Decarbonisation Strategies in Energy Systems Modelling: APV and e-tractors as Flexibility Assets

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Foreword

This thesis, representing the original, unpublished, and independent work of Lucas Goulart Duarte, serves as a partial fulfillment of the requirements for the Master of Science in Renewable Energy and Data Engineering. It is an integral part of the Landgewinn project in collaboration with HSO, where the overarching goal is to model the agricultural sector's synergy with the broader energy system and explore its potential in driving energy system decarbonization. To achieve this, the study will investigate and model three innovative technologies: biochar, agro-PV, and a third technology to be selected in partnership with other project contributors. The author extends heartfelt appreciation to Niklas Hartmann and Meritxell Domènech Monfort for their invaluable guidance, the entire project team, the esteemed professors, and the teaching staff at Hochschule Offenburg for their wealth of knowledge, as well as her supportive family and friends throughout this journey.

It's Halloween, and we can be anything. - Phoebe Bridgers

Declaration of Authorship

I declare in lieu of an oath that the Master Thesis submitted has been produced by me without illegal help from other persons. I state that all passages which have been taken out of publications of all means or unpublished material either whole or in part, in words or ideas, have been marked as quotations in the relevant passage. I also confirm that the quotes included show the extent of the original quotes and are marked as such. I know that a false declaration will have legal consequences.

Offenburg, 26.10.2023

Lucas Goulart Duarte

Abstract

Decarbonisation Strategies in Energy Systems Modelling: APV and e-tractors as Flexibility Assets

This work presents an analysis of the impact of introducing Agrophotovoltaic technologies and electric tractors into Germany's energy system. Agrophotovoltaics involves installing photovoltaic systems in agricultural areas, allowing for dual usage of the land for both energy generation and food production. Electric tractors, which are agricultural machinery powered by electric motors, can also function as energy storage units, providing flexibility to the grid. The analysis includes a sensitivity study to understand how the availability of agricultural land influences Agrophotovoltaic investments, followed by the examination of various scenarios that involve converting diesel tractors to electric tractors. These scenarios are based on the current CO_2 emission reduction targets set by the German Government, aiming for a 65% reduction below 1990 levels by 2030 and achieving zero emissions by 2045. The results indicate that approximately 3% of available agricultural land is necessary to establish a viable energy mix in Germany. Furthermore, the expansion of electric tractors tends to reduce the overall system costs and enhances the energy-cost-efficiency of Agrophotovoltaic investments.

Keywords: Energy Transition, Energy System Model, Agrophotovoltaics, Electric Tractors

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1. Introduction

Long-term decarbonization requires progressive long-term electrification. Therefore, ambitious mid and long-term targets have been set in all energy sectors reaching as far forward as 2050. A fundamental transformation of Germany's power system, including a shift from coal and nuclear to renewable energy is expected. Other fossil-fuel intensive sectors, such as transportation, heating, and cooling, are also crucial to the complete *Energiewende* [1].

In order to solve the climate crisis, more installation of Photovoltaics (PV[1]) systems and Wind turbines are urgently needed. However, land for such investments can be quite competitive, due to the growing global population and consecutive growing demand for food. Therefore, the concept of Agrophotovoltaics was developed, which mitigates the future competition for space with the dual use of land. It offers the possibility of installing large PV systems on open land while keeping the ground clear for food production [2]. Another solution to address today's global greenhouse gas emissions is the conversion of diesel tractors, which are vital agricultural machinery, into electric tractors [3]. These not only fulfill essential agricultural activities for adequate food production but their battery systems could serve as flexibility assets in the grid, following the Vehicle-to-grid approach [4].

Regarding the numerous ideas and possibilities that could assist in addressing today's climate problems, energy system models are applied to gain a better understanding of present and future most important research questions. Given the complexity of the energy sector, some energy models focus specifically on an aspect of a process or a subsector, while others cover energy-economy interactions at the national and international levels. These models rely on data, technology specification, skilled operators, and computational power [5].

This study aims to investigate the integration of the two aforementioned technologies, Agrophotovoltaics and Electric Tractors. An open-source energy system model software, PyPSA-Eur, is employed to accomplish the objectives of the research. The new technologies were implemented and integrated into the model's workflow. APV technologies followed the same logic as that used for solar panels, and electric tractors were created in a manner similar to batteries. APV and electric tractors are assumed to mutually influence each other's development in the energy system because an electric tractor is utilized at the same location as

[1] Photovoltaics

APVs and can charge more efficiently than directly from the grid. The following questions are aimed to be addressed:

- What is the electricity consumption of electric tractors within the grid?
- To what extent does the integration of electric tractors impact the expansion of APV in the energy system?
- Can electric tractors serve as a viable flexibility option within the energy system?
- What is the projected potential of APV in Germany for the years 2030 and 2045?
- What is the projected regional potential of APV in Germany for the years 2030 and 2045?

The structure of the work is divided into five chapters: Introduction, Literature Review, Methods, Results and Discussions, and Conclusion. The first chapter, 1 Introduction, is where the reader is right now. The second chapter, 2 Literature Review, summarizes the necessary information to carry out this research. The third chapter, 3 Methods, describes how the work is executed, for example, implementations and modifications in the energy system model, data utilized, and studied scenarios. Followed by 4 Results and Discussions, where results are quantified and visualized for interpretation. At last, 5 Conclusion, which summarizes the main insights from the study and recommends further work and research ideas.

2. Literature Review

2.1. Energy Transition: Energiewende

In Germany a low-carbon energy system based on renewable energy is under development, known as "Energiewende". In order to fight climate change, a policy is formed, which considers all sectors of the economy. Initial strategies are the phase-out of nuclear power, improvement of energy security, and guaranteeing industrial competitiveness and growth. The energy transition aims to expand renewables within the power sector while limiting global warming to 1.5°C. Initially, the strategy aimed to reduce 55% of Greenhouse gas (GHG[1]) emissions by 2030 compared to 1990 levels, and a reduction between 80% to 95% by 2050. Additionally, renewable sources should take a share of 30% by 2030 in the energy sector and at least 60% by 2050 [1].

Historically, power generation in Germany has been based on hard coal, lignite, and nuclear. However, falling costs of wind energy and PV have launched renewable energy as an important player in Germany's power production. Figure 2.1 shows that 45.5% of energy generation came from renewable sources in 2022. Among renewable sources, wind and solar energies have the largest growth potential in Germany. Biomass growth is limited because of costs, land-used constraints, and sustainability concerns [1].

The German government decided to shut down nuclear power plants after the events in Fukushima on March 11, 2011. These power plants were considered highly productive and important for the energy system [6]. However, Russia's invasion of Ukraine forced the government to delay the plan to close the final three plants. Closure was postponed from December 2022 to April 2023. As of now, no nuclear power plants are active on the grid [7].

Coal plays an important role in Germany's energy mix compared to other European Union (EU[2]) member states. As seen in Figure 2.1, in 2022 19.7% of energy generation came from brown coal/lignite, and 11% from hard coal. Primary consumption of coal causes 45% of all German energy-related CO_2-emissions [8]. As of February 2023, Germany's government aims to bring forward coal exit to 2030 which is earlier than the previously established goal of 2038 [9].

[1] Greenhouse gas
[2] European Union

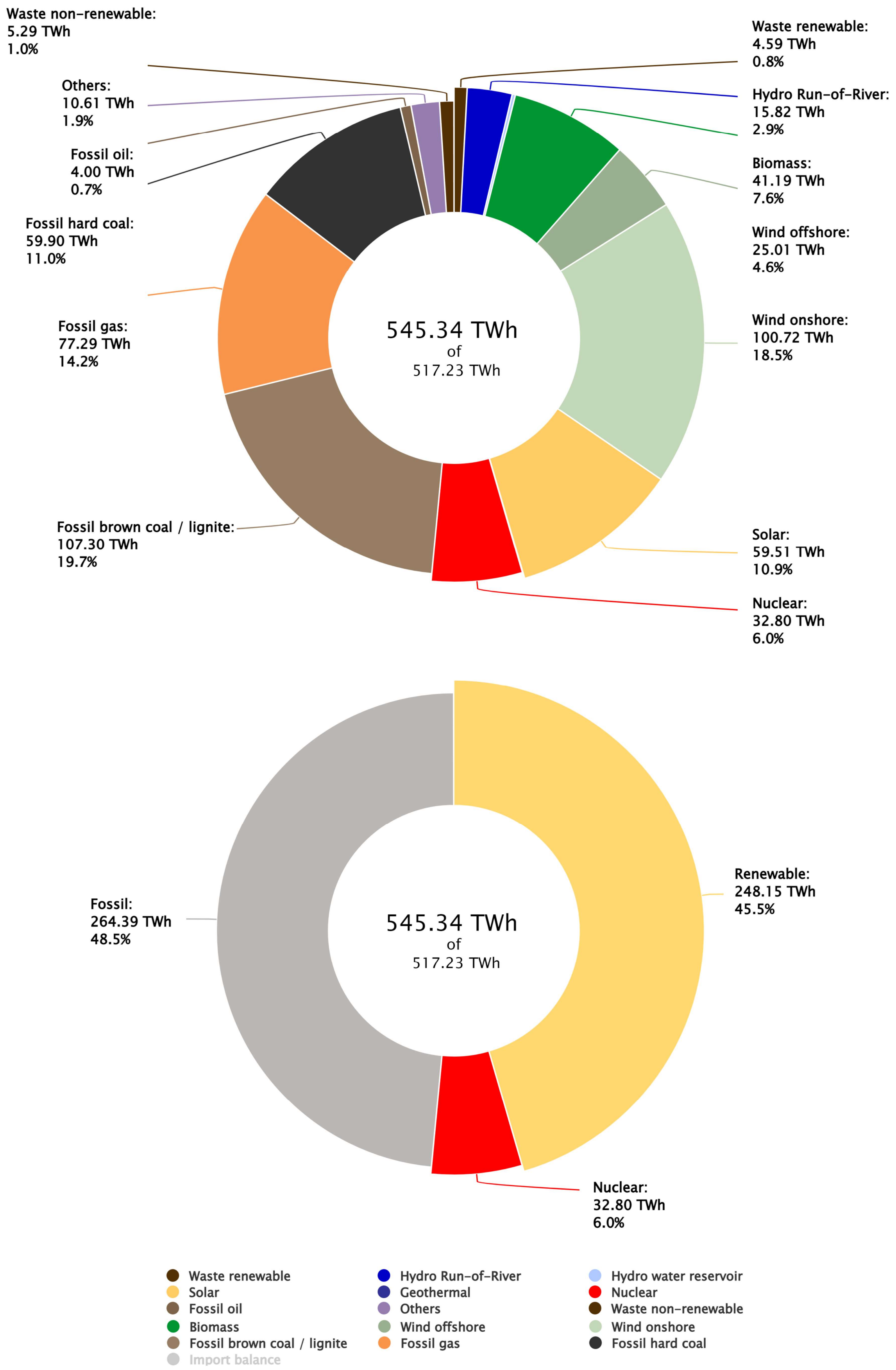

Figure 2.1: Total net electricity generation in Germany in 2022 [10].

Figure 2.2 shows the path to complete decarbonization by 2045. As of 2022, Germany released two major packages — the Easter and Summer Packages (each comprising several individual reform efforts) — aimed at addressing various areas necessary to accelerate renewable growth. Currently, Germany aims to achieve greenhouse gas neutrality by 2045. Targets include cutting emissions by at least 65% by 2030 compared to 1990 levels and achieving an 88% reduction by 2040. Furthermore, a new target for the share of renewables in power consumption for 2030 has been established for 2030, set at a minimum of 80% [11].

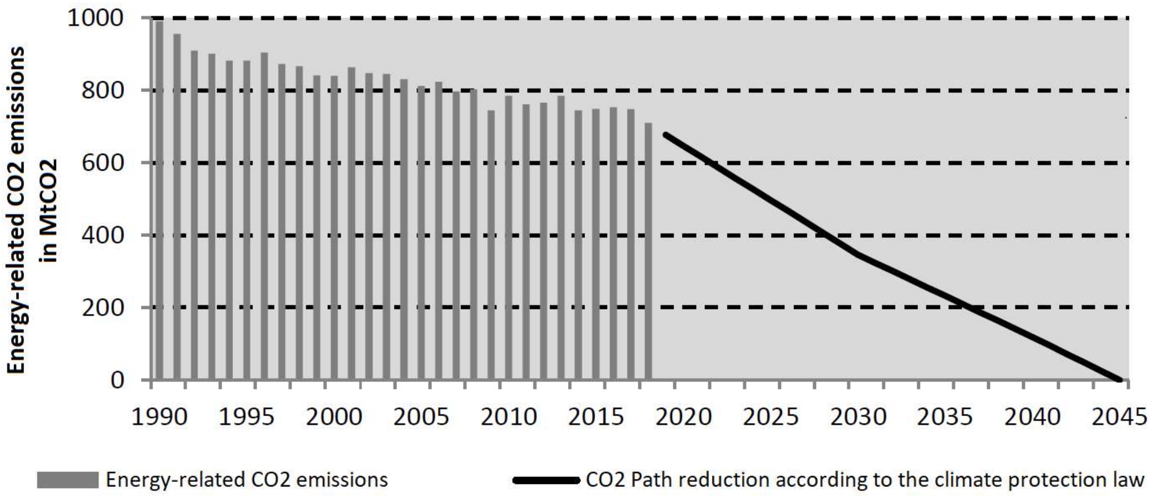

Figure 2.2: CO_2 target path from 2030 to 2045 compared to 1990 [12].

In a climate-neutral future, electricity will be the primary energy in the energy system. Electrification and the production of green hydrogen (H_2) will increase and, consequently, demand more electricity. By 2045, when zero emissions are achieved, electricity consumption will reach about 1000 TWh. The share of renewables will be 100%, phasing out all fossil fuels. It is realistic to assume that retrofitted gas-fired power plants that use green hydrogen will cover part of the demand, and so will stored or imported electricity. Battery storage, electric vehicles, heat pumps, and other technologies, will effectively increase the flexibility of the grid, which will operate efficiently even with a high share of fluctuating feed-in. Figure 2.3 shows the prognosis of electricity consumption for past and future years, spanning from 2018 to 2045. Electricity demand is expected to nearly double from 2018 (595 TWh) to 2045 (1017 TWh) [13].

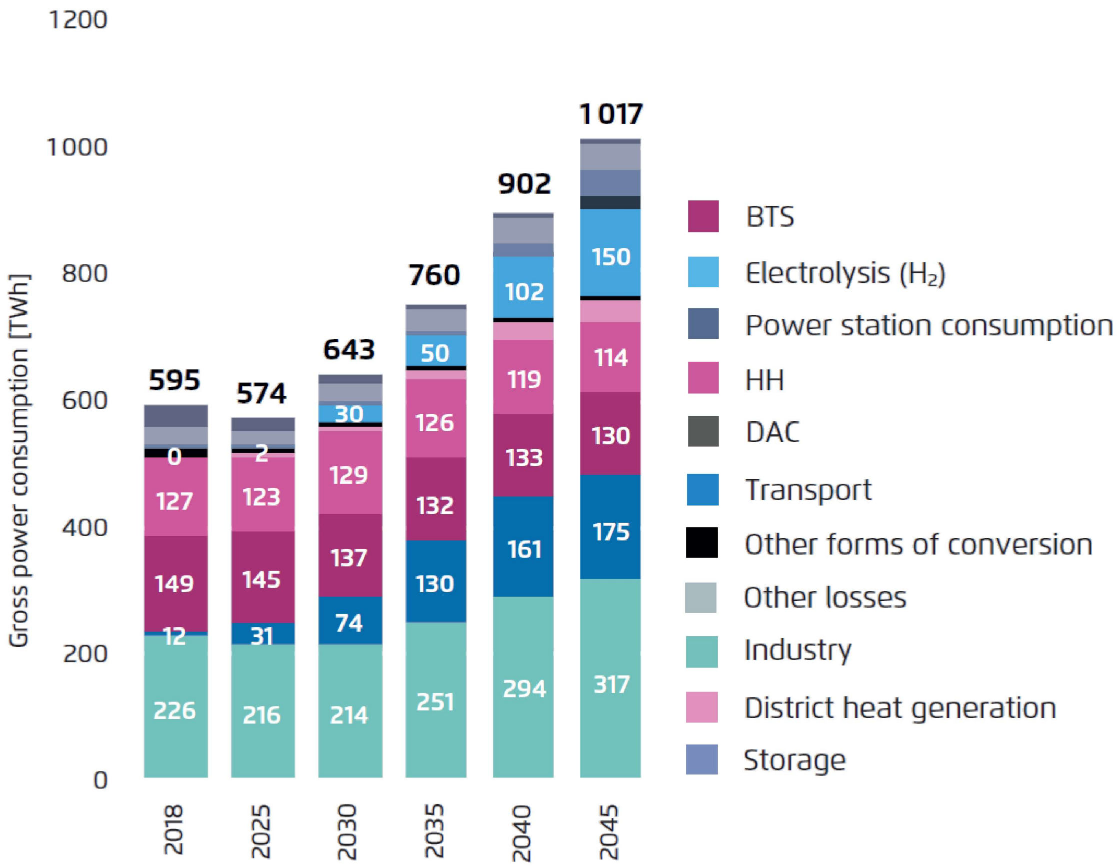

Figure 2.3: Gross power consumption in different years [13].

2.2. Agrophotovoltaics: APV

Agrophotovoltaic (APV[3]) is a concept for photovoltaic systems that are implemented in conjunction with food production on the same land area. It was conceived because PV installation on open areas is the lowest-cost option; however, the conflict between energy and food production on land use is undesirable, leading to concerns about the loss of arable land, which gave rise to the principle [14].

When PV panels are mounted at a sufficient height from the ground, cultivation practices can normally be carried out. However, the impact of APVs on agricultural activities is still poorly understood and must be further studied [15]. Research indicates that crop growth rates under agrophotovoltaic systems remain unaffected, except during the early stages of crop development. The presence of PV modules, similar to trees, offers several advantages; they reduce evapotranspiration, which is particularly beneficial during dry seasons. Additionally, they provide shade that protects crops from excessive heat and helps mitigate soil temperature [16]–[18]

[3]Agrophotovoltaic

The EU Solar Energy Strategy calls for an additional photovoltaic capacity of 450 GWp between 2021 and 2030 in all EU member states, which would require four times more than the current increase of the nominal, over 720 GWp by 2030. Approximately 50% of this capacity is expected to be deployed as ground-mounted system in agricultural areas. Coverage of only 1% of Utilised Agricultural Area (UAA[4]) with APV systems translates into roughly 944 GW, which is half of the amount yielded by traditional ground-mounted PV systems and approximately 5 times more than the EU installed capacity in 2022 [19].

Germany requires between 300 and 450 GWp of PV installed capacity by 2045. However, the true technical feasibility can only be determined when considering regulatory and economic contexts. The German Institute for Standardization released the "DIN SPEC 91434", which outlines requirements for the primary agricultural use of APVs. The standard aims to clearly distinguish APV systems from conventional ground-mounted systems, which is likely to be a key prerequisite for ensuring APV systems are successfully brought to market. Costs of APV differ from ground-mounted systems and depend on factors such as installed capacity, agricultural activity, position and the PV module technology used. Table 2.1 points out where each APV type is used [2].

APV systems	Use	Examples
Overhead/Interspace PV with vertical clearance	Permanent and perennial crops	Fruits, berries, viticulture, hops
	Single-year and long-term crops	Arable crops, vegetables, alternating grassland, fodder
	Permanent grassland with mowing	Intensive and extensive commercial grassland
	Permanent grassland with pasture	Permanent pasture, pasture rotation (e.g., cattle, poultry, sheep, pigs and goats)

Table 2.1.: Overview of categories and forms of land use as set out in DIN SPEC 91434 [2]

[4] Utilised Agricultural Area

Figure 2.4: Agrophotovoltaic research site at Lake Constance [2].

2.3. Farm Machinery: Electric Tractors

Germany's agriculture greenhouse gas emissions were about 7.4% of total emissions in 2021 [20], which is considered a small part, compared to the energy industry or the transport sector. Farming has been said to be complicated to decarbonize, as many emissions related to animals, soil, and food are hard to avoid or reduce. However, Germany's new target of becoming climate neutral by 2045 has made it a priority that all sectors aspire to a no-emissions scenario. Emissions that are not avoidable need efforts of carbon uptake and sequestration [21].

Figure 2.5 shows a decline in total agricultural emissions, mainly due to a reduction in livestock numbers and the amount of applied synthetic fertilizers. As for fuel consumption (green), the same level is observed. Fuels are used to power farm machinery, which consists mainly of tractors. In order to follow the Climate Protection Act estimate and transition from dependence on fossil fuel, energy-efficient electric tractors are promising alternative technologies. Electric agricultural machinery could enable further automation of farm work and precision farming. Furthermore, electric systems demand less maintenance, which maximizes the utilization ratio for the machinery [22].

A comprehensive survey report on the technological status and market readiness of Zero-Emission off-road equipment indicates that segments of agricultural equipment that utilize low-speed and lightweight machinery are currently poised for decarbonization. Vineyards and orchards in California have already deployed Solectrac e70N battery-electric tractors, built for vineyards and similar smaller-scale farming operations. Another successful case is Monarch's battery-electric tractors, which reported average savings of $2,655 in fuel per tractor. However, the upfront purchase price for these tractors remains significantly more ex-

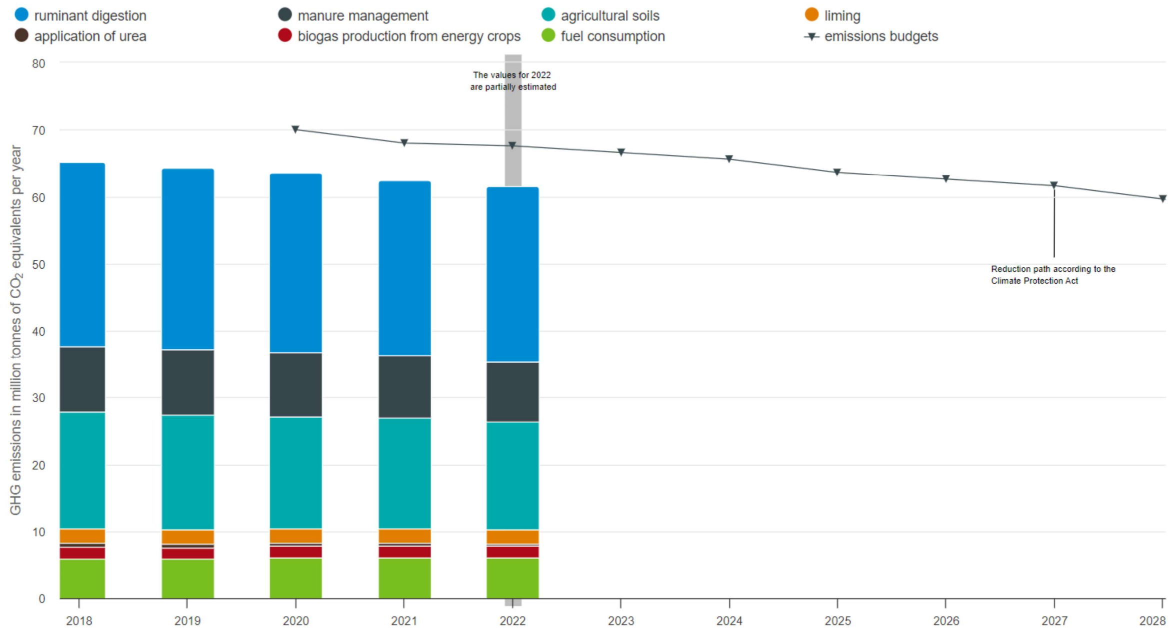

Figure 2.5: Greenhouse gas emissions from agriculture from 2018 to 2022, Climate Protection Act estimate [20]

pensive than Internal Combustion Engine (ICE[5]) tractors. Furthermore, agricultural equipment often sits unused for long periods and then undergoes phases of dawn-to-dusk intensive use, which brings uncertainty about battery self-discharge [23].

On a dairy farm, an electrically autonomous tractor was compared to a conventional tractor using a simulated model. The study concluded that it is feasible to replace a 160 kW conventional tractor with two autonomous battery-powered tractors equipped with 36 kW motors and 113 kWh batteries, resulting in a 15% cost reduction [24]. Figure 2.6 shows the total monthly operational hours for a whole year. Tractors are used between April and October, and long unused hours are observed throughout the year.

As the emerging concept of smart grid continues to grow, Electric Vehicles (EVs[6]) play a new role: energy exchange with the power grid. This is equally applicable to Electric Tractors (e-tractors[7]), allowing them to participate in grid interactions. EVs are can charge with energy from the grid with the plug-in function and deliver the energy back to the grid via a bidirectional charger. The charging and discharging capability of batteries and concepts like Vehicle-to-grid (V2G[8]) have become attractive in recent years and should turn into reality in the near future [4].

Germany's fleet of tractors is summarized in Table 2.2. The total number is around 1.7 million tractors as of 2022, representing a 9.7% increase from the previous year, and an average annual growth rate of 2.9% over the past 5 years. Tractors are categorized into four

[5] Internal Combustion Engine
[6] Electric Vehicles
[7] Electric Tractors
[8] Vehicle-to-grid

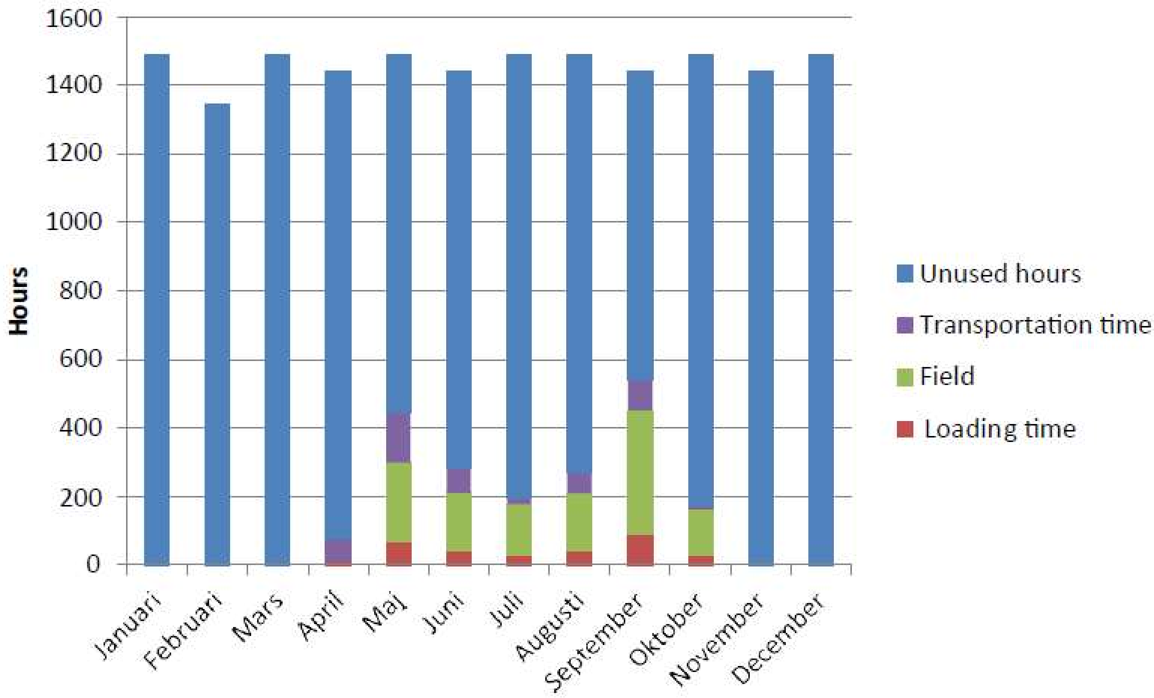

Figure 2.6: Electric tractors monthly usage [24]

power ranges: < 30 kW, 31 - 50 kW, 51 - 70 kW, > 90 kW [25]. Field hours are defined based on tractor power, typically ranging between 300 and 500 hours [26].

Power [kW]	Field Hours	Amount
< 30	300	480,280
31 - 50	325	473,204
51 - 70	425	337,124
71 - 90	500	148,220
> 90	500	263,217

Table 2.2.: Germany's current fleet of tractors.

To estimate the potential capacity for electrification within the tractor fleet, and subsequent flexibility to the grid, the following equations are outlined. Equation 2.1 estimates annual gasoline consumption by tractors. This equation is sourced from [27].

$$Q_{avg} = 0.305 * P_{PTO} \tag{2.1}$$

Where:

- Q_{avg} = average gasoline consumption [Lh^{-1}],
- P_{PTO} = maximum power take-off [kW].

Diesel consumption on a volumetric basis is approximately 73% of gasoline consumption [27]. An estimative for P_{PTO} is approximately 85% of engine power, due to various gear transmission friction [28]. Equation 2.2 represents the final electricity demand required to power an electric tractor, of which 1.6% of the total consumption is due to idle consumption. Idle consumption is a state in which tractors are stationary, and the engine is not subjected to any substantial load [29]

$$P_{in} = 0.73 * 0.85 * 0.0098 * (0.4/0.9) * Q_{avg} \tag{2.2}$$

Where:

- 0.0098 is a conversion constant of the energy content of a liter of diesel $[MWh]$ [30],
- 0.4 is the average efficiency for diesel engines [31],
- 0.9 is the average efficiency for electric motors [31].

2.4. Energy System Modelling

Model	Highlights	Language	Year
MATPOWER [32]	Intended for solving steady-state power system simulation and optimization problems, such as: power flow (PF), continuation power flow (CPF), extensible optimal power flow (OPF), unit commitment (UC) and stochastic, secure multi-interval OPF/UC.	Matlab	2011
pandapower [33]	Combines the data analysis library pandas and the power flow solver PYPOWER [34] to create an easy to use network calculation program aimed at automation of analysis and optimization in power systems.	Python	2018
GridCal [35]	Extension of PYPOWER that includes OPF, time series, Blackout cascading, short circuit, grid reduction.	Python	2018
PSAT [36]	Includes power flow, continuation power flow, optimal power flow, small signal stability analysis, and time domain simulation. All operations can be assessed by means of graphical user interfaces.	Matlab	2008
Calliope [37]	Designed to analyse systems with arbitrarily high spatial and temporal resolution, with a scale-agnostic mathematical formulation permitting analyses ranging from single urban districts to countries and continents.	Python	2018
OSeMOSYS [38]	Simple, open, flexible and transparent manner to support teaching. It is based on free software and optimizes using a free solver. This model replicates the results of many popular tools.	GNUMath prog, Python, GAMS	2011
oemof [39]	Aims to be a loose organisational frame for tools in the wide field of (energy) system modelling. Every project is managed by their own developer team but we share some developer and design rules to make it easier to understand each other's tools.	Python	2018

Table 2.3.: Open source energy system models

Energy system models first emerged in the early 1970s due to growing concerns about energy supply, future demand-supply dynamics, and interactions between energy-environment, and energy-economy. These models vary in their specifications, including differences in data and technologies, as well as in their purpose, philosophy, features, and capabilities. Electricity-related models often tend to rely on optimization as the basic approach. This typically involves a cost minimization objective function, a set of decision variables, and a set of constraints that ensure the feasible range of the decision variables [5].

Optimization problems can be challenging to solve, particularly when they are non-linear, non-convex, or discrete in nature. Specialized softwares are often employed for solving linear, quadratic, discrete, and other equations. Energy system models typically involve linear problems, which can be solved using the simplex algorithm or interior-point algorithms [40].

Table 2.3 references open-source energy system models. These models not only provide access to the source code but also allow free redistribution and modifications without discrimination in usage [41].

2.4.1. Research studies

A wide range of topics can be researched utilizing the aforementioned open-source energy system models, from power flow analysis to whole operational studies and generation and transmission expansion planning studies.

AC power flow analysis in the pandapower framework can be solved using three implemented algorithms: Gauss–Seidel method (G–S), Newton–Raphson method (N–R), and Newton–Raphson method with Iwamoto multipliers (N–R–I). Quantitative analysis of pandapower implementations reveals that the first algorithm, Gauss–Seidel, is the least robust in terms of computational efficiency [42].

A detailed outline of the power plant system optimization for Denmark has been done utilizing oemof. An energy system analysis was conducted for 2018, with an additional estimation-based analysis for 2030. It was found that in 2030, electricity generation will exceed demand by nearly 40%, primarily due to a substantial increase in the share of electricity generation from offshore and onshore wind power plants [43].

Scenario-based analysis using the PyPSA framework [44] was conducted on the German energy system, providing insights into the energy transition from 2020 to 2050, considering new CO_2 allowance strategies. Results indicate that under the current emission reduction strategy, the country will exceed its CO_2 budget. The analysis recommends a significant increase in the emission tax to reduce CO_2 emissions. Figure 2.7 illustrates various emission scenarios in comparison to the current strategy [45].

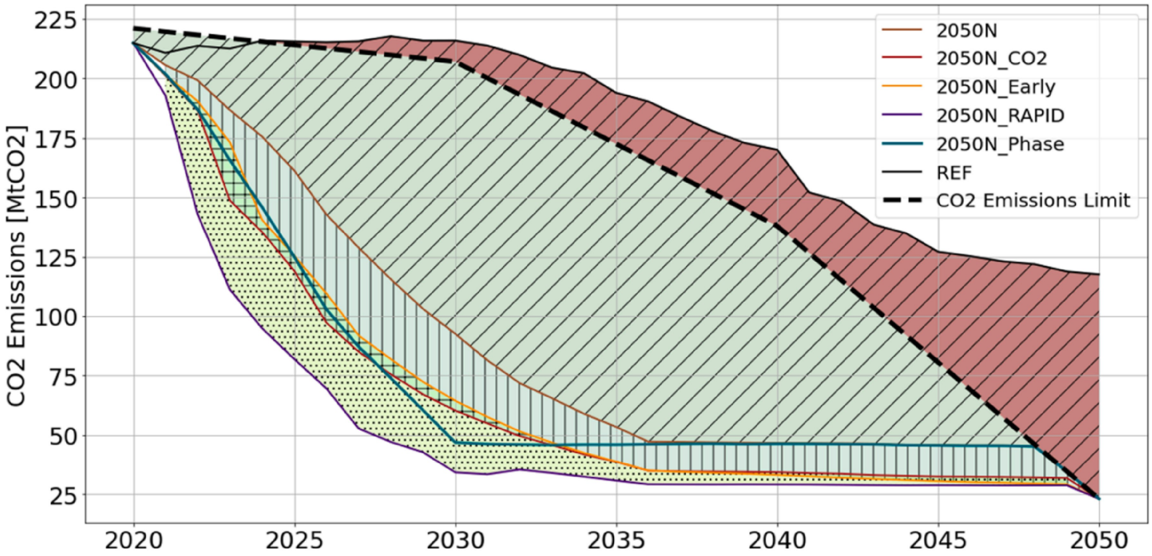

Figure 2.7: Cumulative scenarios emissions [45].

2.5. Python for Power System Analysis: PyPSA

PyPSA is a free software toolbox for simulating and optimizing energy power systems. It was developed to help in understanding the increasing complexity of the electricity system, utilizing multiple time periods for unit commitment in the era of widespread integration of renewable energy. It models the operation and optimal investment of the energy system, connecting components listed in Table 2.4 [44].

Buses are the fundamental nodes, to which all other components attach, enforcing energy conservation. Energy flows in generators (in), storage units or stores (in and out), and loads (out). Both static and time-varying data are stored in pandas DataFrames, enabling efficient calculations. For easy user input and to ensure consistency, unit conventions are employed, such as $MW/MVA/MVar$ for power, h for time, MWh for energy. Sign convention follows other major software packages, equally to MATPOWER and PYPOWER [46].

Figure 2.8 illustrates a minimal example where various components, such as Buses, Lines, Generators, and Loads, have been interconnected to create a three-bus network. This network can be optimized for optimal load flow and capacities with PyPSA through an accessor method defined as *optimize()*.

PyPSA optimizes the dispatch and capacities of generation and storage and the transmission infrastructure. The load is assumed inelastic, which means that it must be met in every snapshot. For most functionalities, continuous variables are used for optimization; binary variables are only implemented for unit commitment. Equation 2.3 represents the objective function, which minimizes the total system cost [46].

Component	Functionality
Network	Container for all other network components.
Bus	Fundamental nodes to which all other components attach.
Carrier	Energy carrier (e.g. wind, solar, gas, etc.).
Load	A consumer of energy.
Generator	Generator whose feed-in can be flexible subject to minimum loading or minimum down and up times, or variable according to a given time series of power availability.
Storage Unit	A device that can shift energy from one time to another, subject to efficiency losses.
Store	A more fundamental storage object with no restrictions on charging or discharging power.
Shunt Impedance	An impedance in shunt to a bus.
Line	A branch which connects two buses of the same voltage.
Transformer	A branch which connects two buses of different voltages.
Link	A branch with a controllable power flow between two buses.

Table 2.4.: PyPSA components [44].

$$min_{F_l g_{n,s,t} h_{n,s,t} suc_{n,s,t} sdc_{n,s,t}} \Bigg[\sum_{n,s} c_{n,s} \overline{g}_{n,s} + \sum_{n,s} c_{n,s} \overline{h}_{n,s} + \sum_{l} c_l F_l \\ + \sum_{t} w_t \left(\sum_{n,s} o_{n,s,t} g_{n,s,t} + \sum_{n,s} o_{n,s,t} h_{n,s,t} \right) + \sum_{t} (suc_{n,s,t} + sdc_{n,s,t}) \Bigg] \tag{2.3}$$

Where:

- $n \in N = 0, ...|N| - 1$: label the buses
- $t \in T = 0, ...|T| - 1$: label the snapshots
- $l \in L = 0, ...|L| - 1$: label the branches
- $s \in S = 0, ...|S| - 1$: label the different generator/storage types at each bus
- $w_{n,s}$: weighting of time in the objective function
- $g_{n,s,t}$: dispatch of generator s at bus at time t
- $\overline{g}_{n,s}$: nominal power of generator s at bus n
- $\overline{g}_{n,s,t}$: availability of generator s at bus n at time t per unit of nominal power
- $suc_{n,s,t}$: start-up cost if generator with unit commitment is started at time t
- $sdc_{n,s,t}$: shut-down cost if generator with unit commitment is shut down at time t
- $c_{n,s}$: capital cost of extending generator nominal power by one MW
- $o_{n,s}$: marginal cost of dispatch generator for one MWh

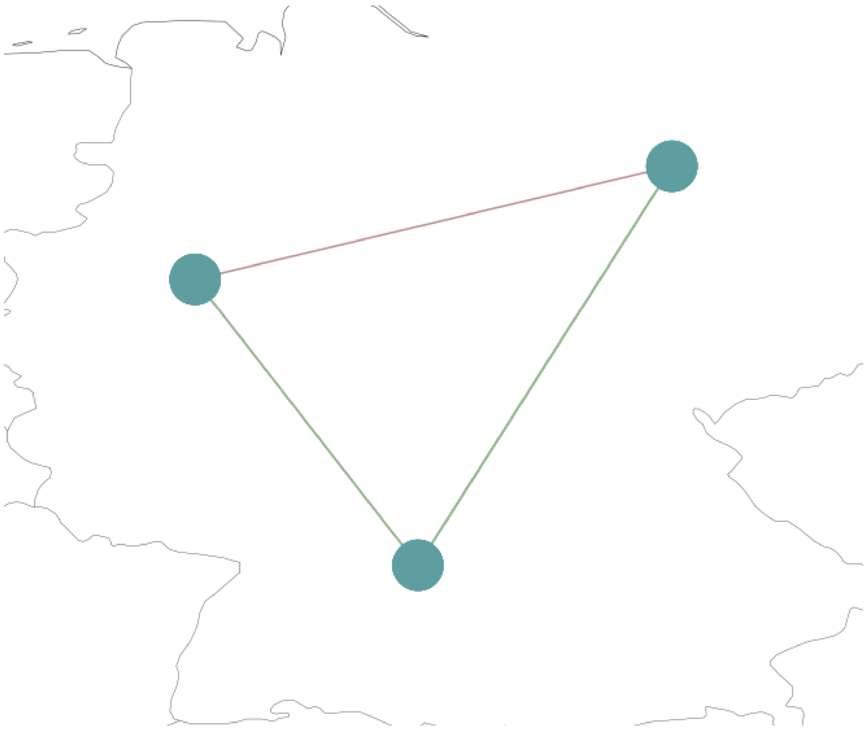

Figure 2.8: Three-buses network: minimal example.

- F_l: capacity of branch l

Variables for storage uptake, state of charge, and the voltage angle for each bus do not appear in the previous equation. Additionally, components have to follow certain constraints, which are explained in the PyPSA documentation.

Finally, Global constraints related to primary energy are also implemented. CO_2 emissions can be limited by a CAP_{CO_2}, which come from generators whose energy carriers have CO_2 emissions and from stores and storage units whose storage medium releases or absorbs CO_2 when it is converted. Equation 2.4 describes the global constraint, with e_s as CO_2-equivalent-tonne-per-MWh, $\eta_{n,s}$ as the generator efficiency [46].

$$\sum_{n,s,t} \frac{1}{\eta_{n,s}} w_t.g_{n,s,t}.e_{n,s} + \sum_{n,s} (e_{n,s,t=-1} - e_{n,s,t=|T|-1}).e_{n,s} \leq CAP_{CO_2} \tag{2.4}$$

2.5.1. An open optimization model of the European transmission system: PyPSA-Eur

The first open model dataset of the full European Network of Transmission System Operators for Electricity (ENTSO-E[9]), PyPSA-Eur, is used to study transformations in energy systems, such as decarbonization of heating and transport. It is constructed using the PyPSA

[9] European Network of Transmission System Operators for Electricity

framework. It incorporates grid data, a power plant database with geo-data, time series data for electrical load and wind, solar and hydroelectric availability, and geographic potentials for the expansion of wind and solar power, which constitute significant elements within the model. Figure 2.9 shows the transmission network of all current transmission lines and additional ones that are under or close to construction [47].

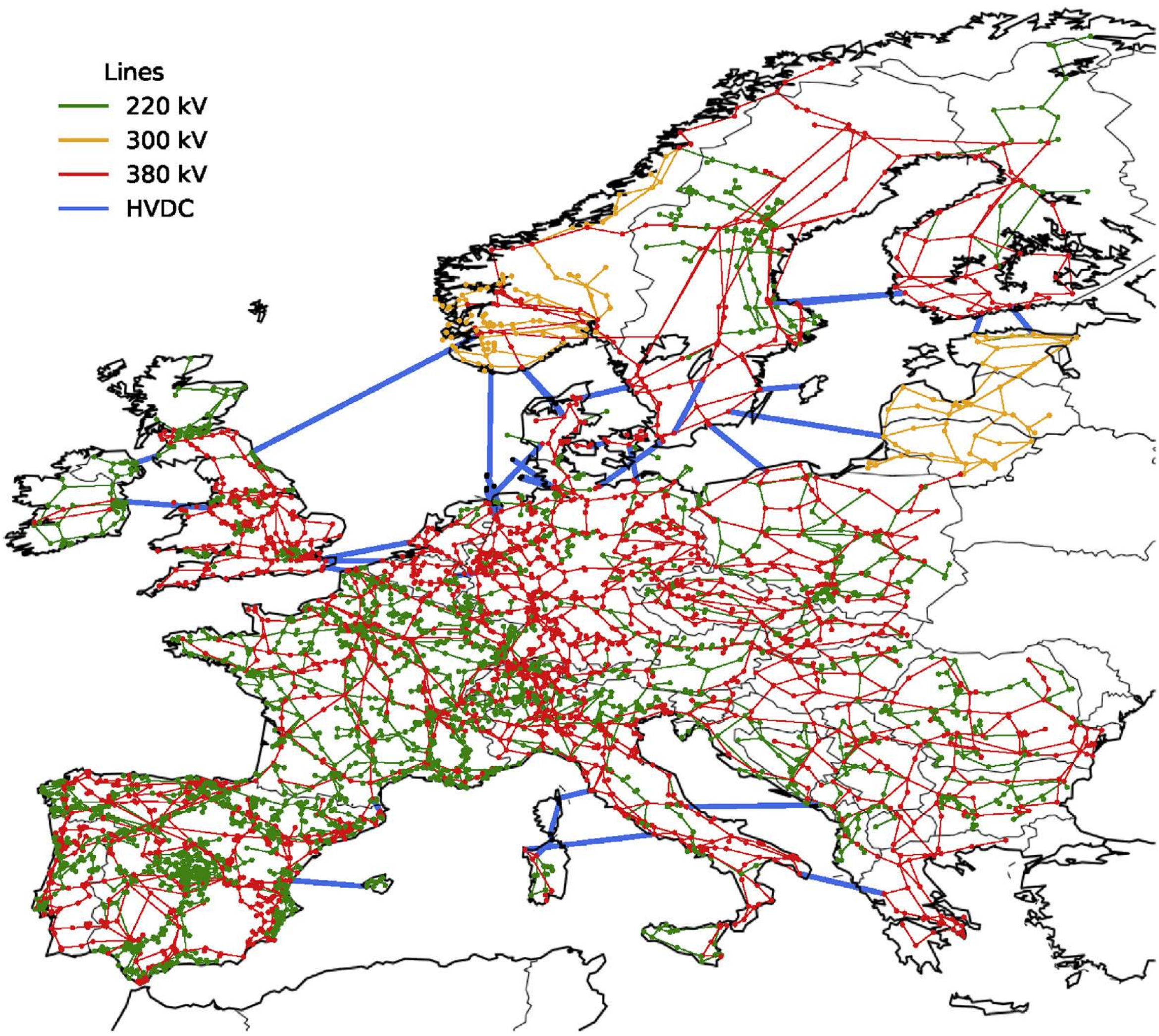

Figure 2.9: ENTSOE-E Transmission network model [47].

PyPSA-Eur has a wide variety of customizable and configurable features that must be specified in a *config.yaml* file located in its root directory. Through this file, users can interact with PyPSA-Eur and run as many different analyses as they want. The configuration file is human-readable and presents a simple and clean structure, following hierarchical order by indentation. Listing 2.1 gives an example of what configuration looks like in PyPSA-Eur.

```
scenario:
  simpl: [’’]
  ll: [’copt’]
  clusters: [3]
  opts: [$CO_2$L-1H-Ep]
```

Listing 2.1: Configuration file: scenario [47].

PyPSA-Eur uses a workflow management system as a tool to create reproducible and scalable data analysis. A complete workflow for an electricity system model is attached in Appendix A.

Workflow Management: snakemake

Snakemake is a workflow management tool that enables reproducible data analyses with adaptability and transparency. It allows modification for further investigation, i.e. extended or slightly different research questions, and provides an ergonomic, combined, unified representation of all steps involved in data analysis [48].

Its automation process works through decomposition into steps represented as *rules*. Each rule describes how to obtain a set of output files from a set of input files. Input or output files can be either stored on disk or in remote storage (Amazon S3, Google Storage). *Wildcards* turn rules generic, for example, an output file of the form *results/by-country/{country}.csv*, with *{country}* being a wildcard that can be replaced with any non-empty string [48].

```
configfile: "config.yaml"

rule all:
  input:
    expand(
    "results/plots/{country}.hist.pdf",
    country=config["countries"]
  )
```

Listing 2.2: A Snakemake Rule.

By replacing wildcards, each rule, as seen in Figure 2.10, is transformed into a job that is automatically deduced and executed to produce the defined output files. Snakemake systematically verifies whether all input files for all jobs are either generated by another job or already present in the used storage. From this inference, Snakemake obtains a Directed acyclic graph (DAG[10]) of jobs. The workflow is designed to allow maximum readability [48].

[10] Directed acyclic graph

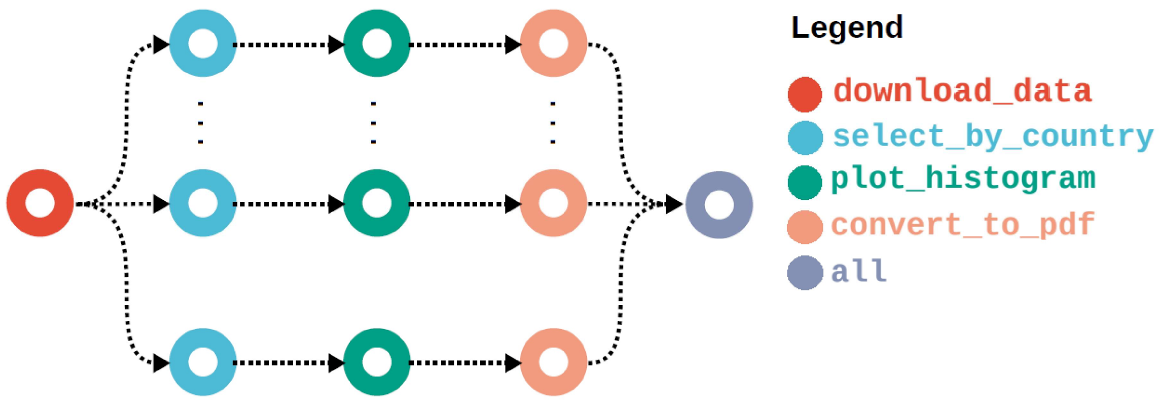

Figure 2.10: Representation of a Directed acyclic graph. Adapted from [48]

3. Methods

In order to answer the research questions mentioned in this work, the methodology in Figure 3.1 is employed. Initially, PyPSA and PyPSA-Eur frameworks are fully understood. Followed by the implementation of APV and e-tractors as technologies and parallel research of specific information for each technology. After the integration of new technologies, adaptation to some PyPSA-Eur scripts was necessary, such as modifications in the workflow management script and the solver's constraints. During the scenarios step, parameters are defined for use in the optimization step, where possible future energy systems are obtained. Finally, a thorough analysis is carried out, which includes visualization and quantitative examination as tools.

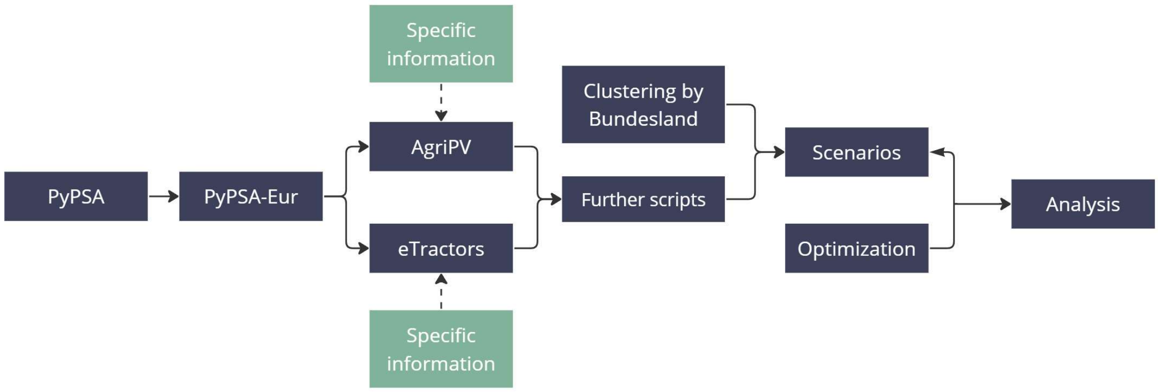

Figure 3.1: Methodology scheme.

Figure 3.2 illustrates a simplified version of the analyzed energy system. In this diagram, horizontal lines represent buses, to which components are connected. Arrows indicate the direction of energy flow within components. Each block represents a key PyPSA component within the system. Demand and Field Work are Load components (orange blocks), responsible for drawing electricity from the grid. Sources represent generators (dark blue blocks), such as solar and wind power plants, as well as coal and lignite power plants. APV, also a generator component, is set to its own bus so analysis can be carried out. Flexibility, also separated from the main bus, and e-tractors are store components (light green blocks) designed to store energy and help balance the grid.

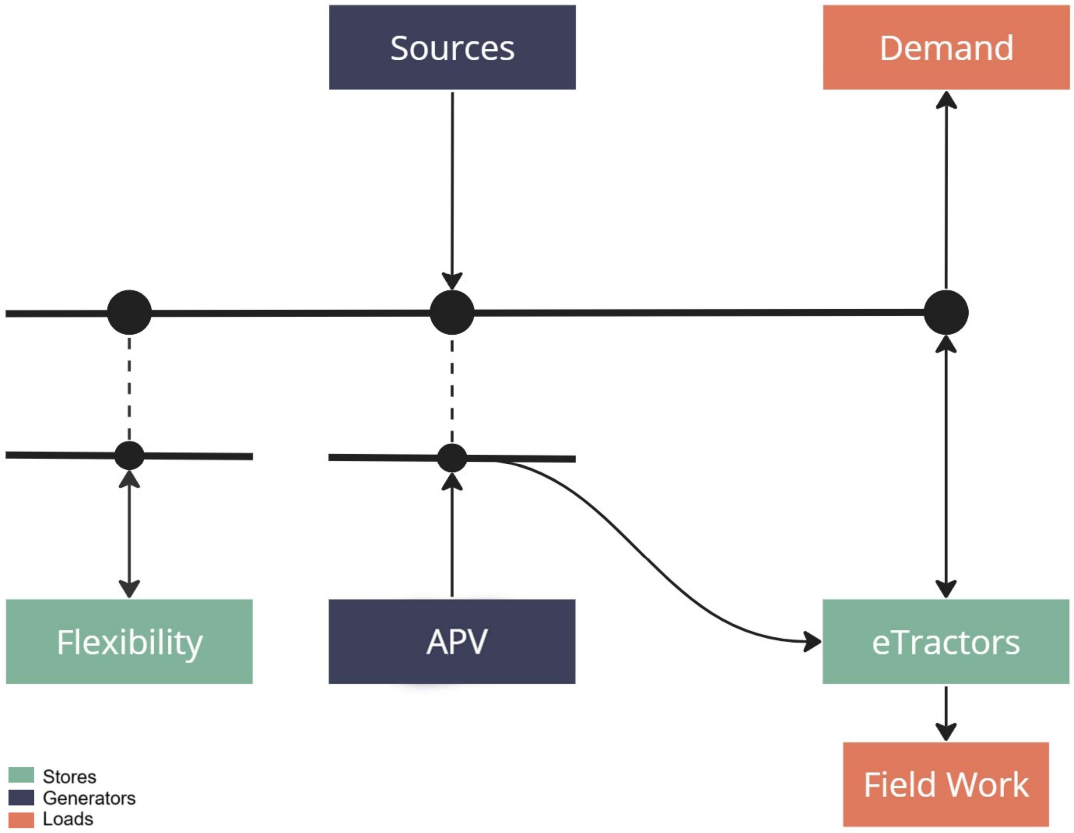

Figure 3.2: Energy System's illustration.

3.1. APV implementation in PyPSA-Eur

Status	Script
Modified	config.yaml
Modified	Snakefile
Modified	scripts/rule_renewable_profiles

Table 3.1.: Summary of modified scripts for APV's implementation.

PyPSA-Eur uses Snakemake rule *build_renewable_profiles* to calculate information for renewable sources, excluding hydro, such as the installable capacity (based on land use), the available generation time series (based on weather data), among others. Technologies of interest can be informed in the *config* file. APV technologies can be implemented similarly to *solar*. Listing 3.1 shows part of the mentioned code.

```
renewable:
  solar:
    cutout: europe-2013-sarah
    resource:
      method: pv
      panel: CSi
      orientation:
```

```
      slope: 35.
      azimuth: 180.
    capacity_per_sqkm: 1 # 100 MW/km2 -> 1% Land Availability = 1
    corine: [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,
            12, 13, 14, 15, 16, 17, 18, 19, 20, 26, 31, 32]
    natura: true
    potential: simple
    clip_p_max_pu: 1.e-2
```

Listing 3.1: Configuration file: renewable [47].

To include APV technologies in the aforementioned rule, *solar* parameters were replicated. Three types of APV are to be considered, named as APV_grass for grassland, APV_arable for arable farms, and APV_horti for horticulture. Table 3.2 summarizes the considered parameters based on the APV Guide by Fraunhofer ISE [2].

Parameters	Grassland	Arable farm	Horticulture
slope	90	0	0
azimuth	180	180	180
capacity_ per_ sqkm	30	60	70
corine	18	12, 13, 14	15, 16, 17, 19, 20

Table 3.2.: APV's parameters input in PyPSA-Eur.

Figure 3.3: a: grassland, b: arable farm, c: horticulture

Parameter *capacity_per_sqkm* is expressed in MW/km^2. However, it considers the Land Availability (LA[1]) in this study, so only a percentage of the total capacity is provided as a parameter; *corine* specifies areas according to CORINE Land Cover [49] and were defined as in Table 3.3. Grassland includes dense grass cover not under a rotation system. Arable farm considers cultivated areas regularly plowed and generally under a rotation system. Horticulture stands for crops that are not under a rotation system, which provide repeated harvest and occupy the land for a long period of time.

GRID_CODE	LABEL1	LABEL2	LABEL3
12	Agricultural areas	Arable land	Non-irrigated arable land
13	Agricultural areas	Arable land	Permanently irrigated land
14	Agricultural areas	Arable land	Rice fields
15	Agricultural areas	Permanent crops	Vineyards
16	Agricultural areas	Permanent crops	Fruit trees and berry plantations
17	Agricultural areas	Permanent crops	Olive groves
18	Agricultural areas	Pastures	Pastures
19	Agricultural areas	Heterogeneous agricultural areas	Annual crops associated with permanent crops
20	Agricultural areas	Heterogeneous agricultural areas	Complex cultivation patterns

Table 3.3.: Agricultural Area according to CORINE Land Cover.

3.1.1. Further scripts

Besides the previous modifications, no new scripts were necessary for APV's implementation. However, some simple modifications were needed in the further PyPSA-Eur scripts. In the *config* file, a new scenario wildcard was added: *land_availability*, which takes the percentage of land available for APV's installation. In *Snakefile*, this wildcard has to be constrained in *wildcard_constraints* to only take values between 1 and 10. Additionally, the rule *build_renewable_profiles* was modified; inside the input file "regions", the conditional statement that checks for onshore regions was modified to include APV technologies alongside onwind and solar.

[1] Land Availability

3.2. e-tractors implementation in PyPSA-Eur

Status	Script
Modified	config.yaml
Modified	Snakefile
New	scripts/build_etractors_load
New	scripts/add_etractors
Modified	scripts/solve_network

Table 3.4.: Summary of modified/new scripts for e-tractor's implementation.

As a first step taken for the implementation of e-tractors into PyPSA-Eur system, an initial search on tractors' usage was carried out. Information on tractors' categories (power and yearly hour usage) was assembled. It was assumed that the number of current diesel tractors would stay constant until the year 2045. This information can be found in the Literature Review in Table 2.2.

Based on that information and equations that convert energy usage from a diesel tractor to an e-tractor, plus the load profile of Figure 2.6, a script that generates a load profile for e-tractors and availability for charging and discharging to the grid was produced, named as *build_etractors_load*. Load and availability profiles consider field work between April and October. It randomly assigns 8 hours of usage per day, with 1 hour being idle work, between 6am and 7pm, excluding weekends. Load is calculated considering a complete transition from diesel tractors to e-tractors, and it defines the total load for each category of e-tractors. Finally, the script uses the current wildcard *e-tractors* that corresponds to the transition from diesel tractors to e-tractors (30%, 70%, 100%). Depending on the considered percentile of e-tractors in the energy system, it multiples the percentile by the load profile for each tractor category, resulting in the final load and availability profiles.

Figure 3.4 illustrates the logic behind the e-tractor model. The model was highly inspired by the battery model included in the PyPSA-Eur script *add_extra_components*. All e-tractors are defined as a large store that provides energy to an external load. The battery can be charged directly from the grid, with losses, or from APV, without losses. It consists of a Store, Load, and three Links. However, in the same script - and only when e-tractors are of interest -, two additional steps were necessary: (1) the definition of a new carrier (e-tractor) and new buses for the e-tractor model, and (2) the definition of new buses for APV generators, and the addition of new Link components, which connect APV and the main grid bus.

The Store component connects to the new e-tractor buses, inheriting the energy carrier. It becomes the fundamental component in the model, working as the battery of an e-tractor. It was programmed as a non-extendable component, due to the analysis logic: each scenario has a defined ratio of e-tractors in the system (30%, 70%, or 100%). Therefore, in the

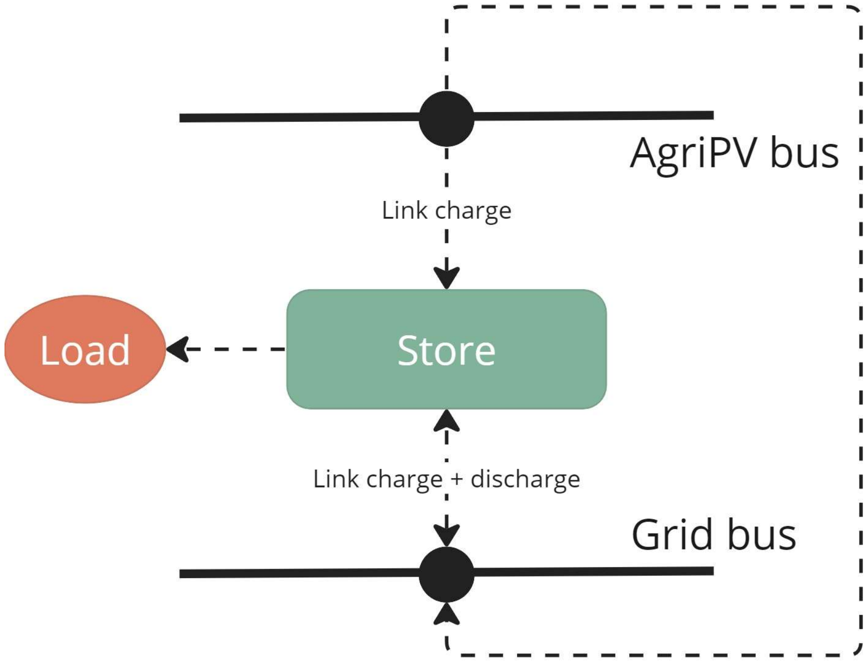

Figure 3.4: Electric tractor's components illustration.

store component, it is necessary to define *e_nom* (nominal energy capacity) and *e_max_pu* (relative nominal energy capacity). The battery capacity represented by *e_nom* is the sum of the capacities of all e-tractor batteries in the system. The relative value *e_max_pu* depends on whether a particular e-tractor is in field work or not. For example, if an e-tractor with a larger battery is unavailable for charge or discharge, the relative nominal capacity should decrease more compared to a scenario where an e-tractor with a smaller battery size is unavailable.

Only one Link attaches the e-tractor to the APV, and it functions as a charger. Therefore, energy is drawn from APVs to the e-tractors. For this charger, no losses are considered, due to the assumption that APVs are installed directly where electricity is needed. Two Link components attach APV to the grid with a certain loss of efficiency; one serves as a charger, and the other as a discharger. It's important to note that all three links are considered non-extendable components, which means they are created with a maximum nominal capacity. However, similarly to the relative value in the store components, *p_nom_pu* dictates the availability of the capacity for charging and discharging. A supercharger with a capacity of 150 kW, CHAdeMO-Stecker, for each e-tractor was selected. Therefore, the maximum potential charging or discharging capacity is determined by the number of e-tractors without field work for each time step during an optimization process.

3.2.1. Further Modifications

Further modifications include addition of wildcards for e-tractors' ratio/transition and a configuration variable named *non_ext_carriers* (non-extendable carriers) for the integration of e-tractors in *config* file, new rules in *Snakefile* for the integration of new e-tractors' scripts, and a new set of constraints in the *solve_network* script.

Referring to the latter modification, a new function named *add_etractor_constraints* was added to *solve_network*. If parallel charging by Grid-e-tractor link and APV-e-tractor link occurs, the total charging capacity would be doubled. Therefore, it is necessary to limit the capacity to a maximum, which is the number of available e-tractors at every timestep.

3.3. Clustering by Bundesland: Regional potential

Status	Script
Modified	config.yaml
Modified	Snakefile
Modified	scripts/add_etractors
Modified	scripts/build_etractors_load
New	scripts/build_etractors_load_regional
New	scripts/create_custom_busmap

Table 3.5.: Summary of modified/new scripts for regional analysis implementation.

In order to assess the regional potential for APV and e-tractors' expansion, further modifications to PyPSA-Eur scripts and new scripts are needed. A new boolean parameter was added to *config* file to inform if regional analysis is of interest or not. In *Snakefile*, this variable is assessed; if true, the rule *create_custom_busmap* generates a custom busmap for Germany using NUTS3 regions. The e-tractors' load profile is defined in *build_etractors_load_regional* according to the potential in each Bundesland, i.e states with more e-tractors will have a higher load profile. Additional modifications to *add_etractors* were necessary, due to the components implementation logic.

All modifications were done considering 13 Clusters that represent German states. Bremen, Berlin and Hamburg were clustered together with Nieder-sachsen, Brandenburg and Schleswig-Holstein, respectively. Therefore, if any other country is of interest, the described analysis will break down due to the specificities of each country. Table 3.6 represents the buses' mapping accordingly.

Bus	Bundesland
DE0 1	Baden-Württemberg
DE0 2	Bayern
DE0 4	Brandenburg and Berlin
DE0 7	Hessen
DE0 8	Mecklenburg-Vorpommern
DE0 9	Nieder-sachsen and Bremen
DE0 A	Nordrhein-Westfallen
DE0 B	Rheinland-Pfalz
DE0 C	Saarland
DE0 D	Sachsen
DE0 E	Sachsen-Anhalt
DE0 F	Schleswig-Holstein and Hamburg
DE0 G	Thüringen

Table 3.6.: Buses' mapping for regional analysis.

3.4. Data

PyPSA-Eur has part of the needed data already in its Git repository. Otherwise, PyPSA-Eur retrieves data from outside sources, due to the file sizes. Table 3.7 summarizes the rules and what data it downloads.

Snakemake rule	Data
retrieve_databundle	NUTS3 shapes, EEZ shapes, CORINE Landcover, Natura 2000, historic yearly totals of hydro generation, GDP and POP.
retrieve_load_data	Load data for each country.
retrieve_cutout	Weather data from two sources: ERA5 and SARAH-2.
retrieve_natura_raster	Already rasterized version of Natura 2000 natural protection areas to reduce computation times.

Table 3.7.: Summary of rules that retrieve data.

In addition to data from PyPSA-Eur and data downloaded by the aforementioned rules, new data had to be manually collected for analysis with APV and e-tractors. This data is stored as CSV files in *data* folder. For example, data from table 2.2 is used when calculating the e-tractors' load profile. Similarly, regional data for the regional load profile of e-tractors is also required. These are named, respectively, *tractors_data.csv* and *tractors_data_regional.csv*.

Costs for technologies, including investment and marginal costs, lifetime in years, Fixed operation and maintenance (FOM[2]) in %/year, Variable operation and maintenance (VOM[3]) in $/MWh_{el}$, etc., for years 2030 and 2045 are retrieved from the newest version of PyPSA-

[2]Fixed operation and maintenance
[3]Variable operation and maintenance

Eur and stored in *data* folder. Capital costs are summarized in Table 3.8. Final capital costs are annualized to net present costs with a discount rate over the economic lifetime using the annuity factor. Marginal costs are calculated using VOM, fuel costs and efficiency.

Technology	**Investment costs [€/kWel]**	
	2030	**2045**
CCGT	830.0	807.5
OCGT	435.25	417.7
biomass	2209.0	2209.0
coal	767.0	613.6
lignite	3845.5	3845.5
oil	343.0	337.75
onwind	1035.5	970.3
offwind	1523.5	1397.7
solar rooftop	636.7	500.3
solar utility	347.5	277.8

Table 3.8.: PyPSA-EUR investment cost assumptions.

Furthermore, costs for APV technologies were required for analysis, and these costs were incorporated into both the 2030 and 2045 data files. According to PyPSA-Eur data, there is an 32% decrease in investment costs for solar between 2020 and 2030, followed by a 20% decrease between 2030 and 2045. This same cost-reduction trend is also applied to APV technologies. Table 3.9 displays the costs for APV considered in this study, which 2020 costs come from APV Guide by Fraunhofer ISE [2].

APV technology	**Marginal cost [€/MWhel]**	**Investment costs [€/kWel]**		
		2020	**2030**	**2045**
Grassland	0.126	786.0	534.5	427.6
Arable farm	0.126	1128.0	767.0	613.6
Horticulture	0.132	982.0	667.7	534.2

Table 3.9.: APV costs.

3.5. Scenarios

Figure 3.5 corresponds to a scheme summarizing the main scenarios of this study. It is divided into three key points: CO_2 limits, land availability for implementation of APV, and e-tractors' transition.

CO_2 limits are defined according to the German decarbonization path. As of 2030, GHG emissions should be down 65% compared to 1990 levels. By 2045, the energy system must achieve complete decarbonization. Following a study conducted by Agora Energiewende,

Figure 3.5: Scenarios' scheme.

for total decarbonization in 2045, the limit set for the energy sector by 2030 should be 98 $MtCO_{2eq}$. The same study suggests an increase in demand of 12% for 2030 (643 TWh), and 100% increase for 2045 (1017 TWh), compared to 2013 [13]. A sensitivity analysis of the land availability for APV is of interest due to the uncertainty surrounding the actual area available for installations. For reference scenarios, the same land availability is explored, but only using solar power plants, i.e only agriculture CORINE Land Cover areas are taken into account for this sensitivity analysis. In the following scenarios, land availability for solar power plants was held constant at 1%. Finally, the integration of e-tractors is evaluated. A gradual increase in the number of e-tractors is investigated in combination with APV. For the reference scenario, neither APV nor e-tractors are implemented.

In this study, the considered conventional power plants include OCGT, CCGT, geothermal, biomass, oil, coal, and lignite. Additionally, the renewable power plants considered are offshore wind-ac, offshore wind-dc, onshore wind, run-of-river, and biomass. All scenarios assumed a carbon tax rate of 200 €$/tCO_2$. These scenarios were grouped into three final buses for simplification and solving purposes.

Figure 3.6 represents a summary of the scenarios in this study. Four scenarios are considered. Scenario 1 (2030 Reference scenario), Scenario 2 (2045 Reference scenario), Scenario 3 (2030 with solar + APV + e-tractors), and Scenario 4 (2045 with solar + APV + e-tractors). Two sensitivity analysis are executed: agricultural land availability and e-tractors integration. Land availability analysis is of interest for all scenarios. Additionally, a sensitivity analysis for evaluation of e-tractors effects is carried out only in Scenarios 3 and 4.

			2030 **Partly decarbonized:** -65% CO2 / 1990	**2045** **Fully decarbonized:** Null emissions
Flexibility allowed	Reference	Only solar technology: grount-mounted PV systems		
	Comparative	Solar + APV + e-tractors		
		0%	No e-tractors	
		30%	Initial conversion of diesel tractors to e-tractors	
		70%	Advanced conversion of diesel tractors to e-tractors	
		100%	Full conversion of diesel tractors to e-tractors	

Figure 3.6: Main scenarios for analysis.

3.6. Agrophotovoltaics land availability

In this study, a sensitivity analysis of agricultural land availability is of interest. In PyPSA-Eur, solar technologies are considered as one and are allowed to be installed in many CORINE Land Cover areas. In other words, the same technology that is installed in urban areas is also installed in agricultural areas. However, APV differs in techno-economic characteristics from common ground-mounted or rooftop solar panels. Therefore, it's interesting to understand how this diversification affects an energy system. Table 3.10 shows the maximum total nominal capacity for each land cover level. The availability of solar technology remains constant, while variations in agricultural land cover are examined. Maximum capacities are lower than those in reference scenarios due to the lower generation capacity per square kilometer. If at least 6% of the agriculture area is available for APV installation, there is a 634.3 GW capacity potential to be explored. Arable farming is the area with the most potential, around 450 GW.

Solar technology	**Maximum Nominal Capacity [GW]**		
	1%	**3%**	**6%**
Ground-mounted	29.50	29.50	29.50
Grassland	10.48	31.50	62.90
Arable farming	74.73	224.20	448.40
Horticulture	15.59	46.77	93.50
Total	130.30	331.90	634.30

Table 3.10.: Maximum capacities for solar and APV technologies for different land availability.

3.7. Electric tractors' load profile

Load profiles for e-tractors were generated for each scenario based on the transition from diesel tractors to electric tractors. Table 3.11 provides information on the number of e-tractors categorized by power for different integration levels (30%, 70%, and 100%).

Power [kW]	**30%**	**70%**	**100%**
< 30	144,084	336,196	480,280
31 - 50	141,961	331,243	473,204
51 - 70	101,137	235,987	337,124
71 - 90	44,466	103,754	148,220
> 90	78,965	184,252	263,217

Table 3.11.: Fleet of e-tractors for each scenario.

Figure 3.7 displays the total energy demand for e-tractors at each transition level. For the scenario with only 30% of e-tractors in the system, an estimated 8.5 TWh of energy in a year would be required. A complete transition from diesel tractors to e-tractors would necessitate a total of 28.2 TWh, representing 4.4% of the electric demand in 2030 and 2.8% of the electric demand in 2045.

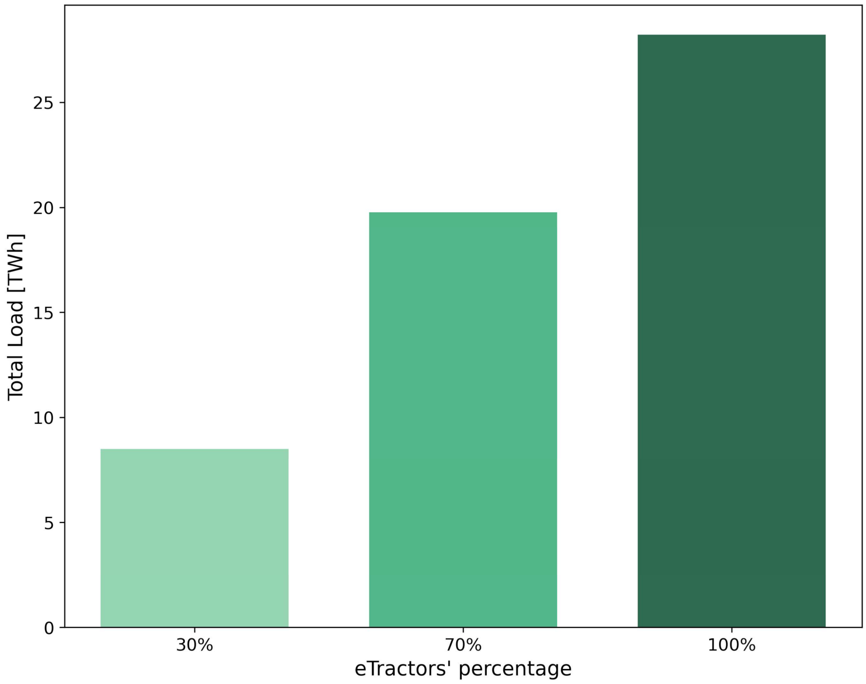

Figure 3.7: Electric tractors Total Energy Demand per scenario.

Figure 3.8 shows the distribution of load per unit for an e-tractor through the year. Usage starts in April and ends in October. Figure 3.9 represents the load in a week for a complete transition to e-tractors. In this study, it was assumed that no field work is performed on weekends, and each e-tractor is used for at least 8 hours, with working hours beginning between 6 am and 11 am. Additionally, a minimum of 1 hour of idle consumption is considered as part of daily e-tractor usage.

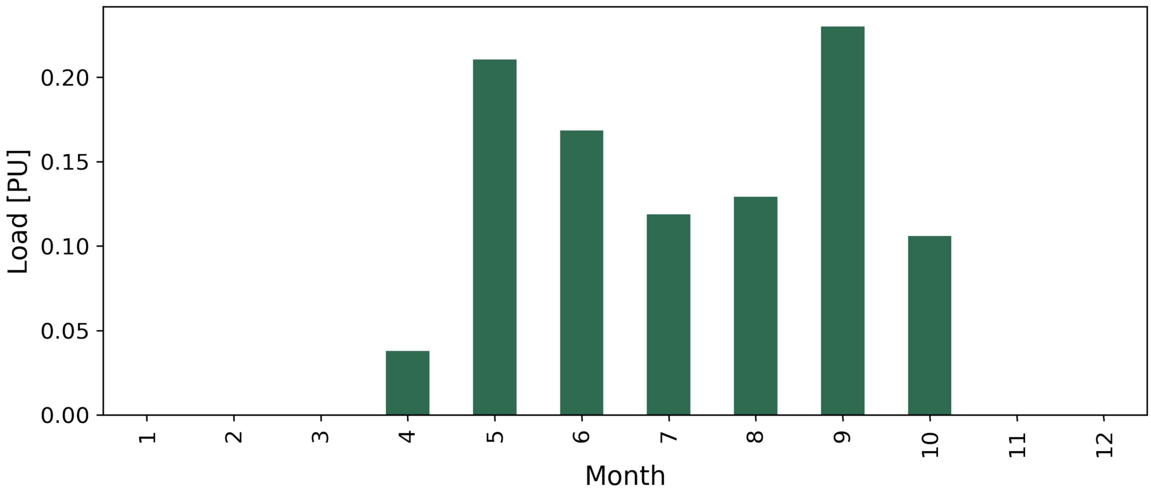

Figure 3.8: e-tractors Total Load per scenario.

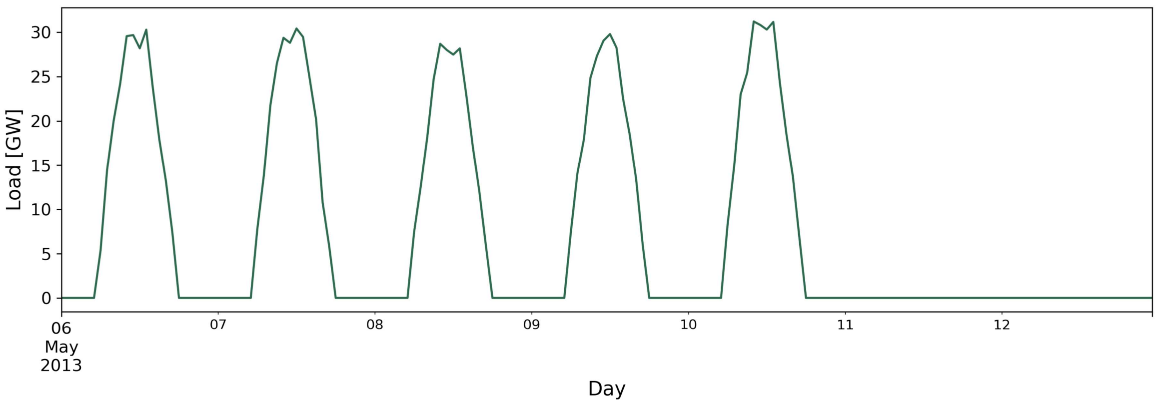

Figure 3.9: e-tractors' weekly Load profile.

4. Results and Discussion

In this section, the results from the optimization of different energy system scenarios will be analyzed. APV technologies' relevance in the system will be evaluated, as well as what is e-tractors' value in the system, integrated into APV. Initially, a general evaluation of the sensitivity analysis of agricultural land availability, clustered into three buses representing the entire state of Germany, is observed. A regional study follows, where the potential of each German Bundesland is examined.

For all studied scenarios, capital and marginal costs are shared, depending on the year of study. Table 4.1 summarizes the final annualized capital costs and marginal costs for each technology. Null capital costs stand for no new investments on that specific technology because these are already built into the energy system. Marginal costs take into account CO_2 emissions costs, therefore, technologies that emmit CO_2 have higher marginal costs.

Technology	**Marginal cost [€/MWhel]**	**Investment costs [€/MWel]**	
		2030	**2045**
CCGT	104.22	0	0
OCGT	147.60	0	0
biomass	14.90	0	0
coal	234.30	0	0
lignite	260.80	0	0
oil	297.40	0	0
onwind	0.03	96,085	89,644
offwind-ac	0.03	196,619	181,459
offwind-dc	0.03	217,734	202,574
solar	0.02	37,948	30,522
APV, grassland	0.019	50,515	40,839
APV, arable farm	0.019	72,488	58,604
APV, horticulture	0.024	63,103	51,020
H_2	0.01	796.3	796.3
battery	0.019	9,177.8	5,128.9
e-tractor	0.009	0	0

Table 4.1.: Technology marginal costs and annualized capital costs.

4.1. Reference scenarios

Reference scenarios for each agriculture land availability are analyzed. The maximum nominal capacities for solar technology in these scenarios are in Table 4.2, 211.2 GW with 1% land availability, 574.5 GW with 3% land availability, and 1119.5 GW with 6% land availability. Figure 4.1 shows the energy systems' power plant mix for both years, 2030 and 2045. In 2030, the objective is partial decarbonization, and renewable sources predominate, such as solar, onwind, and offwind-dc. Conventional power plants are also present in the system, including CCGT, coal, and lignite. The total optimal capacity to cover demand and reach the CO_2 limit in the system is about 400 GW with 1% land availability, and 440 GW with 3% and 6% . Investments in solar technology change with increasing land availability, from 1% to 3%. On the other hand, no increase is observed from 3% to 6% land availability, possibly because the CO_2 limits are met with only 3% land availability, and the maximum nominal capacity for solar is not used to the limit. Similarly, in the 2045 scenarios, which aim for zero CO_2 emissions, an increase in solar technology investment is expected with more available land. For instance, if only 1% of agricultural areas are available, approximately 100 GW more investment in onwind is suggested compared to 3% and 6% land availability. However, with 3% and 6% agricultural area availability, an increase in solar investments is observed. The total system capacity lies around 780 GW, 870 GW, and 880 GW, respectively, for 1%, 3%, and 6% land availability. The difference between 3% and 6% scenarios is due to more investment in solar technology.

Maximum Nominal Capacity [GW]		
1%	**3%**	**6%**
211.2	574.5	1119.5

Table 4.2.: Maximum capacities for solar technology, reference scenarios.

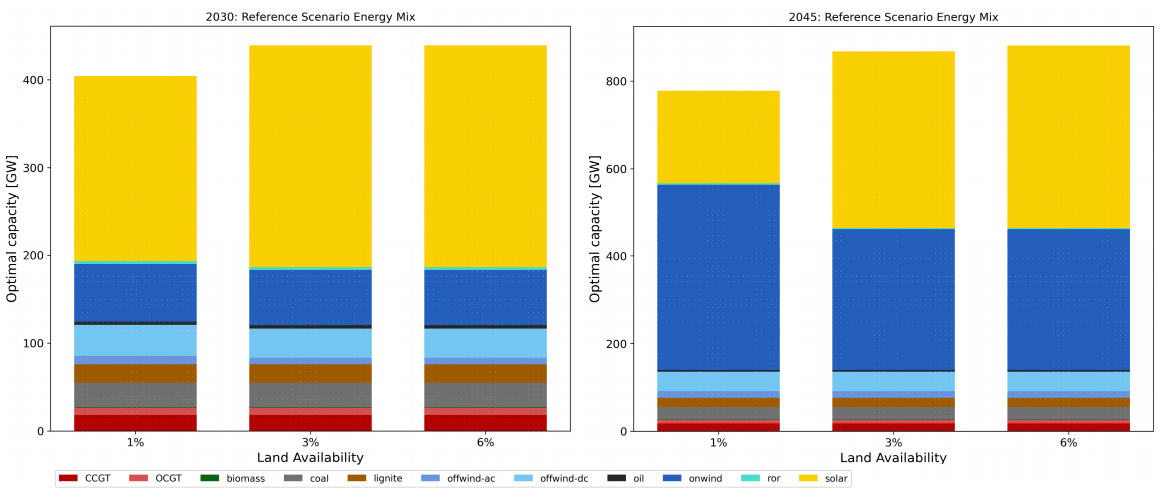

Figure 4.1: Optimal Capacity in 2030 and 2045, Reference Scenarios

Figure 4.2 displays optimal energy capacities for flexibility options for reference scenarios. For 2030, lower flexibility capacities than 2045 scenarios are necessary to meet CO_2 limits. In 2030, the analysis suggests having a larger capacity with more hydrogen options and batteries when there is less solar energy available in the system to meet energy needs. Conversely, when more solar energy is integrated, the suggestion is to have less capacity but rely primarily on batteries. This is due to the higher investment costs for Electrolysis and Fuel Cells (H_2 options), compared to batteries. In 2045, the opposite is observed, where the analysis suggests investing in H_2 options is more cost-efficient than investing heavily in batteries. The impact of agricultural land availability, i.e. the expansion of solar energy, is presented in different way for 2030 and 2045 scenarios. In 2030, as more solar is integrated, batteries become the most important flexibility option. In 2045, as more solar is integrated, a slight decrease in battery capacity can be observed.

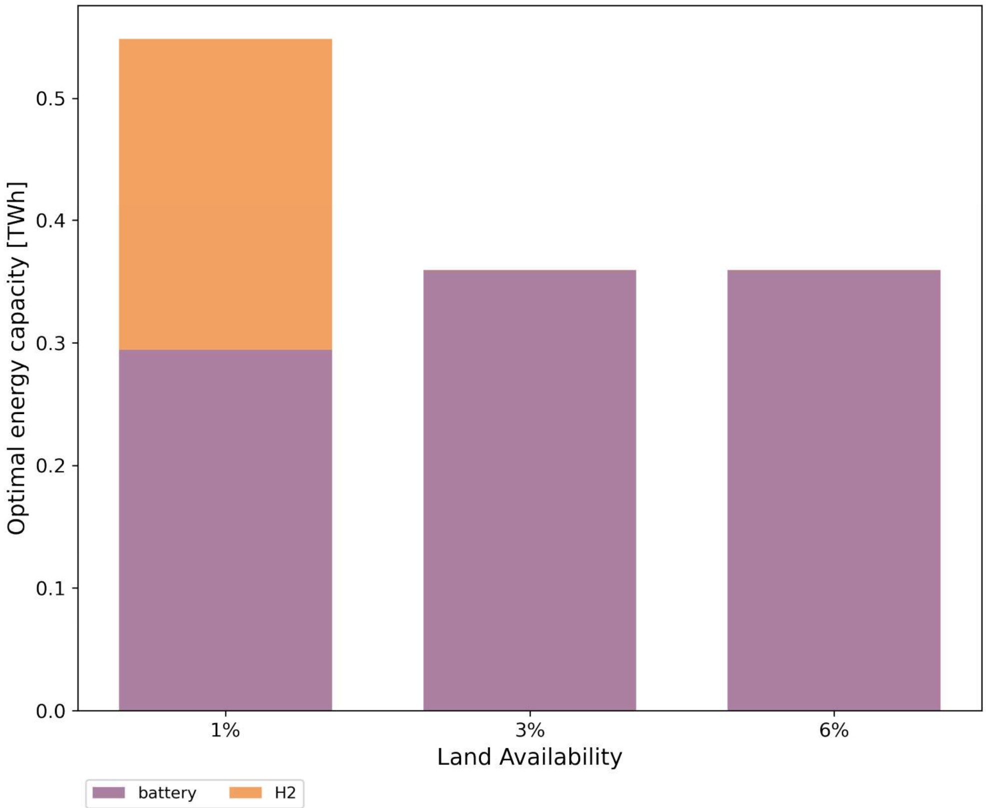

Figure 4.2: Optimal Capacity for flexibility units in 2030 and 2045, Reference Scenarios

Full Load Hour (FLH[1]) is a measure of utilization used to compare different technologies within the energy system. It is defined by the total energy generated or stored in a year over the nominal capacity or nominal energy of a store. Figures 4.3 and 4.4 show the FLH for all reference scenarios for 2030 and 2045. It is clear that conventional power plants are used

[1]Full Load Hour

only in 2030 scenarios, providing base load, as long as the CO_2 limit is not surpassed. In 2045, no conventional power plants are used, due to the CO_2 emissions costs and the high penetration of renewable sources to avoid CO_2 emissions combined with the expansion of H_2 options and batteries.

As for stores FLH, it is noticeable how batteries present higher FLH than H_2 options. Specially in 2045, FLH for H_2 can be half of batteries units, while having a much larger optimal energy capacity. This could be related to the low energy conversion between electricity and hydrogen

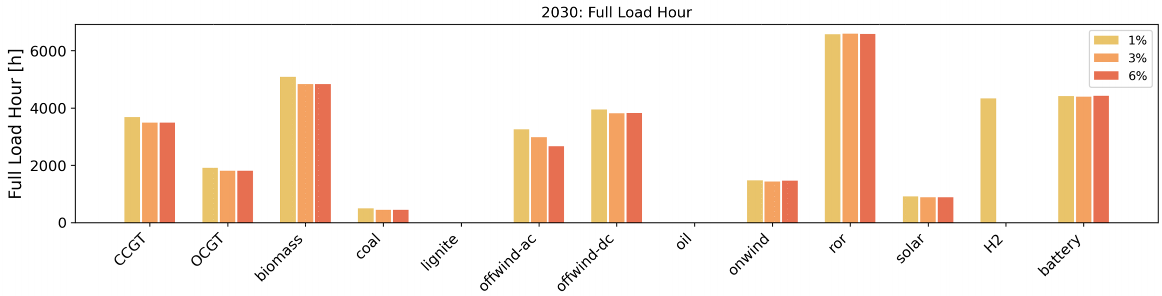

Figure 4.3: 2030: Full Load Hour, Land Availability Reference Scenarios

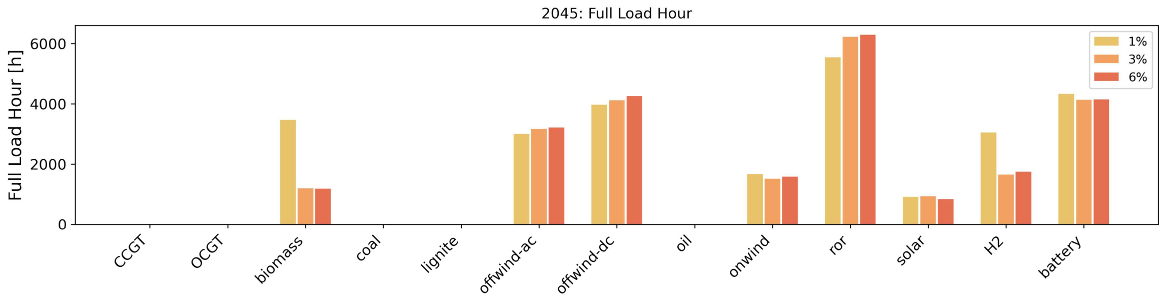

Figure 4.4: 2045: Full Load Hour, Land Availability Reference Scenarios

The following Figures 4.5, 4.6, 4.7, and 4.8, represent the Unit Commitment including flexibility options for 2030 and 2045 scenarios with 3% agricultural land availability. In 2030, during the winter months (February), baseload is provided by conventional power plants (CCGT, OCGT and coal). Wind energy provides a second source of baseload, with added fluctuability. It is observed a ramp-down / shut-down of coal power plants, whenever solar energy is available. Additionally, energy from batteries provides a supply during peak hours, when renewable energy is not enough. In the summer (July), a lot more solar energy is available. Therefore, conventional power plants are less often used and more surplus energy can be stored in the batteries for later usage.

In 2045 scenarios, store units' importance is even clearer. Due to the high renewable sources penetration and its fluctuability, it is necessary to integrate store units for later usage of exceeding electricity generation to attend to the load demand. As seen in the previous FLH plots, H_2 units utilization ratio is lower than that of batteries, due to the lower efficiency. Batteries store electricity and must supply electricity, whilst H_2 stores store green hydrogen by Electrolysis and supply electricity by Fuel Cells. As more H_2 capacity is installed due to lower investment costs, H_2 takes a more important role in flexibility. Nevertheless, batteries still provide flexibility, supplementing that of Fuel Cells.

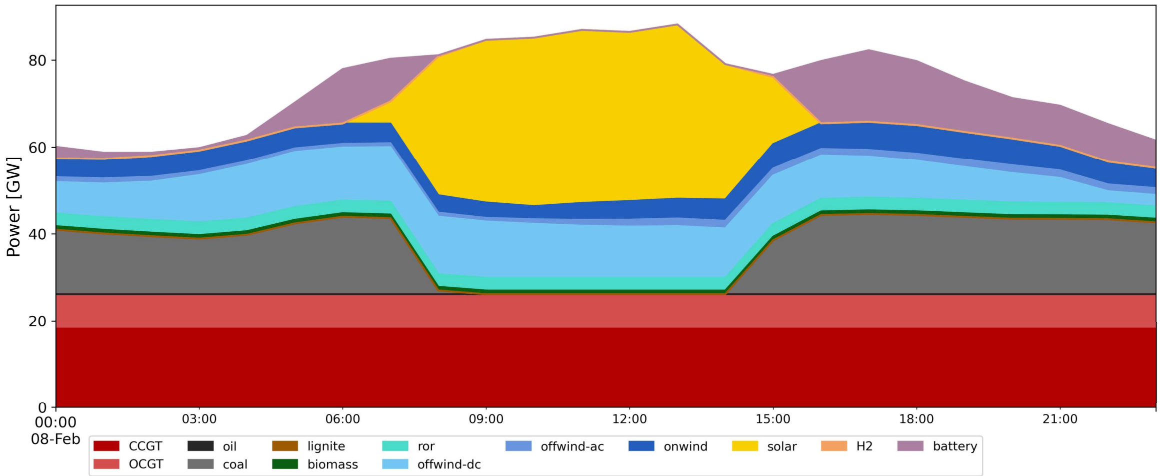

Figure 4.5: 2030: Unit Commitment with 3% of Land Availability, February

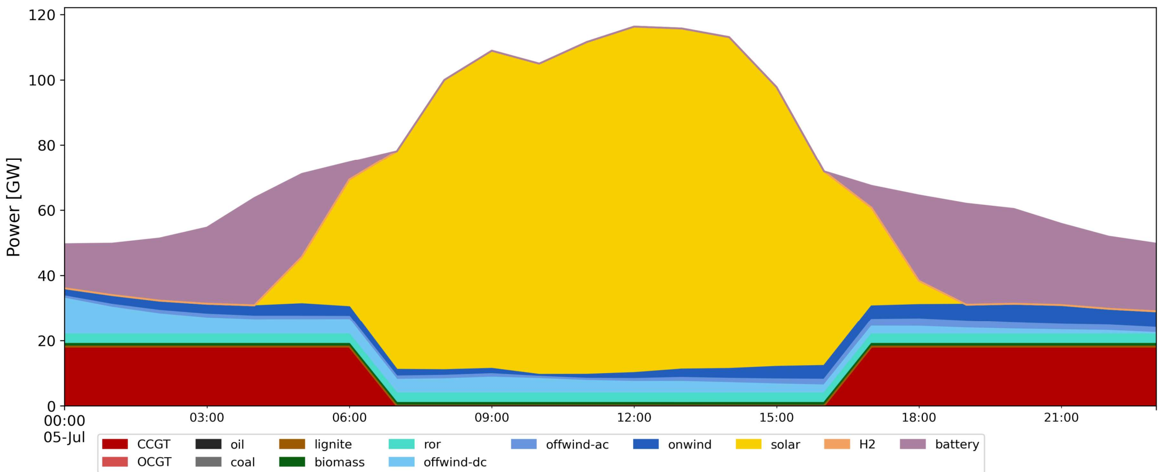

Figure 4.6: 2030: Unit Commitment with 3% of Land Availability, July

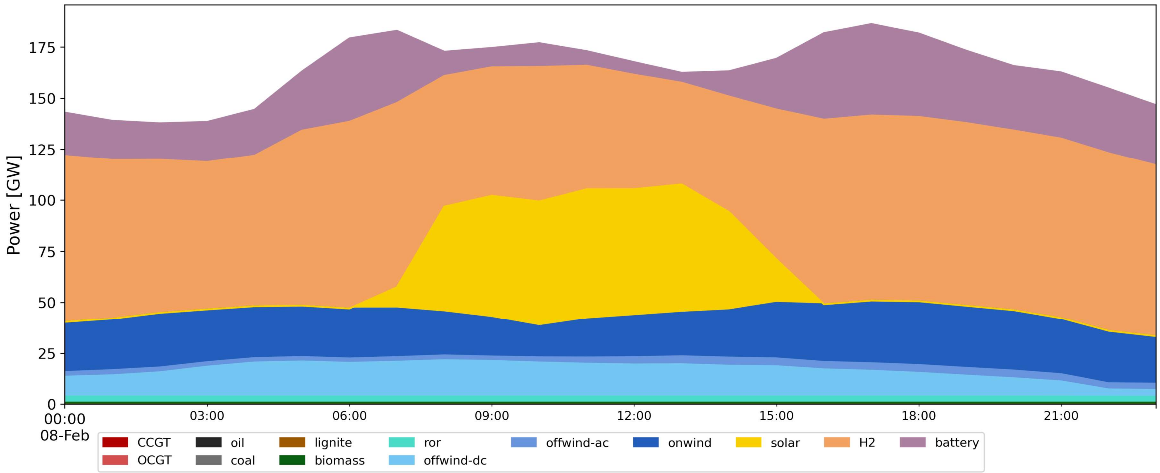

Figure 4.7: 2045: Unit Commitment with 3% of Land Availability, February

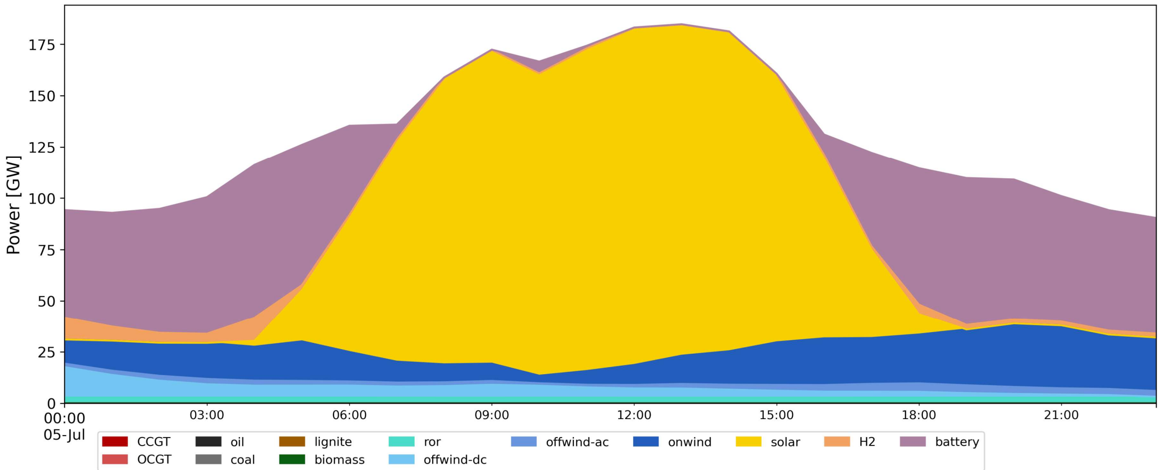

Figure 4.8: 2045: Unit Commitment with 3% of Land Availability, July

Table 4.3 presents the final costs of all reference scenarios. Final costs are calculated as marginal costs and capital costs for all technologies, based on the discount rate, lifetime, investment, fixed operation and maintenance, variable operation and maintenance, fuel costs, efficiency, and carbon-dioxide intensity. Costs for 2030, partially decarbonized, are lower than those of 2045, completely decarbonized. For 2030, costs are similar or the same, possibly because the agricultural land availability does not significantly impact the energy mix. However, in 2045, there is a noticeable decrease in cost with higher land availability.

Land Availability	2030	2045
1%	41.1 b€	108.5 b€
3%	40.9 b€	103.5 b€
6%	40.8 b€	102.9 b€

Table 4.3.: Energy systems' costs for reference scenarios.

4.2. Comparative scenarios

A comparative study was conducted to assess an energy system with APV and e-tractors as pivotal technologies. To address the following research questions, a land availability sensitivity analysis was implemented, along with the integration of APV technologies and e-tractors into PyPSA-Eur.

- What is the electricity consumption of electric tractors within the grid?
- To what extent does the integration of electric tractors impact the expansion of APV in the energy system?
- Can electric tractors serve as a viable flexibility option within the energy system?
- What is the projected potential of APV in Germany for the years 2030 and 2045?
- What is the projected regional potential of APV in Germany for the years 2030 and 2045?

4.2.1. APV and e-tractors integrated scenarios

Further scenarios were analyzed to assess the impact of integrating e-tractors with APV technologies. It was assumed that e-tractors have a direct link to APV technologies, enhancing charging and efficiency. The maximum availability of land for solar technology is kept constant at 1%, hence contact optimal capacity throughout the scenarios. Figures 4.9 and 4.10 display the optimal capacities of all power plants in each scenario, grouped by agricultural land availability. From a visual standpoint, as e-tractors are introduced into the system, the total optimal capacity increases. In 2030 at 100% e-tractors transition, with only 1% land availability, total optimal capacity lies around 350 GW, whilst it lies at about 400 GW with 6% land availability. This increase could be attributed to the fact that e-tractors contribute to the overall load of the system; at the 100% integration level, they contribute 4.4% more load in 2030 and 2.8% more load in 2045.

However, when comparing total capacity between land availability levels of 1% and 6%, it becomes evident that the 6% availability scenario has a higher overall optimal capacity. At only 1% of agricultural land availability, e-tractors' transition barely affects the total optimal capacity in the system, other than increasing onwind investment to, possibly, cover e-tractors' load. On the other hand, if more agricultural land is available, as e-tractors are introduced into the energy system, much more APV capacity is installed, whilst onwind investments are kept constant.

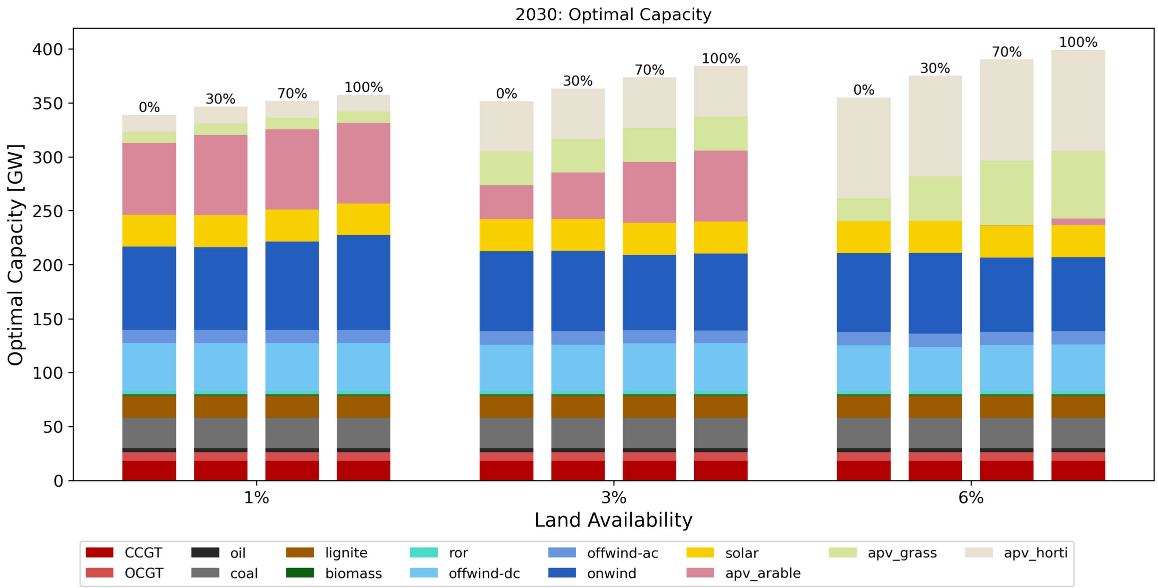

Figure 4.9: 2030: Optimal Capacities per scenarios with APV and e-tractors, land availability included.

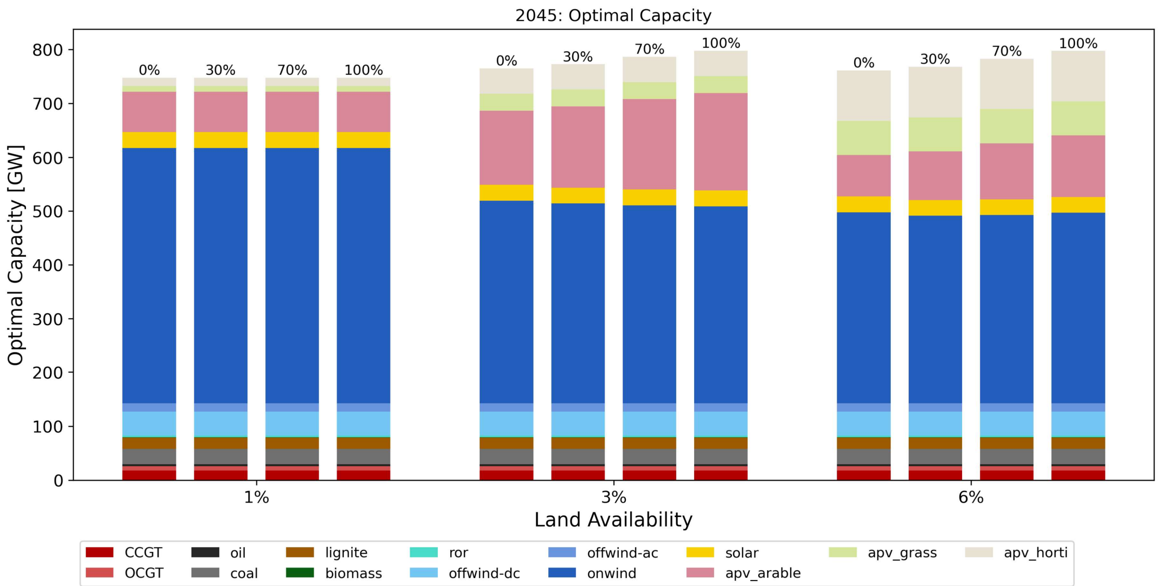

Figure 4.10: 2045: Optimal Capacities per scenarios with APV and e-tractors, land availability included.

Figures 4.11 and 4.12 show the total energy generated by power plants in the system. For both year scenarios, 2030 and 2045, at 1% agricultural land availability, an increase in energy generated by onwind and offwind sources is observed. APV seems to generate a constant amount of energy disregarding the increase of e-tractors in the system. This is a direct effect of the land availability, i.e. the maximum installed capacity is reached in both scenarios with only 1% landa availability. On the other hand, as more land is available, the opposite is found. As e-tractors are introduced into the system, more energy is generated by APV options and less by other sources. This might be a direct effect of the more cost-efficient energy store created by APV and e-tractors.

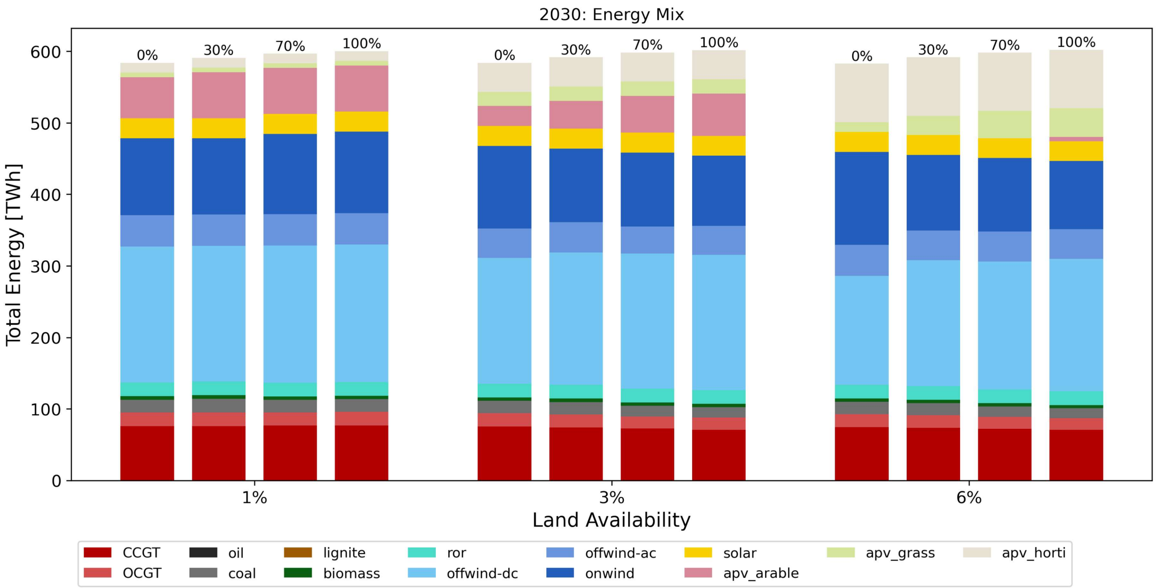

Figure 4.11: 2030: Total Energy per scenario with APV and e-tractors, land availability included.

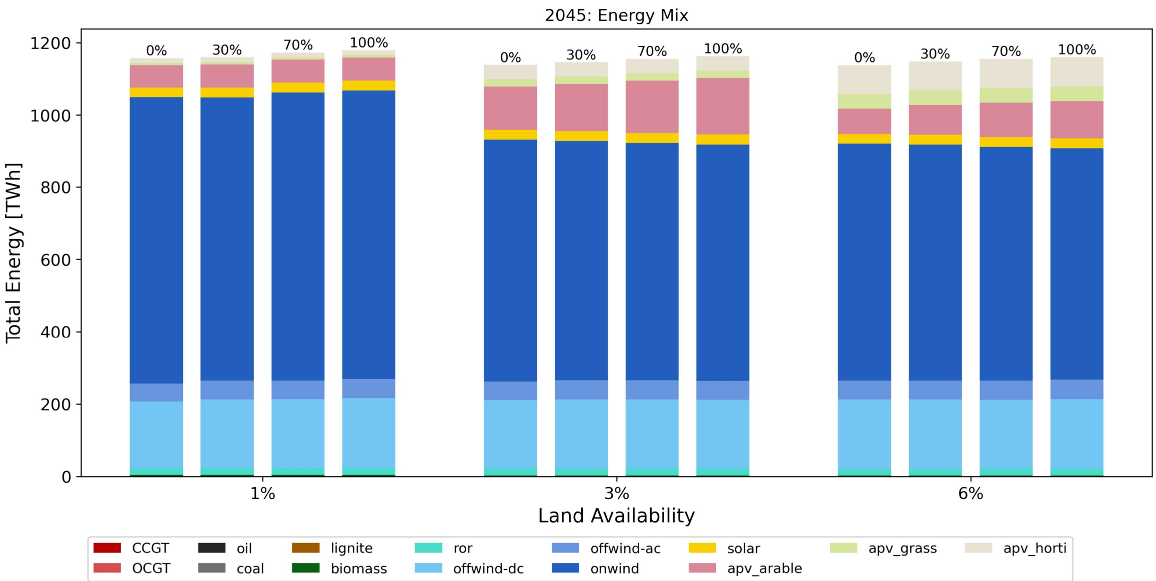

Figure 4.12: 2045: Total Energy per scenario with APV and e-tractors, land availability included.

Stores optimal maximal capacity can be observed in Figure 4.13 for 2030 and in Figure 4.14 for 2045. As seen in the 2030 scenarios, the integration of e-tractors onto the grid gradually makes other sources of flexibility obsolete. A complete transition from diesel tractors to electric tractors with a successful integration between APV and e-tractors would provide most of the necessary flexibility to the grid to achieve the 2030 CO_2 emissions goals. However, the situation is different in the 2045 scenario, where most of the energy capacity is provided by H_2 stores. This could be related to the higher load demand and penetration of wind energy.

Otherwise, between 1% and 3% land availability scenarios, a significant drop in energy capacity is observed. In Figure 4.10), a drop of optimal onwind capacity is also seen between these scenarios. Therefore, the further installation of APV capacity decreases investments in onwind power plants; consequently decreasing the necessity for H_2 stores. It is worth mentioning the gradual increase in optimal energy capacity for the 1% scenarios as e-tractors are integrated. This could be related to the e-tractors load demand, which lies around 25 TWh for a complete transition (100%). The cheapest option in these scenarios is to expand H_2 stores to supply the extra load coming from e-tractors.

Figure 4.13: 2030: Total Optimal Energy Capacity per scenario for stores, land availability included.

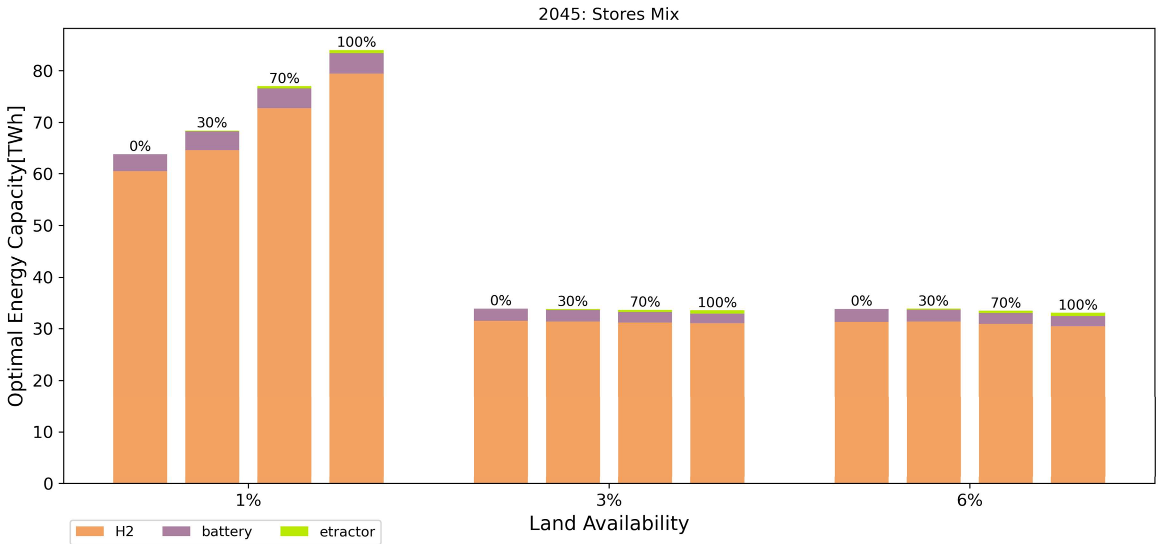

Figure 4.14: 2045: Total Optimal Energy Capacity per scenario for stores, land availability included.

The following Figures 4.15 and 4.16 show the FLH for each power plant and store unit in scenarios with 100% e-tractors in the system. Obvious contrast between results for 1% land availability and 3% and 6% land availability is visible. Scenarios with 1% land availability in 2030 demand more of conventional power plants. In 2045, the only conventional power plant allowed in biomass, because it does not emit CO_2; therefore, H_2 stores are highly utilized for compensation.

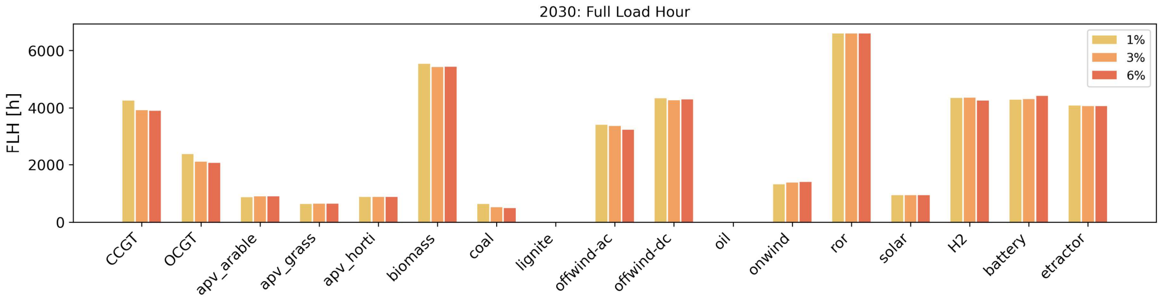

Figure 4.15: 2030: Full Load Hour, 100% e-tractors.

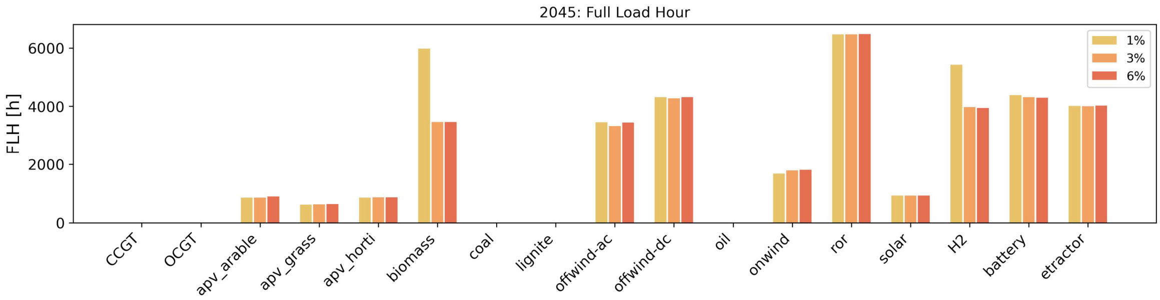

Figure 4.16: 2045: Full Load Hour, 100% e-tractors.

Figures 4.17, 4.18, 4.19, and 4.20 are unit commitment plots which show the generation of power by power plants and discharge of flexibility options for scenarios with 3% agricultural land availability for years 2030 and 2045.

In February of 2030 (Figure 4.17), conventional power plants have an important role in providing base load. Wind sources follow with a big portion of generation, most importantly offwind-dc. Solar generation is rather scarce, divided into four categories: solar, APV in arable lang, APV in grassland, and APV in horticulture. Solar energy provided by APV in arable farms is the biggest energy provider. Additional load coming from e-tractors' flexibility ability is also seen, especially in peak hours. This energy mix differs from the reference scenario (4.5) in lignite generation and solar generation. In the reference scenario, more solar energy is present due to the higher power capacity per square meter considered (APV is assumed to generate less energy), allowing a shutdown of lignite plants between 9am and 15 am.

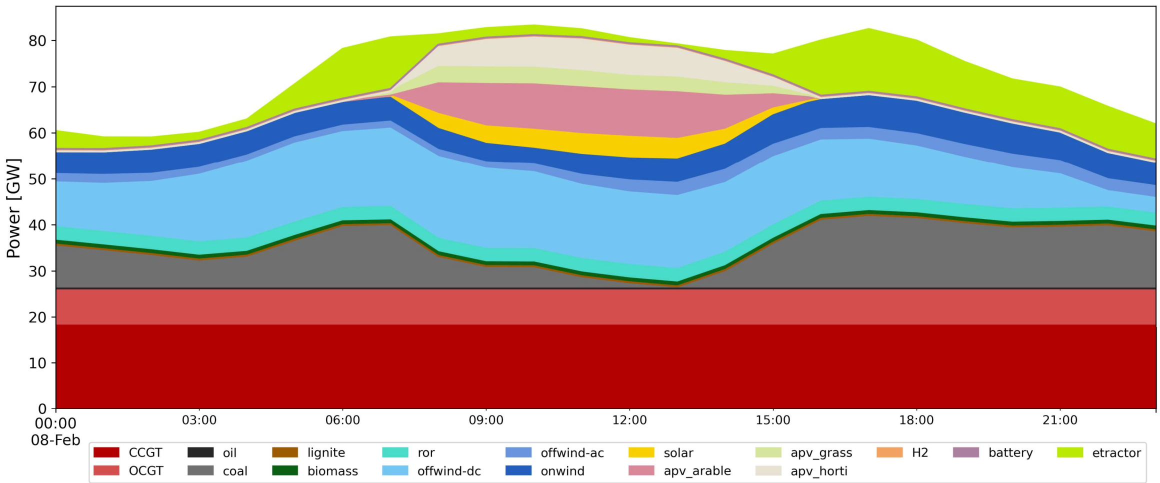

Figure 4.17: 2030: Unit Commitment with 3% of Land Availability, February

Figure 4.18 shows a summer month for a 2030 scenario. Differently from a winter day, much more energy is generated by solar and APV technologies. A supply coming from e-tractors is also observed at nighttime, providing previously-stored electricity. This plot slightly differs from the reference scenario (Figure 4.6), due to the lower solar and APV feed-in. Therefore, a higher generation from conventional power plants is observed.

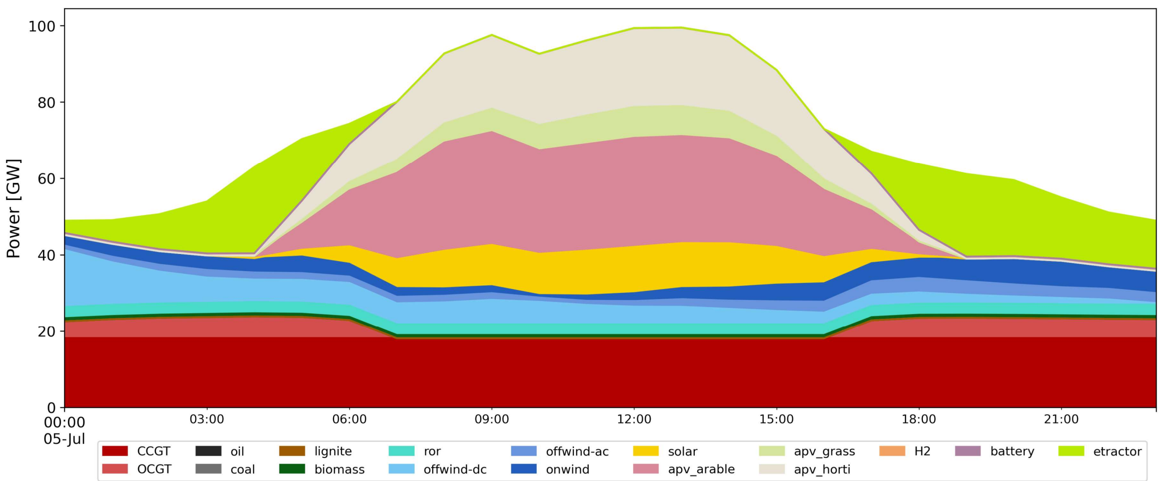

Figure 4.18: 2030: Unit Commitment with 3% of Land Availability, July

In the following 2045 scenarios, where no conventional power plants are allowed due to CO_2 emissions, a very high supply coming for flexibility options is observed. Base load coming from wind sources is observed, followed by a high feed-in coming from H_2 stores. Batteries and e-tractors add to flexibility options. Especially in winter months, H_2 is used basically as base load, providing contact supply. On a summer day, the supply coming from flexibility is just as important, but during the daytime solar and APV technologies contribute intensively.

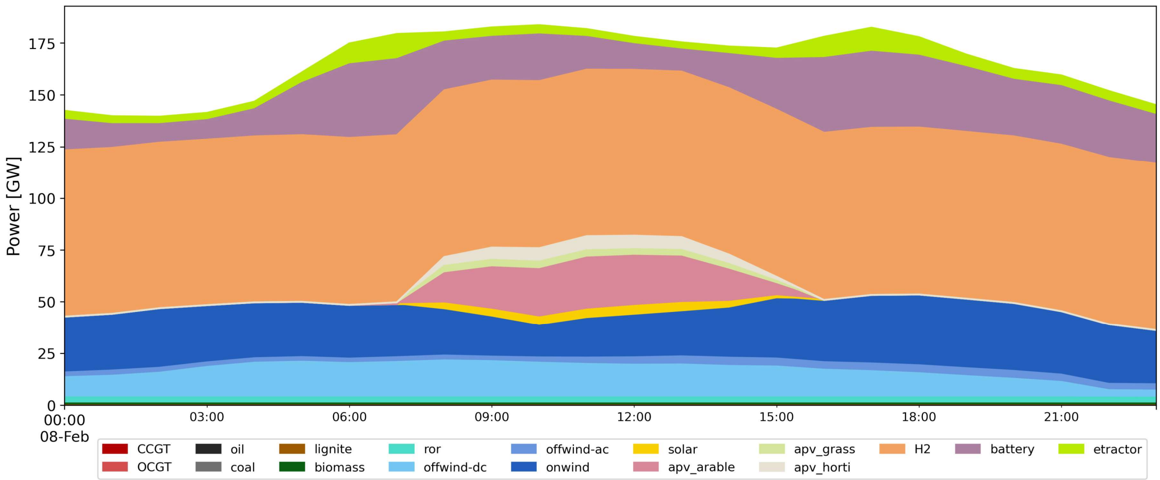

Figure 4.19: 2045: Unit Commitment with 3% of Land Availability, February

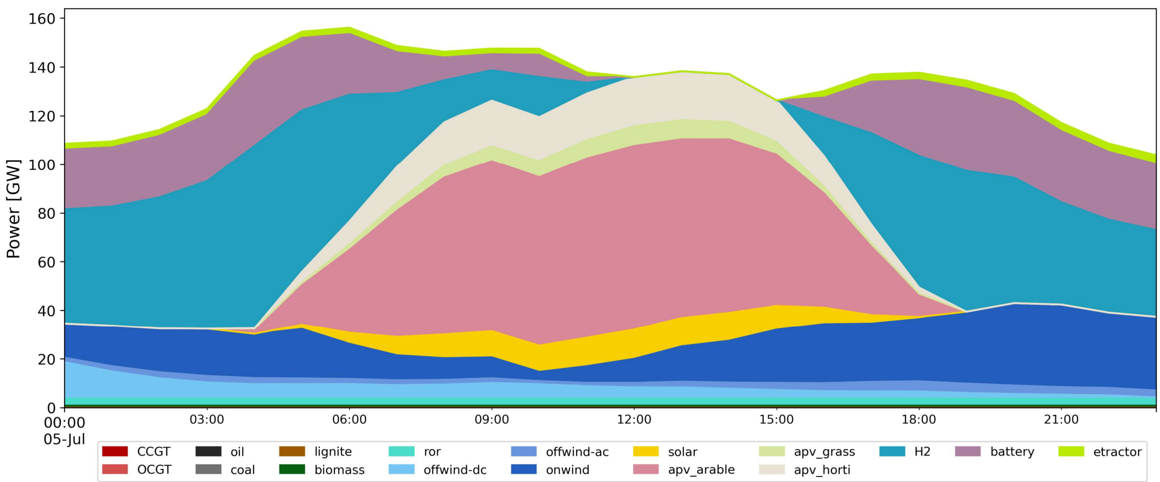

Figure 4.20: 2045: Unit Commitment with 3% of Land Availability, July

Table 4.4 shows the final network costs for all studied scenarios. A visible trend is the decrease in costs with expansion of e-tractors in the energy system, allowing less investments in store units and more cost-efficient investments in APV technologies. The only exception to this rule is for 1% LA, due to the low APVs' capacity availability for expansion; i.e. it is necessary to invest in other technologies (onwind power or store units) to cover the additional load coming from e-tractors.

LA	**Electric tractors**							
	2030 [b€]				**2045 [b€]**			
	0%	**30%**	**70%**	**100%**	**0%**	**30%**	**70%**	**100%**
1%	46.5	45.4	44.8	44.7	141.3	145.2	152.1	157.5
3%	46.1	44.9	44.1	43.9	113.7	112.8	111.7	111.0
6%	45.7	44.5	43.6	43.4	112.1	111.1	109.9	109.2

Table 4.4.: Energy systems' costs for comparative scenarios.

4.2.2. Electric Tractors: APV expansion, charging and discharging

Figures 4.21 and 4.22 show the total optimal nominal capacity of APV technologies for all studied scenarios. Data is grouped by agricultural land availability, and each bar is an e-tractor scenario (0%, 30%, 70%, 100%). These plots represent the projected potential of APV in Germany for the years 2030 and 2045. All scenarios, except 1% land availability, present an increase in APV investments as e-tractors are integrated into the energy system. For 1% scenarios, since APV investments are not allowed, it is necessary to expand store units or other sources of energy, as discussed in the previous section of this work.

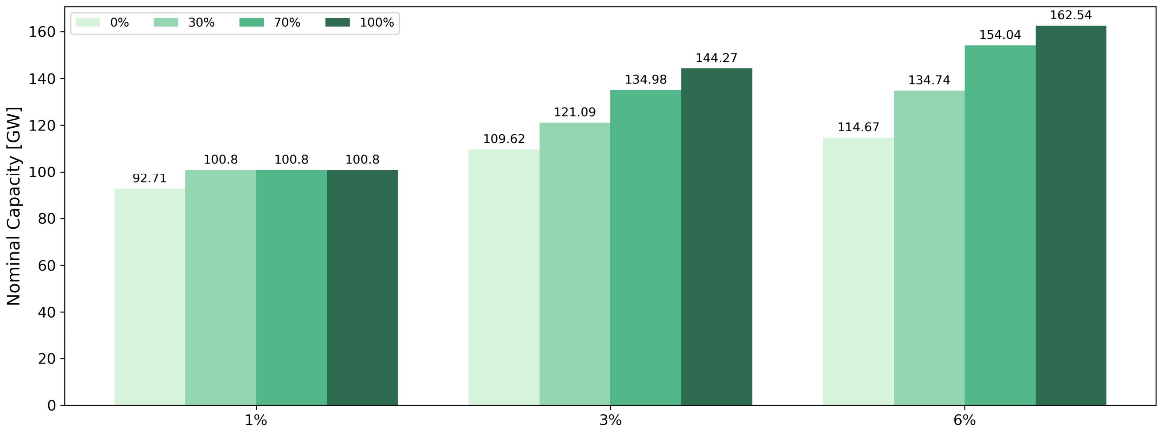

Figure 4.21: 2030: APVs' Nominal Capacity

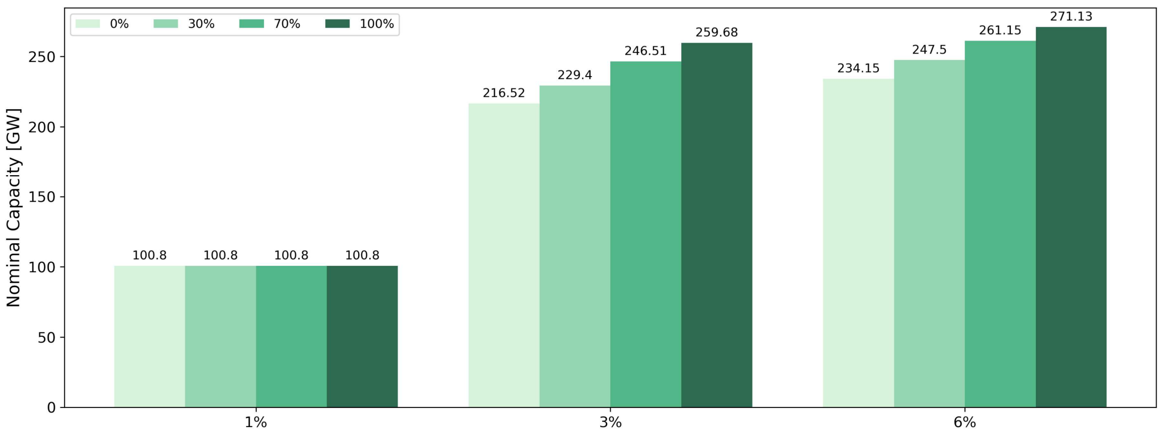

Figure 4.22: 2045: APVs' Nominal Capacity

In this work, APVs were directly integrated to e-tractors with the assumption that no energy loss occurs during the charge of the electric tractor's battery. Therefore, Figures 4.23 and 4.24 show the total energy flowing from APV to e-tractor for all scenarios with e-tractors.

A full transformation of diesel tractor to e-tractors adds to the grid a total load of approximately 25 TWh. Noticeably, the total energy flowing from APV to e-tractors is higher than the e-tractors' field work load demand; for example, approximately 56 TWh for a complete integration of e-tractors with 3% LA in 2030, and 65 TWh for a complete integration of e-tractors with 3% LA in 2045. The extra energy is stored and adds flexibility to the grid.

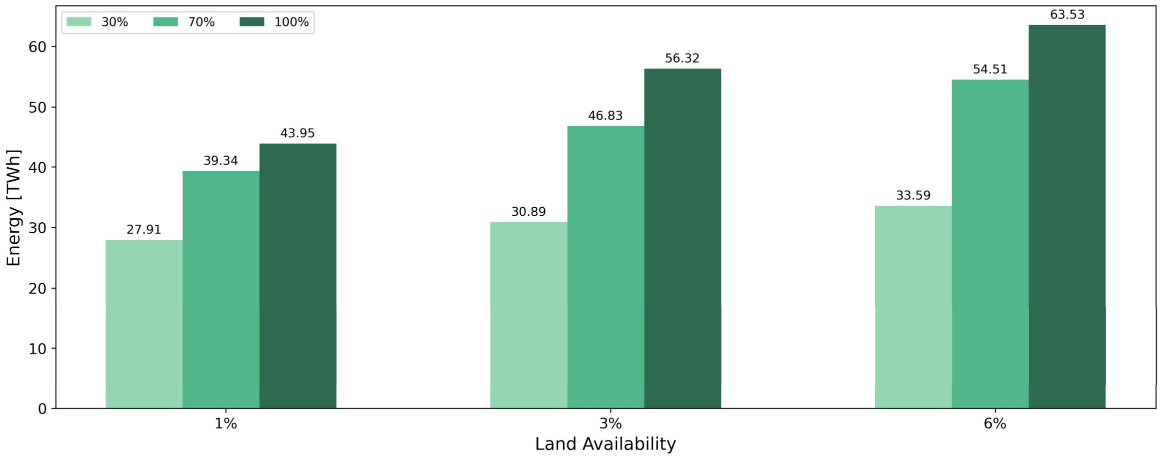

Figure 4.23: 2030: APVs' Energy to e-tractors

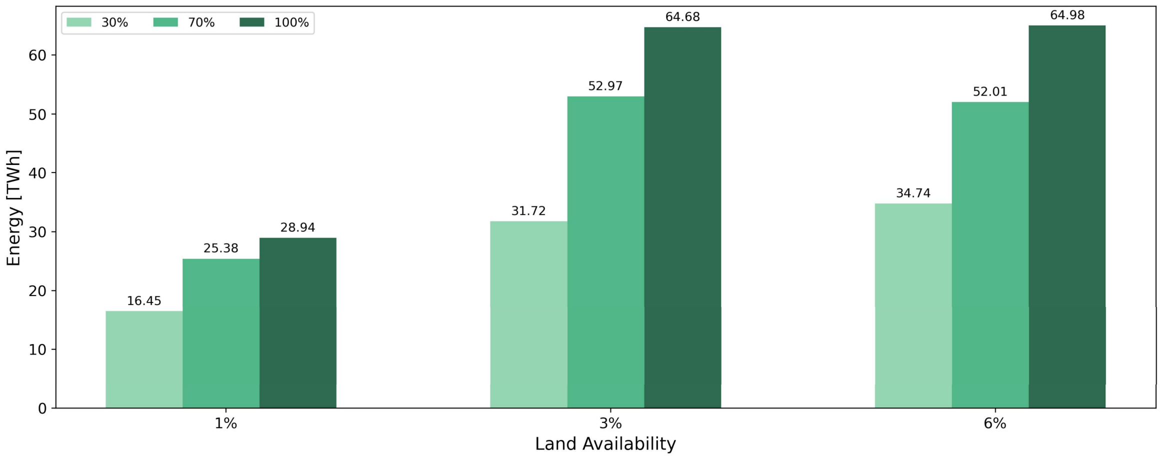

Figure 4.24: 2045: APVs' Energy to e-tractors

Additional to the APV charge, e-tractors can also be charged using electricity from the grid. Figures 4.25 and 4.26 show the total energy flows for all scenarios. Electric tractors will be charged using the grid whenever they need load for field work or if storing electricity makes the system less expensive. These plots do not present an obvious trend, but it is visible that, in 2045 with only 1% agriculture LA, e-tractors highly depend on energy from the grid.

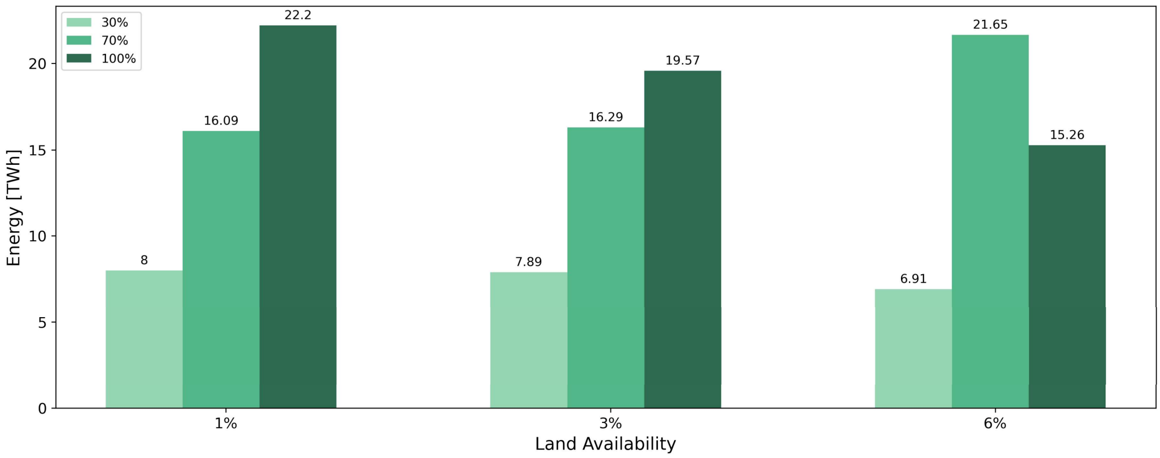

Figure 4.25: 2030: Grid Energy to e-tractors

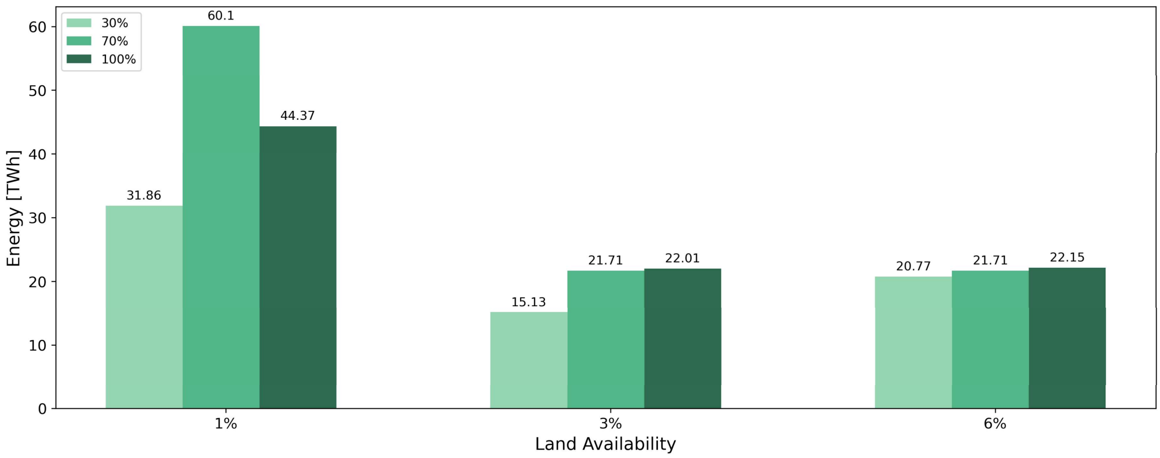

Figure 4.26: 2045: Grid Energy to e-tractors

4.3. Regional analysis

In this section, the results of a regional analysis will be examined. A fixed agriculture land availability of 3% for APV is chosen based on the results of the previous section, and a complete conversion of diesel tractors into electric tractors is considered for each year of interest (2030: partly decarbonized and 2045: full decarbonized). Table 4.5 shows each APV technologies' maximum available nominal capacity in Germany's Bundesländer. Bayern (57.68 GW) has the highest potential for APV investments, followed by Nieder-sachsen and Bremen (50.67 GW), and Nordrhein-Westfallen (32.02 GW). Overall, APV for arable farms presents the highest capacity potential (224.18 GW), followed by APV for horticulture (46.77 GW) and APV for grasslands (31.45 GW).

Bundesland	**Maximum Nominal Capacity [GW]**			
	Grassland	**Arable farm**	**Horticulture**	**Total**
Baden-Württemberg	3.25	15.76	9.63	28.65
Bayern	7.35	35.5	14.85	57.68
Brandenburg and Berlin	1.33	16.65	0.16	18.14
Hessen	1.76	11.08	3.05	15.99
Mecklenburg-Vorpommern	1.22	13.83	0.20	15.25
Nieder-sachsen and Bremen	6.2	39.49	4.97	50.67
Nordrhein-Westfallen	3.02	23.97	5.03	32.02
Rheinland-Pfalz	1.47	5.75	2.68	9.90
Saarland	0.37	1.06	0.87	2.30
Sachsen	0.64	15.33	0.96	16.94
Sachsen-Anhalt	0.84	20.09	0.21	21.15
Schleswig-Holstein and Hamburg	3.25	14.52	3.61	21.38
Thüringen	0.74	11.06	0.53	12.33
Total	31.45	224.18	46.77	302.40

Table 4.5.: Regional APV's maximum nominal capacity.

The portion of energy generation of each technology in the energy for a 2030 partly decarbonized scenario, considering APV and e-tractors in the system, is seen in Figure 4.27:a. In 2030, the energy demand in Germany is estimated to be 643 TWh, whilst the energy sector's CO_2 emissions are limited to 98 Mt/CO_2e. The technologies that generate the most energy are Onshore Wind (89.21 GW installed capacity), Offshore Wind DC (39.06 GW installed capacity), CCGT (18.12 GW installed capacity), APV for arable farm (73.45 GW installed capacity), and APV for horticulture (46.77 GW installed capacity). It is important to note that the maximum available land for solar technology is set at 1%, therefore expansion is at its maximum in this scenario.

Figure 4.27:b shows the portion of energy generation of each technology in the energy for a 2045 fully decarbonized scenario, considering APV and e-tractors in the system. In 2045, the energy demand in Germany is estimated to be 1017 TWh, whilst the energy sector's CO_2 emissions are limited to null. The technologies that generate the most energy are Onshore Wind (391.45 GW installed capacity), Offshore Wind DC (44.50 GW installed capacity), Offshore Wind AC (15.51 GW installed capacity), and APV for arable farm (176.23 GW installed capacity). As for solar technology, the same previous statement applies, which indicates a 1% land availability, which results in maximum installed capacity.

In 2030, CCGT will generate a significant portion of the total energy demand due to permissible CO_2 emissions. However, by 2045, no CO_2 emissions are allowed. Therefore, more investments are needed to compensate for the loss of CCGT as a base load, leading to an increased reliance on Wind technologies. Between 2030 and 2045, approximately 300 GW more in Onshore Wind investments are required. Similarly, for APV technologies, an additional 100 GW of investments for arable farms are suggested from 2030 to 2045.

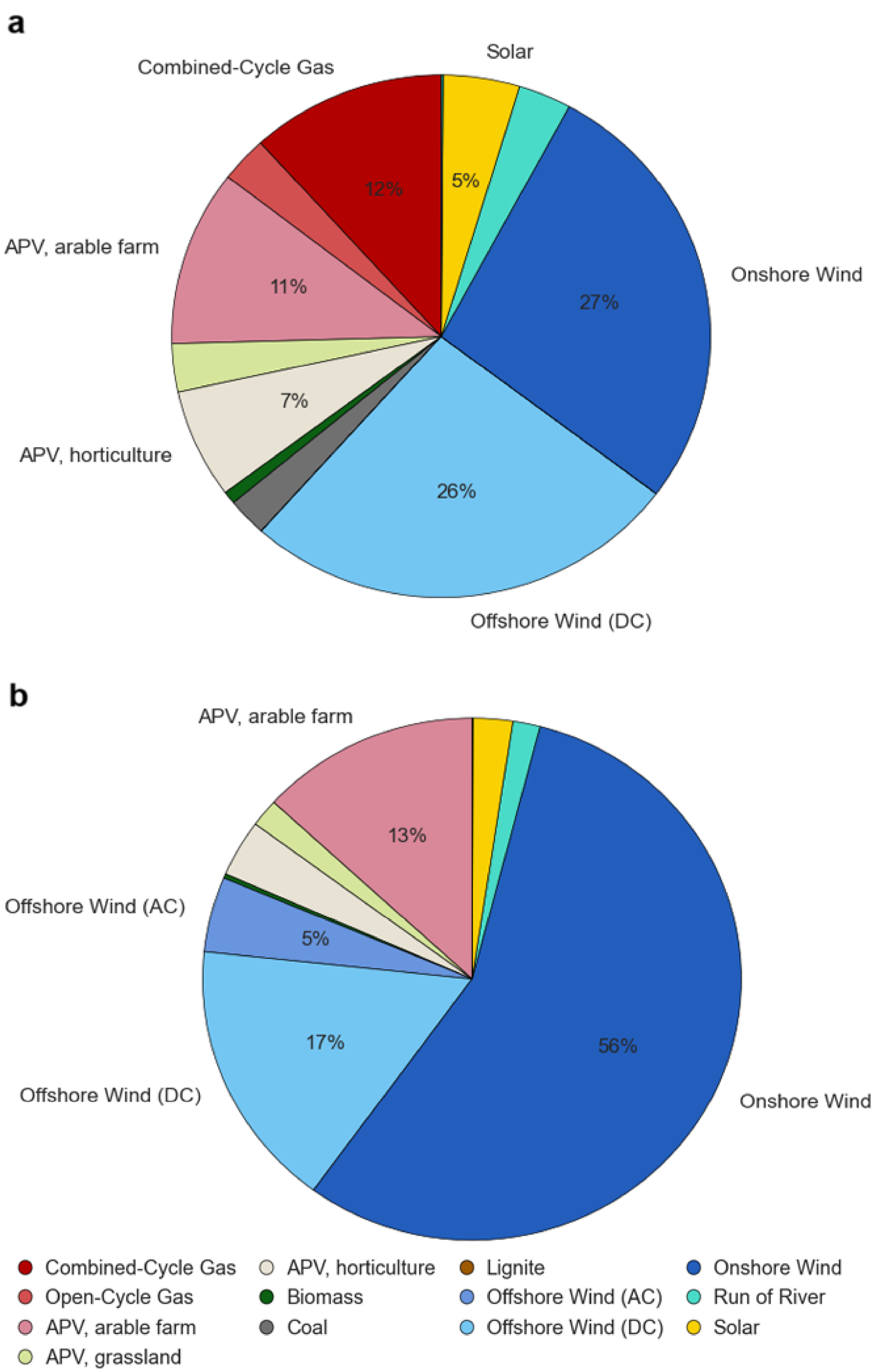

Figure 4.27: Share of total energy generated per power plant (a: 2030, b: 2045)

The regional distribution of power plants across the German states for a 2030 partially decarbonized scenario is shown in Figure 4.28:a. Two primary renewable energy sources dominate the energy mix: solar energy and wind energy. Southern states have primarily integrated solar technologies into their mix, with significant investments in APV technologies due to the high solar potential in the southern areas. In contrast, northern states have made substantial investments in onshore and offshore wind power plants. Additionally, PyPSA-EUR suggests investments in transmission expansion throughout the entire grid, ranging from 10 to 30 GW more for each connection point.

Figure 4.28:b represents the regional distribution of power plants across the German states for a 2045 fully decarbonized scenario. Two main renewable energy sources continue to dominate the energy mix: solar energy and wind energy. Both sources are highly explored in southern and northern regions due to the high load demand. This differs from the 2030 scenario, which suggests more solar investments in the south and more wind investments in the northwest and north regions, due to higher power potential. In other words, in 2045, it is expected that both solar and wind investments will be distributed throughout the entire country due to the lack of conventional power plants to meet base load needs. From South to North, and East to West, both solar energy sources and wind energy sources are important to meet Germany's 2045 load demand. Transmission expansion remains a top priority in this scenario.

Figure 4.29:a illustrates the distribution of energy capacity in Germany for a 2030 scenario. In this scenario, there is a complete shift from diesel tractors to e-tractors, which can serve as flexible assets in the grid. It's important to note that this scenario is considered unrealistic due to the current lack of infrastructure and technological maturity. Nevertheless, under these assumptions, e-tractors could potentially meet most of the flexibility requirements for a partially decarbonized 2030 scenario. The only exception is the northern regions, where investments in H_2 storage are recommended due to lower solar and APV energy potential (which efficiently charge e-tractors' batteries) and higher wind energy potential. The optimal total energy capacity for flexibility assets lies below 1 TWh, approximate 800 GWh.

As for a fully decarbonized scenario in 2045, as shown in Figure 4.29:b, e-tractors as flexibility assets fall short of meeting the grid's significantly increased flexibility needs. In this scenario, optimal results recommend investments in H_2 storage facilities across the entire country, encompassing both southern and northern regions, in line with the proposed increase in wind energy investments. Additionally, battery investments are advisable, particularly in states where e-tractors do not play a major role in providing flexibility. The optimal total energy capacity for flexibility assets increases from 2030 to 2045 by more than 30 times, reaching approximately 33 TWh.

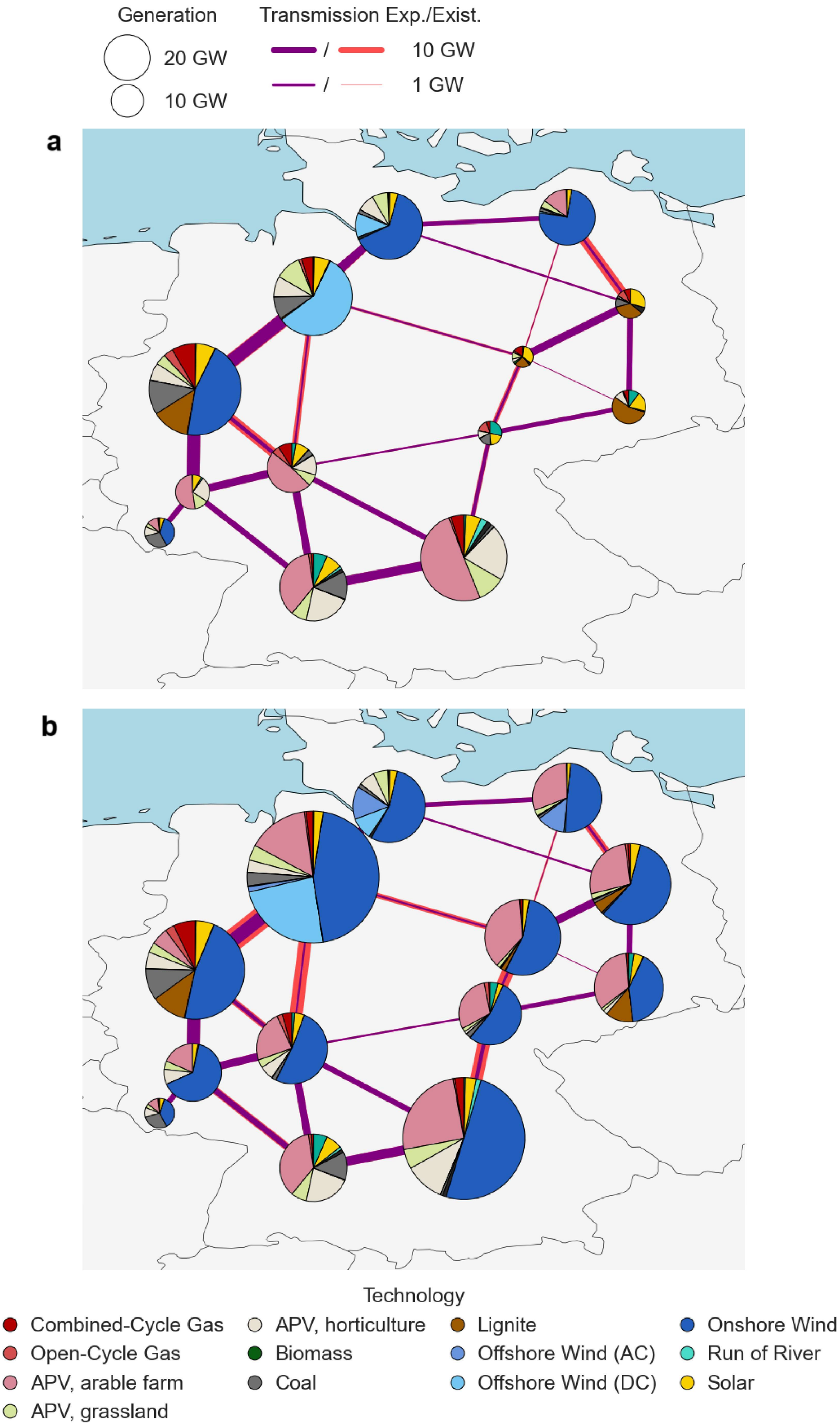

Figure 4.28: Regional distribution of power plants' capacties (a: 2030, b: 2045)

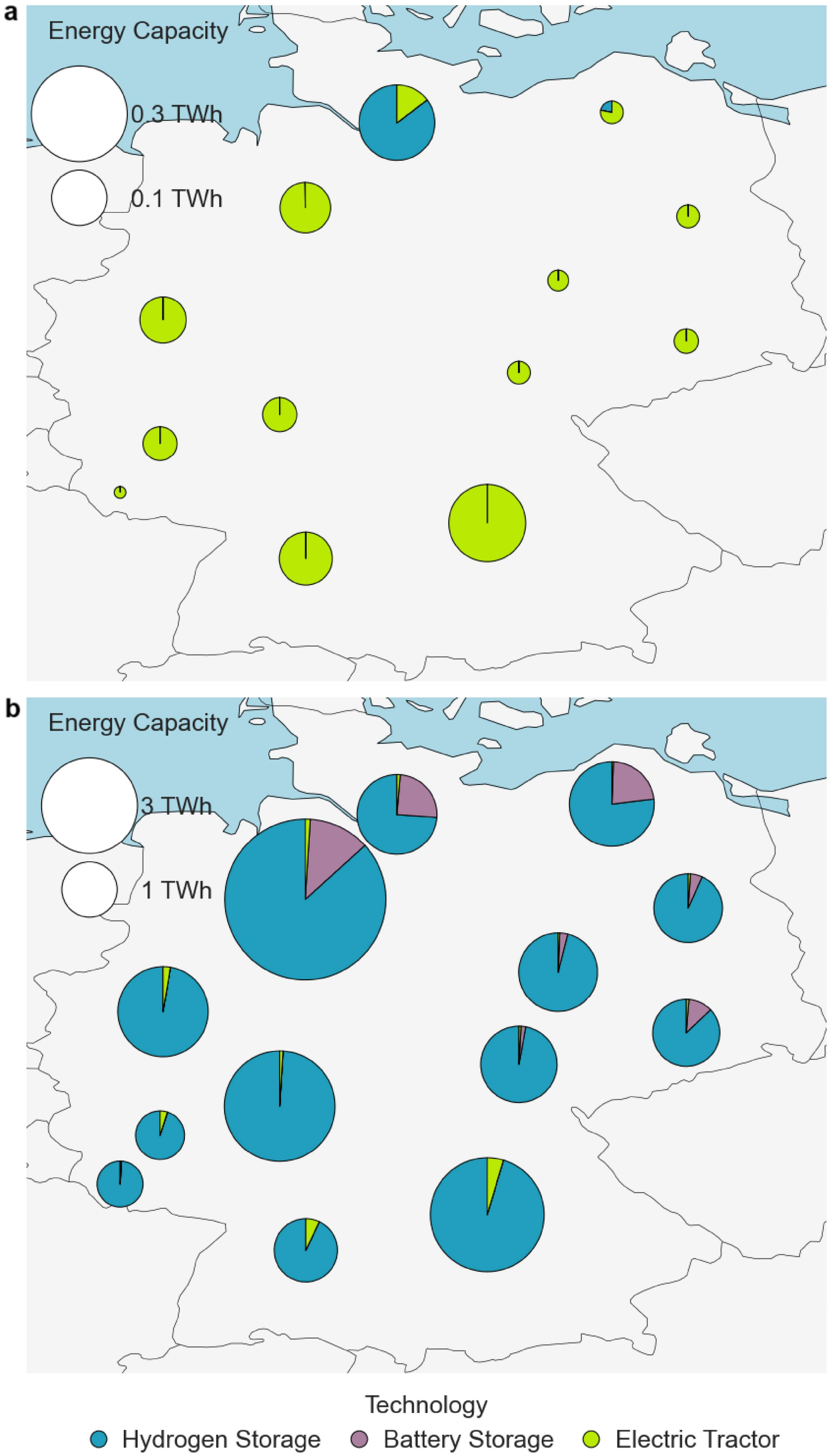

Figure 4.29: Regional distribution of flexibility assets (a: 2030, b: 2045)

Table 4.6 summarizes the total energy capacity of e-tractors for each German State. The whole fleet of e-tractors' energy capacity is of 629.38 GWh. The states with most capacities are Bayern (193.54 GWh), Baden-Württemberg (91.39 GWh), Nieder-sachsen and Bremen (82.96 GWh), and Nordrhein-Westfallen (70.15 GWh). This energy capacity is assumed to be completely available only during winter months, between November and March, when e-tractors are not used for agricultural activities. When they are put into fieldwork, part of the energy capacity is unavailable for flexibility purposes.

Bundesland	**Energy Capacity [GWh]**
Baden-Württemberg	91.39
Bayern	193.54
Brandenburg and Berlin	17.12
Hessen	38.10
Mecklenburg-Vorpommern	13.14
Nieder-sachsen and Bremen	82.96
Nordrhein-Westfallen	70.15
Rheinland-Pfalz	37.65
Saarland	4.40
Sachsen	19.34
Sachsen-Anhalt	14.12
Schleswig-Holstein and Hamburg	27.49
Thüringen	16.98
Total	629.38

Table 4.6.: Regional e-tractor's energy capacity.

Table 4.7 presents the total energy generation by APV technologies for each German State in 2030 and 2045. When comparing both scenarios, Bayern, Baden-Württemberg, Hessen, Rheinland-Pfalz and Saarland had already reached their maximum potential energy generation by 2030; by 2045, there is no increase in generation for these states. Contrarily, other states exhibit the opposite trend, with more APV generation present by 2045 compared to 2030. States such as Brandenburg and Berlin, Sachsen, Sachsen-Anhalt and Thüringen generate less than 1 TWh by 2030; however, their generation increases by 2045, adding further 100 GW to total capacity. If the total optimal capacity for 2045 is compared to the available maximum capacity in Table 4.5, only about 50 GW remains. States located in most southern regions tend to be priorities for APV investments, due to the higher solar energy potential. This fact is the reason why Bayern and Baden-Württemberg reach their maximum potential by 2030, while more northern States such as Brandenburg, Berlin, and Sachsen receive investments only by 2045.

Bundesland	Opt. Capacity [GW]		Energy Gen. [TWh]	
	2030	**2045**	**2030**	**2045**
Baden-Württemberg	28.65	28.65	25.33	25.27
Bayern	57.68	57.68	49.96	49.89
Brandenburg and Berlin	0.16	18.14	0.13	15.09
Hessen	15.99	15.99	13.52	13.46
Mecklenburg-Vorpommern	5.64	15.25	4.58	12.81
Nieder-sachsen and Bremen	11.18	35.97	8.02	28.64
Nordrhein-Westfallen	8.04	13.28	6.04	10.38
Rheinland-Pfalz	9.90	9.90	8.37	8.31
Saarland	2.30	2.30	1.95	1.91
Sachsen	0.96	16.94	0.79	13.99
Sachsen-Anhalt	0.65	21.15	0.45	17.78
Schleswig-Holstein and Hamburg	6.86	6.86	5.08	5.04
Thüringen	0.53	12.33	0.44	10.15
Total	148.54	254.44	124.66	212.72

Table 4.7.: Regional APVs' energy generation.

The unit commitment of two different regions is analyzed in the following text. Niedersachsen and Bayern are located in opposite regions in German, Northwest and Southeast, respectively. The regions present different energy mixes in regard to renewable sources, which will impact how power plants interact with the grid.

The following Figure 4.30 illustrates the unit commitment in Niedersachsen during the winter and summer months of 2030. Niedersachsen's energy mix in 2030 is composed mainly of Offshore Wind DC, CCGT and coal, solar and APV for grassland. On the 8th of February, during winter, coal is utilized as a base load power source from 5h to 7h and again from 15h to 24h. Similarly, discharging from e-tractors is also observed. During the hours between 7h and 15h, both coal power generation and e-tractor discharging are ramped-down. These effects could be attributed to peak hours and solar generation, where both coal power plants and e-tractors are compensating for the lack of load in the grid. Additionally, a high power generation from Offshore Wind DC is present. Solar generation is quite insignificant in Niedersachsen in this specific case. On the 5th of July, a summer day, similar effects related to e-tractors are observed, but no coal power plants are activated. On the other hand, way less power is generated from Offshore Wind DC, and solar and APV energy is also present during the daytime.

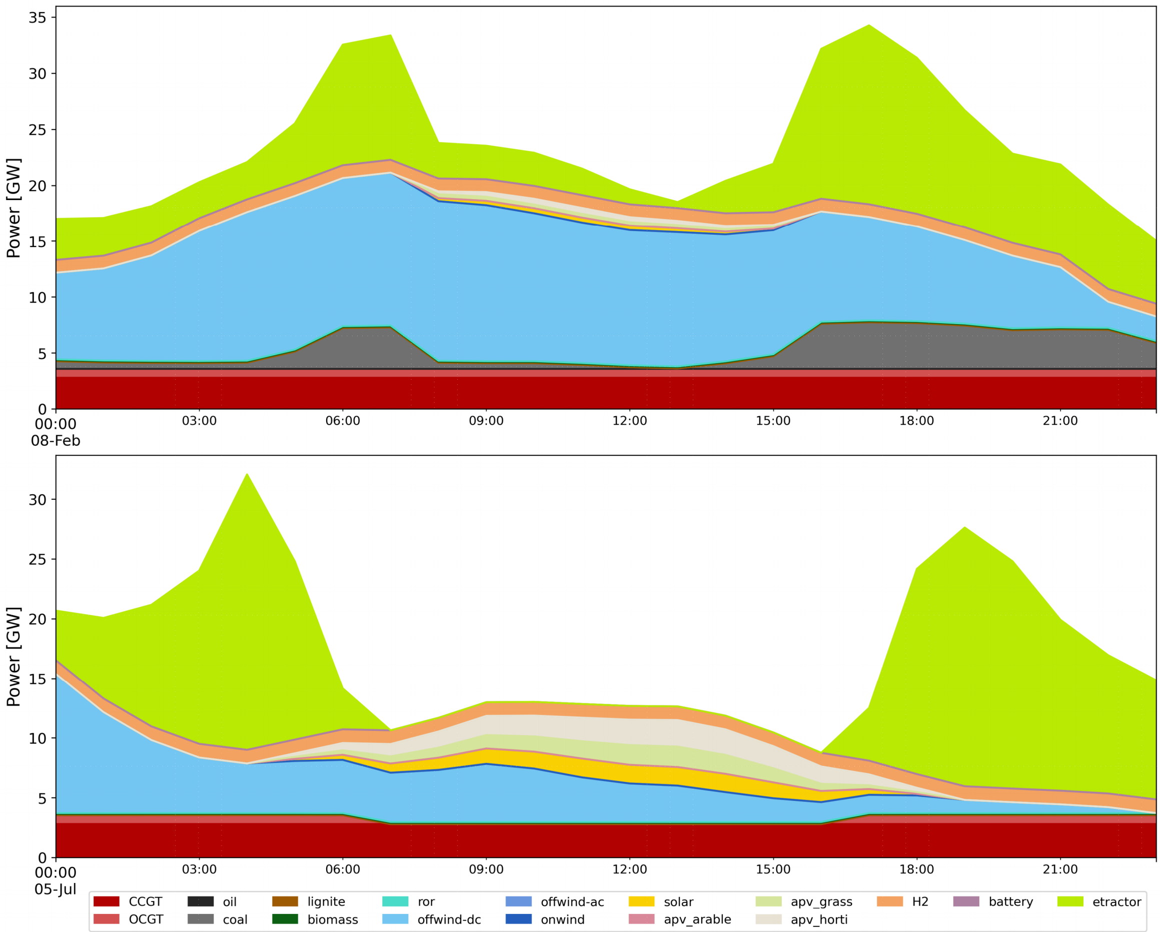

Figure 4.30: 2030: Unit Commitment in Niedersachsen, February and July

The following Figure 4.31 illustrates the unit commitment in Bayern during the winter and summer months of 2030. Bayern's energy mix in 2030 is composed mainly of solar and APV technologies (arable farm, horticulture and grassland), CCGT and run of river. On the 8th of February, during winter, baseload is composed of CCGT and OCGT together with run of river. At daytime, solar energy is generated by solar and APV technologies. Additionally, e-tractors are used throughout the day and during peak hours. It is assumed that e-tractors do not take part in agricultural activities during winter months, therefore, they are always available as store units. On the 5th of July, during summer, solar and APV generation take a higher share of the total energy generation. The usage of e-tractor units decreases, due to fieldwork (between 7h and 19h).

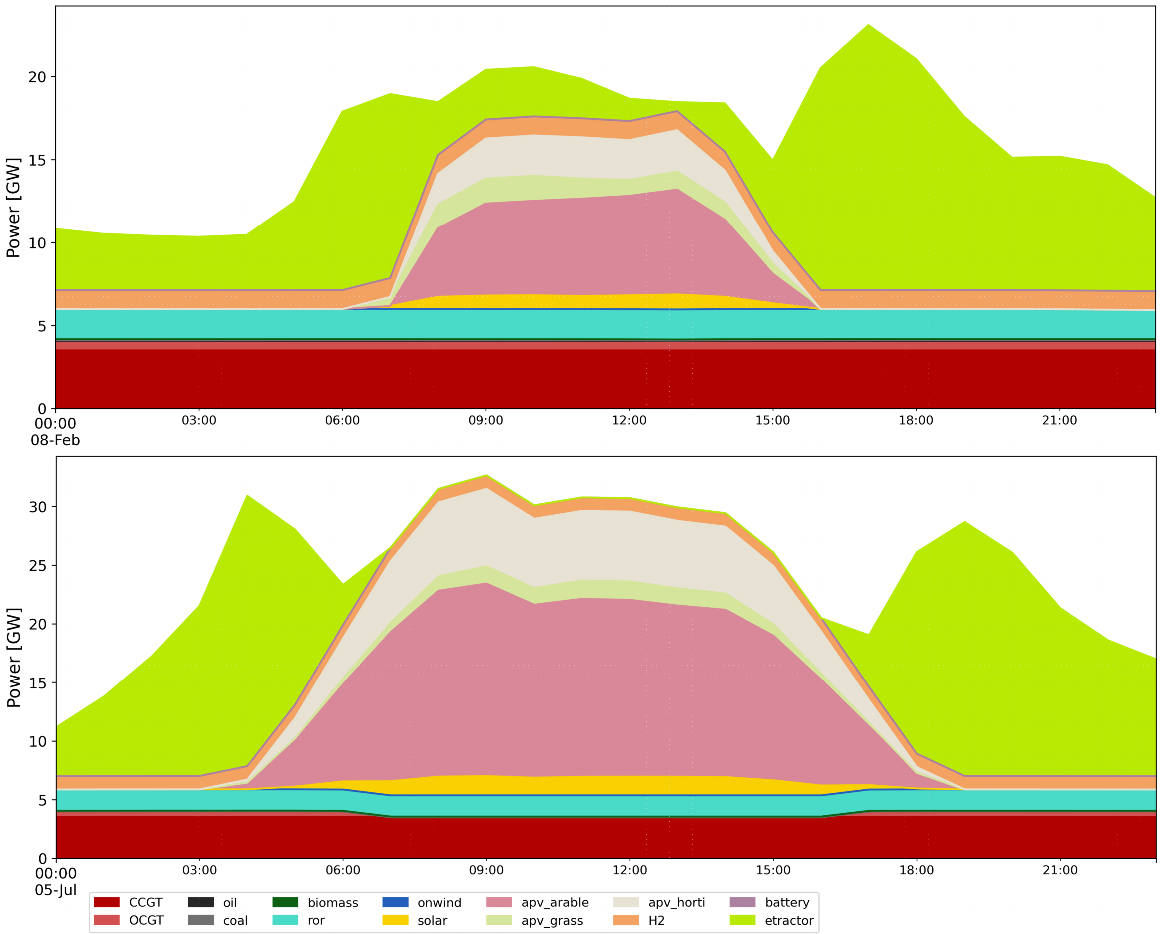

Figure 4.31: 2030: Unit Commitment in Bayern, February and July

5. Conclusion

This study successfully incorporates APV technologies and e-tractors into the open-source energy system model PyPSA-Eur. Necessary information about these technologies was gathered from the literature to conduct comprehensive analyses and assess their impact on the energy system. Research questions were presented and definitely answered.

Regarding reference scenarios and land availability, when insufficient land for APV technologies is considered, more storage units are required to achieve the 2030 and 2045 CO_2 emissions targets. The impact of limited land availability becomes more evident in the 2045 scenarios, with significantly higher investments in onshore wind when there is only 1% land availability. However, with 3% or 6% land availability, there is a substantial decrease in wind investments and a corresponding increase in solar investments. Regarding energy storage in 2045, there is not much difference observed depending on land availability, primarily due to the higher load and the absence of baseload power from conventional sources, as a zero CO_2 emissions goal is pursued. Given the highly fluctuating nature of renewable energies, energy storage units are of paramount importance. The maximum capacities for solar technologies in these scenarios are 211.2 GW, 574.5 GW, and 1119.5 GW for 1%, 3%, and 6% land availability, respectively.

When APV is taken into consideration, the maximum solar and APV technologies capacity amounts to 130.3 GW, 331.90 GW, and 634.30 GW for 1%, 3%, and 6% land availability, respectively. A decrease in capacity is observed because the installation specifics of APV technologies result in lower power capacity compared to ground-mounted solar PV panels.

The electric tractor load demand has been calculated. If the current diesel tractor fleet is converted to electric tractors, a total of 28.2 TWh of electricity would be required to power these agricultural machines. This load represents 4.4% of the projected load in 2030 and 2.8% in 2045.

The interaction between APV and e-tractors was analyzed. In both analyzed years, 2030 and 2045, an increase in APV investments is observed when e-tractors are integrated into the system alongside APV. In this model, electric tractors do not have marginal costs for operation or efficiency losses when charging from APV, unlike batteries or H_2 options, which do incur losses. Therefore, it is cost-efficient to use e-tractors as flexibility assets, and the expansion of APVs can be correlated with the expansion of e-tractors.

Regarding energy storage units, specifically by 2030 CO_2 emission targets, the expansion of e-tractors significantly reduces the need for other flexibility options, showing potential as flexibility options. The same effect is not as pronounced in the 2045 targets, as the need for energy storage remains substantial. However, if we consider that the expansion of APV and e-tractors occurs gradually over the years, implementing them simultaneously should still be cost-efficient. It's worth noting that costs for e-tractor infrastructure are not factored in here, so this effect could be less cost-efficient.

In this work, APV potential in Germany for 2030 spawns from 93 GW to 163 GW. This metric varies according to land availability (min. 1%) and number of e-tractors in the system (max. 100%). Therefore, the maximum potential is obtained with a complete conversion of diesel tractors to e-tractors and their use as flexibility assets. Similarly for 2045, APV potential spawns from 101 GW (1% land availability and no e-tractors) to 271 GW (6% land availability and 100% e-tractors).

A regional analysis highlights each region/state's potential for APV expansion in Germany. States such as Baden-Württemberg, Bayern, Niedersachsen, and Nordrhein-Westfallen present the highest potential for APV expansion. However, due to varying weather conditions, states in southern regions generate more solar and APV electricity than northern regions. In the 2030 scenario, APV technologies are predominantly installed in southern regions, while wind technologies dominate in the north. By 2045, both technologies will see expansion in both regions due to increased load demand.

Finally, the potential of e-tractors as flexibility assets is summarized by region. States such as Bayern, Baden-Württemberg, Niedersachsen, and Nordrhein-Westfalen exhibit the highest potential for e-tractors. These states also have the most extensive agricultural areas.

5.1. Further Work Recommendations

- **Explore the actual regional availability of land for APV installations in greater detail:** To enhance the precision of the results, it is crucial to precisely determine the regional availability of agricultural land. For instance, it may be the case that only grassland is less available in northern states, while in southern regions, the availability could be higher.
- **Enhance the discretization of electric tractor loads:** To achieve more accurate modeling, ensure precise power range assignments for electric tractors in relation to spe-

cific APV technologies. Additionally, conduct further research on tractor operation patterns, months of usage, and related factors.

- **Create electric tractor models that are extendable to better understand the interaction between APV and electric tractors:** Extending this technology in a more dynamic manner would enable greater interactivity in analysis and a more transparent understanding of the energy system. This is important as investments in electric tractors will depend on cost assumptions related to other technologies.
- **Consider electric tractor infrastructure costs, such as charging stations and integration with APV:** For an accurate definition of electric tractors, it is advisable to consider infrastructure components. Investment costs and marginal costs are crucial factors for making more informed assumptions.

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A. Appendix

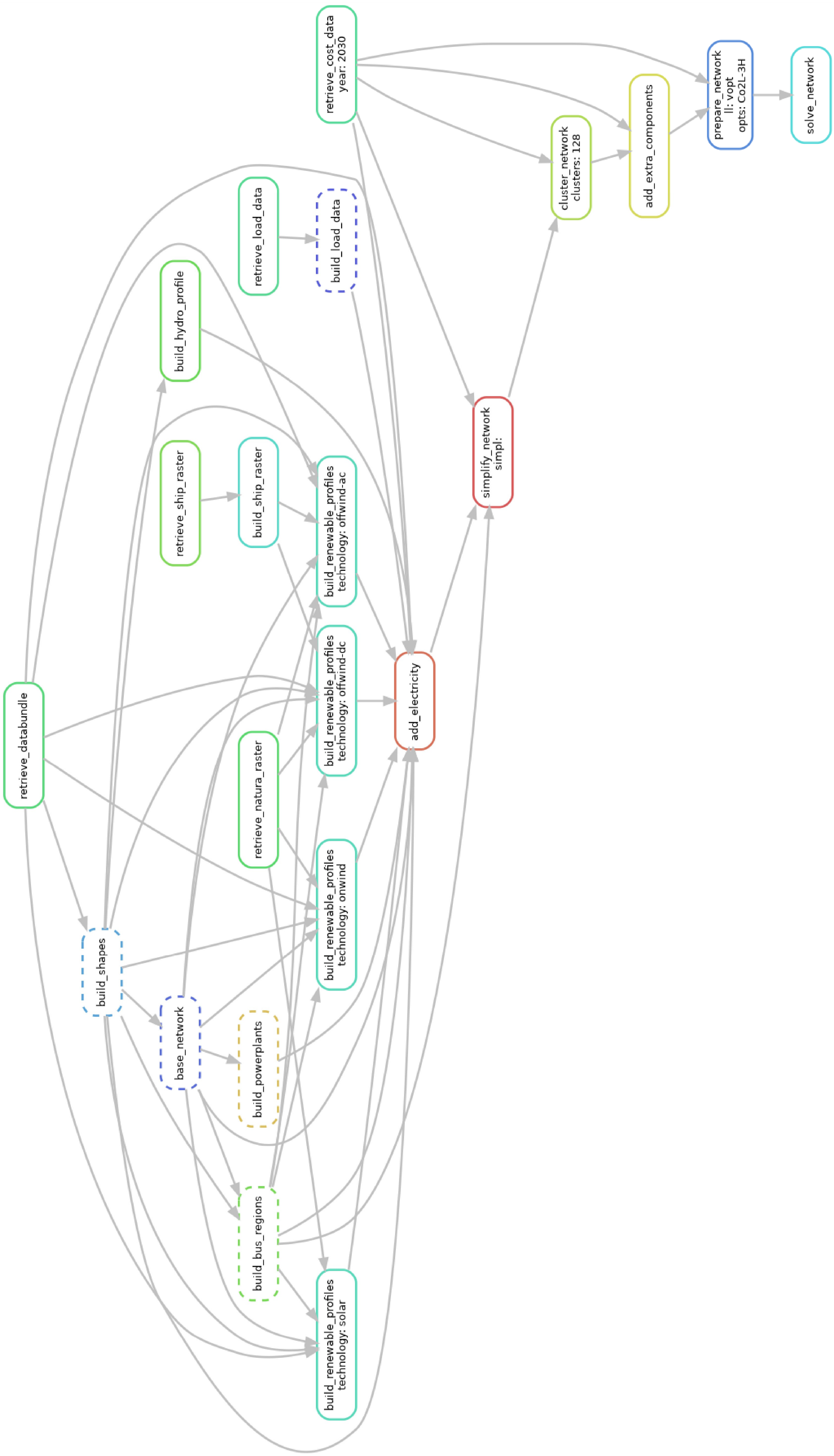

Figure A.1: Generated DAG for a PyPSA-Eur Analysis [47]