CUR: currency; SOC: State of Charge; DoD: Depth of Discharge; w- weighting

publication type or chosen license to distribute the tools. This implies, that there is a balance between short-term and long-term functions in the assessed energy modeling tools. In terms of 'functions considered', none of the assessed tools is an excellent short-term (or long-term) energy modeling tool or a very poor long-term (or short-term) energy modeling tool. Based on the previous assessment, Switch, TEMOA, OSeMOSYS, and pyPSA are the preferred open source tools of choice. While Switch, OSeMOSYS, and TEMOA focus on medium and long-term expansion planning, the focus of pyPSA is short and medium-term operation. The strength of TEMOA, Switch, and OSeMOSYS is to consider details such as multi-year investment, year-varying capital and operational costs, and budget and emission constraints. pyPSA, on the other side, is considering more details in short-term unit commitment like optimal power flow, feasible ramp rates, minimum up- and down-time, as well as startup costs.

5.2. Unfulfilled functions

The following paragraphs discuss some unfulfilled technical functions and explain why it is necessary to consider them accordingly in energy modeling tools able to fulfill individual project feasibility requirements:

- None of the considered tools is able to distinguish between hot and cold startups, nor do they consider the number of starts a day of conventional technologies such as gas turbines, steam turbines, and fuel cells. For a more realistic economic evaluation of ramping capabilities, this is an important function to be considered as it makes a difference if a power plant is started preheated or not [60].
- None of the currently available tools considers detailed gaseous, liquid, and thermal energy distribution where detailed physical attributes such as temperature, pressure, velocity, and mass flow are incorporated. They only consider linear and predefined constant loss factors. Details including pressure, mass flow, or temperature are assumed to be incorporated into energy flow data. For a more realistic assessment of thermal storage, also the temperature level of the storage should be considered [58,59,61].
- None of the tools currently allows the use of advanced or alternative objective functions including maximizing profit and maximizing efficiency. Only DER-CAM allows the use of minimizing emissions and a multi-objective function where costs and emissions are incorporated. For sensitivity assessments, it might be useful to have such a function available [62]. To maximize profits, fees paid and earned from other parties have to be incorporated as well [22,50].
- In general, within short-term optimization tools, budget constraints cannot be added as a further restriction while long-term planning tools allow such constraints to be added. This might be a useful function to better understand cash limitations while optimizing operation [4].
- All assessed optimization tools are assuming perfect foresight. A more flexible model would allow to use rolling foresight to mimic market-related behavior such as day-ahead markets [62].
- While most tools are able to define multiple energies to be used in one technology, it is not possible to limit the use of one fuel at a time [4].
- None of the examined tools consider functions such as part-load impacts on efficiency and power output or details on technology aging and degradation. Furthermore, none of them consider environmental conditions including temperature and humidity to more accurately determine spatial and temporal impacts [55,56]. Most publications considering non-linear impacts limit themselves to one detail to be assessed as non-linear. [63], for example, considers non-linear coefficients of performance (COP) of a ground-source heat pump (GSHP) which is driven by the difference between soil temperature and the GSHP outlet water temperature. [64] considers potential generation output and heat rates as predefined

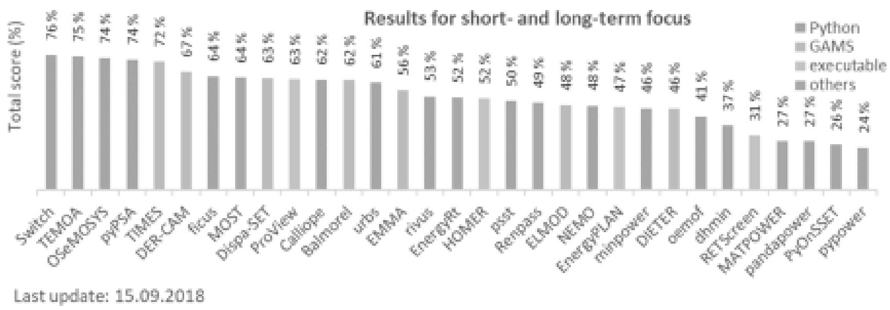


Fig. 1. Evaluation results with combined short- and long-term focus.

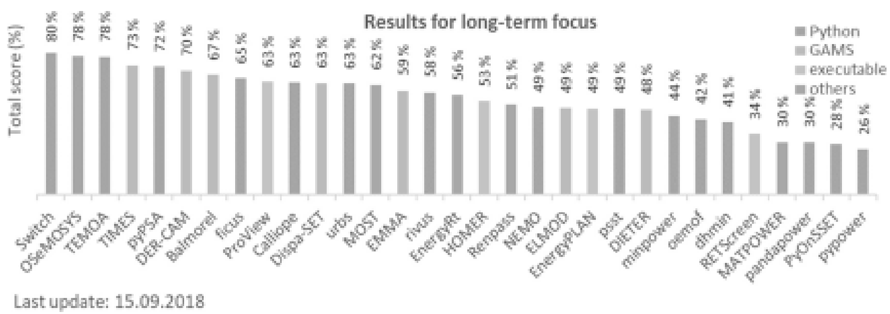


Fig. 2. Evaluation results with long-term focus.

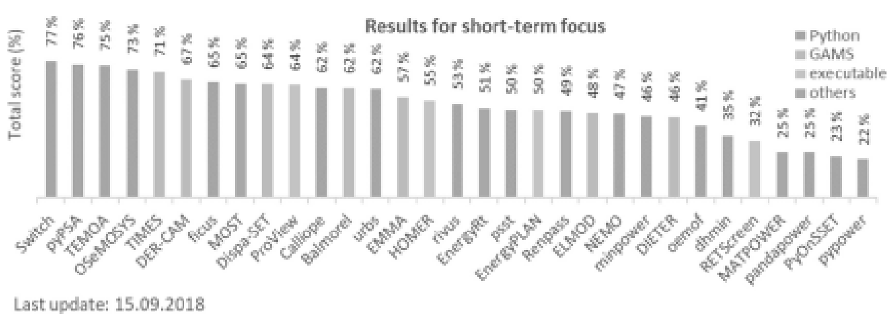


Fig. 3. Evaluation results with short-term focus.

values and instead of using a non-linear function, they use the special ordered sets (SOS) approach to consider non-linear behavior in a linear formulation. [65] does incorporate non-linear gas compressor work where the gas pressure, temperature, density, compressibility, and mass flow are modeled.

- No model has a detailed storage model incorporated where the State-of-Charge, as well as the Depth-of-Discharge, are considered into health considerations. Especially for long-term planning purposes, this is an important function to assess more realistic scenarios [66].
- No maintenance planning is considered in the assessed open source tools. It might add value for customers such as industry and utility to know when maintenance should be scheduled in the most economical way [57,67]. Knowing when planned outages should be assumed in advance can increase the planning accuracy of production forecasts.
- Only long-term planning tools such as TEMOA and OSeMOSYS are able to consider time-varying capital and operational costs (CapEx, OpEx). As fuel prices are changing over time, also expenditures should be considered as time-varying to capture these impacts. This allows considering the tradeoff between capital and operational costs. As an example, in power generation initial investment costs represent between 10% and 40% of total life-cycle cost for conventional power generation technologies while it is between 60% and 95% for renewable power generation technologies depending on size, technology selected, operating regime, and region to be installed [68]. Factors such as capital costs, operational costs, efficiency, and economy of scale should be able to be considered in advanced frameworks [69].
- None of the tools considers the risk level or appetite from investors. Also, system reliability indicators are not considered yet. Especially with increasing share of volatile renewables, this might be necessary to consider [56].

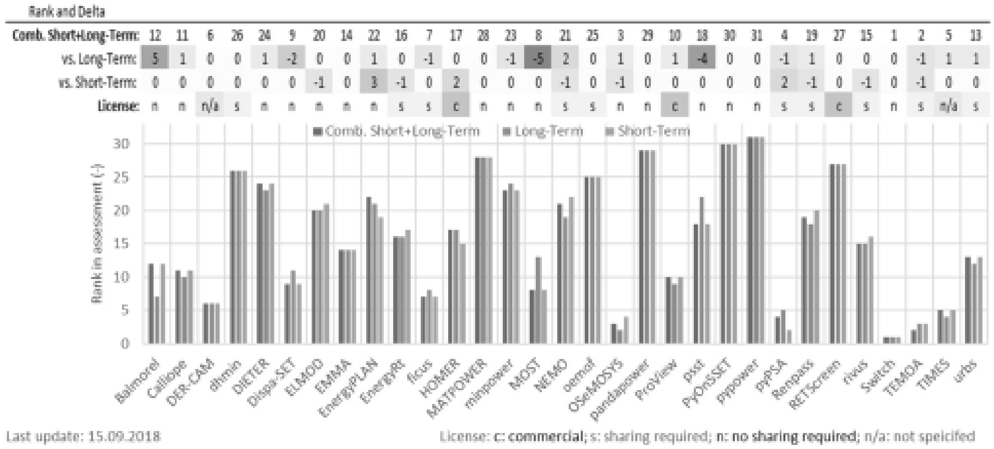


Fig. 4. Ranking in the different evaluations.

This list provides ideas about functions to add in the assessed modeling tools. The recommendations focus on functions necessary to improve result accuracy from a technical and economic perspective. However, improvements in other areas such as representation and consideration of stochastic information, use of synthetic profiles for load or RES, and optimization algorithms are not considered.

6. Conclusion

Recently open source tool development has received increased attention as more and more publicly available energy modeling tools are shared via GitHub. Open source, in general, attracts users from different organizations and disciplines to work together on a project. As each of the developers has different purposes and main focus the implementation of functions vary a lot. Nevertheless, until now the success of open source tool development within energy modeling is limited but shows potential. Many open source modeling tools are available and differ in terms of targeted functionality. Therefore, it is difficult to compare them. The purpose of this work was to evaluate 31 energy modeling tools based on 81 proposed modeling details. 17 out of 31 assessed models are based on Python. Considering publicly available information, Switch, TEMOA, OSeMOSYS, and pyPSA are considered the top-performing open source tools within this assessment. If the interest lies in a long-term planning horizon (10 years and more), Switch, OSeMOSYS, and TEMOA might be excellent choices; however, if the interest lies in short-term planning and small timesteps considering details such as ramping constraints, pyPSA might be the preferred tool. Comparing open source with commercial closed source energy modeling tools, it can be seen that open source tools are getting closer to the functionality of closed source tools. Within the operational assessment pyPSA even takes over both of the commercial closed source tools. As shown by projects such as the United Nations "Atlantis, Integrated Systems Analysis of Energy", open source tools like OSeMOSYS are also seen as mature enough to be used for regional power system planning [70]. Despite significant contributions to date, there remains a number of key challenges, e.g. incorporating very high shares of volatile renewables [9,71], considering simultaneous generation expansion and transmission planning and operation considering MES [72–74], and uncertainty [75].

7. Future work

Future work might integrate some of the recommended functions (e.g. cold and hot startup costs) into one of the top performing tools. The assessed models show significant room for improvement in that regard. For example, pyPSA is not able to consider spinning reserve or forecasting errors within the dispatch procedure [76], and OSeMOSYS and TEMOA do not incorporate functions such as power flow or unit commitment. None of the top-ranked open source tools permits the use of different objective functions, which would allow creating Pareto curves to identify the most suitable solutions depending on the objective function [77]. Future work might improve the available assessment of technical functions by adding e.g. more details around the optimization methods and adds performance (run-time) aspects as well.

Acknowledgments

The authors gratefully acknowledge valuable comments and support from colleagues within the University of Innsbruck, Institute for Construction and Materials Science, Unit of Energy Efficient Buildings, and from former colleagues and friends within Saudi Aramco as well as from anonymous reviewers.

References

[1] Bazilian M, Rice A, Rotich J, Howells M, DeCarolis J, Macmillan S, Brooks C, Bauer F, Liebreich M. Open source software and crowdsourcing for energy analysis. Energy Policy 2012;49:149–53.
[2] Pfeffinger S. Energy scientists must show their workings. Nature 2017;542:393.
[3] Pfenninger S, DeCarolis J, Hirt L, Quoilin S, Staffell I. The importance of open data and software: is energy research lagging behind? Energy Policy 2017;101:211–5.
[4] Hunter K, Sreepathi S, DeCarolis J. Modeling for insight using tools for energy model optimization and analysis (Temoa). Energy Econ 2013;40:339–49.
[5] Milano F. Power system modelling and scripting. London: Springer; 2010.
[6] Carpaneto E, Chicco G, Mancarella P, Russo A. Cogeneration planning under uncertainty. Part II: decision theory-based assessment of planning alternatives. Appl Energy 2011;88(4):1075–83.
[7] Milano F. "A python-based software tool for power system analysis," In: Proceedings of the IEEE Power & Energy Society General Meeting, Vancouver, BC; 2013.
[8] openmod. "Openmod Open Models," openmod initiative. [Online]; 2017. Available: ⟨https://wiki.openmod-initiative.org/wiki/Open_Models⟩. [Accessed 9 December 2017].
[9] Brown T, Hörsch J, Schlachtberger D. "Python for Power System Analysis (PyPSA): Free Software for Planning Energy Systems with High Shares of Renewables," in Proceedings of the 1st international conference on large-scale grid integration of renewable energy in India, Delhi; 2017.
[10] Walter H, Epple B. Numerical simulation of power plants and firing systems. Vienna: Springer; 2017.
[11] Mendes G, Ioakimidis C, Ferrão P. On the planning and analysis of Integrated Community Energy Systems: a review and survey of available tools. Renew Sustain Energy Rev 2011;15(9):4836–54.
[12] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 2014;33:74–86.
[13] Allegrini J, Orehounig K, Mavromatidis G, Ruesch F, Dorer V, Evins R. A review of

modeling approaches and tools for the simulation of district-scale energy systems. Renew Sustain Energy Rev 2015;52:1391–404.
[14] Van Beuzekom I, Gibescu M, Slootwe J. "A review of multi-energy system planning and optimization tools for sustainable urban development," In: Proceedings of the IEEE Eindhoven PowerTech, Eindhoven; 2015.
[15] Mancarella P, Andersson G, Peças-Lopes J, Bell K. "Modeling of integrated multi-energy systems: Drivers, requirements, and opportunities," In: Proceedings of the Power Systems Computation Conference (PSCC), Genoa; 2016.
[16] Ma T, Wu J, Hao L. Energy flow modeling and optimal operation analysis of the micro energy grid based on energy hub. Energy Convers Manag 2017;133:292–306.
[17] Morvaj B, Evins R, Carmeliet J. Optimization framework for distributed energy systems with integrated electrical grid constraints. Appl. Energy 2016;171:296–313.
[18] Mohammad M, Noorollahi Y, Mohammadi-ivatloo B, Yousefi H. Energy hub: from a model to a concept - A review. Renew Sustain Energy Rev 2017;80:1512–27.
[19] Hall L, Buckley A. A review of energy systems models in the UK: prevalent usage and categorisation. Appl Energy 2016;169:607–28.
[20] Toba A, Seck M. Modeling social, economic, Technical & environmental components in an energy system. Procedia Comput Sci 2015;95:400–7.
[21] Sameti M, Haghighat F. Optimization approaches in district heating and cooling thermal network. Energy Build 2017;140:121–30.
[22] Mashayekh S, Stadler M, Cardoso G, Heleno M. A mixed integer linear programming approach for optimal der portfolio, sizing, and placement in multi-energy microgrids. Appl Energy 2016;187:154–68.
[23] Lund H. Renewable energy systems: a smart energy systems approach to the choice and modeling of 100% renewable solutions. 2nd ed Burlington, USA: Academic Press; 2014.
[24] Prasanna A, Dorer V, Vetterli N. Optimisation of a district energy system with a low temperature network. Energy 2017;137:632–48.
[25] Gu W, Wang J, Lu S, Luo Z, Wu. C. Optimal operation for integrated energy system considering thermal inertia of district heating network and buildings. Appl Energy 2017;190:234–46.
[26] Delangle A, Lambert R, Shah N, Ach S, Markides C. Modeling and optimizing the marginal expansion of an existing district heating network. Energy 2017;140(1):209–23.
[27] NREL. "Energy Systems Analysis Tools," National Renewable Energy Laboratory. [Online]. Available: ⟨https://www.nrel.gov/analysis/energy-systems-tools.html⟩. [Accessed 28 December 2017].
[28] NREL. "System Advisor Model (SAM)," National Renewable Energy Laboratory. [Online]. Available: ⟨https://sam.nrel.gov/⟩. [Accessed 28 December 2017].
[29] SimTech. "What is IPSEpro?," SimTech GmbH. [Online]. Available: ⟨http://www.simtechnology.com/CMS/index.php/ipsepro⟩. [Accessed 28 December 2017].
[30] Jung N, Depew C., "Building a Digital Twin of Your Process Plant with Unified Lifecycle Simulation," Schneider Electric. [Online]. Available: ⟨https://software-solutions.schneider-electric.com/hubfs/Campaign%20Assets/SimCentral/WhitePaper_SE-LIO-SimSci_UnifiedLifecycleSimulation_05-17.pdf⟩. [Accessed 28 December 2017].
[31] PSS*SINCAL - Efficient Planning Software for Electricity and Pipe Networks, Siemens. 2017. [Online]. Available: ⟨http://www.aan.siemens.com/venezuela/Documents/2017/Mayo%202017/4.%20General%20PSS-Sincal.pdf⟩. [Accessed 27 December 2017].
[32] Allan BA. A More Reusable Modeling System. 1997. [Online]. Available: ⟨http://www.cs.cmu.edu/~ascendFTP/pdffiles/benthesis.pdf⟩. [Accessed 28 December 2017].
[33] Papalexandr K, Pistikopoulos E. A multiperiod MINLP model for the synthesis of flexible heat and mass exchange networks. Comput Chem Eng 1994;18(11–12):1125–39.
[34] Kon L, Wu Y, Maravelias C. Simultaneous utility and heat exchanger area targeting for integrated process synthesis and heat integration. Ind Eng Chem Res 2017;56(41):11847–59.
[35] Kong L, Sen S, Henae C, Dumesi J, Maravelias C. A superstructure-based framework for simultaneous process synthesis, heat integration, and utility plant design. Comput Chem Eng 2016;Vols. 68–84:91.
[36] Milano F, Vanfretti L. State of the Art and Future of OSS for Power Systems. In: Proceedings of the IEEE Power & Energy Society General Meeting, Calgary, AB; 2009.
[37] Quoilin S, Kavvadias K. "The Dispa-SET model,"European Commission's Joint Research Centre (JRC). 2017. [Online]. Available: ⟨http://www.dispaset.eu/en/latest/index.html⟩. [Accessed 9 December 2017].
[38] Hart E, Laird C, Watson J, Woodruf D. Pyomo: Optimization Modeling in Python. 2nd, ed. New York: Springer; 2017.
[39] Zimmerma R, Murillo-Sánche C, Thomas R. MATPOWER: steady-state operations, planning and analysis tools for power systems research and education. IEEE Trans Power Syst 2011;26(1):12–9.
[40] Uni Kassel. "pandapower," University Kasel, 2017. [Online]. Available: ⟨https://www.uni-kassel.de/eecs/en/fachgebiete/e2n/software/pandapower.html⟩. [accessed 09 December 2017].
[41] Siddiqui A, Marnay C, Edwards J, Firestone R, Ghos S, Stadler M. Effects of a CarbonTax on microgrid combined heat and power adoption. J Energy Eng, Am Soc Civil Eng 2005;131(1):2–25.
[42] Chacon S, Straub B., "Pro Git," Git, 2014. [Online]. Available: ⟨https://git-scm.com/book/en/v2⟩. [accessed 7 April 2018].
[43] Chinneck J. "Practical Optimization: A Gentle Introduction," Carleton University, 2015. [Online]. Available: ⟨http://www.sce.carleton.ca/faculty/chinneck/po.html⟩. [accessed 23 November 2017].
[44] Murillo-Sánchez C, Zimmerma R, Anderson C, Thomas R. Secure planning and operations of systems with stochastic sources, energy storage and active demand. IEEE Trans Smart Grid 2013;4(4):2220–9.
[45] Koltsaklis N, Dagoumas A, Kopanos G, Pistikopoulos E, Georgiadis M. A spatial multi-period long-term energy planning model: a case study of the Greek power system. Appl Energy 2014;115:456–82.
[46] Palmintier B, Webster M. Impact of unit commitment constraints on generation expansion planning with renewables. In: Proceedings of the IEEE PES General Meeting; 2011.
[47] Despres J, Hadjsai N, Criqu P, Noirot I. Modelling the impacts of variable renewable sources on the power sector: reconsidering the typology of energy modelling tools. Energy 2015;80:486–95.
[48] Fripp M. "Switch: a planning tool for power systems with large shares of intermittent renewable energy. Environ Sci Technol 2012;46(11):6371–8.
[49] Burger M, Graeber B, Schindlmayr G. Managing energy risks: an integrated view on power and other energy markets. West Sussec: John Wiley & Sons; 2007.
[50] Mashayek S, Stadler M, Cardoso G, Heleno M, Madathil S, Nagarajan H, Ben R, Mueller-Stoffels M, L X, Wang J. security-constrained design of isolated multi-energy microgrids. IEEE Trans Power Syst 2017;99:1.
[51] Voll P, Klaffke C, Henne M, Bardow A. Automated superstructure-based synthesis and optimization of distributed energy supply systems. Energy 2013;50:374–88.
[52] Majewsk D, Lampe M, Voll P, Bardow A. TRusT: a Two-stage robustness trade-off approach for the design of decentralized energy supply systems. Energy 2017;118:590–9.
[53] Bordin C, Gordin A, Vido D. An optimization approach for district heating strategic network design. Eur J Oper Res 2016;252:296–307.
[54] Ondeck A, Edgar T, Baldea. M. A multi-scale framework for simultaneous optimization of the design and operating strategy of residential CHP systems. Appl Energy 2017;206:1495–511.
[55] Kallrath J, Pardalos P, Rebennac S, Scheidt M. Optimization in the energy industry. Berlin: Springer; 2009.
[56] Cano E, Groissböck M, Moguerza J, Stadle M. A strategic optimization model for energy systems Planning. Energy Build 2014;81:416–23.
[57] Manzini R, Accors R, Cennerazzo T, Ferrar E, Maranes F. The scheduling of maintenance. A resource-constraints mixed integer linear programming model. Comput Ind Eng 2015;87:561–8.
[58] Jiménez-Gutiérrez A, Lona-Ramíre J, Ponce-Ortega J, El-Halwag M. An MINLP model for the simultaneous integration of energy, mass and properties in water networks. Comput Chem Eng 2014;71:52–66.
[59] Sirvent M, Kanelakis N, Geissler B, Biskas P. Linearized model for optimization of coupled electricity and natural gas systems. Modern Power Syst Clean Energy 2017;5(3):364–74.
[60] Morales-España G, Correa-Posada, C, Ramos A. Tight and compact MIP formulation of Con? Guration-based combined-cycle units. IEEE Trans Power Syst 2016;31(2):1350–9.
[61] Pröll T, Hofbauer H. Development and application of a simulation tool for biomass gasification based processes. Int J Chem React Eng 2008;6(1):1–56.
[62] DLR. "Model Deployment for Systems Analysis, Energy system model REMix,; 2016. [Online]. Available: ⟨http://www.dlr.de/tt/desktopdefault.aspx/tabid-8990/⟩. [Accessed 3 March 2017].
[63] Zheng X, Wu G, Qiu Y, Zhan X, Shah N, Li N, Zhao Y. A MINLP multi-objective optimization model for operational planning of a case study CCHP system in urban China. Appl Energy 2018;210:1126–40.
[64] Koltsaklis N, Giannakaki M, Georgiadis M. Optimal energy planning and scheduling of microgrids. Chem Eng Res Des 2017;99:1–15.
[65] Rose R, Schmidt M, Steinbac M, Willert B. Computational optimization of gas compressor stations: minlp models vs. continuous reformulations. Math Methods Oper Res 2016;83(3):409–44.
[66] Bordin C, Anuta H, Crossland A, Gutierrez I, Den C, Vigo D. A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration. Renew Energy 2017;101:417–30.
[67] Floudas C, Lin X. Mixed integer linear programming in process scheduling - modeling, algorithms, and applications. Ann Oper Res 2005;139:131–62.
[68] Atilgan B, Azapagic A. An integrated life cycle sustainability assessment of electricity generation in Turkey. Energy Policy 2016;93:168–86.
[69] Henbest S, Mills L, Orlandi I, Serhal A, Pathania R., "Levelised Cost of Electricity: DFID 28 priority countries," GOV.UK, 1 January 2015. [Online]. Available: ⟨https://www.gov.uk/dfid-research-outputs/levelised-cost-of-electricity-dfid-28-priority-countries⟩. [Accessed 8 December 2017].
[70] UN. "Atlantis, Integrated Systems Analysis of Energy," United Nations. 2017. [Online]. Available: ⟨https://unite.un.org/sites/unite.un.org/files/app-desa-atlantis/index.html⟩. [Accessed 15 April 2017].
[71] Oree V, Sayed Hassen S, Fleming P. Generation expansion planning optimisation with renewable energy integration: a review. Renew Sustain Energy Rev 2017;69:790–803.
[72] Sellak H, Ouhbi B, Frikgh B, Palomares I. Towards next-generation energy planning decision-making: an expert-based framework for intelligent decision support. Renew Sustain Energy Rev 2017;80:1544–77.
[73] Barati F, Seifi H, Sadegh Sepasian M, Shafie-khah M, Catalao J. Multi-period integrated framework of generation, transmission, and natural gas grid expansion planning for large-scale systems. IEEE Trans Power Syst 2015;30(5):2527–37.
[74] Guerra O, Tejada D, Reklaitis. G. An optimization framework for the integrated planning of generation and transmission expansion in interconnected power

Paper 2

Renewable Energy 160 (2020) 1396–1407

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Impact of spatial renewable resource quality on optimum renewable expansion

Markus Groissböck, Doctoral Student

University of Innsbruck (UIBK), Institute for Construction and Materials Science, Technikerstraße 15, 6020, Innsbruck, Austria

A R T I C L E I N F O

Article history:
Received 8 March 2020
Received in revised form
12 June 2020
Accepted 9 July 2020
Available online 23 July 2020

Keywords:
Renewables
Optimal expansion paths
Impact of renewable quality

A B S T R A C T

Renewable energy sources (RES) are becoming more and more cost-competitive globally. Generally, optimization methods are used to identify the most economic setup of individual power systems. In such cases, only the final state of the power system is of interest. This study contributes to the discussion on how to reach a 100% RES driven power system by assessing the importance of RES quality in selected European countries and identifies optimal strategies based on different objective functions (e.g., lowest capex requirement, lowest or largest curtailment). In a scenario in which economics is the only driver for optimal RES expansion, the 'min. LCOE' path with a strong focus on Wind would be used. If residential users are targeted to contribute as much as possible the 'max. capacity' case with a Solar PV-Wind ratio of 0.65 ± 0.35 would be selected. If the overall aim is to produce maximal excess electricity to be used in other sectors the 'max. curtailment' or 'max. zero load' cases should be considered where mainly Solar PV would be the technology of choice.

1. Introduction

In large parts of the world fluctuating renewable energy sources (RES), primarily Solar Photovoltaic (PV) and (onshore/offshore) Wind, are already cost-competitive compared to new build conventional generation such as gas turbines, steam turbines, combined cycle gas turbines, and internal combustion engines [1]. Wherever RES is not fully cost-competitive yet, countries support its installation through policy towards full decarbonization of power systems [2]. While efficiency improvement is one of the key measures to reach temperatures "well below 2°C", linking all energy-consuming sectors (power, industry, transport, and building; known as 'sector coupling') is essential for full decarbonization in the long run [3]. It becomes a trade-off and a timing issue for effective efficiency improvement and RES expansion. Child et al. (2019) have shown how an optimal system could look like for Europe and the entire World [1]. As a result of sector coupling, the electricity demand would increase significantly because of electrifying all processes. It would become the backbone of the future energy system. And it would consider as much RES as necessary to fulfill the entire energy demand in a fully decarbonized, integrated and interconnected system.

Kreifels et al. (2014) have demonstrated the optimal expansion plan for Solar PV and Wind in the case of Germany [4]. Within their study, the optimal share of RES was defined as the highest installed capacity of RES within a specific curtailment rate. The authors found that a balanced Solar PV-Wind ratio of 1.075 ± 0.225. In their assessed RES expansion scenario, the optimal expansion starts with a ratio of >1, indicating that more Solar PV than Wind should be installed. With an installed capacity of Solar PV of more than 100 GW (or ~25% above peak demand with a current peak demand in Germany of ~80 GW) the ratio becomes <1. This implies that more Wind than Solar PV should be added later on (see Fig. 1 for the expansion matrix of 200 GW or 250% of peak demand of Solar PV and Wind based on Germany's RES and power demand profiles). The shift towards more Wind is driven by the fact that power provided by Wind is more evenly distributed during the entire day while Solar PV's contribution is limited to day (sun shine) hours. Once the optimal day contribution is reached the incremental Wind capacity has less curtailment as an incremental Solar PV capacity.

Burger (2019) shows a more detailed view below 60 GW (or ~75% of current German's peak demand) on the actual installed capacity mix as well the optimal mix of Solar PV and Wind (see Fig. 2) [5]. This figure compares the optimal RES expansion with the real Solar PV/Wind expansion observed between 2000 and 2017 in Germany. Burger identifies a RES capacity gap based on his definition of optimal RES expansion. For 2017, the figure shows a Solar

E-mail address: markus.groissboeck@student.uibk.ac.at.

https://doi.org/10.1016/j.renene.2020.07.041
0960-1481/

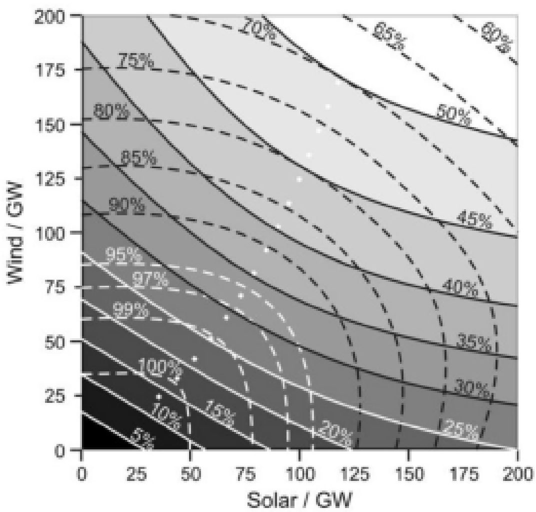


Fig. 1. Optimal share of Wind - Solar PV in Germany [4].

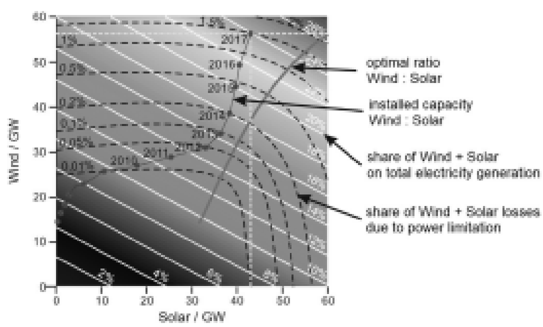


Fig. 2. Optimal share of Wind - Solar PV in Germany [5].

PV capacity gap of more than 15 GW to reach the optimal Solar PV-Wind ratio.

Both publications (Kreifels et al. (2014) [4] and Burger (2019) [5]) are based on the same definition of an optimal RES expansion (highest installed capacity of RES within a specific curtailment rate), and both are considering German Solar PV and Wind profiles. While the assumptions made by Burger (2019) are not transparent, Kreifels et al. (2014) use data for 2011 and 2012. Both publications follow the same methodology and share the same limitations:

- ignore the cost of RES,
- focus on one country (one 'RES profile quality') only,
- do not discuss the importance of RES quality (different locations), and
- use only one definition of optimal RES.

The term 'RES quality' is a substitute for how much RES power generation can be expected throughout an entire year considering multi-year data.

Consequently, this study contributes to state-of-the-art generation expansion planning (GEP) by giving additional insights into the importance of RES quality towards high RES share power systems and show multiple ways of optimal RES expansion towards a very high share of RES. Different RES qualities are considered throughout this study by using hourly multi-year RES power generation data from different European countries. The RES expansion towards very high share of RES is assessed through different objective functions (e.g., minimizing and maximizing of curtailment, zero demand load hours, and cost of power generation).

The structure of the remaining study is as follows: Section 2 contains a literature review about existing approaches to the problem of high RES expansion. Section 3 describes the methodology considered in this study. Section 4 presents the case study assumptions and the results of the analysis. Section 5 and Section 6 contain a discussion and conclusion while suggested possible enhancement options for future work are added after the conclusion.

2. Literature review

Tersteegen et al. (2013) optimized the energy system for Germany for 2023 and 2033 [6]. The authors considered cost reductions through experience and scaling effects for Solar PV and (onshore/offshore) Wind. Detailed annual capacity additions, but also other demand details outside of the power sector, were not considered. Grid expansion was seen as an important prerequisite for the 'Energiewende' (Engl. energy transition) in Germany. As the study was already conducted in 2013, the findings show that Battery Energy Storage (BES) will only be economically feasible if the cost drops by 80% until 2033. They also found that such a cost reduction was very unlikely. Only six years later this was found to be unrealistic based on the assumption that BES cost would take more time to decrease and, as such, more grid expansion would be needed for a high share of RES expansion [1]. This study demonstrates that the cost reduction assumption has a significant impact on the outcome of the optimization. The authors do not assess different optimal RES expansion plans and do ignore the impact on different RES qualities.

Budischak et al. (2013) used a dynamic programming approach to identify the least-cost combination of onshore/offshore Wind and Solar PV, combined with BES and fuel cells [7]. The authors found that RES capacity with about three-times the peak demand is required to power the PJM power system between 90 and 99.9% of the time. To reach RES penetration (share of energy) of 99.9%, storage duration of 9–72 h needs to be provided to have enough energy shifting capabilities. The authors only modeled the year 2030. No optimal RES expansion plan and different RES quality discussion is available in their assessment.

Huber et al. (2014) evaluated the flexibility requirements for three different systems (Saxony, Germany, and Europe) with 50% RES penetration [8]. The authors found that the assessed RES share, the RES mix, and the system's size (balancing area size) have a large impact on the variability of the net load. To minimize data bias, data between 2001 and 2010 were used. The authors did not assess the RES quality and do not show an optimal RES evolution scenario as they used predefined shares of RES (e.g., 50% RES with 20% being Solar PV).

Tafarte et al. (2014) optimized the German power system for 2030 and 2050 for a RES share of 50 and 80% [9]. The significant difference to other optimization approaches was that Solar PV is considered with east, south, and west directed modules. By doing so, the combination of all three directions was more able to cover the before midday (~10 a.m.), the midday, and the afternoon (~2 p.m.) peak depending on RES penetration. Also, Wind was adjusted towards an advanced Wind energy converter in which the hub heights were increased (towards 130 m) to substantially boost the full load hours (FLH) from 1500 to 3500 h/year. This increase of FLH reduced the need for installed Wind capacity by about 50% and increased the installed PV capacity by about 25%; a split of 5%, 49%, and 46% (south, east, and west-directed modules) was found optimal. The authors only considered a single year of data and did not show an optimal RES expansion path within this assessment.

Sun et al. (2016) assessed the possible contribution to China's Intended Nationally Determined Contribution (INDC) by analyzing nine scenarios (a base case 'business-as-usual' BAU, and eight other scenarios) with 40% RES by 2030 using a multi-criteria assessment (MCA) [10]. The MCA considered total cost, total capacity, excess electricity, carbon dioxide (CO_2) emissions, and direct job creation. In their assessment, a high amount of excess electricity was considered as a disadvantage since sector coupling was not part of their scope of analysis. The assessment was performed with the modeling tool ENERGYPLAN and was based on a single 'typical' year. As a result, there is no discussion of the optimal RES expansion plan or different RES qualities.

Zappa & van den Broek (2018) can be credited with the development of the European RES optimization approach based on spatial conditions for Solar PV and Wind [11]. The authors used GIS-based constraints on rooftop and utility-scale Solar PV, and onshore and offshore Wind capacities available in Europe. The objective function was to minimize residual demand or maximize RES generation. The authors considered power demand only and neglected potential synergies with the transport and industry sector. They found that optimization is a viable tool for selecting Solar PV and Wind locations based on spatial details, while there is little evidence of this being considered in reality. The implemented optimization minimized the residual demand and found a mix of 74% Wind and 26% Solar PV (in total 1144 GW) as optimal to meet 82% of the European power demand. The authors neglected to show an optimal RES expansion path while they did consider different RES qualities in their spatial approach.

Zappa et al. (2019) found that a European power system could manage 100% RES even in the most severe historical weather conditions observed between 1979 and 2015 with the same level of system adequacy as today [12]. Such a system would need 90% of conventional generation capacity, an increase of 233% of cross-border transmission capacity, and a well-integrated operation of heat pumps and electric vehicles. Besides a continuous Wind deployment of 7.5 GW/a and Solar PV deployment of 15 GW/a, also massive Biomass resources would be required to reach the 100% RES target in Europe by 2050. The authors did not create an optimal RES expansion plan for Europe nor was the impact of RES quality part of their assessment.

As indicated by the conducted literature review research toward high shares of RES has a long history. With the exception of Kreifels et al. (2014) none of the reviewed publications assessed the optimal RES expansion plan. The importance of RES quality was neglected from all assessed publications. While some publications do indicate the importance and need of multi-year time series for demand and RES production very little of the available assessments do consider this in their own work. This study does shed light into the implications of different RES quality available in the individual countries in Europe and how optimal RES expansion plans could look like.

3. Methodology

Inspired by Burger (2019) [5] and developed by Kreifels et al. (2014) [4], this study assesses the optimal RES expansion by comparing different optimal RES expansion paths. To overcome the limitations of Burger (2019) and Kreifels et al. (2014) the author developed the following list of optimal RES expansion paths:

- RES capacity with specific curtailment rate [5],
- curtailment,
- levelized cost of electricity (LCOE), and
- zero net load hours.

Within this study, minimizing curtailment, LCOE, and zero net load hours and maximizing capacity, curtailment, and zero net load hours are considered to be useful for optimal RES expansion planning and are assessed in separate scenarios. The case 'minimize capacity' is unnecessary as the power contribution from Wind is usually higher than from Solar PV (exceptions might be e.g., Macedonia MK, and Slovenia SI - see Fig. 3). This study uses pure power-related key performance indicators (KPI's) such as curtailment and LCOE for the assessment. Other KPI's such as security of supply, national manufacturing and aspects of local content (e.g., jobs, value creation) are ignored [13]. This study focuses on mixed Solar PV-Wind expansion as this is currently seen as the technologies of choice with lower constraints compared to other RES technologies such as Hydropower or Biomass.

Historically measured hourly time series for load and RES profiles are based on open-power-system-data.org [14] and renewables.ninja [15]. Both sources provide hourly profile data as publicly available data. Fig. 3 shows the average capacity factors for Solar PV and Wind for the entire data set of the covered 36 countries.

This study defines four conditions with special combinations of Solar PV and Wind qualities: a) very good Solar PV, very good Wind; 2) very good Solar PV, very bad Wind; 3) very bad Solar PV, very good Wind; and 4) very bad Solar PV, very bad Wind. Specific countries are selected to represent different RES quality conditions. Based on the available data and defined conditions the following countries have been identified for suited candidates (see Table 1,

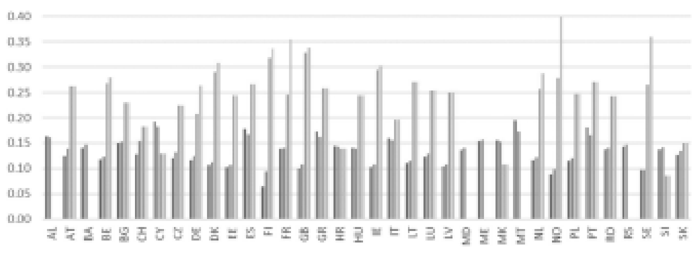


Fig. 3. Average capacity factors of PV and Wind.

Table 1
Country list and considered rationale.

Wind Quality	Solar PV Quality	Country Code	Country Name
–	++	CY	Cyprus
–	–	CZ	Czech Republic
++	–	NO	Norway
++	++	PT	Portugal

'++': very good RES quality, '–': very bad RES quality):

Besides these countries selected based on RES qualities, Austria has been added because of the location of the University of Innsbruck, and Germany has been added as it is one of the main countries within Europe considering renewables integration and energy exchange with its neighboring countries.

The publicly available time series starts for Austria (AT), Czech Republic (CZ), Germany (DE), and Portugal (PT) in 2006, for Norway (NO) in 2010, and for Cyprus (CY) in 2013; all data end in 2016 [16]. To avoid annual biases, but consider the meteorological differences from year to year, the entire time series (e.g., 2006–2016 for AT) was used as a whole instead of individual years. For this study, each year of the demand profiles has been scaled to a peak demand of 10,000 MW to assess the impact of seasonal demand and renewables profile variation and not the growth of the individual demand profiles or other aspects such as efficiency improvements. The 10,000 MW represents an average power system demand which can be found several times in Europe and also in the considered countries, e.g., PT with 8700 MW, CZ with 10,800 MW, and AT with 11,900 MW.

To support medium- and long-term optimal RES expansion path decisions, this study includes multiple years of data, different quality of renewables, and different combinations and RES penetration (0–200% compared to peak demand in 0.5% steps). The overall program logic shown in Fig. 4 has been implemented in the programming language Julia [17].

Step 1 is to select the first country to assess (in alphabetical order it starts with AT). Based on the available data set Step 2 selects the first available year (e.g., 2006). Step 3 and 4 are initializing Solar PV and Wind capacity additions with 0% (of peak demand) to calculate the initial situation without RES in Step 5. Subsequently, and as long as not reaching the maximum of 200%, 0.5% is added for Solar PV and Wind. Finally, if 200% of Solar PV and Wind have been considered in the calculations, Step 6 initiates the next available year to be considered (up to, e.g., 2016). As already indicated above, this study used all available data at once to avoid data (weather, RES power generation and power demand) contortions through individual years. After finalizing all years, Step 7 initiates the next country for assessment. If all countries have been calculated, the simulation of all scenarios is finished.

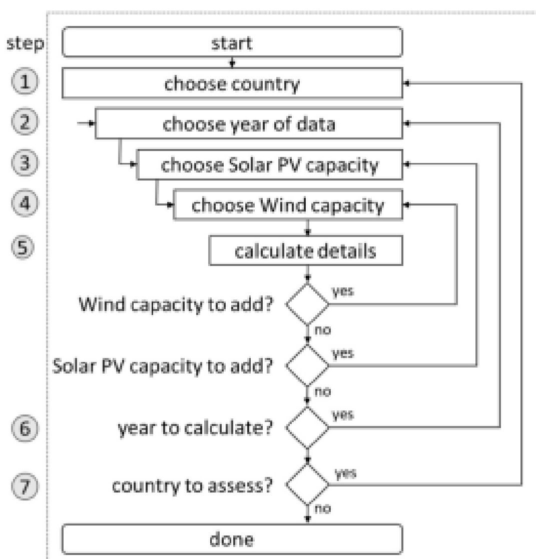


Fig. 4. Methodology.

4. Case study

Based on the introduced methodology, the case study assesses the selected countries' RES quality conditions and the impact of multi-year RES profiles together with their respective demand profiles.

4.1. Assumptions

Fig. 5 and Table 2 show the normalized load duration curves (LDC) and common KPI's generally used in GEP based on the available hourly time series for the assessed countries (AT, CY, CZ, DE, NO, and PT).

The average LDC based on data from CY shows the highest seasonal swing within the assessed data set as cooling demand is high in summer, but there is no or limited electric heating demand in winter. The LDC for DE shows the lowest seasonal swing as heating and cooling is traditionally not powered by electricity in DE. Heating demand is usually covered either through district heating systems (with, e.g., biomass or coal) or through individual natural gas boilers.

Fig. 6, Fig. 7, and Table 3 show the RES duration curves for the selected countries and the average FLH of the considered RES profiles.

There is a significant difference within the considered Solar PV profiles (Fig. 6), while the considered Wind profiles seem more

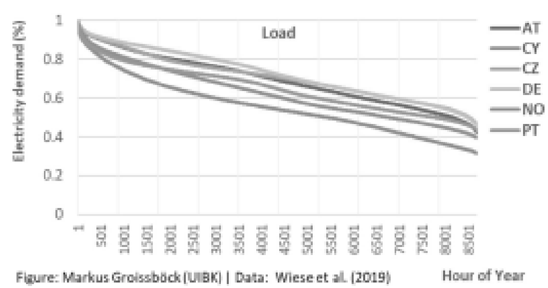


Fig. 5. Average load duration curves.

Table 2
Demand KPIs (based on [14]).

KPI (–)	AT	CY	CZ	DE	NO	PT
Peak-to-Base	2.34	3.17	2.14	2.16	2.52	2.29
Peak-to-Average	1.44	1.78	1.41	1.38	1.59	1.53
Average	0.70	0.56	0.71	0.73	0.63	0.65
Base	0.43	0.32	0.47	0.46	0.40	0.44

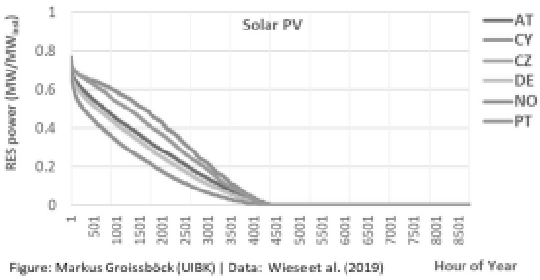


Fig. 6. Average Solar PV duration curves.

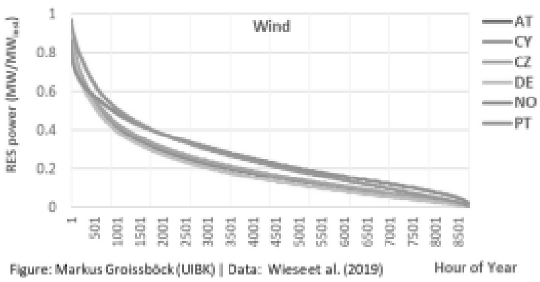


Fig. 7. Average Wind duration curves.

comparable (Fig. 7). One reason might be that the shown average RES duration curves are averaged over the available period of times (e.g., for AT between 2006 and 2016). It would also imply that the Wind resources are more equally distributed throughout Europe while the quality of Solar PV depends more on the latitude of the country of interest.

The KPI FLH is based on the average power generation for the individual RES profile. It does not consider that Solar PV usually has direct current (DC)-to-alternating current (AC) power conversion losses and a significant temperature-dependent power production efficiency. The power generation through Solar PV is always lower as ~80% of the installed capacity, while Wind reaches close to its full power output.

Specific capital expenditures per kW installed capacity are assumed to follow a power curve function (see eq. (1)):

$$P_n = a \cdot n^b \tag{1}$$

where P_n is the specific price (in EUR/kW) for a known size n (in MW), and a and b are the power coefficients estimated within this study to fit available cost estimates (see Table 4). The project price or the capital expenditure is the specific price times the size of the project.

To calculate a constant annuity of this RES price, the capital recovery factor (CRF) is calculated (see eq. (2)) [18]:

$$CRF = \frac{i \cdot (1+i)^n}{(1+i)^n - 1} \tag{2}$$

where i is the interest rate (%) and n the number of years the annuity should be considered. For the purpose of this study, the interest rate is assumed to be 4% and the annuity should be paid for a term of 20 years for all technologies and countries.

Table 3
RES KPIs.

KPI (−)	AT	CY	CZ	DE	NO	PT
FLH Solar PV	0.14	0.18	0.13	0.13	0.10	0.17
FLH Wind	0.21	0.21	0.21	0.19	0.26	0.26
Avg-to-Peak Solar PV	0.19	0.24	0.18	0.18	0.14	0.22
Avg-to-Peak Wind	0.23	0.22	0.23	0.20	0.31	0.27

Table 4
Power curve coefficients (based on [18]).

Power coefficient	Solar PV	Wind
a	1350	1750
b	−0.05	−0.05

Table 5
RES generation KPI's.

(in percent)	AT	CY	CZ	DE	NO	PT
RES power gen.	101.8	122.5	97.5	89.9	111.7	120.0
RES useful	73.7	78.0	71.3	67.1	82.1	82.2
RES unused	28.1	44.5	26.2	22.8	29.6	37.8

Finally, the levelized cost of electricity (LCOE) estimates the price per MWh electricity produced required to meet a predefined level of return within the overall project lifetime. Within this study a simplified LCOE approach is calculated ignoring, e.g., tax and depreciation effects and a decrease in power generation during the technical project lifetime (see eq. (3)) [19]:

$$LCOE = \frac{n \cdot P_n \cdot (CRF + FOM) + P_p \cdot VOM}{P_p} \tag{3}$$

where FOM is the fixed annual operation and maintenance (O&M) costs (in % of capex expenditure), VOM the variable power generation costs (in EUR/kWh), and P_p the useful annual RES power production (kWh/a). For this study, the FOM costs are assumed to be 2% of overall capital expenditure. No VOM costs are assumed for Solar PV and Wind. By considering only the useful RES power generated, which is the difference between total RES power generated and the curtailed RES power, the simple LCOE results in power generation cost increase once curtailment occurs. For simplification the impact of different interest rates and therefore different CRFs is ignored as the focus of this study is the impact of RES quality (see Table 6 for a complete list of simplifications and explanations). Publications such as Child et al. (2019) do neglect differences in cost and financing assumptions between regions or countries as proper cost and financing details depend on more than the country [1]. The experience of the project developer, the financing structure of the project, the policy stability or the RES technology experience of the host country are additional examples of details such high-level assessments cannot accomplish [20]. Besides that, changing e.g. the interest rate for the assessed technologies, while keeping the cost assumption unchanged would not impact the result as long as the RES price stays unchanged.

To provide some background in the development of RES within the assessed countries, Fig. 8–10 provide some details about the changes in terms of power capacity and power generation. Fig. 8 shows the share of installed capacity of Wind, Solar PV, and other RES for all considered countries while Fig. 9 shows the share of power generation. Fig. 10 shows the share of power generation of Solar PV combined with Wind, other RES, and Thermal power generation. The data points shown are between 2000 and 2017.

Table 6
Limitations and explanations.

Limitation	Explanation
• only individual country perspectives have been considered without transmission and distribution (T&D) limitations within the country itself ('copperplate approach'),	• RES placing is not the aim of this study,
• no inter-country power exchanges are considered,	• finding optimal locations is not the aim of this study,
• RES profiles always show the same hourly production pattern independent from RES penetration,	• RES profiles are the sum of hundreds of RES projects, • finding optimal locations is not the aim of this study,
• RES and demand profiles are historical time series,	• the change of profiles is not the aim of this study,
• RES costs and financing parameters are assumed to be the same in all countries,	• the overall economics are not the focus of this study,
• RES cost does not change over time,	• speed of RES expansion is not the focus of this study,
• potential for Solar PV and Wind is assumed to be at least twice the peak demand,	• potential assessment is not the focus of this study,
• pure Solar PV and Wind expansion is considered although other RES technologies such as Hydropower or Biomass, are available as well,	• overall optimal renewable mix is not the focus of this study,
• storage solutions have not been considered,	• storage sizing and placing is not the aim of this study,
• only electricity demand is considered,	• heat, cold, and other end use are not the focus of this study,
• unit commitment and economic dispatch principles and other technical details (e.g., up/down ramp rates, min. up/down time) are not considered.	• thermal power plant GEP is not aim for this study.

Each dot at the line represents a year. As bigger the dot gets as closer it is towards the last available year 2017. Each of the triangle figures includes an example how to use the corresponding axes (see orange, blue, and black arrows): the orange line downwards represents the left axis and the downwards moving lines, the blue horizontal line represents the right axis and the straight leftwards moving lines, and the black line showing upwards represents the lower axis and the upward right moving lines.

The only country showing no steady development is CY as the share of 'Other RES' rose from 0 to 8 MW while Wind and Solar PV have changed a little bit between 2007 and 2009 only. In 2010 and 2011, the Wind additions were 82 and 52 MW while Solar PV started to have strong additions after 2013. AT and NO have a very strong focus on non-Solar PV/Wind RES capacity, mainly Hydropower generation. The case of NO shows that the contribution through of other RES (Hydropower) is so dominant, that even adding ~ 2 GW of Wind capacity has very little impact towards the country's energy mix. PT has a very strong focus on Wind and neglectable Solar PV capacity is installed. Until 2007 DE (see orange line) had a very strong focus on Wind additions before the Solar PV feed-in-tariffs (FiT) were introduces and changed the power generation landscape significantly. It was until 2015 before Wind got more attention again.

In the case of DE, the share of installed capacity moved towards a significant combination of Solar PV and Wind while the RES power production still is dominated by other RES, such as Biomass and Hydropower plants. Compared with Fig. 8 the line for the case DE is less continuous as the annual power production out of especially Wind fluctuates a lot as the Wind quality is less constant over the assess period of time (between 2000 and 2017). AT's non-Solar PV/Wind RES, such as Hydro and Biomass power plants, have much higher FLHs than Solar PV and Wind and therefore the share of 'Other RES' dominates even with significant additions in Wind and Solar PV (compare with Fig. 8). PT on the other hand, uses mainly Hydro and Wind power generation, where both have high FLHs and also high fluctuation between the assessed years.

While the contribution of Solar PV and Wind increased significantly within the RES power capacity and RES power generation, the contribution compared to Thermal power generation only changed significantly in DE and PT. Fig. 10 shows zigzag movements for the case of PT as the RES production out of 'Other RES' varies between 20 and 40% (see orange axis), a result of the changing weather conditions which have strong impact on the provided electricity out of Hydropower. Same explanation is valid for AT where 'Other RES' varies between 65 and 90%. An extreme example is NO where Solar PV and Wind have almost no contribution towards the RES power generation as it is almost exclusively based on

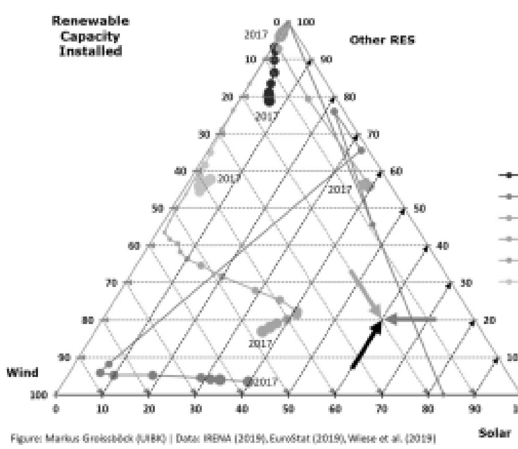


Fig. 8. RES capacity share progress between 2000 and 2017 [23,24].

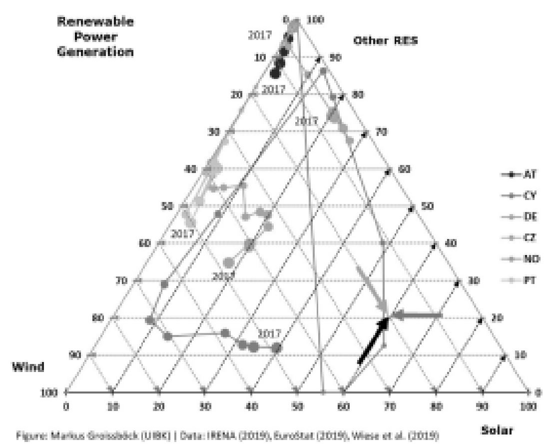


Fig. 9. RES generation share progress between 2000 and 2017 [23,24].

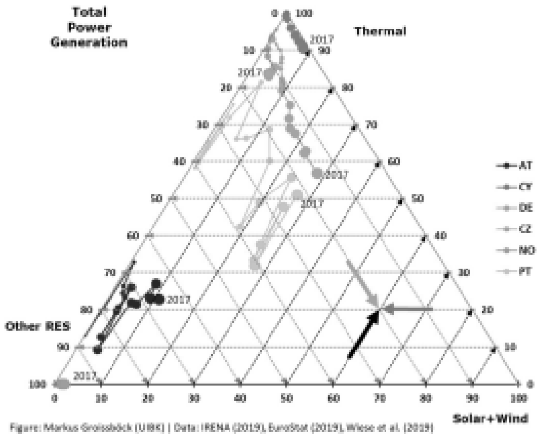


Fig. 10. RES-vs-Thermal generation share progress between 2000 and 2017 [23,24].

Hydropower.

4.2. Results

As already mentioned in the methodology section, this study shows the results for the considered countries to identify the optimal RES paths for a very large RES penetration (per technology) of up to 200% compared to its peak demand. To make the cases comparable between each other all demand profiles have been scaled to a peak demand of 10,000 MW.

Figs. 11–16 show individual scenarios per graph as results of all individual runs combined per country for the assessed optimal RES paths. The horizontal axis shows the Solar PV share and the vertical axis shows the Wind share (both in percent of peak demand, up to 200%). Each grey line in the individual graphs shows the optimal RES expansion path for individual years (e.g., 2006 to 2016). The black line shows the optimal RES expansion using the entire time series, e.g., 2006–2016. The sub-graph titled 'max. capacity' represents the 'RES capacity with specific curtailment' case as shown by Burger (2009) [5] and Kreifels et al. (2014) [4]. The sub-graphs 'min. curtailment' and 'max. curtailment' represent the minimize and maximize curtailment cases. The sub-graph 'min. LCOE' represents the minimize LCOE case. And finally, the 'min. zero load' and 'max. zero load' sub-graphs show the results for the minimize and maximize zero net load hour cases.

Each of the grey lines represents the optimal RES installation path for using a single year of data. The black line represents the optimal RES installation path using all available years of data. Like in some cases below the case 'min. LCOE' shows an interesting result as single years would favor pure Solar PV capacity additions while in general most of the years are favoring pure Wind capacity additions. This is the result of the variability of the historical data. Wind output seems to be a little bit more volatile as Solar PV between individual years.

The green line within the case 'max. capacity' represents the results out of Kreifels et al. (2014).

A more detailed discussion of the results based on these figures is available in Section 5.

Table 5 shows the maximum RES share within the case study countries considering the mentioned constraints discussed in the methodology section. Only in cases with excellent RES qualities in

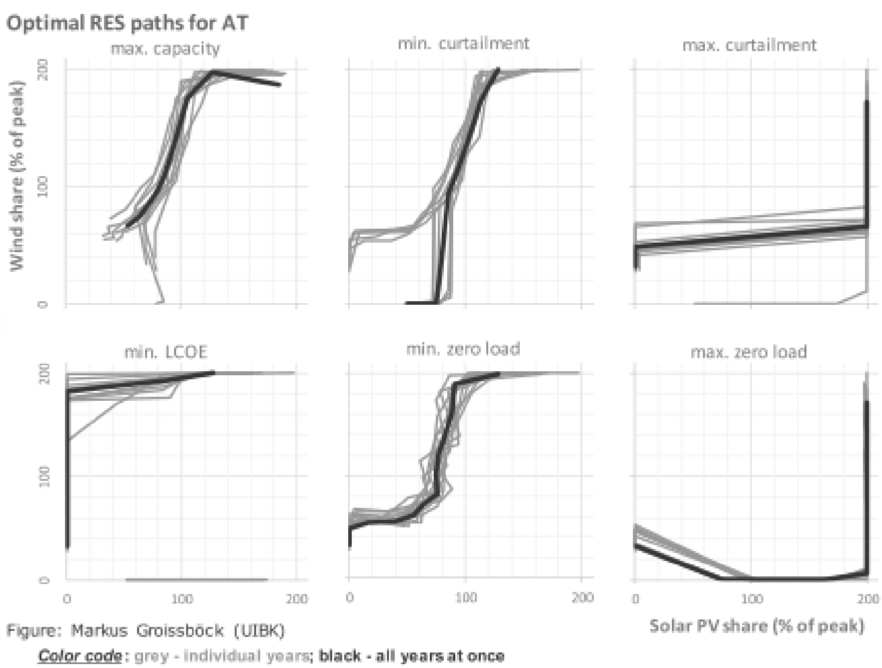


Fig. 11. Simulation results for AT.

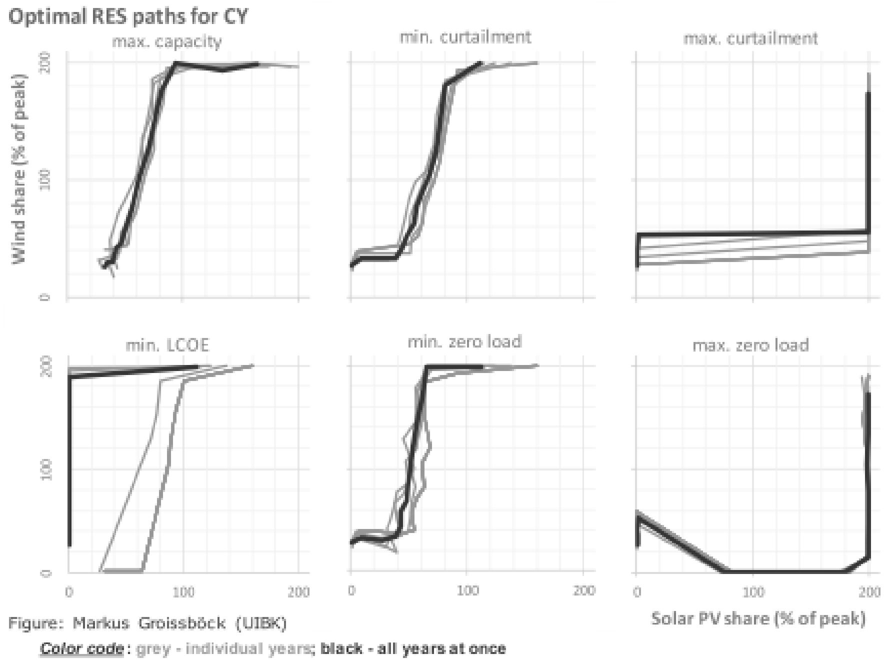


Fig. 12. Simulation results for CY.

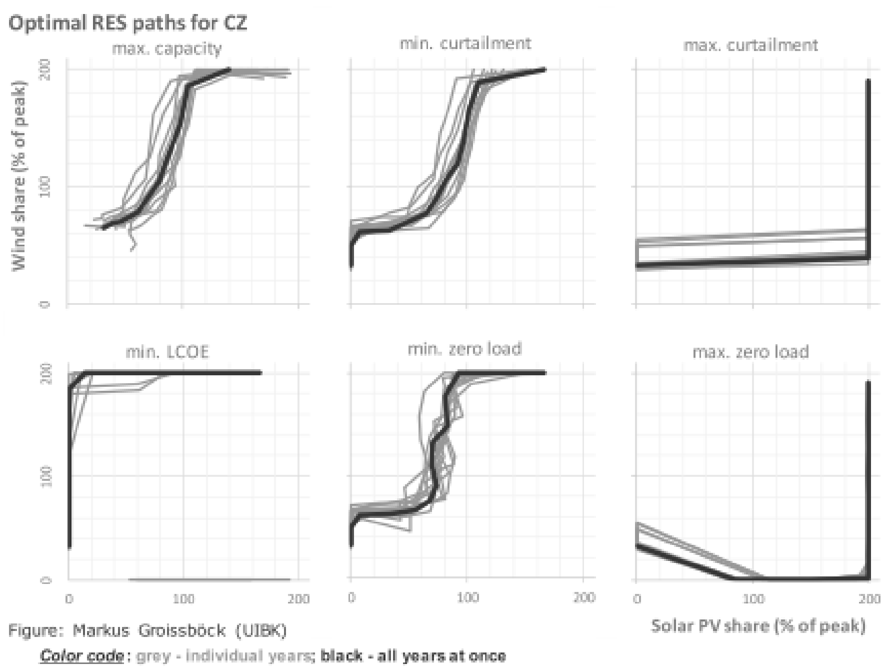


Fig. 13. Simulation results for CZ.

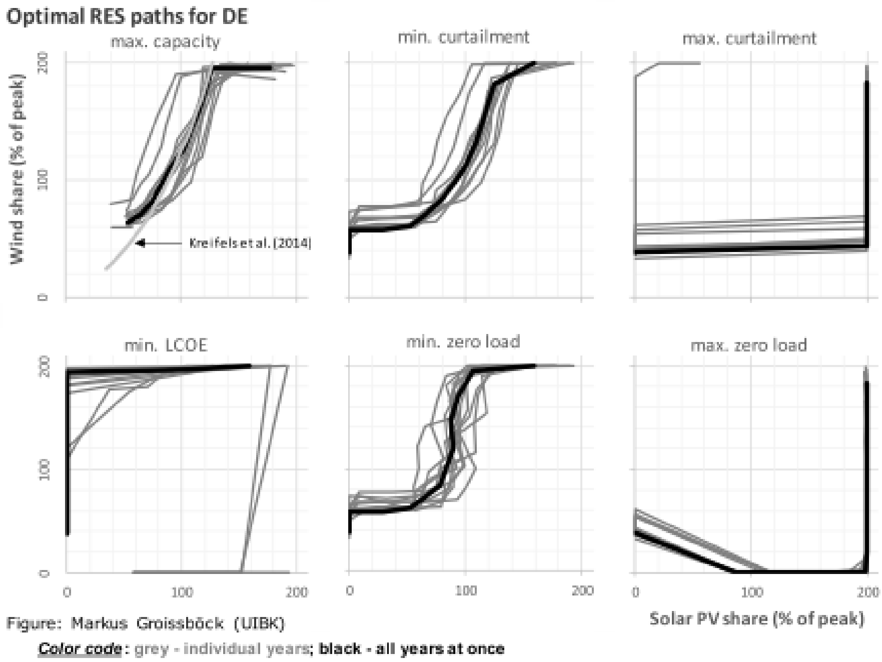


Fig. 14. Simulation results for DE.

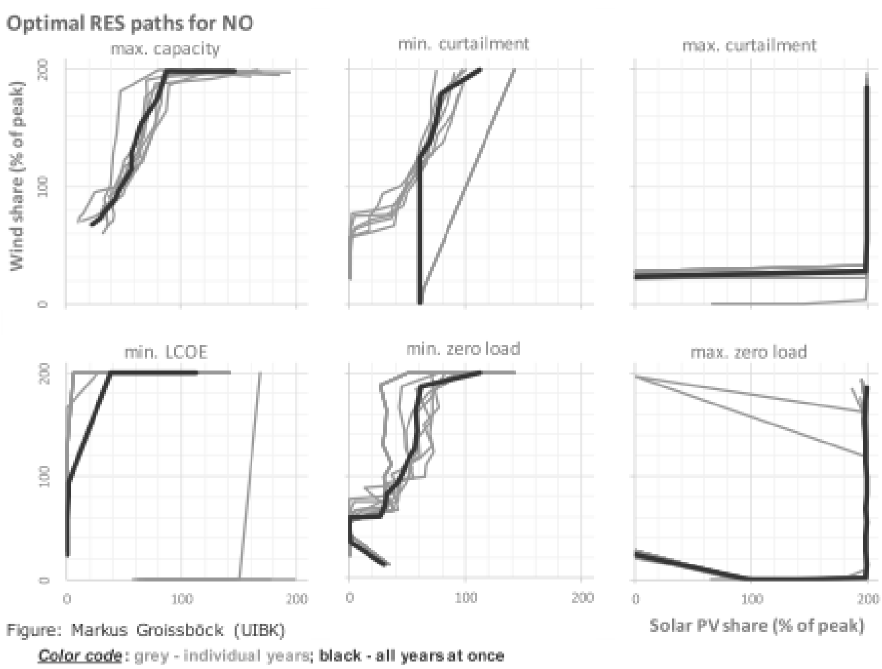


Fig. 15. Simulation results for NO.

one of the assessed technologies (CY, NO and PT) the assessment shows that the used RES expansion matrix can reach above 100% of power generation out of RES. AT could be close to RES self-generation if annual storage losses (including charging, standby losses, and discharging) are <1.8%.

5. Discussion

5.1. Limitations of the methodology

Before the results are discussed, Table 6 highlights the limitations of the methodology to add more clarity to the results discussed subsequently. Most limitations do not have a significant impact on the results or are not the main focus of this study and represent a list of considerations for upcoming studies.

5.2. Discussion and findings

A detailed discussion of the different optimal RES paths is conducted before the overall results are analyzed. The analysis is based on the average unbiased results, as shown in Fig. 17, knowing that individual years will deviate from them. The small zigzag movements (in Figs. 11–17) are the result of the RES matrix (200% × 200% of peak demand) considered in this study in which a RES expansion step of 0.5% has been selected and shows non-steady results in some cases. Fig. 17 represents the summary of Figs. 11–16 and therefore is the basis for the upcoming discussion. In all sub-graphs the dotted lines indicate a ratio of 3, 0.65, and 1 of installed Wind vs. Solar PV. Within the left top sub-figure, the optimal RES path from Kreifels et al. (2014) was added for better comparison.

The 'max. capacity' curves represent the approach of Kreifels et al. (2014) and share some common curve shape as all of them reach 200% of Wind capacity before 80–130% Solar PV is added (see Figs. 1 and 2). The difference lies in the detail. Up to ~50 GW the analysis of Kreifels et al. (2014) suggest a ratio of >1 which would ask for more Solar PV than Wind installed capacity. Up to ~100 GW their analysis results ration of ~1. It's after the peak demand of the German (DE) system (~80 GW) when the ratio trends to the final value of ~0.65 which asks for about 50% higher installed capacity out of Wind vs. Solar PV. Kreifels et al. (2014) finding shows excellent for the RES quality of DE and shows a smoother path as this study. The optimal expansion path for NO and CY would tend towards a ratio of <0.5 which means that Wind should have more than twice the installed capacity of Solar PV. In CY and NO, both countries with very good Wind quality, the optimal Wind-Solar PV ratio is ~0.45. Within the assessed RES quality cases, the optimal RES path with the highest RES capacity installed is favoring Wind over Solar PV.

Compared to the previous 'max. capacity' case, the 'min. curtailment' case has slightly higher Solar PV contributions until the curves reach the 200% Wind capacity. The reason for this is the better fit of Solar PV to the daily demand profiles. The optimal RES path based on 'min. zero load' has less Solar PV contribution as the previously mentioned cases. The 'min. LCOE' case is in all circumstances dominated by almost exclusive Wind expansions. For the Norwegian case, ~50% of Solar PV would be added before the Wind capacity reaches more than 180%. An interesting finding for the Portuguese (PT) case is that Solar PV would be preferred over Wind with the assumed RES cost and generation profiles as this is not reflected at all in the current RES policy which focused historically a lot on adding Wind and moves now more towards Solar PV [21]. To support sector coupling through excess RES electricity, the cases 'max. curtailment' and 'max. zero load' should be considered. In both cases, up to 50% Wind would be added before the RES

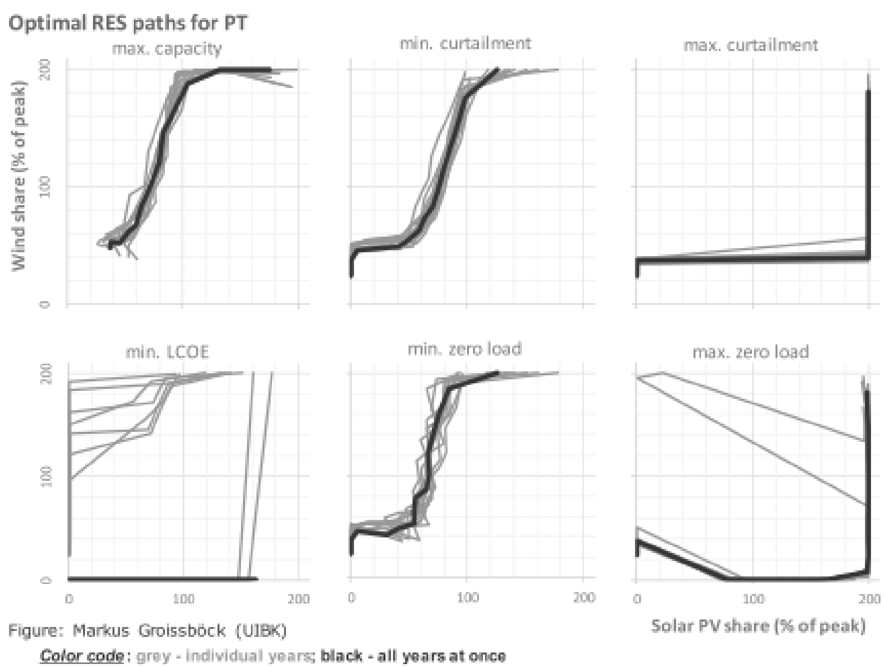


Fig. 16. Simulation results for PT.

1406 M. Groissböck / Renewable Energy 160 (2020) 1396–1407

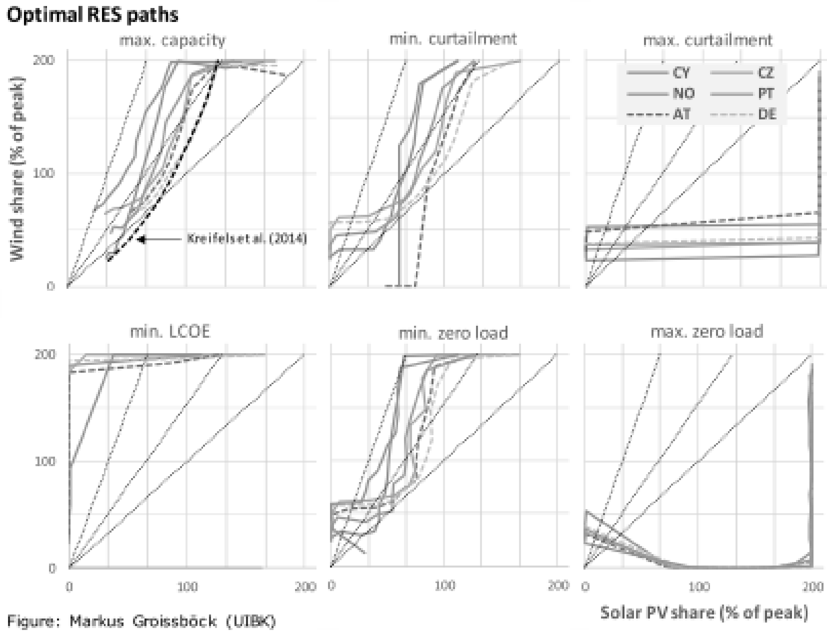


Fig. 17. Overall simulation results.

expansion would be solely based on Solar PV. Adding the 50% of Wind capacity would cover most of the night and cold season demand so that adding Solar PV afterwards can be used for other purposes such as sector coupling.

Budischak et al. (2013) found that RES capacity of about 300% of peak demand and significant amount of storage is needed to reach >90% RES contribution within the PJM market. The results of this study suggest that RES capacity of about 200% is already able to fulfil 90–122% of the energy demand in the assessed countries (see Table 5).

6. Conclusion

In large parts of the world, fluctuating RES, mainly Solar PV and Onshore/Offshore Wind, is already cost-competitive compared to new build conventional generation, such as gas turbines, steam turbines, combined cycle gas turbines, and internal combustion engines. As a result, sector coupling forces the power sector to become the backbone of the future energy system. Most of the time, optimization is used to identify the high-share or 100% RES case, but the way towards this is mostly unaddressed. Consequently, this study contributes to state-of-the-art GEP in adding insights into the importance of RES quality towards high RES share power systems and shows multiple ways of optimal RES expansion towards a very high share of RES.

The results in Figs. 11–16 show overlapping curve shapes while also indicating differences in how the optimal RES expansion path could be realized based on local conditions. It can be concluded that the shapes for 'max. capacity ', 'min. curtailment', and 'min. zero load' show similar evolutionary paths. Also, the paths for 'max. curtailment' and 'max. zero load' show similar shapes. It can be argued that the impact of RES quality is minor and is more dictated by the overarching objective function (see Table 7). If economics were the only driver, the cost of power generation ('min. LCOE') path with a strong focus on Wind would be the guide for RES expansion planning. If residential users are targeted to contribute as much as possible to the RES expansion, the cases 'max. curtailment', 'max. zero load') should be selected. If the overall aim is to produce excess electricity to be used in other sectors, one of the sector coupling approaches ('max. curtailment', 'max. zero load') should be selected where Solar PV would be the technology of choice.

Publications such as Kreifels et al. (2014) or Zappa et al. (2019) indicate that centralized power storage (such as Pumped

Table 7
Optimal RES paths as objective function of aim.

Overall aim	Objective function					
	max. capacity	minimum curtailment	maximum curtailment	minimum LCOE	Minimum zero load	Maximum zero load
Opt. RES power	x	x			x	
Focus Solar PV			x			x
Focus Wind	x	x		x	x	
Least power cost				x		
Sector coupling			x			x

Hydropower, or Battery Energy Storage) does allow higher RES integration. Further research shall incorporate large-scale storage (e.g., thermal storage, hydrogen) for seasonal energy shifts and small-scale prosumers (e.g., domestic use of BES, e-mobility) for short-term energy shifts to gain more insights into how much variability of RES can be taken out with storage and sector coupling going forward. The assessment of different energy storage charge and discharge algorithms might be another field of upcoming work [22].

CRediT authorship contribution statement

Markus Groissböck: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Supervision.

Declaration of competing interest

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

Acknowledgment

The author gratefully acknowledges valuable comments and input from various anonymous reviewers during the review process and from colleagues within the University of Innsbruck, Institute for Construction and Materials Science, Unit of Energy Efficient Buildings.

References

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

[2] IRENA, Accelerating the Energy Transition Through Innovation, A Working Paper Based on Global REmap Analysis [Online], The International Renewable Energy Agency, 2017. Available: http://www.irena.org/remap. (Accessed 9 September 2019).

[3] I. Conti, Sector Coupling and Sector Integration [Online], Florence School of Regulation - European University Institute, 2018. Available: http://www.fsr.eui.eu/sector-coupling-and-sector-integration/. (Accessed 2 September 2019).

[4] N. Kreifels, J.N. Mayer, B. Burger, C. Wittwer, Analysis of photovoltaics and wind power in future renewable energy scenarios, Energy Technol. 2 (2014) 29–33, https://doi.org/10.1002/ente.20130090.

[5] B. Burger, Öffentliche Nettostromerzeugung in Deutschland im Jahr 2018 [Online], Fraunhofer Institut fuer Solare Energiesysteme ISE, 2019. Available: https://www.ise.fraunhofer.de/content/dam/ise/de/documents/news/2019/Stromerzeugung_2018_3.pdf. (Accessed 2 September 2019).

[6] B. Tersteegen, C. Pape, D. Fürstenwerth, Cost Optimal Expansion of Renewables in Germany - A Comparison of Strategies for Expanding Wind and Solar Power in Germany [Online], Agora Energiewende, 2013. Available: https://www.agora-energiewende.de/fileadmin2/Projekte/2012/Kostenoptmaler-Ausbau-EE/Agora_Study_Cost_Optimal_Expansion_of_Renewables_in_Germany_Summary.pdf. (Accessed 8 September 2019).

[7] C. Budischak, D. Sewell, H. Thomson, L. Mach, D.E. Veron, W. Kempton, Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time, Power Sources 225 (2013) 60–74, https://doi.org/10.1016/j.jpowsour.2012.09.054.

[8] M. Huber, D. Dimkova, T. Hamacher, Integration of wind and solar power in Europe - assessment of flexibility requirements, Energy 69 (2014) 236–246, https://doi.org/10.1016/j.energy.2014.02.109.

[9] P. Tafarte, S. Das, M. Eichhorn, D. Thrän, Small adaptations, big impacts: options for an optimized mix of variable renewable energy sources, Energy 72 (2014) 80–92, https://doi.org/10.1016/j.energy.2014.04.094.

[10] X. Sun, B. Zhang, X. Tang, B.C. McLellan, M. Höök, Sustainable energy transitions in China: renewable options and impacts on the electricity system, Energies 9 (12) (2016) 1–20, https://doi.org/10.3390/en9120980, 980.

[11] W. Zappa, M. van den Broek, Analysing the potential of integrating wind and solar power in Europe using spatial optimisation under various scenarios, Renew. Sustain. Energy Rev. 94 (2018) 1192–1216, https://doi.org/10.1016/j.rser.2018.05.071.

[12] W. Zappa, M. Junginger, M. van den Broek, Is a 100% renewable European power system feasible by 2050? Appl. Energy 223–234 (2019) 1029–1050, https://doi.org/10.1016/j.apenergy.2018.08.109.

[13] IRENA, A Word on Low Cost Renewables - The Renewables Breakthrough - How to Secure Low Cost Renewables [Online], The International Renewable Energy Agency, 2018. Available, https://www.agora-energiewende.de/fileadmin2/Projekte/2018/A_word_on/Agora_Energiewende_a_word_on_low-cost-renewables_WEB.pdf. (Accessed 16 October 2019).

[14] F. Wiese, I. Schlecht, W.D. Bunke, Cl Gerbaultet, L. Hirth, M. Jahn, F. Kunz, C. Lorenz, J. Mühlenpfordt, J. Reimann, W.P. Schill, Open power system data – frictionless data for electricity system modelling, Appl. Energy 236 (2019) 401–409, https://doi.org/10.1016/j.apenergy.2018.11.097.

[15] S. Pfenninger, I. Staffell, Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data, Energy 114 (2016) 1251–1265, https://doi.org/10.1016/j.energy.2016.08.060.

[16] OPSD, A Free and Open Data Platform for Power System Modelling [Online], Open Power System Data, 2019. Available: https://open-power-system-data.org/. (Accessed 20 August 2019).

[17] Julia, The Julia Programming Language, Version 1.1.1 [Online], The Julia Project, 2019. Available: https://julialang.org/. (Accessed 22 August 2019).

[18] Lazard, Levelized Cost of Energy Analysis V12.0 [Online], Lazard LLC, 2018. Available: https://www.lazard.com/. (Accessed 20 August 2019).

[19] NREL, Renewable Energy Cost Modeling: a toolkit for establishing Cost-Based incentives in the United States [Online], National Renewable Energy Laboratory, 2011. Available: https://www.nrel.gov/docs/fy11osti/51093.pdf. (Accessed 29 September 2019).

[20] P. Noothout, D. de Jager, L. Tesnière, S. van Rooijen, N. Karypidis, R. Brückmann, F. Jirouš, B. Breitschopf, D. Angelopoulos, D. Doukas, I. Konstantinavičiūtė, G. Resch, The impact of risks in renewable energy investments and the role of smart policies, DiaCore (2016). Available: http://diacore.eu/images/files2/WP3-Final%20Report/diacore-2016-impact-of-risk-in-res-investments.pdf. (Accessed 10 June 2020).

[21] Wood Mackenzie, Portugal's World Record-Breaking Solar PV Auction [Online], Wood Mackenzie, 2019. Available: https://www.woodmac.com/press-releases/portugals-world-record-breaking-solar-pv-auction/. (Accessed 7 June 2020).

[22] S. Auer, J. Liße, S. Mandha, C. Horn, Hybrid microgrid planning using selected Open-Source frameworks [Online], Energynautics GmbH (2019). Available: http://hybridpowersystems.org/wp-content/uploads/sites/13/2019/06/6B_2_HYB19_029_presentation_Auer_Sabine.pdf. (Accessed 28 September 2019).

[23] EuroStat, Supply, Transformation and Consumption of Electricity - Annual Data [Online], European Commission, 2019. Available: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_105a&lang=en. (Accessed 18 February 2019).

[24] IRENA, Renewable Energy Statistics 2018 [Online], The International Renewable Energy Agency, 2018. Available: https://www.irena.org/publications/2018/Jul/Renewable-Energy-Statistics-2018. (Accessed 18 February 2019).

Markus Groissböck is a doctoral student of Energy Systems Engineering at the Institute for Construction and Materials Science, Unit of Energy Efficient Buildings, University of Innsbruck. In 2009, he earned a Bachelor degree in Energy Economics from the University of Applied Sciences Kufstein, Austria, as well as a Master degree from the University of Applied Sciences Burgenland, Austria, and a Master degree from the University of Liverpool in Sustainable Energy Systems and Operations and Supply Chain Management (Oil and Gas), UK, in 2011 and 2016, respectively. His research interests lie in medium- and long-term investment planning within the power and energy sector considering distributed and variable energy resources on district and regional level.

Paper 3

Applied Energy 277 (2020) 115567

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Impact of renewable resource quality on security of supply with high shares of renewable energies

Markus Groissböck[a,*], Alexandre Gusmão[b]

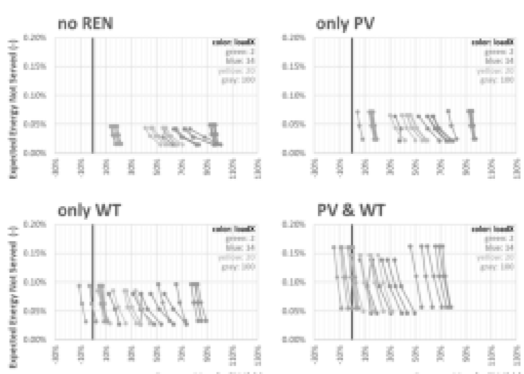
[a] University of Innsbruck, Institute for Construction and Materials Science, Innsbruck, Austria
[b] Alexandre Gusmão, Lisbon, Portugal

HIGHLIGHTS

- Consider different renewable profile qualities.
- Assess different levels of renewables power contribution.
- Avoid weather bias by using multi-year data sets.
- Identify reserve margin requirements towards 100% renewable power.
- Locations with good renewable energy resources might end with reduced reserve margins.

GRAPHICAL ABSTRACT

Change of RM vs. EENS with different renewables additions, keeping LOLH between 1 and 3.



ARTICLE INFO

Keywords:
Renewable energy sources
Generation expansion planning
Reliability
Expected energy not served
Loss of load hours

ABSTRACT

Globally, renewable energy sources (RES) are getting more and more competitive even without subsidies. In general, optimization methods are used to identify the most economic setup of individual power systems. This study contributes to the discussion on how much reserve capacity a power system should have to ensure reliable electricity supply in assessing the explicit and probabilistic system reliability metric loss of load hours (LOLH) as well as expected energy not served (EENS) within a dynamic programming approach. Multi-year RES profiles from different locations are used to identify the minimum reserve margin (RM) requirements using LOLH and EENS as planning criterions. The findings indicate, that using RM as the only reliability constraint within optimization is not appropriate as a too high assumption on RM would increase the required conventional generation capacity unnecessarily and a too low assumption would risk reliable power supply. Using LOLH as the single metric for reliable power system planning, the EENS would grow with increasing RES contribution. This is the result due to the concept of LOLH as the amount of electricity not supplied is not part of the metric, only the hours of power undersupply are. On the other hand, a constant assumption of EENS is misleading as well as the concept of EENS does not consider the number of hours the power service can't be fulfilled. Therefore, the recommendation is to use LOLH and EENS simultaneously in a single optimization framework as shown within this study.

* Corresponding author.
E-mail addresses: markus.groissboeck@student.uibk.ac.at (M. Groissböck), lapas.gusmao@gmail.com (A. Gusmão).

https://doi.org/10.1016/j.apenergy.2020.115567
Received 20 January 2020; Received in revised form 4 May 2020; Accepted 18 July 2020
Available online 27 July 2020

1. Introduction

Fluctuating renewable energy (Solar Photovoltaic and Wind) is currently cost competitive with new build conventional power generation in large parts of the world [1]. In addition, policy support towards decarbonization of power is driving uptake even in areas that are not as cost competitive. Generation expansion planning (GEP) in its nature is a nonlinear dynamic problem to be solved under given restrictions and constraints [2]. In general, the purpose of GEP is to minimize required investment for new generation capacity and operational costs, including fuel costs to maximize the power plant owner's profit under a defined reliability metric target. The role of renewable energy sources (RES) in mitigating fuel consumption is well-known. Also, the additional role of RES in contributing to the peak demand fulfillment of the power system, or in other words, avoiding additional conventional power plants to be built for fulfilling the same peak demand is quite well understood. Peak demand fulfillment is measured by the effective load carrying capability (ELCC) of the added RES capacity [3,4]. It is known that the ELCC from RES lessens as its penetration of the system's capacity increases. Therefore, it is important to understand the cost compromise between the savings on fuel with increasing penetration, and the ELCC of the additional capacity added under the same reliability target [5].

Each and every energy system is assessed in the triangle of energy security (guided through policies and regulation), finance (directed through economics), and climate change mitigation (steered through environmental impact assessments) to reach energy justice (led through law and policies) [6]. Security of supply is the availability of power generation to satisfy customers demand at most or at all moments [7]. Nonlinear reliability measure as e.g., loss of load hours (LOLH) cannot be considered in traditional optimization approaches (e. g., linear programming) [8]. Therefore, open source optimization models use indirect reliability measures such as expected energy not served (EENS) or reserve margin (RM). By doing so it is implicit assumed that the security of supply is fulfilled for the assessed system. What is still missing is a deep understanding on how the resource quality of RES does impact system reliability measures such as EENS, RM and how to use such measures in optimization frameworks.

Consequently, this study contributes to the state-of-the-art open source generation expansion planning in adding the probabilistic dimensions (measured in a) LOLH, expressed in hours/year, sometimes also known as loss of load expectation (LOLE), and EENS, expressed in annual energy not delivered, expressed in percent of annual energy demand) in a dynamic programming framework. Hereby, a reliability constrained least-cost GEP is completed for several European countries to identify the capability of different renewable resource quality towards power system reliability participation.

The structure of the remaining study is as follows: Chapter II contains a literature review assessing traditional reliability criteria and best practices in power system studies. Chapter III includes the methodology discussing the least-cost generation expansion planning considering a dynamic programming approach. Chapter IV presents the considered case study based on several European countries. Chapter V and Chapter VI contains a discussion and conclusion around the finding out of the case study, and Chapter VII suggests possible enhancement options for future work.

2. Literature review

The total system life cycle costs of a power system should consider socioeconomic costs, emerging from the potential costs raised by society over the periods of non-served energy by the system. Therefore, Billinton & Allan defines two main approaches to estimate the socioeconomic costs caused by interrupted power service: implicit and explicit [9]. In the explicit approach, two points of views for the cost of interruptions are common: (i) point of view of the user, which implies that the cost of interruptions may vary widely among consumers' type, and (ii) point of view of the utility, which may indicate a loss of revenue from load not served and/or potential loss of future sales due to customers' reaction to low service reliability [10], or additional penalties from regulation authorities for reliability targets not being met.

Based on Li, transmission expansion planning (TEP) is traditionally grounded in probabilistic assessments, while this is not always the case for GEP [11]. In almost all optimization approaches, security of supply is covered implicitly through hourly profiles of energy demand and renewable power generation, an explicit assumption of an RM and/or expected energy not served (EENS). Unfortunately, this approach does not cover the hourly probabilistic reliability aspect within GEP in comparison with TEP.

Phoon specify common explicit criteria as, e.g. expected energy not served (EENS, expressed in MWh/year) and loss of load frequency (LOLF, expressed in occurrences/year) [12]. EENS represents the sum of energy not served, LOLF represents the number of hours the required energy cannot be supplied as requested. While the criteria EENS is not able to provide any information on how often energy cannot be supplied, LOLF does not add insights into how much energy cannot be provided within a specific period of time. On top of theses disadvantage both criteria do not provide any information on the probabilities of occurrence. Simulation tools such as HOMER, and ENERGYPLAN do ignore such measures as they assume that electricity which is not generated within the boundary of the assessed power system can be purchased from outside easily [13 14]. The measure LOLF cannot be replicated in linear programming (LP). Therefore, well-known optimization tools like DER-CAM, and PyPSA do not considering any of these explicit approaches [15,16].

Augutis et al. highlights that in general there is only one criterion considered in economic-optimization models: cost [17]. They argue that energy security has to be considered above economic considerations as the availability of power is crucial in today's society and economy. They indicate that the case study results are very sensitive towards system size and specificity of the assessed system. The authors added more details to the Open Source Energy Modelling System (OSeMOSYS) to incorporate security of supply. The authors introduced the define their own key performance indicator (KPI): the energy security coefficient (ESC, between 0 and 1). The ESC incorporates the EENS, the cost increase, and how long the disturbance lasted. An ESC from 1 is a perfect resilience system where a disturbance has no impact on energy prices as well as energy supply quality. Unfortunately, they do not assess the importance of RES quality over time.

DeCarolis et al. drafted a guidance paper on how energy system optimization models (ESOMs) should be used to optimize their outcomes based on their collective modelling experience [18]. Two of their guiding principles are (a) "make the analysis as simple as possible and as complex as necessary", and (b) "re-evaluate the modelling approach and objectives throughout the analysis". While state-of-the-art open source optimization frameworks are using RM and EENS they do not assess the individuality of the system, nor do they validate their input assumptions in that regards. This es exactly where this study adds its value as multi RES qualities are assessed in a combined RM-EENS-LOLH approach.

Newell et al. show a generic view on how the reserve margin (RM) correlates with the system reliability (measured in LOLH) as well as the expected energy not served (EENS) (measured in percent of annual power demand, also known as expected unserved energy, EUE) (see Fig. 1) [7]. The RM defines how much the total installed power plant fleet, including all types of dispatchable power generation technologies, should be above the expected peak demand to guarantee a reliable and secure power operation under 'all' circumstances. As mentioned above, RES does contribute to RM in some way. Unfortunately, their publication does not shed light on the impact of high shares of renewables towards required RM as well as towards EUE.

Priesmann et al. assesses when to use simple and when to use more

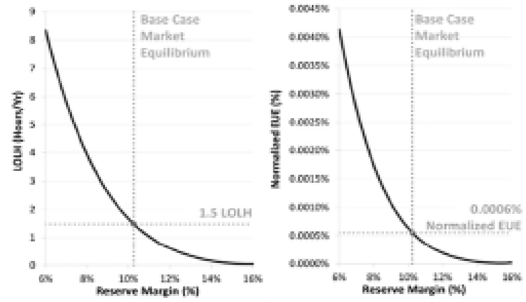


Fig. 1. Varying reliability metrics (LOLH, EUE) with reserve margin [7].

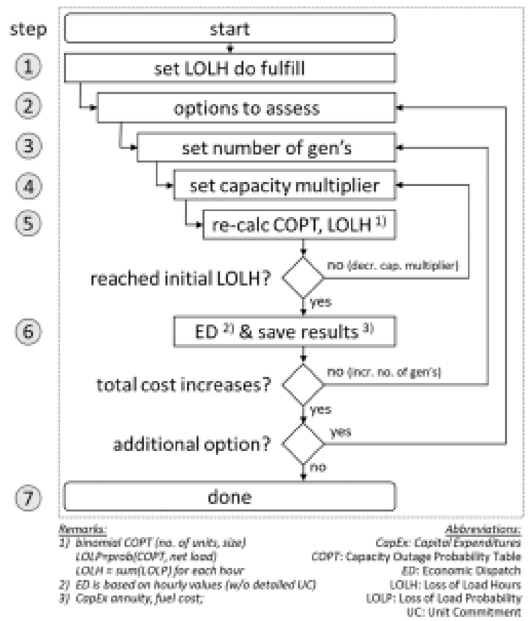


Fig. 2. Methodology [5].

complex optimization models [19]. They assess if there is a positive correlation between model complexity and result accuracy. There finding is that within power system optimization a certain degree if complexity is required for accurate results. Nevertheless, good balance

Table 1
Country list and considered rationale.

Country Code	Country Name	Solar PV Quality	Wind quality
CY	Cyprus	++	–
CZ	Czech Republic	–	–
NO	Norway	–	++
PT	Portugal	++	++

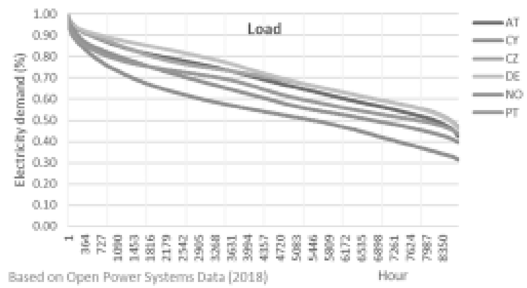


Fig. 4. Average load duration curves [22].

Table 2
Demand KPIs (based on [22]).

KPI (–)	AT	CY	CZ	DE	NO	PT
Peak-to-Base	2.34	3.17	2.14	2.16	2.52	2.29
Peak-to-Average	1.44	1.78	1.41	1.38	1.59	1.53
Average	0.70	0.56	0.71	0.73	0.63	0.65
Base	0.43	0.32	0.47	0.46	0.40	0.44

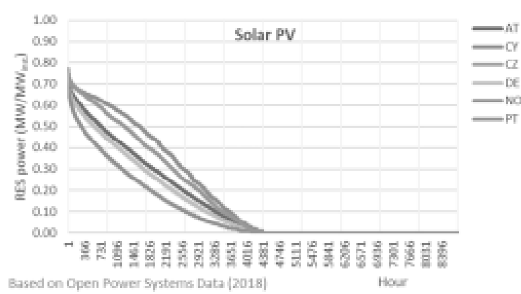


Fig. 5. Average Solar PV duration curves (based on [22]).

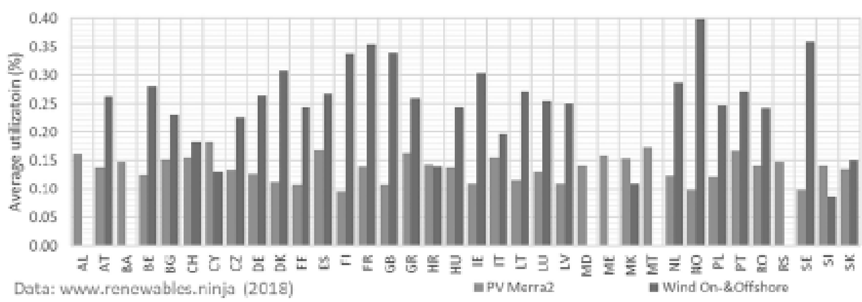


Fig. 3. Long-term average capacity factors of Solar PV and Wind [27,28].

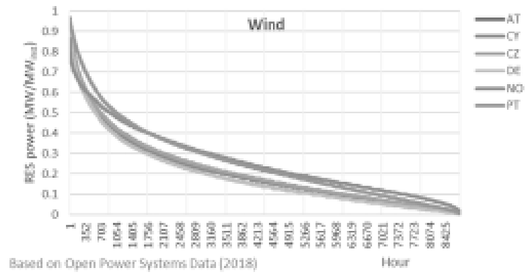


Fig. 6. Average Wind duration curves (based on [22]).

Table 3
RES KPIs (based on [22]).

KPI (–)	AT	CY	CZ	DE	NO	PT
FLH Solar PV	0.14	0.18	0.13	0.13	0.10	0.17
FLH Wind	0.21	0.21	0.21	0.19	0.26	0.26
Avg-to-peak Solar PV	0.19	0.24	0.18	0.18	0.14	0.22
Avg-to-peak Wind	0.23	0.22	0.23	0.20	0.31	0.27

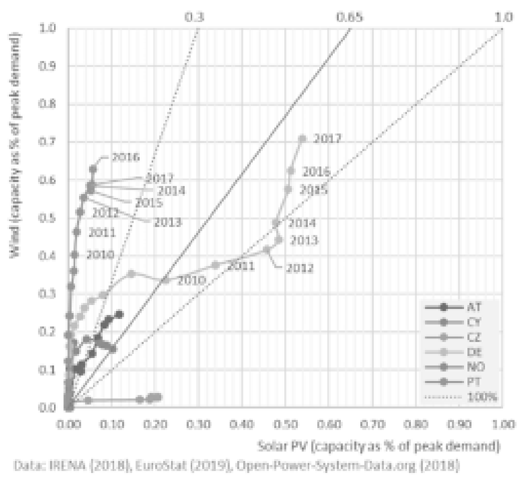


Fig. 7. Wind & Solar PV vs. peak demand progress [22,30,31].

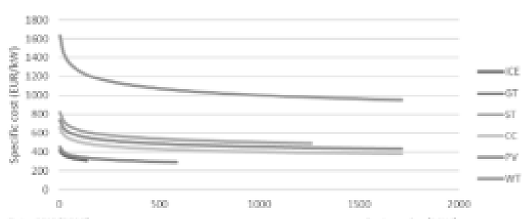


Fig. 8. Assumptions for specific costs [37,38].

between data requirements and data quality together with model complexity should be considered. Unfortunately, the assessed case study does not assess the impact of RES quality as well as security of supply KPIs.

Seck et al. incorporates short-term power system operation constraints into GEP in a case study of France [20]. The authors add a

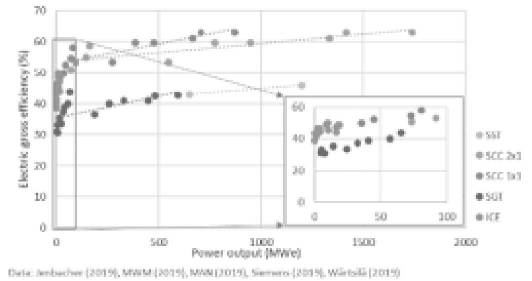


Fig. 9. Assumptions for electric efficiencies [32–36].

reliability KPI related to kinetic reserves into the optimization model TIMES-FR. They assess the power system grid stability within an electricity share of 65% out of RES. The result indicates that around 55% of the entire flexibility demand should be fulfilled by conventional power generations such as combined cycle gas turbines. Unfortunately, the authors do not assess the importance of RES quality while the kinetic reserve discussion is out of the scope of the authors of this study.

In the implicit approach, perhaps the most traditional method, a comparison of various expansion alternatives is studied under the assumption that each of the alternatives is able to provide the same level of reliability criterion (e.g. LOLH = 1 h/a). This means there is an implicit socioeconomic cost associated to the selected criterion. In this study, the implicit approach is used. Variations on the reliability criterion mean different implicit socioeconomic costs of power interruptions. Therefore, to assume, for instance, a higher LOLH criterion for the expanded system implies a lower socioeconomic cost implication due to power interruptions and vice versa. The socioeconomic cost should be part of GEP and, therefore, within the cost minimization process. This would incorporate the socioeconomic costs into all costs and, therefore, be part of the total system costs. This would consider the expected non-served energy costs with the potential losses from social benefits as well as required investments and fuel and maintenance costs. Social benefits are, in its simplest way and ignoring the differences in customer segments, measured as a fraction of the gross domestic product divided by the total energy demand throughout the year [14]. This is a simple approach to estimate the value of lost load (VOLL) indicator. CEPA argues that a more accurate way of estimating VOLL would be based on customers' willingness to pay for reliable energy supply or the loss of value from loss of supply [21]. Of course, different customer segments in different countries and different individual customers would need different VOLL estimates to reflect their specific situations.

3. Methodology

Stimulated by Newell et al. [7], this study assesses the security of supply through a dynamic programming approach, in which the reserve margin (RM) and expected energy not served (EENS) are results to fulfill the predefined reliability level expressed in loss of load hours (LOLH). To support medium- and long-term aspects of GEP, the assessment includes:

- multiple years of data [22],
- normalized demand profiles,
- different quality of renewables based on historical renewable profiles (low Solar PV/low Wind, low Solar PV/high Wind, high Solar PV/high Wind, and high Solar PV/low Wind),
- variations of RES capacity (0 and 200% of peak demand),
- different levels of system reliability (in LOLH, between 0 and 10) [23],
- different system sizes (10 to 100,000 MW system sizes).

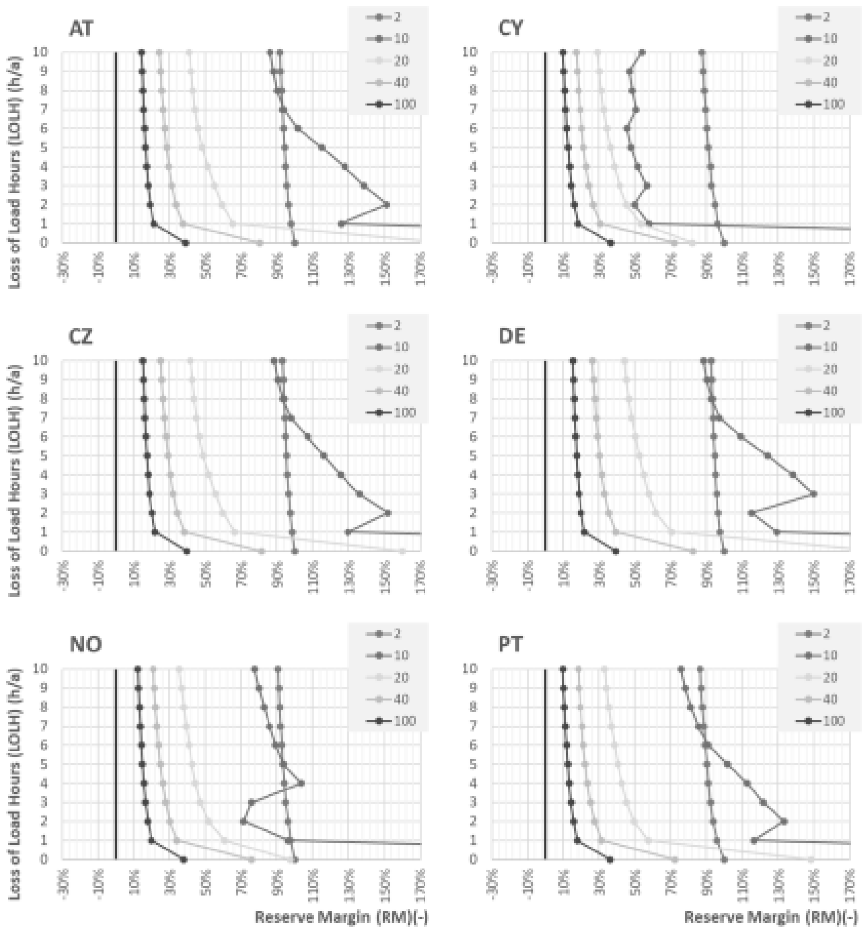


Fig. 10. RM vs. LOLH results without any RES.

The overall program logic shown in Fig. 2 has been implemented in the programming language Julia [24].

Step 1 is to select the first system reliability target to assess (LOLH, measured in hours/year, starting from 0). Based on the available data set, Step 2 selects the first option to assess (e.g., no RES with a load multiplier of 0.01). Step 3 and 4 are initializing the number of units to be considered (starting with 0) and the maximum allowed capacity multiplier (starting with 15) to calculate the initial situation without RES in Step 5. Subsequently, and as long as being above the targeted system reliability, the capacity multiplier is decreased. If the required system reliability is reached, a simplified economic dispatch is done, and the result is saved (Step 6). As soon as the total system is increasing, the processing of the current option is finished. If there is an additional option to assess (LOLH $\leq$ 10), the program does continue with the next option (in Step 3, increase LOLH by 1). Otherwise, the simulation is finished after all options to be assessed are calculated.

In the case of the presence of RES, net load should be considered as the input for the LOLH convolution instead of load (see Eq. (1)) [22].

$$Load_{net,t} = Load_t - RES_t \tag{1}$$

where $Load_{net,t}$ is the net load for hour t (in MWh), $Load_t$ as load without any RES contribution at hour t (in MWh), and RES_t with the RES contribution at hour t (in MWh).

Maintaining the current LOLH expectation, e.g., the power generation interruption risk level, is the core assumption behind probabilistic GEP. Therefore, the initial task is to calculate a system's LOLH for an initial generation fleet and the peak load to fulfill. Subsequently, additional LOLH's are calculated assuming different RES additions. After adding new RES generation, the need for conventional generation in comparison to the original system is reduced while fulfilling the same system reliability.

Solar PV and Wind are seen as key within future energy scenarios [25]. These resources – sun shine and winds – are available globally. Other resources, such as hydropower or geothermal power, are based on special environmental requirements (like hills or special soil) and are therefore not included in this assessment. Also, the contribution of hydropower and geothermal power towards the total energy system is quite limited in its technical and economic potential. A similar argumentation is valid for wave energy, biomass, and waste-to-energy.

LOLH does cover the risk of not being able to fulfil the customers energy demand in a probabilistic way. As the aim of this study is not to explore additional kind of uncertainties and risks or to do an exhaustive risk analysis (including identifying all possible risk factors related to power generation such as economics risks, hydrological risks,

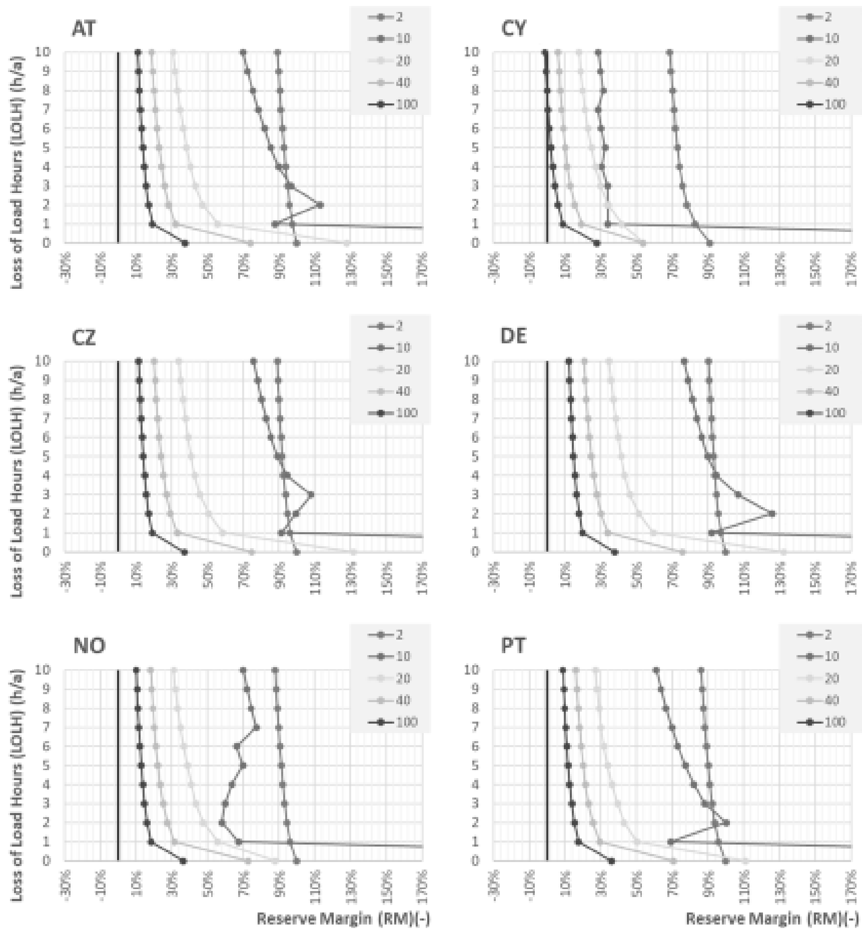


Fig. 11. RM vs. LOLH results with Solar PV.

engineering risks, human risks, or social risks) [26]. Also, additional benefits such as being able to generate more power as required is not considered here.

4. Case study

Based on the discussed methodology, the case study assesses the selected countries' RES quality conditions and the impact of multi-year RES profiles together with their respective demand profiles.

4.1. Assumptions

Historically measured hourly time series for load, weather, and RES profiles are based on open-power-system-data.org and renewables.ninja, which provide data as open source [22,27,28]. Fig. 3 shows the average capacity factors of Solar PV and Wind for the entire data set of more than 30 countries.

Based on these data, this study defines conditions with special combinations of Solar PV and Wind qualities. Therefore, specific countries are selected to represent different RES quality conditions ('++': very good, '−': very bad RES quality) (see Table 1):

Besides these countries, Austria has been added because of the location of the University of Innsbruck, and Germany has been added as it is one of the main countries within Europe under discussion regarding renewables integration and energy exchange with its neighboring countries. For Austria (AT), Czech Republic (CZ), Germany (DE), and Portugal (PT), the public available time series starts in 2006, for Norway (NO) in 2010, and for Cyprus (CY) in 2013; all data end in 2016 [22]. To avoid annual biases, but still consider the meteorological differences from year to year, the entire time series (e.g., 2006–2016 for AT) was used as a whole instead of individual years. For this study, each year of the demand profiles has been scaled to a peak demand of 1000 MW to assess the impact of seasonal demand and renewables profile variation instead of the individual demand profiles' growth.

While the peak demand for all assessments is assumed to be equal, Fig. 4 and Table 2 show the differences in terms of load duration curves (LDC) as well as some common KPI used in power system planning. In 2017, the peak demand for the assessed countries (AT, CY, CZ, DE, NO, PT) was 12, 1, 11, 79, 23, and 9 GW, respectively [22]. Therefore, harmonized power demand cases (between 0.01 and 100 GW) are assessed.

The average LDC based on data from CY shows the highest seasonal swing within the assessed data set as cooling demand is high in summer, but there is no or limited electric heating demand in winter.

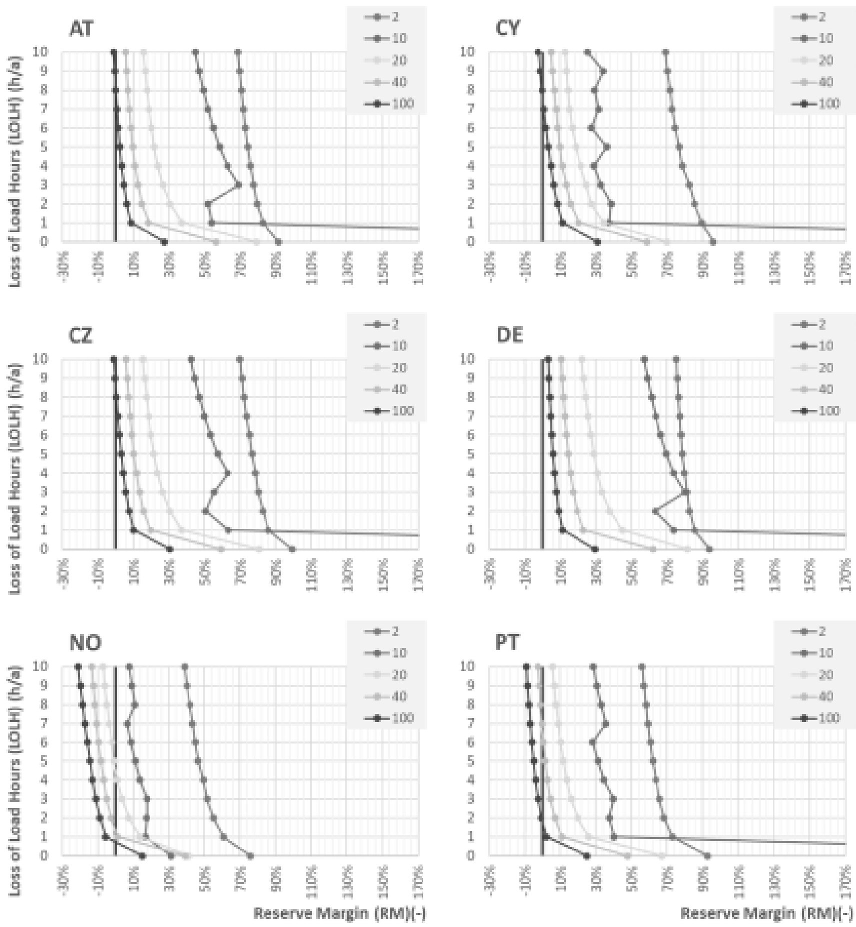


Fig. 12. RM vs. LOLH results with Wind.

The LDC for DE shows the lowest seasonal swing as heating and cooling is traditionally not powered by electricity in DE. Heating demand is usually covered either through district heating systems (with, e.g., biomass or coal) or through individual natural gas boilers.

Figs. 5, 6, and Table 3 show the RES duration curves for the selected countries as well as the average full load hours (FLH) (also known as utilization rate) of the considered RES profiles.

There is a significant difference within the considered Solar PV profiles (Fig. 5), while the considered Wind profiles seem more comparable (Fig. 6). One reason might be that the shown average RES duration curves are averaged over the available period of times (e.g., for AT between 2006 and 2016). It would also imply that the Wind resources are more equally distributed throughout Europe while the quality of Solar PV depends more on the latitude of the country of interest.

The KPI FLH is based on the average power generation for the individual RES profile. It is not considered that Solar PV usually has DC-AC power conversion losses as well as a temperature-dependent power production efficiency. Therefore, the power generation through Solar PV is always lower as −80% of the installed capacity, while Wind reaches close to its full power output.

Fig. 7 shows the installed capacity of Solar PV and Wind vs. the countries' peak demand for the years 2000 until 2017 for all considered countries. Based on Groissböck, the grey line (starting at 0.0/0.0 and reaching 0.65/1.0) represents the ideal mix of RES with the lines to the left as well as to the right show the bandwidth of optimal RES expansion [29]. The ideal mix reveres to the RES mix with minimum curtailment as described in detail in [29].

In general, AT, CY, and DE show a very good fit towards the optimal RES expansion mix. CY sees a stagnation in its Solar PV additions compared to power demand growth. Until today, PT mainly concentrates on Wind while CZ mainly focuses on Solar PV additions. In general, non-optimal solutions exist as a result of market biases of individual technologies or the use of policy instruments (e.g., feed in tariffs, FiT) favoring one technology for individual reasons (e.g., 'kick-starting' a domestic industry, supporting employment programs).

Fig. 8 shows the considered specific costs, while Fig. 9 shows the considered efficiencies as a function of unit size. The maximum allowed sizes for the individual technologies are 80, 593, 1200, and 1740 MW for ICE, GT, ST, and CC, respectively [32–36].

The forced outage rate (FOR) of the conventional generators is assumed to be 10%, including the required maintenance and the startup-reliability.

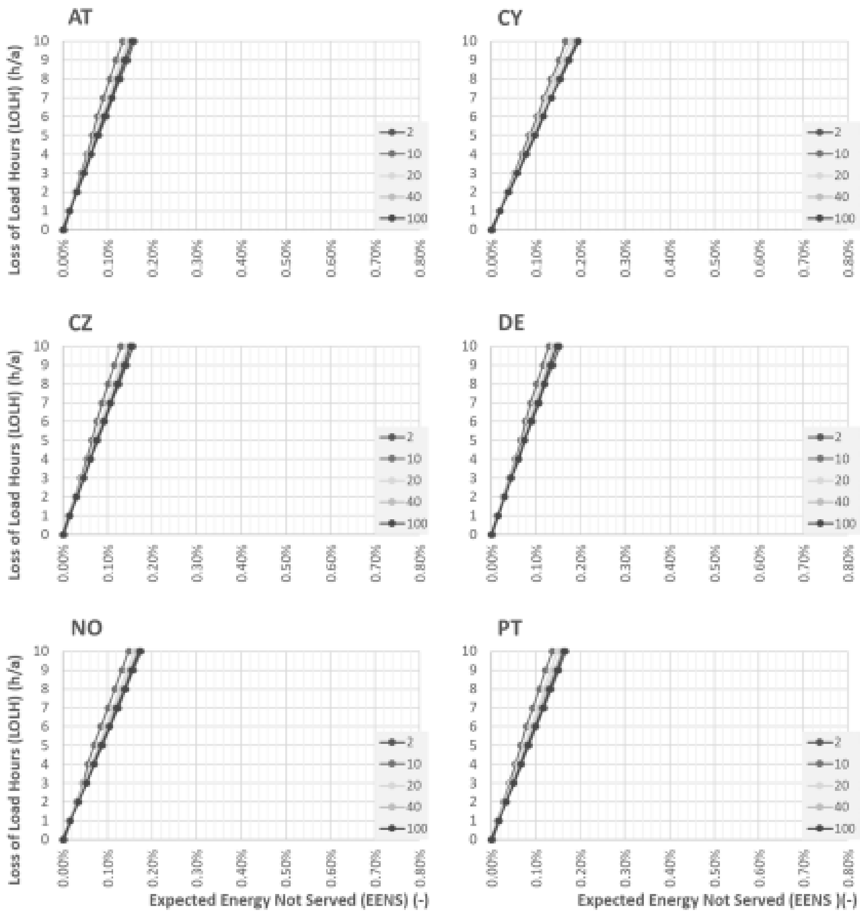


Fig. 13. EENS vs. LOLH results without RES.

4.2. Results

As already mentioned in the methodology section, this study shows the results for the considered countries to identify the impact of very large RES penetration of up to 200% compared to its peak demand towards RM requirements.

Figs. 10 and 12 show individual results in each graph as results of all individual runs combined per country (in ascending order) where each dot represents an individual run. The horizontal axis shows the RM (in percent), and the vertical axis shows the LOLH (in hours per year). Each line represents one of the assessed system sizes (as multiples of 1000 MW). The red horizontal line indicates the position of 0% RM. The case 'no RES' represents the pure conventional setup ignoring any RES. While the case 'only PV' considers 200% of Solar PV (and no Wind), the case 'only Wind' incorporates 200% Wind (and no Solar PV) generation. The case 'PV & WT' represents the incorporation of 200% of Solar PV as well as 200% of Wind generation at the same time.Fig. 11.

Figs. 13–15 show individual results per graph as results of all individual runs combined per country. The horizontal axis shows the EENS (in percent of total power demand), and the vertical axis shows the LOLH (in hours per year).

5. Discussion

5.1. Limitations of the Methodology

Before the results are discussed, Table 4 highlights the limitations of the methodology to add more clarity to the examination. Most limitations do not have a significant impact on the results or are not the main focus of this study but do represent a list of considerations for upcoming studies.

5.2. Discussion and findings

Tables 5 and 6 show the summary for RM and EENS for all assess sizes. The grey cells indicate the largest and orange the smallest values within the individual columns, respectively.

This summary of all cases shows very clearly that it is not possible to assume one single RM for all different demand profile cases. Within the case 'no RES', the RM is between 45% and 68% to fulfill the system reliability requirements. For typical LOLH expectations of 1 and 2 h/a, Figs. 10–12 show that smaller systems need up to 272% RM while large systems need about 17% RM (−1.7*FOR). The possible RM reduction through adding Solar PV or Wind results in between 6% and 22% or 18% and 49% lower RM requirements. While Wind can reduce the RM

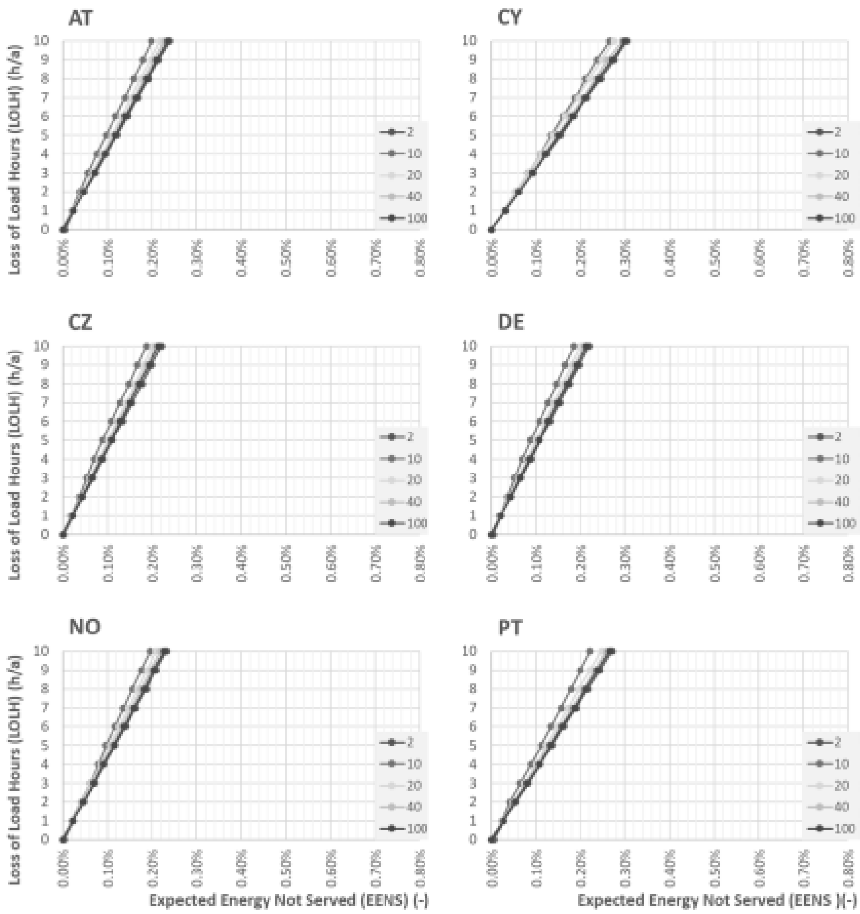


Fig. 14. EENS vs. LOLH results with Solar PV.

much more than Solar PV, there is again no pattern on how one single RM would be defined. Combined Solar PV and Wind is able to reduce the RM by between 38% and 54%. This shows clearly that using RM as an assumption for optimization is not appropriate. A too high assumption on RM would increase the required conventional generation capacity unnecessarily.

The decrease in RM between the 'no RES' cases and the 'only PV' cases are mainly between 0% and 30% for all assessed cases; except CY, where the decline on RM is between 10% and 30%. The reduction in RM between the 'no RES' cases and the 'only Wind' cases are mainly in the range of 10% and 30%; only NO shows a drop between 30% and 50%. The decrease in RM between the 'no RES' case and the 'PV & WT' case is mainly between 20% and 50%; only NO shows reductions of between 30% and 60%. These changes in RM are the result of LOLH $\geq$ 1, as for LOLH = 0, the changes can be as high as 513%.

The decrease in RM requirements in the 'only WT' cases is in all countries higher than in the 'only PV' while the 'PV & WT' case is always higher than the 'only WT' case. Interestingly, the differential RM reduction between the 'only WT' and the 'PV & WT' case is always higher than the 'only PV' case. This means that adding Solar PV and Wind at the same time always improves the RM reduction potential (independent of whether the quality of Solar PV or Wind is better). This is because the combination of Solar PV and Wind always has a better fit towards the residual demand curve than Solar PV or Wind only.

Within the case 'no RES', the EENS is between 0.08% and 0.10% to fulfill the system reliability requirements. The system size has no significant impact on the EENS to expect. The 'no RES' case shows EENS between 0.013% and 0.020%. Adding Solar PV or Wind increases the EENS by 0.019% and 0.032%, respectively. Within the assumptions of this study the EENS increase can be linearized by multiplying the EENS with LOLH = 1, with the aspired LOLH for the assessed power system (e.g., LOLH = 2 results in 0.038% and 0.064% for Solar PV and Wind). Adding Solar PV and Wind at the same time increases EENS to 0.035% and 0.087%. As this clearly shows, when using LOLH as an assumption for optimization, the EENS will grow with increasing RES capacity installed. This is because LOLH does not cover the amount of non-supplied electricity. On the other side, a stringent and constant assumption of EENS would be too constraining for the GEP.

Table 7 shows the decrease in FLH as an additional result of this study. The values represent the average full load hours of the installed conventional generation and as such the smaller the value the greater the reduction in FLH for conventional plant.

The highest FLHs can be found for DE as DE's normalized power demand (see Fig. 4) is the highest one of the assessed cases. As the RES quality is only average, there is no change to overcome this burden without installing additional RES capacity above the 200% peak

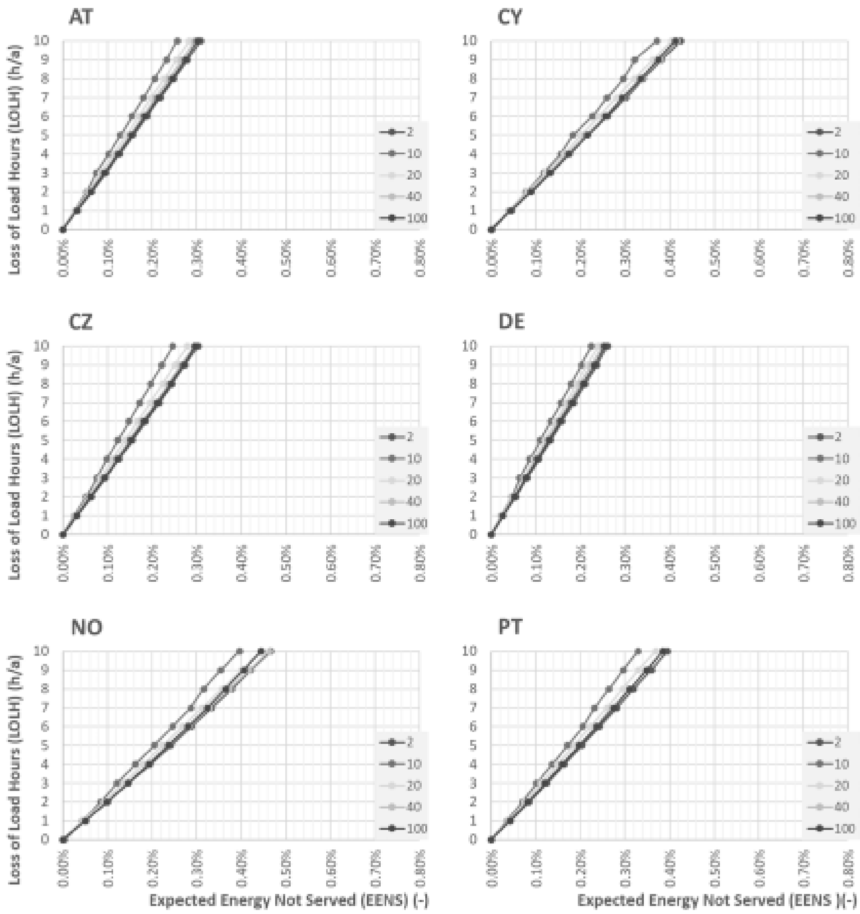


Fig. 15. EENS vs. LOLH results with Wind.

Table 4
Limitations and explanations.

Limitation	Explanation
• Only individual country perspectives have been considered without transmission and distribution (T&D) limitations within the country itself ('copperplate approach'),	• RES placing is not the aim of this study,
• No inter-country power exchanges are considered,	• Finding optimal locations is not the aim of this study,
• RES profiles always show the same hourly production pattern independent from RES penetration,	• RES profiles are the sum of hundreds of RES projects, • Finding optimal locations is not the aim of this study,
• RES and demand profiles are historical time series,	• The change of profiles is not the aim of this study,
• RES costs and financing parameters are assumed to be the same in all countries,	• The overall economics are not the focus of this study,
• Potential for Solar PV and Wind is assumed to be at least twice the peak demand,	• Potential assessment is not the focus of this study,
• Pure Solar PV and Wind expansion is considered although other RES technologies such as Hydropower or Biomass, are available as well,	• Overall optimal renewable mix is not the focus of this study,
• Storage solutions have not been considered,	• Storage sizing and placing is not the aim of this study,
• Only electricity demand is considered,	• Heat, cold, and other end-uses are not the focus of this study,
• Unit commitment and economic dispatch principles, as well as other technical details (e.g., up/down ramp rates, min. up/down time), are not considered.	• Thermal power plant GEP is not the aim for this study.

Table 5
Median RM per country and case.

Case Country	No RES	Only PV	Δ no RES	Only WT	Δ no RES	PV & WT	Δ no RES
AT	64%	49%	−15%	34%	−30%	16%	−48%
CY	45%	23%	−22%	26%	−18%	7%	−38%
CZ	65%	53%	−12%	30%	−35%	20%	−45%
DE	68%	53%	−15%	44%	−24%	24%	−44%
NO	54%	48%	−6%	5%	−49%	0%	−54%
PT	54%	44%	−11%	22%	−32%	9%	−45%
Avg.	58%	45%	−13%	27%	−31%	13%	−46%

Table 6
Median multiplier of EENS per country and case.

Case Country	No RES	Only PV	Only WT	PV & WT
AT	0.080%	0.120%	0.154%	0.262%
CY	0.098%	0.151%	0.219%	0.370%
CZ	0.079%	0.111%	0.152%	0.237%
DE	0.077%	0.110%	0.132%	0.203%
NO	0.088%	0.115%	0.242%	0.388%
PT	0.082%	0.135%	0.199%	0.411%
Avg.	0.084%	0.124%	0.183%	0.312%

Table 7
Median FLH per country and case.

Case Country	No RES	Only PV	Only WT	PV & WT
AT	42.3%	31.0%	24.1%	15.7%
CY	38.3%	25.3%	19.0%	11.4%
CZ	42.9%	32.5%	25.6%	16.9%
DE	43.1%	32.9%	27.1%	19.2%
NO	40.6%	31.8%	17.3%	11.2%
PT	42.1%	28.1%	19.3%	10.6%
Avg.	41.6%	30.3%	22.1%	14.2%

demand assumption (which is out of the current scope of this study). The highest reduction of FLH happens to be in the cases of CY, NO and PT, which are the countries with the best Solar PV and Wind qualities, respectively. The 'only Wind' cases reduce FLH significantly more than the 'only PV' cases. The lowest reduction of FLH can be observed in NO for the 'only PV' case and in DE for the two other cases.

Fig. 16 shows the results of four selected demand cases (load multiplier of 2, 14, 20, and 100) without differentiating the countries for a required system reliability (measured in LOLH, hours/year) between 1 and 3. The red line indicates no (0%) reserve margin (RM). Each group of colors represents one of the mentioned demand cases (country profiles). The visualization makes it obvious that there is no recognizable pattern within the different demand cases and RES/country qualities. Adding more RES into the power generation mix does increase EENS as the residual demand profiles gets more and more step like (instead of the usual smooth sinus like demand duration curve) and decreases RM slightly. Considering multi-year data of demand and RES profiles does not decrease the RM as much as indicated by other studies (between 7 and 29% with up to 30% RES contribution based on annual energy demand) based on single year of data [39]. The difficulty lies in predicting the amount of RM decrease for long-term GEP. As there is no pattern visible, the only recommendation at this point can be to assess LOLH and EENS for each GEP activity (characterized by e.g., system size, RES quality, RES penetration) individually.

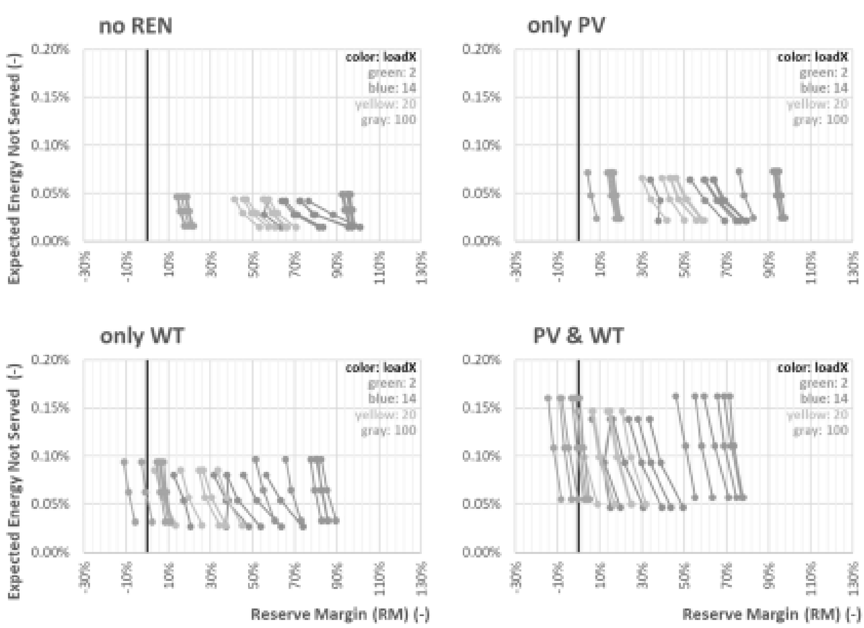


Fig. 16. Change of RM vs. EENS with different RES additions (1 ≥ LOLH ≤ 3).

6. Conclusion

Renewable energy sources (RES) are becoming more and more cost-competitive globally. Generally, optimization methods are used to identify the most economic setup of individual power systems given certain constraints. To the best of the author's knowledge, none of the available open-source energy optimization tools are able to consider socioeconomic costs in an explicit manner by assuming that non-supplied power has a predefined economic value. The explicit way is neither able to define in advance how long power cannot be supplied completely nor how much of electricity will not be supplied. Until today, most of the global electricity systems have limited contribution of RES. This study contributes to the discussion on how much reserve capacity a power system should have to ensure reliable electricity supply in assessing the explicit and probabilistic system reliability metric loss of load hours (LOLH) as well as expected energy not served (EENS).

The results highlight the complicated situation regarding assumptions around reserve margin (RM) and expected energy not served (EENS). In this study, Cyprus and Portugal are the countries with the best Solar PV quality, but their change in reserve margin with PV additions is very different. Cyprus results show the highest change, while the Portugal results show the second lowest change. Similarly, in the 'only WT' cases, Norway and Portugal are the countries with the best Wind quality, but also their change in reserve margin is very different with Wind additions. Norway shows the highest decrease in reserve margin, while for Portugal the change is about average with the other countries studied. The changes in reserve margin are on average: 9%, 29%, and 43% for the cases 'only PV', 'only WT', and 'PV&WT', respectively.

Looking into the changes in EENS also highlights a difficult picture: (a) within the 'only PV' cases, the change in EENS is between 0.005% and 0.010%, (b) within the 'only WT' cases, the change is between 0.010% and 0.028%, and (c) within the 'PV & WT' cases, the change is between 0.023% and 0.060%. The only pattern identifiable is that high-quality RES results in higher EENS. In the absence of storage capacities, the net load gets more and more step-like (instead of the usual smooth sinus like curve).

Therefore, using reserve margin as an assumption for optimization is not appropriate. A too high assumption on reserve margin would increase the required conventional generation capacity unnecessarily. Using LOLH as the single metric for power system planning, the EENS will increase with growing renewable capacity installed. This is because LOLH does not cover the amount of unsupplied electricity, it only counts the hours power can't be fulfilled entirely. On the other side, a stringent and constant assumption of EENS would be too constraining for GEP. Therefore, the recommendation is to use LOLH and EENS simultaneously to incorporate a proper reserve margin in a single optimization framework as done within this study.

7. Future work

Further research could incorporate large-scale storage (e.g., Pumped Hydro, Hydrogen) as well as small-scale prosumers (e.g., Battery Energy Storage) into the assessment to gain more insights into how much variability of renewable energy can be taken out with storage and as a result how much value it might provide. This would include an assessment of different energy storage charge and discharge algorithms to maximize such value as well as assess different grid stability supporting options [40]. Ideally these considerations should incorporate unit commitment, economic dispatch principles, and other technical details (such as up/down ramp rates, and minimum up/down time) to better reflect real-world conditions [16].

CRediT authorship contribution statement

Markus Groissböck: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Alexandre Gusmão:** Methodology, Validation, Formal analysis, Writing - review & editing.

Declaration of Competing Interest

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

Acknowledgement

Preliminary results of this research have been presented at the 13th Conference on Energy Economics and Technology (ENERDAY 2019) held at the TU Dresden (Germany) on April 12, 2019.

The author(s) gratefully acknowledge valuable comments and input from various anonymous reviewers during the review process, from visitors and participants at the ENERDAY 2019, as well as from colleagues within the University of Innsbruck, Institute for Construction and Materials Science, Unit of Energy Efficient Buildings.

References

[1] European Commission. 2030 Energy strategy. European Commission. Available: http://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/2030-energy-strategy [accessed 21 February 2019].
[2] Wogrin S, Centeno E, Barquin J. Generation capacity expansion in liberalized electricity markets: a stochastic MPEC approach. IEEE Trans Power Syst 2011;26:2526–32. https://doi.org/10.1109/TPWRS.2011.2138728.
[3] Caglar R. The effect of generation capacity expansion on the reliability indices. The Chamber of Electrical Engineers (UCTEA); 2015. Available: http://www.emo.org.tr/ekler/711ab32f69d23c5_ek.pdf [accessed 15 January 2019].
[4] Garver LL. Effective load carrying capability of generating units. IEEE Trans Power App Syst 1966;85(8):910–9. https://doi.org/10.1109/TPAS.1966.291652.
[5] Gusmao A, Groissböck M. Capacity value of photovoltaic and wind power plants in an isolated mini-grid in the Kingdom of Saudi Arabia, 2015 Saudi Arabia Smart Grid (SASG), 7–9 Dec. 2015; 2015. doi: 10.1109/SASG.2015.7449275.
[6] Heffron RJ, McCauley B. The concept of energy justice across the disciplines. Energy Policy 2017;105:658–67. https://doi.org/10.1016/j.enpol.2017.03.018.
[7] Newell S, Carroll R, Kaluzhny A, Spees K, Carden K, Wintermantel N, Krasny A. Estimation of the market equilibrium and economically optimal reserve margins for the ERCOT Region – 2018 Update. The Brattle Group; 2018. Available: http://www.ercot.com/content/wcm/lists/143980/10.12.2018_ERCOT_MERM_Report_Final_Draft.pdf [accessed 5 May 2019].
[8] Neumann F, Brown T. Heuristics for transmission expansion planning in low-carbon energy system models. In: 16th International conference on the European Energy Market (EEM 19), 18–20 September 2019, Ljubljana, Slovenia; 2019.
[9] Billinton R, Allan RN. Reliability evaluation of power systems. 2nd ed. New York: Springer; 1996.
[10] Shipley RB, Patton AD, Denison JS. Power reliability cost vs. worth. IEEE Trans Power App Syst 1972;PAS-91(5). https://doi.org/10.1109/TPAS.1972.293204.
[11] Li W. Probabilistic transmission system planning. New Jersey: John Wiley & Sons Inc; 2011.
[12] Phoon HY. Generation System Reliability Evaluations with Intermittent Renewables. University of Strathclyde; 2006. Available: http://www.esru.strath.ac.uk/Documents/MSc_2006/phoon.pdf [accessed 13 January 2019].
[13] Kumar P, Pukale R, Kumabhar N, Patil U. Optimal design configuration using HOMER. Procedia Technol 2016;24:499–504. https://doi.org/10.1016/j.protcy.2016.05.085.
[14] EA. Investigation into the Value of Lost Load in New Zealand - Report on methodology and key findings, ERCOT; 2013. Available: https://www.ea.govt.nz/dmsdocument/12365 [accessed 15 January 2019].
[15] Mashayekh S, Stadler S, Cardoso G, Heleno M, Madathil SC, Nagarajan H, et al. Security-constrained design of isolated multi-energy microgrids. IEEE Trans Power Syst 2017;99. https://doi.org/10.1109/TPWRS.2017.2748060.
[16] Brown T, Hörsch J, Schlachtberger D. PyPSA: Python for Power System Analysis, 2018. J Open Res Softw 2018; 6(1), arXiv:1707.09913, doi: 10.5334/jors.188.
[17] Augutis J, Martišauskas L, Krikštolaitis R. Energy mix optimization from an energy security perspective. Energy Convers Manage 2015;90:300–14. https://doi.org/10.1016/j.enconman.2014.11.033.
[18] DeCarolis J, Daly H, Dodds P, Keppo I, Li F, McDowall W, et al. Formalizing best practice for energy system optimization modelling. Appl Energy 2017;194:184–98. https://doi.org/10.1016/j.apenergy.2017.03.001.

[19] Priesmann J, Nolting L, Praktiknjo A. Are complex energy system models more accurate? An intra-model comparison of power system optimization models. Appl Energy 2019;255:113783https://doi.org/10.1016/j.apenergy.2019.113783.

[20] Seck GS, Krakowski V, Assoumou E, Maïzi N, Mazauric V. Embedding power system's reliability within a long-term Energy System Optimization Model: Linking high renewable energy integration and future grid stability for France by 2050. Appl Energy 2020;257:114037https://doi.org/10.1016/j.apenergy.2019.114037.

[21] CEPA. Study on the Estimation of the Value of Lost Load of Electricity in Europe. Agency for the Cooperation of Energy Regulators; 2018. Available: https://www.acer.europa.eu/en/Electricity/Infrastructure_and_network%20development/Infrastructure/Documents/CEPA%20study%20on%20the%20Value%20of%20Lost%20Load%20in%20the%20electricity%20supply.pdf [accessed 16 November 2019].

[22] OPSD. Open Power System Data – A free and open data platform for power system modelling; 2019. Available: https://open-power-system-data.org/ [accessed 10 January 2019].

[23] EC. Final Report of the Sector Inquiry on Capacity Mechanisms, COM(2016)-752 final. European Commission; 2016. Available: https://ec.europa.eu/energy/sites/ener/files/documents/swd_2016_385_f1_other_staff_working_paper_en_v3_p1_870001.pdf [accessed 18 February 2019].

[24] Julia. The Julia programming language; 2019. Available: https://julialang.org/ [accessed 22 January 2019].

[25] Kreifels N, Mayer JN, Burger B, Wittwer C. Analysis of photovoltaics and wind power in future renewable energy scenarios. Energy Technol 2014;2:29–33. https://doi.org/10.1002/ente.201300090.

[26] Li R, Jiang Z, Ji C, Li A, Yu S. An improved risk-benefit collaborative grey target decision model and its application in the decision making of load adjustment schemes. Energy 2018;156:387–400. https://doi.org/10.1016/j.energy.2018.05.119.

[27] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 2016;114:1251–65. https://doi.org/10.1016/j.energy.2016.08.060.

[28] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224–39. https://doi.org/10.1016/j.energy.2016.08.068.

[29] Groissböck M. Impact of spatial renewable resource quality on optimum renewable expansion; Renewable Energy 2020; accepted.

[30] EuroStat. Supply, transformation and consumption of electricity – annual data. European Commission; 2019. Available: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_105a&lang=en [accessed 18 February 2019].

[31] IRENA. Renewable Energy Statistics 2018. The International Renewable Energy Agency, Abu Dhabi; 2018. Available: https://www.irena.org/publications/2018/Jul/Renewable-Energy-Statistics-2018 [accessed 18 February 2019].

[32] Siemens. Forward-thinking power generation, Utilizing conventional and renewable energy sources efficiently; 2019. Available: https://new.siemens.com/us/en/products/energy/power-generation.html [accessed 20 February 2019].

[33] Jenbacher. Reciprocating Gas Engines, INNIO; 2019. Available: https://www.innio.com/en/products [accessed 20 February 2019].

[34] MWM. Gas Engines/Gensets, Caterpillar Energy Solutions; 2019. Available: https://www.mwm.net/mwm-chp-gas-engines-gensets-cogeneration/gas-engines-power-generators/ [accessed 20 February 2019].

[35] MAN. MAN Engines, MAN; 2019. Available: https://www.engines.man.eu/global/en/index.html [accessed 20 February 2019].

[36] Wärtsilä. Products, Wärtsilä; 2019. Available: https://www.wartsila.com/products [accessed 20 February 2019].

[37] Gas Turbine World. 2016-17 Handbook, vol. 32; 2017.

[38] BEIS. Electricity generation costs. Department for business, energy & industrial strategy; 2016. Available: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/566567/BEIS_Electricity_Generation_Cost_Report.pdf [accessed 10 March 2019].

[39] NREL. Eastern renewable generation integration study, National Renewable Energy Laboratory; 2016. Available: https://www.nrel.gov/grid/ergis.html [accessed 20 January 2019].

[40] Johnson SC, Rhodes JD, Webber ME. Understanding the impact of non-synchronous wind and solar generation on grid stability and identifying mitigation pathways. Appl Energy 2020; 262: 114492, doi: 10.1016/j.apenergy.2020.114492.

Markus Groissböck is a doctoral student of Energy Systems Engineering at the Institute for Construction and Materials Science, Unit of Energy Efficient Buildings, University of Innsbruck. In 2009, he earned a Bachelor degree in Energy Economics from the University of Applied Sciences Kufstein, Austria, as well as a Master degree from the University of Applied Sciences Burgenland, Austria, and a Master degree from the University of Liverpool in Sustainable Energy Systems and Operations and Supply Chain Management (Oil and Gas), UK, in 2011 and 2016, respectively. His research interests lie in medium- and long-term investment planning within the power and energy sector considering distributed and renewable energy resources on district and regional level.

Alexandre Gusmão has been a Renewable Energy Business Developer for more than 15 years, covering a portfolio of projects from Wind, Solar PV, Hydro, and Biomass. His research interests lie in planning for renewable integration in power grids and mini-grids and forecasting natural energy resources and asset prices.

Paper 4

International Journal of Sustainable Energy Planning and Management Vol. 31 2021 109–120

International Journal of
Sustainable Energy Planning and Management

Energy hub optimization framework based on open-source software & data - review of frameworks and a concept for districts & industrial parks

Markus Groissböck*

Institute for Construction and Materials Science, University of Innsbruck, Innrain 52, 6020 Innsbruck, Austria

ABSTRACT:

Multi-model energy systems are gaining importance in a world where different types of energy, such as electricity, natural gas, hydrogen, and hot water, are used to create more complex but also more economic energy systems to support defossilization. While the research community is using open source for a long-time collaborative work on open-source tools is not yet the norm within the research community. To increase the open and sharing efforts between research organizations governments are driving publicly funded projects to share their outcomes. Today no open-source modelling framework exists able to assess different optimization tools. The proposed open-source framework is based on the principle of maximizing the reuse of existing data, software snippets and packages, and add individual code only as necessary. An intensive software package screening identified six suitable open-source tools (and their contributors) to be partly incorporated into the proposed open-source framework. The best tools of individual contributors has been combined and further improved by adding supplementary features such as a scenery model to incorporate shadowing and elevation effects on conventional and renewable power generation technologies are included. Going forward, this approach allows to expand research into urban air assessment in which traffic and energy emissions can be assessed jointly.

Keywords

Open source;
Energy hub;
Energy system modeling;
City multi modal energy systems;

http://doi.org/10.5278/ijsepm.6243

1. Introduction

The European Green Deal is one of the six priorities of the European Commission between 2019 and 2024 [1]. This Green Deal aims to lead the European Union (EU) into a sustainable and net-zero greenhouse gas emission society by latest 2050. Figure 1 shows how the Green Deal aims to change the European energy system from a linear and non-sustainable into a sustainable and fully integrated circular ecosystem. The most important principles are to electrify all end-use sectors as much as they can and to use clean biofuels for the sectors that cannot be electrified in an economic manner (such as heavy industry and long-distance transportation). The vision of the EU and its Member States could and should be an aspiration for municipalities, districts, and industrial parks.

All energy system design tool assessments known to the author are covering high-level details, such as numbers of regions, types of technology, or types of energy being able to be modeled in their analysis [2]. Their study is another piece of work focusing on abstract details, such as the categorization of conducted studies, as well as on considered features, or energy coverage of the model. It then defines which of the assessed details are seen as mandatory, complementary, or facultative. It does cover a lot of details of modeling, such as spatial resolution, time horizon, path dependencies, energy independence, and social acceptance of individual solutions. However, it does not assess in detail how the

*Corresponding author - e-mail: markus.groissboeck@student.uibk.ac.at

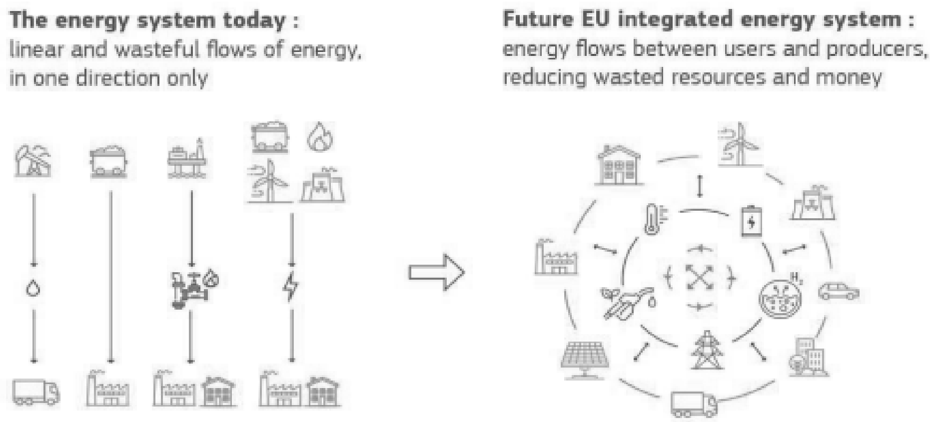


Figure 1: Aim of the European Green Deal [1]

individual aspects are implemented (mathematically formulated) in the optimization model. This kind of model assessment is very common and has been done for over a decade now [3].

To the best knowledge of the author, the first comprehensive attempt analyzing which constraints are incorporated in individual optimization tools was done by the author himself [4]. He analyzed 31 energy models (mainly open-source) and, thereby, assessed 81 modeling details, such as power flow (PF), optimal PF (OPF), security-constrained OPF, or unit commitment (UC) versus security-constrained UC. This level of analysis still does not allow assessing the whole potential of the individual modeling tools. Merely a few months later, a publication from Priesmann et al. was assessing 160 combinations of modeling details to answer the question if complex models are more accurate than simple ones [5]. Therefore, to avoid being bias for one or another reason during the model pre-selection and assessment, this work aims to provide a framework definition to allow a detailed assessment of open-source tools.

With the two exceptions mentioned above, today's energy tool assessment covers only high-level details. The work from Priesmann et al. can be seen as a groundwork complementary to the overall aim of this work. While their focus was on how adding or removing a modeling detail impacts the solution time and accuracy of the solution, they have not assessed the results of several energy modeling tools. The aim of this work is to create an open-source framework that offers the possibility of an unbiased energy system tool comparison.

The structure of the remaining paper is as follows: Chapter II contains an introduction into the concept and idea of energy hubs and a brief overview demonstrating the importance of open source and where it stands today. Chapter III shows the detailed methodology of this project and highlights some of the encountered problems. Chapter IV discusses the preliminary results. Chapter V summarizes the findings, draws a conclusion, and presents proposed next steps within this research work.

2. Literature Review

The first part of the literature review provides an introduction of the *energy hub* concept combined with a brief history around energy system design. The second part of this chapter will show the origins of open-source research in energy system modelling and the status-quo.

2.1. Energy hub

The term *energy hub* was coined by Geidl et al. [6]. In their concept, the exchange of energy between energy hubs was possible within one physical pipe combining electricity, thermal energy, and chemical energy (as shown in Figure 2). Especially for urban areas and industrial parks, this concept was seen as a perfect fit to cover heat and electricity demand through, e.g., combined heat and power applications at the same time.

Figure 3 shows a generalized example of an energy hub containing the typical elements “electrical transformer, gas turbine, heat exchanger, battery storage, hot water storage, and absorption chiller” as well as a wood

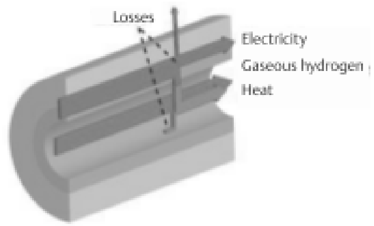


Figure 2: Possible layout of an energy interconnector [6]

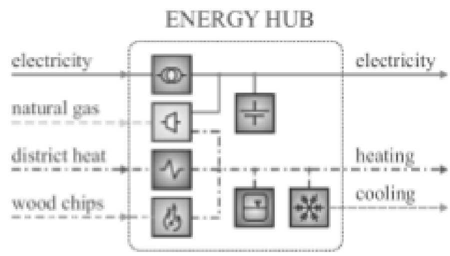


Figure 3: Exemplary energy hub [6]

chip furnace [6]. This energy hub was a key element in the "Vision of Future Energy Networks" project. Energy hubs could be extended through considering additional input streams (e.g., water, hydrogen, and carbon dioxide) as well as additional output streams representing 'power-to-X' options (e.g., green/blue/grey hydrogen, synthetic methane, methanol, ammonia, and carbon dioxide). From a mathematical modeling perspective, energy hubs are units (locations) where multiple forms of energy can be either converted (e.g., wood chips to heat), conditioned (e.g., electricity use in appliances), or stored (e.g., battery storage) for later use. All this transformation and processing comes with conversion and storage losses. It creates a place where all available and possible future energy carriers can have interactions to minimize the overall system cost.

While an energy hub has some inputs (such as electricity, natural gas, and district heating), it has to fulfill the energy demand within the energy hub (such as power demand, heating or cooling loads, or compressed air demand). It can be used to forward any or all of the energy carriers to other energy hubs through transportation (such as power lines, and natural gas or district heating pipelines). Within the energy hub, energy conditioning can happen through, e.g., combined heat and power technologies, compressors, or heat exchangers. Energy hubs can represent industrial facilities, larger buildings, but also rural and urban districts or isolated systems.

In 1997, Bruckner focused on overall energy efficiency improvements through the optimal configuration of available energy technologies [7]. In 2004, Biberacher concentrated on the implementation of geographical information systems (GIS) into the optimization model to optimize the long-term energy fulfillment on a national scale [8]. Both did not include a detailed energy model assessment in their work. In 2007, Geidl focused purely on the modeling aspect of energy hubs as his work was the first of its kind considering multiple forms of energy jointly within one expansion planning and operation application [9].

Connolly et al. listed 68 tools and investigated 37 out of them with the aim to validate if they can be used for renewable energy integration assessments [10]. While there were no typical applications identified a screening for the use of the individual tools was examined. The 'ideal' tool depends on the final use case: e.g., building or energy system analysis, energy-sectors to consider, technologies to consider, and time parameters the tool is able to deal with. Nevertheless, the paper claims to provide 'the information necessary to direct the decision-maker towards a suitable energy tool for an analysis that must be completed'.

In 2011, Mendes et al. focused on energy modeling assessments with a special interest in communities and districts [3]. The analysis was based on a survey of available bottom-up energy models for optimal planning of integrated community energy systems (including HOMER, DER-CAM, EAM, MARKAL/TIMES, RETScreen, and R2RES). After describing and examining these tools, a SWOT (strengths, weaknesses, opportunities, and threats) analysis was conducted. A detailed overview of approaches on how to optimize problems in energy distribution networks (such as simulated annealing, genetic algorithms, tabu search, and particle swarm optimization) was also presented. The overall finding was that DER-CAM is an appropriate energy model for optimized energy provisioning for communities.

In 2014, Mancarella provided a detailed overview of existing concepts and evaluation models within the multi-energy system (MES) community [11]. Based on this work, MES aims to increase the final energy conversion, optimizes the split into centralized and decentralized energy conversion technologies, and increases the energy system flexibility. MES is characterized by its spatial, multi-service, multi-energy, and network perspective and an ideal concept for integrating different energy sectors (nowadays known as 'sector coupling' or 'integrated energy systems') which traditionally have been treated in isolation. A brief discussion about the features of MES tools also considered the tools RETScreen, EnergyPLAN, DER-CAM, and eTransport. The study aimed to show the state-of-the-art of MES concepts and models but did not conduct a detailed assessment.

In 2017, Dorfner provided a very brief overview of optimization tools based on an assessment conducted Keirstead et al. [12]. The only tools discussed are MARKAL, TIMES, and MESSAGE as the study's objective was to provide open-source tools (via the source code sharing platform github.com) to support the idea of maintainability of models, reproducibility of case studies, and co-optimization of heat and electricity carriers. Their work reviewed 219 papers and identified five key areas of practice: "technology design, building design, urban climate, systems design, and policy assessment" [13]. A great future for urban energy system modelling is seen if challenges such as model complexity and data uncertainty can be resolved.

In 2017, Thiem looked briefly into existing tools such as Balmorel, DER-CAM, EnergyPLAN, energyPRO, HOMER, MARKAL&TIMES, MGEOS, RETScreen, TOP-Energy, TRNSYS, and urbs [14]. After a brief discussion of these tools, the focus of the remaining literature review focused on six groups of applications (see Table 1). The groups have been created based on existing energy model reviews and the scope of optimization tools (such as spatial dimension, covered model details, and type of optimization problem) but no. The focus of his research lies within group 5 with the aim to design multi-modal energy systems under consideration of part-load efficiencies.

In 2020, Ridha et al. assessed surveys collected during the MODEX (Model Experiments) project in which the research center Projektträger Jülich asked modelers to provide their views on a questionnaire [15]. The survey data was analyzed based on the criteria of mathematical complexity (e.g., LP, MILP, MINLP, stochastic), temporal complexity (e.g., temporal resolution and horizon of planning), spatial complexity (e.g., geographical resolution and horizon), and system complexity (e.g., modeled scope). The focus of their work was to assess how complexity can be reduced through clustering, through use of less techno-economic details such as ramp rates, or through use of less information about the individual sectors to consider. Therefore, the common practice is that energy system modeling tools set their focus on their area of interest and ignore other aspects to decrease the complexity of the overall problem to a level on which available optimization solvers are able to deliver results in a reasonable time.

Also, in 2020, Prina et al. provided a novel classification schemes for bottom-up energy system modelling tools [16]. They identified two main categories and challenges: resolution and transparency. Hereby, resolution is further divided into time resolution, space resolution, techno-economic detail, and details around sector coupling. Their valuation with low, medium, and high shows that there is no tool which has been benchmarked with 'high' in all categories. The closest to reach this is the open-source optimization tool PyPSA followed by the commercial tool PLEXOS. The only category where PyPSA has received a rating of 'medium' is within the category 'sector coupling'. It is not transparent why optimization tools such as Oemof, Calliope, and Ficus have been rated with 'high' in this category as to the best knowledge of the author the tools have very similar or almost the same capabilities in this regard. Another top ranked tool is the LUT model which unfortunately is not available for the public. EnergyPLAN, a simulation tools, is also mentioned in this paper. It is freeware but not open source. Therefore, only freely available and open-source models such as PyPSA, oemof, Calliope, and Ficus have been considered in this work going forward.

Table 1: Classification of previous research [14]

<table>
<tr><th>Group</th><th>Description</th><th colspan="2">Type of optimization problem</th></tr>
<tr><td>1</td><td>Large-scale grid studies relying on simplified models</td><td rowspan="3">LP</td><td rowspan="2"></td></tr>
<tr><td>2</td><td>Simple tools for quick assessments of small-scale energy systems</td></tr>
<tr><td>3</td><td>Buildings & city district energy system design studies with simplified models</td><td rowspan="4">MILP</td></tr>
<tr><td>4</td><td>On-site energy system studies with additional features</td><td rowspan="3"></td></tr>
<tr><td>5</td><td>Mixed-integer linear programming with part-load efficiencies</td></tr>
<tr><td>6</td><td>Mixed-integer nonlinear programming with complex models</td></tr>
</table>

1.2. Open source

Open source has a long history within information technology where several leading software packages have been made available to the public (e.g., Apache - web server, Netscape - browser, MySQL - database, Linux - operating system) [17]. Unfortunately, in research and development (R&D) as well as in some companies, there are serious ethical, security, and commercial concerns that open source is more threat than an organization can benefit from [18]. The fear relates to unwanted exposure from, e.g., flawed source code, data, or analysis. Another assumption is that time-consuming activities (such as programming, verifying results, or writing documentation) are competitive advantages. Perhaps it is only natural that sometimes the institutional and personal inertia stops organizations and people from following open-source principles.

But what are some of these open-source principles? First, adding transparency to the source code and allowing peer review increases the quality of the software package, which then can also be used by other organizations instead of writing the same piece of functionality again. A peer review process can also lead to increased collaboration. With a focus on R&D, this also means that sharing data, models, and results increases productivity through burden-sharing. As a result, the focus can be set on doing something new and helpful for society instead of repeating necessary, important, but sometimes monotonic tasks.

Of importance within the R&D community is that only results, which are seen and challenged from other parts of the community, are useful to R&D and the overall society. Everything else can be considered self-adulation. An ethical argument is that if R&D is funded by public money, the results should be publicly available as well. Open access to data, source code, energy system models, and results is crucial for a balanced social and political debate. On top of this, R&D needs to support the public and scientific discourse to model for insights and thereby increasing transparency about possible opportunities and risks [19].

Fostering open source to get more transparency and repeatability of analysis was written by DeCarolis et al. [20]. One of the main findings was that a thorough review of results and conclusions is currently impossible. A multi-national research team (Howells et al.), in which DeCarolis was part of, developed the first open-source energy modeling tools: OSeMOSYS (Open Source Energy Modeling System) [21]. One of the key features of OSeMOSYS's implementation is the mathematical formulation in 'plain English' meaning that the mathematical formulation is basically the documentation as well. The formulation has less than five pages of documentation and an easily accessible code. This slim formulation of course comes with the downside of having a simple optimization tool covering only the most necessary techno-economic details.

DeCarolis et al. started the development of another open-source energy modeling tool: Temoa (Tools for Energy Model Optimization and Analysis) [22]. The design of this tool aims for more tractable uncertainty analysis and utilization of multi-core high-performance computing to perform rigorous uncertainty investigation. Pfenninger et al. highlighted that energy models and data are an important part of energy policy assessments [23]. They also found that open up R&D, including models and data, would show immense benefits for all participating parties inside and outside of R&D.

Hülk et al. represent one of the latest open-source energy modeling approaches: oemof (Open Energy Modeling Framework - A modular open-source framework to model energy supply systems) [24]. This initiative aims to provide flexible and generic components to model cross-sectoral (e.g., heat, power, mobility) and multi-regional open, modular, and transparent models allowing everyone to contribute (community-driven). Publications stemming from this imitative became the steppingstone for an overall open R&D community, in which raw data, model formulation, energy model choice, raw results, interpretation, and dissemination is shared transparently with interested people. Its recommended to read papers such as Prina et al. for more detailed discussions about strengths and weaknesses of different energy system models [16].

Figure 4 shows how an overall open-source energy system modeling project might be divided into several distinct process steps in which individual R&D communities and projects contribute to one or several of these process steps. An often-ignored step is the numerical solver, as the R&D community assumes access to commercial solvers; some of them are free or very affordable for academics.

Table 2 shows some of the exemplary open-source related initiatives, which have been launched several years ago and in which process steps they are active in. The table shows five of numerous evolving initiatives and platforms and compares them with the overall aim of this work. The grey cells indicate an area in which the

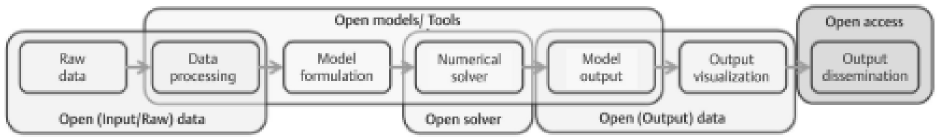


Figure 4: Distinct steps within the open-source discussion (based on [25])

Table 2: Examples of open-source initiatives

Examples	Raw Data	Data Processing	Model Formulation	Numerical Solver	Model Output	Output Visualization	Output Dissemination
Open Energy Modeling Initiative [25]							
Energy Modeling Platform Europe [26]							
Open Power System Data [27]							
Computational Infrastructure for Operations Research [28]							
Open Street Map [29]							
This work – link to existing work	API	Python	Pyomo	NEOS			OA journals, arXiv, …

individual initiative and platform is active. While some of them cover a wide range of the process, others are focused on one of the required process steps. The suggested framework aims to support the entire process with limited efforts by developers using existing software and data.

Of course, open and transparent R&D has to be incentivized. Closer cooperation between national and international R&D bodies is necessary to reduce parallel efforts and duplication of work. Therefore, a very important step for implementation of open R&D has been initiated in July 2019: The Open Data Directive (EU) 2019/1024 of the European Parliament and of the Council of 20 June 2019 on open data and the re-use of public sector information [30]. This directive has to be implemented in all Member States until July 2021.

A final remark related to open source is that licensing plays a part that must not be underestimated as it defines what the user can do with the shared source code, data, or models. Morrison provides a very detailed overview of available licenses used in the space of open source and open data [31]. Using one of the licenses from the GPL family results in the highest copyleft while ISC, MIT, BSD, and Apache-based licenses are very permissive granting the user a wide range of activities, including the use of the code and/or data in their commercial products.

3. Methodology

The initial step of this research was to assess existing open-source software tools and to better understand their strengths and weaknesses [4]. A thorough screening of 31 energy modeling tools was based on characterizing them into 12 applications and 81 functions. The applications cover the geographical scope (or use) of the tool (house, industry, district, city, region or country), types of covered energy (electricity, heat, natural gas), being an open-source tool, and is it an optimization or a simulation tool. The functions screening cover aspects such as hourly or variable time steps, altermatic or direct current modeling of power transmission, (security-constrained) unit commitment details and (security-constrained) economic dispatch. The conclusion from this initial work was that open-source energy system modeling tools are ready for serious use compared to commercially available tools. Possible enhancements could be considering the impact of ambient air conditions, part-load behavior, and redundancy aspects. The top scoring tools (Switch Model 2.0 [32], Temoa [20], OSeMOSYS [21], and PyPSA [33]) and about 50% of the assessed tools were based on the programming language Python. As a result, further assessments represented in this work focuses on Python-based tools solely.

The second step of the research involved the assessment of additional tools, software packages, and software snippets to identify what the open-source community has done already and what can be used as a basis for this work. A summary of the assessed Python packages and snipes is available online at Zenodo [34]. As usually for engineering tasks, the difficulty lies in the details: the number of Python-based packages are almost countless. By the end of September 2020, more than 260,000 packages have been registered at pypi.org [35], neglecting thousands of additional software snippets and tools shared via github.com [36], gitlab.com [37], or other code sharing platforms with millions of registered repositories and active developers. This shows one of the biggest downsides of open-source package writing: there is no or very limited coordination between the countless number of packages. Duplicate work also happens in the open-source community. It's very hard to keep track with all the frequent changes as well as new developments. Also, relying on some of these packages means that if there is a (major) redesign of the package once has to adjust accordingly.

The here proposed open-source framework divides the required process steps between having no data at the top of the process (see the left box in Figure 5) and having all data, results, and visualization in eleven steps (indicated by small numbers within the workflow). The right box in Figure 5 shows a selection of assessed tools and data, which have been found useful in the proposed framework. The text in bold marked with a times sign (*) shows where enhancement by the author is considered or have been incorporated already.

The author's sophisticated research revealed that there was no tool considering the z-coordinate within a detailed GIS representation shared within the open-source community. This means that none of the assessed tools considers a proper scenery model in which elevation details are included. Another insufficiently addressed aspect within the tools is profile clustering. Most of them are not able to adequately deal with multiple time-series at once (e.g., multiple energy demands and price time-series).

4. Preliminary Results

The preliminary assessment highlights six open-source oriented R&D contributors where parts of their tools might be incorporated into the here suggested framework (see Table 3). The identified contributors developed several individual tools such as GIS-related data collection, building stock-related load curves, or optimization tool. All of this individual tools usually have been made available by the framework contributors with the

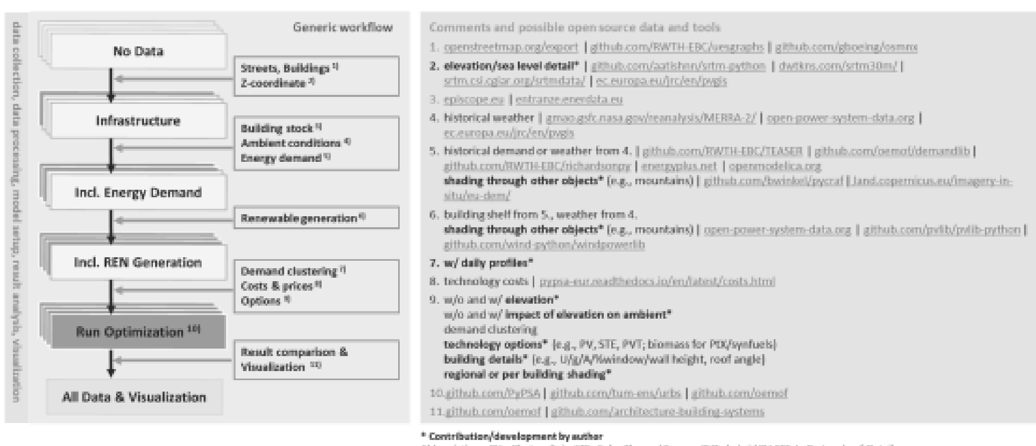


Figure 5: Proposed methodology & selection of considered open-source data and tools

aim to support city or national energy system design. The cells shown in dark blue indicate areas where the individual tools have no or very little contribution to the predefined eleven process steps. Light blue cells indicate a partial contribution. Typical for such assessments, it always depends on the conducted analysis by the author and, therefore, might not reflect the opinion of the open-source framework owners and maintainers.

Regarding the previously mentioned disregard of the GIS z-coordinate, the City Energy Analyst (CEA) tool shown in the last column on the right considers this detail for line and pipeline calculations but not for elevation adjustments of, e.g., efficiency of conventional power generation technologies. As known, individual tools set different focuses. For example, PyPSA's focus is spatial nature, therefore spatial clustering is considered accordingly. Other frameworks, such as the one from FZJ-IEK3-VSA, are focused on time-series aggregation and clustering. Within the proposed framework, both options shall be available to assess the importance of the individual clustering option.

Obviously only European R&D organizations are listed iBased on the conducted analysis, the proposed framework aims to incorporate particular features from

Table 3: Selective contributors and their tools

	*** Spatial focus:**	**≥ State**	**≤ City**	**≥ State**	**≥ State**	**≤ City**	**≤ City**
	Link to contributor page on github:	FZJ-IEK3-VSA	RWTH-EBC	oemof	PyPSA	tum-ens	architecture-building-systems
1	Streets, buildings,	n/a	n/a	n/a	n/a	n/a	CEA
	land use,	n/a	n/a	n/a	n/a	pyGRETA	CEA
	district heating,	n/a	n/a	n/a	n/a	n/a	CEA
	power,	n/a	n/a	n/a	bdw/GridKit	n/a	CEA
	gas, oil, biomass	n/a	n/a	n/a	n/a	n/a	n/a
2	Z-coordinate	n/a	n/a	n/a	n/a	n/a	CEA
3	Building stock	tsib (for EU)	TEASER (for EU)	tabular (for EU)	n/a	n/a	CEA (for CH)
4	Historical ambient conditions	tsib (TRY, TMY, ISO 12831)	pyCity (TRY, TMY)	feedinlib.era5	n/a	n/a	E+ weather files (epw)
5	Energy demand	tsib, tsorb:occupation	pyCity:occupancy, TEASER, AixLib, IBPSA	demandlib	n/a	n/a	CEA
6	Renewable profile	RESKit, windtools	pyCity	feedinlib	Atlite	pyGRETA	CEA
7	Demand Clustering	tsam	pyCity	solph	PyPSA	pyCLARA	n/a
8	Cost & prices, …	n/a	n/a	n/a	Collection (e.g., DEA, DIW, IEA)	n/a	CEA
10	Optimization	FINE	pyCity	solph	PyPSA	pyPRIMA	CEA
	Solvers abstraction	any local (pyomo)	tbd	any local (pyomo)	any local (pyomo)	any local (pyomo)	Gurobi, GA
11	Visualization	n/a	n/a	OEDB	n/a	n/a	n/a
	Design for addition	n/a	n/a	yes	yes	n/a	n/a
	Additional features	n/a	n/a	visio oemof.db	nomopyomo (cbc, gurobi)	n/a	GUI
	Contributors:	FZJ	EBC	RLI, FHF	KIT, FIAS	TUM	ETHZ

* *Spatial focus*: Household, District, City, State, Region, Country, Continent, World

Abbreviations: FZJ: Forschungszentrum Jülich, EBC: RWTH Aachen, E.ON EBC, RLI: Reiner Lemoine Institute, FHF: FH-Flensburg, KIT: Karlsruhe Institute of Technology, FIAS: Frankfurt Institute for Advanced Studies, TUM: Technical University of Munich, ETHZ: Eidgenössische Technische Hochschule Zürich

Table 4: Examples of open-source initiatives

Framework / Process step	FZJ-IEK3-VSA	RWTH-EBC	oemof	PyPSA	tum-ens	architecture-building-systems	new features
1 – Streets, buildings, land use	-	-	-	-	-	-	osmnx
2 – Z-coordinate	-	-	-	-	-	-	pycraf, tkrajina/srtm.py
3 – Building stock	tsib	TEASER	tabular	-	-	-	-
4 – Ambient conditions	-	-	-	-	-	-	OPSD/ weather_data
5 – Energy demand	-	pyCity:occupancy, TEASER	-	-	-	CEA	-
6 – Renewable profile	-	-	feedinlib	-	-	-	pvlib, windlib, Solar3DCity
7 – Demand clustering	tsam	-	-	-	-	-	-
8 – Cost & prices, technologies, …	-	-	-	technology-data	-	-	economy of scale
9 – Options	-	-	-	-	-	-	sensitivity analysis
10 – Optimization	-	-	-	-	pyPRIMA	-	solver: NEOS*
11 – Visualization	-	-	OEDB	-	-	-	-
Additional features	-	-	-	-	-	-	PyPSA: market, reserve margin

* NEOS: free internet-based service for solving numerical optimization problems (http://www.neos-server.org/neos/)

the assessed contributors into a new open-source framework (see Table 4). The table specifies which process step has been taken from which contributor and the according tool to use. For example, step1, the street and building data can be initialized by using the osmnx package. Step 3, as another example, will use the packages tsib, TEASER, and tabular. While a lot of it has been already implemented, severe actions are still required to finish the framework in a first shareable and stable release. Once available in a shareable and stable release, it will be made available via Zenodo [34]. As indicated during the introduction, the ultimate goal is to have a single framework in which several energy optimization tools can be assessed against each other to verify the resulting quality of the individual tools as well as support the decision-making on which one to use for which purpose.

5. Conclusion & Future Work

As a result of increasing interactions between historically isolated energy systems (e.g., electricity, natural gas, hydrogen, and hot water) multi-model energy systems are gaining importance to create more economic and decarbonized energy systems. The term energy hub can be seen as a synonym for a multi-model energy system. Open-source software has a long history. Also, the research community is using open source for a long time. Public companies have realized that cooperation saves costs and increases the speed for go-to-market with new offerings and solutions. Unfortunately, the research community has not fully accepted that collaborative work on open-source tools is more beneficial than working isolated. More and more governments are convinced that publicly funded projects should end in publicly available data and tools.

Hundred thousand of repositories are available on code sharing platforms, and the number is growing daily. The proposed open-source framework in this work is based on the principle of maximizing the reuse of existing data, software snippets, and packages and adding individual code only as much as ultimately necessary. After careful screening of additional software packages, six favorite open-source frameworks have been identified were the best parts of each of these frameworks are combined into a single open-source framework (see Table 3).

Table 3 might give the impression that there exist already six complete frameworks. This is not the case. The listed 6 contributors do have some individual tools which they use in their daily work, but a comprehensive framework does not exist yet. At least non which does fulfil the proposed eleven steps (from having no data towards having all data, results, and visualization, see Figure 5).

To further improve the energy system framework for the purpose of this research, some more features were added (see Table 4). Those features include a scenery model to incorporate shadowing and elevation effects on conventional power generation technologies. By doing so the utilization of limited resources such as human resources could be improved significantly. Going forward, this approach allows for further research, for example, with a focus on city air assessment in which traffic and energy emissions can be assessed jointly with urban climate effects (e.g., heat islands or cold stream through rivers) [38].

The framework test and verification process are still ongoing and will be applied in a demonstration village to ensure proper quality and stability. The aim of the framework test is to ensure the quality of the new framework. Afterward, the framework will be made accessible on Zenodo [37]. Other framework enhancements and evaluations are still ongoing. Within the next weeks, additional energy system models, such as FlexiGIS [39], might be analyzed whether it provides a useful option for consideration. Another aspect to consider is a standardized database schema for saving GIS-related information. Therefore, the current 3D City DB schema might be assessed for its potential fit. A completely different topic for future work could be to assess why open-source R&D is string in Europe but not outside of Europe.

It is good to see that more and more tools within the energy system modelling area are shared and made available for interested R&D community. Unfortunately, cooperation between different R&D organization still is limited to some exceptions. It would be appreciated to see more multi-national R&D efforts working on open-source energy system modelling tools such as the Spine project does [40]. In this project organizations from Finland, Ireland, Belgium, and Sweden cooperate with one from the US.

Acknowledgments

This work has been presented at the 6th International Conference on Smart Energy Systems held at Aalborg University (Denmark) on October 6-7, 2020. The author gratefully acknowledges the invitation for submission by the Editorial Board for a Special issue of International Journal of Sustainable Energy Planning and Management (IJSEPM) [41]. The author gratefully acknowledges valuable comments and input from various anonymous reviewers during the review process, as well as from colleagues within the University of Innsbruck, Institute for Construction and Materials Science, Unit of Energy Efficient Buildings, and the Research Studio Austria iSpace.

References

[1] EC. EU strategy on energy system integration [online], *European Commission*. Available from: https://ec.europa.eu/energy/topics/energy-system-integration/eu-strategy-energy-system-integration_en [accessed 24 September 2020].

[2] Savvidis G, Siala K, Weissbart C, Schmidt L, Borggrefe F, Kumar S, Pittel K, Madlener R, Hufendiek K. The gap between energy policy challenges and model capabilities, *Energy Policy* 2019;125:503-520. https://doi.org/10.1016/j.enpol.2018.10.033.

[3] Mendes G, Ioakimidisa C, Ferrão P. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools, *Renewable and Sustainable Energy Reviews* 2011;15:4836-4854. https://doi.org/10.1016/j.rser.2011.07.067.

[4] Groissböck M. Are open-source energy system optimization tools mature enough for serious use? *Renewable and Sustainable Energy Reviews* 2019;102:234-248. https://doi.org/10.1016/j.rser.2018.11.020.

[5] Priesmann J, Nolting L, Praktiknjo A. Are complex energy system models more accurate? An intra-model comparison of power system optimization models, *Applied Energy* 2019;255:113783. https://doi.org/10.1016/j.apenergy.2019.113783.

[6] Geidl M, Koeppel G, Favre-Perrod P, Klöckl B, Andersson G, Fröhlich K. The Energy Hub - A Powerful Concept for Future Energy Systems [online], *Third Annual Carnegie Mellon Conference on the Electricity Industry*, 13-14 March 2007. Available from: https://research.ece.cmu.edu/electriconf/2007/2007%20Conf%20Papers/Andersson%20Paper%20final.pdf [accessed 3 October 2020].

[7] Bruckner T. Dynamische Energie- und Emissionsoptimierung regionaler Energiesysteme, Doctoral Thesis, Department of Theoretical Physics, University of Würzburg, Germany (1997). https://github.com/robbiemorrison/deeco/blob/master/docs/1997-bruckner-dynamische-energie-und-emissionsoptimierung-regionaler-energiesysteme-phd.pdf.

[8] Biberacher M. Modelling and optimisation of future energy systems using spatial and temporal methods, Doctoral Thesis, Institute for Physics, Experimental Plasma Physics, University of Augsburg, Germany (2004). https://opus.bibliothek.uni-augsburg.de/opus4/frontdoor/index/index/year/2005/docId/67.

[9] Geidl M. Integrated Modeling and Optimization of Multi-Carrier Energy Systems, Doctoral Thesis, Institute for Power Systems and High Voltage Laboratory, ETH Zurich, Switzerland (2007). https://www.research-collection.ethz.ch/handle/20.500.11850/123494.

[10] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems, *Applied Energy* 2010;87(4):1059-1082. https://doi.org/10.1016/j.apenergy.2009.09.026.

[11] Mancarella P. MES (multi-energy systems): An overview of concepts and evaluation models, *Energy* 2014;65:1-17. https://doi.org/10.1016/j.energy.2013.10.041.

[12] Dorfner JF. Open Source Modelling and Optimisation of Energy Infrastructure at Urban Scale, Doctoral Thesis, Department of Electrical and Computer Engineering, Technical University Munich, Germany (2017). https://mediatum.ub.tum.de/1343363.

[13] Keirstead J, Jennings M, Sivakumar A. A review of urban energy system models: Approaches, challenges and opportunities, *Renewable and Sustainable Energy Reviews* 2012;16(6):3847-3866. https://doi.org/10.1016/j.rser.2012.02.047.

[14] Thiem S. Multi-modal on-site energy systems Development and application of a superstructure-based optimization method for energy system design under consideration of part-load efficiencies, Doctoral Thesis, Department of Electrical and Computer Engineering, Technical University Munich, Germany (2017). https://mediatum.ub.tum.de/?id=1342482.

[15] Ridha E, Nolting L, Praktiknjo A. Complexity profiles: A large-scale review of energy system models in terms of complexity, *Energy Strategy Reviews* 2020;30:100515. https://doi.org/10.1016/j.esr.2020.100515.

[16] Prina MG, Manzolini G, Moser D, Nastasi B, Sparber W. Classification and challenges of bottom-up energy system models - A review, *Renewable and Sustainable Energy Reviews* 2020;129:109917. https://doi.org/10.1016/j.rser.2020.109917.

[17] Wikipedia. Open Source [online], *Wikipedia*. Available from https://de.wikipedia.org/wiki/Open_Source [accessed 4 October 2020].

[18] EC. SETIS Magazine November 2016 - Energy Systems Modelling [online], *European Commission*. Available from https://setis.ec.europa.eu/publications/setis-magazine/energy-systems-modeling [accessed 4 October 2020].

[19] Huntington HG, Weyant JP, Sweeney JL. Modeling for insights, not numbers: the experiences of the energy modeling forum, *Omega* 1982;10(5):449-462. https://doi.org/10.1016/0305-0483(82)90002-0.

[20] DeCarolis JF, Hunter K, Sreepathi S. The case for repeatable analysis with energy economy optimization models, *Energy Economics* 2012;34(6):1845-1853. https://doi.org/10.1016/j.eneco.2012.07.004.

[21] Howells M, Rogner H, Strachan N, Heaps C, Huntington H, Kypreos S, Hughes A, Silveira S, DeCarolis JF, Bazillian M, Roehrl A. OSeMOSYS: The Open Source Energy Modeling System: An introduction to its ethos, structure and development, *Energy Policy* 2011;39(10):5850-5870. https://doi.org/10.1016/j.enpol.2011.06.033.

[22] Temoa (Tools for Energy Model Optimization and Analysis) [online]. Available from: https://github.com/TemoaProject [accessed 4 October 2020].

[23] Pfenninger S, DeCarolis JF, Hirth L, Quoilin S, Staffell I. The importance of open data and software: Is energy research lagging behind? *Energy Policy* 2017;101:211-215. https://doi.org/10.1016/j.enpol.2016.11.046.

[24] Hülk L, Müller B, Glauer M, Förster E, Schachler B. Transparency, reproducibility, and quality of energy system analyses - A process to improve scientific work, *Energy Strategy Reviews* 2018;22:264-269. https://doi.org/10.1016/j.esr.2018.08.014.

[25] openmod. Open Energy Modelling Initiative [online]. Available from: https://www.openmod-initiative.org/manifesto.html [accessed 24 September 2020].

[26] EMP-E. Energy Modelling Platform for Europe [online]. Available from: http://www.energymodellingplatform.eu/ [accessed 24 September 2020].

[27] OPSD. Open Power System Data - a free-of-charge data platform for power system modelling [online]. Available from: https://open-power-system-data.org/ [accessed 24 September 2020].

[28] COIN-OR. Computational Infrastructure for Operations Research [online]. Available from: https://www.coin-or.org [accessed 24 September 2020].

[29] OSM. Open Street Map [online]. Available from: https://www.openstreetmap.org/ [accessed 24 September 2020].

[30] EC. Directive (EU) 2019/1024 on open data and the re-use of public sector information [online], *European Commission*. Available from http://data.europa.eu/eli/dir/2019/1024/oj [accessed 4 October 2020].

[31] Morrison R. Energy system modeling: Public transparency, scientific reproducibility, and open development, *Energy Strategy Reviews* 2018;20:49-63. https://doi.org/10.1016/j.esr.2017.12.010.

[32] Johnston J, Enriquez-Auba R, Maluenda B, Fripp M. Switch 2.0: A modern platform for planning high-renewable power systems, *SoftwareX* 2019;10:100251. https://doi.org/10.1016/j.softx.2019.100251.

[33] Brown T, Hörsch J, Schlachtberger D. PyPSA: Python for Power System Analysis, *Journal of Open Research Software* 2018;6(1):4. http://doi.org/10.5334/jors.188.

[34] Groissböck M, Energy hub optimization framework bases on open source [online], Available from: https://doi.org/10.5281/zenodo.4459140 [accessed 23 January 2020].

[35] PyPI. The Python Package Index [online]. Available from: https://pypi.org/ [accessed 24 September 2020].

[36] github [online]. Available from: https://github.com [accessed 24 September 2020].

[37] gitlab [online]. Available from: https://about.gitlab.com/ [accessed 24 September 2020].

[38] Baklanov A, Grimmond CSB, Carlson D, Terblanche D, Tang X, Bouchet V, Lee B, Langendijk G, Kolli RK, Hovsepyan A. From urban meteorology, climate and environment research to integrated city services, *Urban Climate* 2018;23:330-341. http://dx.doi.org/10.1016/j.uclim.2017.05.004.

[39] Alhamwi A, Medjroubi W, Vogt T, Agert C. FlexiGIS: an open source GIS-based platform for the optimisation of flexibility options in urban energy systems, *Energy Procedia* 2018;152:941-946. https://doi.org/10.1016/j.egypro.2018.09.097.

[40] Spine [online], Spine project: Open source toolbox for modelling integrated energy systems. Available from: http://www.spine-model.org/index.htm [accessed 20 September 2020].

[41] Østergaard PA, Johannsen RM, Lund H, Mathiesen BV. Latest Developments in 4th generation district heating and smart energy systems. *International Journal of Sustainable Energy Planning and Management*, 2021;x. http://doi.org/10.5278/ijsepm.6432.

Verpflichtungs- und Einverständniserklärung

Ich erkläre, dass ich meine Dissertation selbständig verfasst und alle in ihr verwendeten Unterlagen, Hilfsmittel und die zugrunde gelegte Literatur genannt habe.

Ich nehme zur Kenntnis, dass auch bei auszugsweiser Veröffentlichung meiner Dissertation die Universität, das/die Institut/e und der/die Arbeitsbereich/e, an dem/denen die Dissertation ausgearbeitet wurde, und die Betreuerin/nen bzw. der/die Betreuer zu nennen sind.

Ich nehme zur Kenntnis, dass meine Dissertation zur internen Dokumentation und Archivierung sowie zur Abgleichung mit der Plagiatssoftware elektronisch im Dateiformat pdf ohne Kennwortschutz bei der/dem Betreuer/in einzureichen ist, wobei auf die elektronisch archivierte Dissertation nur die/der Betreuerin/Betreuer der Dissertation und das studienrechtliche Organ Zugriff haben.

Innsbruck, am 11. Juni 2021 ……………………………………..

Markus Groissböck