Brage Simonsen Sæbøe

# Energy System Modeling: Investigating a decoupled approach to capital cost of energy storage and Vehicle-to-Grid in the European energy system

Master's thesis in Sustainable Energy Systems and Markets
Supervisor: Konstantin Löffler
Co-supervisor: Karlo Hainsch
November 2023

Master's thesis

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## Preface

The research presented in this thesis was conducted as part of the dual degree program *Sustainable Energy Systems and Markets* (SESAM). The program is a collaboration between the universities, Norwegian University of Technology (NTNU) in Trondheim and Technische Universität Berlin (TUB) in Berlin, studying one year at each university. Together the two universities and their collaboration have made this thesis possible. Through the program, two degrees are obtained, M.Sc in *Sustainable Energy* from NTNU, and M.Sc in *Industrial Engineering and Management with a focus on Energy and Resources* from TU Berlin.

I started my SESAM journey at NTNU in Trondheim in 2021. It was a year full of exciting new challenges that sparked an interest in learning more. While at NTNU I joined the project GridVille facilitated by Engineers Without Borders, and was active at Studentersamfundet, which gave a taste of the student life in Trondheim. I continued my journey to TU Berlin in the fall of 2022, which was the start of another exciting academic year. My first meeting with Berlin was a student home of 154 international students with whom I learned to know the city, the language, and the university. I quickly got to know the the Workgroup for Economic and Infrastructure Policy (WIP) where I later would meet my supervisors Dr. Konstantin Löffler and Dr. Karlo Hainsch.

I want to extend my deepest gratitude to Dr. Konstantin Löffler as my main supervisor, whose guidance and mentorship have been invaluable throughout this academic endeavor. His expertise in the field of energy system modeling has helped me steer this thesis toward a comprehensive understanding of the evolving energy landscape and how to model it. Konstantin helped with everything from finding a thesis topic, setting me up with a computer, IT problems, administrative talks, and professional discussions. I also want to thank Dr. Karlo Hainsch, who through the summer of 2023 helped me set the groundwork and understanding of how to model electric vehicles and the function of Vehicle-to-Grid in an effective and realistic manner. I also want to thank Professor Ruud Egging-Bratseth from NTNU for helping me with administrative and professional endeavors at short notice and without hesitation.

A big thanks to both universities, the students, professors, and lecturers I have met throughout these two wonderful years helping me make this possible. Thank you to my colleagues and friends for the wonderful feedback, and lastly thank you to girlfriend and family for their continued support.

*Brage Simonsen Sæbøe, November 2022*

# Abstract

Energy systems across the world are rapidly shifting towards more sustainable ways of energy production, propelled by the urgent challenges of climate change. Variable renewable energy sources such as wind and solar power have emerged as some of the leading energy production technologies for a more sustainable energy system. The natural variability of wind and solar power is changing how the energy system works, and new sources of energy flexibility are needed to balance the system. Several energy storage technologies available today can provide the needed flexibility, but the question of how much storage capacity and which technologies will emerge as the most economically feasible is still to be answered. At the same time, many sectors are electrifying, and more electric energy is needed across energy systems. One of the electrifying sectors, is the transportation sector, with technologies such as battery electric vehicles gaining popularity.

In this thesis energy system modeling is used to analyze two things, the effect the cost structure of energy storage has on the energy system in energy system modeling, and the functionality of Vehicle-to-Grid (V2G) in energy system modeling. Two models have been developed using GENeSYS-MOD and are derived from a previously developed model of the European energy system. The first model, named the Capex model, changes the cost structure of energy storage technologies in the model from an LCOS structure to a decoupled CapEx structure. The decoupled CapEx approach assigns a capital cost to both energy capacity expansion and power capacity expansion of the energy storage technologies as well as a variable cost and a fixed yearly cost. Sensitivities in different parameters are analyzed to give insight into the new model in general and into the robustness of the energy storage technologies in the model. The second model, named the V2G model, changes the way electric cars use electricity from the grid and implements a V2G function. In the V2G model, there is a battery storage unit between the grid and the electric cars. The new V2G function allows the electric cars to discharge to the grid as well as normal charging and driving, but the V2G charging cable comes at a cost of 22 €/kW. The previous model does not have a battery pack between the grid and the electric cars, meaning the cars use electricity from the grid as it is driving. Different charging scenarios and sensitivities on the V2G integration rate are studied to analyze the modeling approach.

The results of the Capex model show that the decoupled CapEx cost structure gives a more conservative investment in energy capacity and power capacity in energy storage technologies. The conservative investment in the Capex model can be thought of as more realistic than the investment seen in the model with the LCOS approach as the dispatch of the storage technologies reminisces better with what is expected in reality.

The results of the V2G model show an increased investment in electric cars across all charging scenarios while energy storage investment decreases when compared to the Capex model. The flexibility introduced to the electric cars through the battery pack and the V2G function decreases the need for the day-to-day flexibility that utility-scale battery storage provides. The investment in electric cars drops and investment in energy storage increases with an increasing V2G integration rate. This indicates that the model prefers to invest in utility-scale lithium-ion batteries for short-term energy storage rather than investing in the V2G charging cables at a cost of 22 €/kW. The dispatch of the electric vehicles is to some degree flawed within the new model, and only worsens at higher V2G integration rates. However, the scenario results show that a stricter charging scenario provides the most realistic results. For future work, the implementation of charging patterns and driving patterns are integral for securing realistic results when applying the method for V2G used in this study.

Overall the Capex model shows the benefits of modeling with a decoupled CapEx approach, and a method of how to apply it. The V2G model has given insights into how V2G can be modeled, and lays the groundwork for further research in V2G modeling. The CapEx model is more or less a model ready for application, while the V2G model requires further work especially within restricting the charging patterns and driving patterns of the V2G participating cars.

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## List of Acronyms

| | |
|---|---|
| A-CAES | adiabatic compressed air energy storage |
| BESS | battery energy storage systems |
| BEV | battery electric vehicle |
| BEVs | battery electric vehicles |
| BOP | balance of plant |
| CAES | compressed air energy storage |
| CapEx | capital expenditure |
| $CO_2$ | carbon dioxide |
| D-CAES | diabatic compressed air energy storage |
| E2P | energy-to-power |
| EPC | engineering, procurement, and construction |
| EU | European Union |
| EVs | electric vehicles |
| GENeSYS-MOD | Global Energy System Model |
| GHG | greenhouse gas |
| GW | gigawatt |
| $H_2$ | hydrogen |
| KPI | key performance indicator |
| KPIs | key performance indicators |
| kWh | kilowatt hour |
| LCOE | levelized cost of electricity |
| LCOS | levelized cost of storage |
| Li-Ion | lithium-ion |
| Mt | megatonne |
| MW | megawatt |
| MWh | megawatt hours |
| NMC | nickel Manganese Cobalt |
| NPV | net present value |
| OpEx | operating expenditure |
| OSeMOSYS | Open Source Energy Modelling System |
| PaT | pump as turbine |
| PCS | power conversion system |
| PHS | pumped hydro storage |
| PJ | petajoule |

| | |
|---|---|
| PV | photovoltaic |
| R&D | research and development |
| redox | reduction–oxidation |
| RES | renewable energy sources |
| RFB | redox flow batteries |
| RPT | reversible pump-turbine |
| SOC | state of charge |
| TWh | terawatt hours |
| V2G | vehicle-to-grid |
| vRES | variable renewable energy sources |
| VRFB | vanadium redox flow batteries |

# 1. Introduction

Climate change has rapidly become a threat to the way humans are living today. The long term effects on the global climate, such as warmer weather conditions, rising sea levels and changes in precipitation caused by global warming affects our way of living and other natural systems. The rising sea levels and the surging amount of extreme weather conditions causes mass migration, food shortages, and in general worsened living conditions. It is agreed upon in the scientific community that the main cause of global warming is greenhouse gas (GHG) emissions. The concern is that without a substantial reduction in GHG emissions the situation continues worsening (Masson-Delmotte et al., 2021). The European Union (EU) has legislated that GHG emission should be lower that 55% by 2030 compared to the reference level in 1990 in the European Climate Law (Commission and for Climate Action, 2019). The EU has also put forward *The European Green Deal* which promise to make Europe climate neutral by 2050, with a close to carbon-free electricity sector (Commission and for Climate Action, 2019).

To achieve the goals set by the EU, a surge in investment in renewable energy technologies has been seen across Europe, especially within wind and solar photovoltaic (PV). Both wind power and solar PV has seen a falling cost as the technologies has become more efficient, and production cost has decreased (Ruggiero, 2022). Both wind and solar PV are so called variable renewable energy sources (vRES). vRES differ from conventional power plants by being non-dispatchable sources of electricity, and production is instead dependent on the natural availability of wind and solar insolation. In 2021, 22% of the energy consumed in the EU came from renewable energy sources (RES), with about 4% coming from vRES (European Environmental Agency, 2023). Although only 4% came from vRES in 2021, both wind power and solar power are rapidly growing, and are expected to be a vital part of the European energy system on the way to net neutrality in 2050 (European Environmental Agency, 2023). An energy system with a high share of vRES fundamentally changes the nature of the power system and how system planning and operating needs to be done compared to power system based on dispatchable technologies. Meeting the demand of electricity with a supply relying on weather conditions requires a significant increase in flexibility in the power system. Flexibility can be introduced to the power system in several ways including by introducing smart systems in the grid, by introducing economical incentives in the market, increasing flexibility on the demand side, or by implementing energy storages (BATSTORM, 2018). This study looks into flexibility through energy storage, and demand side flexibility with the use of the battery packs of battery electric vehicles (BEVs).

Several energy storage technologies have seen a similar cost reduction as wind and solar PV over the last decades, especially batteries (Child et al., 2019). With the falling cost of vRES and energy storage technologies combined with a rising cost of $CO_2$ and hence a rising cost of some conventional power plants, a situation has been created where combining vRES such as solar PV and wind with batteries may offer the lowest cost solution in the future (Ruggiero, 2022). The reduction in price of the technologies and willingness to invest come especially well timed for Europe. The current European system consists of a high share of old, carbon intensive energy generation, with many countries planning to decommission their nuclear power plants before 2050 (Child et al., 2019). For example, in 2022, 57.7% of electricity production in Germany came from conventional energy sources with an average age of above 30 years old(Destatis, 2023; Markewitz et al., 2018). Simultaneously Germnay has decided to shut down its three last operational nuclear power plants with full effect April 15, 2023 (ISE, 2023). This can be seen as an opportunity for Germany and other European countries to replace their older power plants with new RES and batteries without any further or at least with fewer stranded investments.

## 1.1. Energy storage and flexibility

As mentioned previously, Europe has been experiencing a significant increase in renewable energy generation, especially the vRES wind and solar PV. Energy storage technologies can help address the intermittent nature of these vRES by storing excess energy during periods of high generation and releasing it during times of high demand or low generation. This can help balance the grid and ensures that less energy from vRES goes to waste.

Energy storage systems can also provide stability to the grid. That is by managing sudden fluctuations in generation and load in the energy system that disturb the grid, i.e. the frequency of the grid. They can respond by injecting power to the grid in the case of a sudden generation drop or load increase, taking the role of a generator. On the other hand in the case of a sudden increase in generation or drop in load, the battery can take the role as a load. Supplying this type of stability to the grid requires rapid response times which only certain energy storage systems are suitable for, for example Lithium-ion batteries, see section 2.1.3 (Tan and Zhang, 2017).

The previous paragraph describes how energy storage can provide flexibility through fast reaction in the case of sudden fluctuations. However energy storage can also provide flexibility in the case of planned or known fluctuations throughout days, weeks or even months. Planned storage of energy in low-demand periods, for later to supply the stored energy in high-demand periods is a method to provide flexibility. The concept or method is called load shifting, and has especially become a topic with the introduction of solar PV which has a predictable daily production. The demand pattern in a region throughout the day is usually also predictable as the consumption patterns of most people and industries are similar from week to week. This can allow for load shifting through planned charge and discharge of the energy storage systems. It can help alleviate stress on the grid and reduce the need for costly infrastructure upgrades such as transmission capacities (Next Kraftwerke, 2023).

BEVs has become more prevalent in the transportation sector. With a concept called vehicle-to-grid (V2G). V2G is the concept where electric vehicles not only use energy from the grid but also to supply energy to the grid in times where the BEVs are plugged in and not driving for an extended period of time. The BEVs can in theory be used as a conventional battery storage system and provide the same flexibility.

## 1.2. Main research questions and structure

### 1.2.1. Research questions

The main objectives of the thesis is split into two. Two models are developed in the thesis, named Capex model and V2G model, where the V2G model is an extension of the Capex model. The two models answer different research questions and have different scenario- and sensitivity analyses.

#### Decoupled cost-structure of energy storage

The thesis is based on the existing Global Energy System Model (GENeSYS-MOD) built by Konstantin Löffler, Karlo Hainsch, and Thorsten Burandt(Löffler et al., 2017). The main objective of the study is adding and improving the model's existing flexibility and storage options by implementing a new cost structure for energy storage technologies in GENeSYS-MOD. The new cost structure allows for independent investments in storage size (energy capacity) and grid link (power capacity), in contrast to the previous cost structure that was based on a levelized cost of storage (LCOS) with a fixed ratio between storage size and grid link. The decoupled cost structure allows the model to endogenously determine the energy-to-power (E2P) ratio of the respective storage technologies. With this an analysis of the effects of E2P ratios for energy storages can be performed. Three main research quesions have been developed for this study. First, *How does the model investment in energy storage change?*, which is an analysis of the investment in energy capacity and power capacity in the energy storages from 2018 till 2050. Second, *How does the investment in other technologies change?*, which analyses related technologies such as renewable energies, hydrogen related technologies, and the phaseout of fossil based technologies. Third, *Which other change in behaviour can be seen in the model?*, here specifically energy dispatch is being analysed.

### Implementation of V2G

The second objective follows the first, and intends to improve the existing flexibility and storage options of the model, but now with the implementation of BEVs as a storage option and implementation of V2G. The study looks at the effects of flexible charging vs. inflexible charging and how restricting charging and the option of V2G at certain times of the day affects the system. Two main research questions have been developed for this analysis. First, *How does the transportation sector change?*, which analyses the integration of electric vehicles in the system, and how the electric vehicles are being used with the new implemented functions. Second, *How does the energy storage investment change*, similarly to the research question of the first model, this intends to analyse the investment in energy capacity and power capacity in the energy storage technologies from 2018 to 2050.

### 1.2.2. Thesis structure

The structure of the thesis follows the research questions (see Section 1.2.1), which is split into two. All following chapters are influenced by the two models and a split can be seen in most chapters.

The structure of the thesis itself is built up with the chapters *Literature review*, *Methodology*, *Data and analysis assumptions*, *Results*, *Discussion* and *Conclusion*. The literature review introduces the technologies analyzed in the study and a short introduction of energy storage modeling. The methodology introduces the model itself, and changes made to the model in the study. The Data and assumptions section displays the key data used in the study and describes the sensitivities and scenarios that are being analyzed. Results, discussion and conclusion follows by displaying the results, discussing the results and method and ending with a conclusion.

# 2. Literature Review

## 2.1. Energy Storage systems

### 2.1.1. Pumped hydro storage

Pumped hydro storage (PHS) is based upon the same infrastructure as conventional hydro power. The main differences between conventional hydro power and PHS is that PHS needs to have a lower reservoir and that PHS has the ability to pump water from the lower reservoir to the upper reservoir. The basic principal is to turn electric energy into gravitational potential energy by pumping water from the lower reservoir up to the higher reservoir. The energy that is stored as gravitational potential energy can then be turned into mechanical energy by letting the stored water from the upper reservoir flow through a turbine that spins a generator to create electrical energy that can be delivered to the grid. The amount of energy stored in the upper reservoir depends on the amount of the water stored (mass) and on the height difference between the two reservoirs also known as head. The rated power of a PHS plant depends on the flow rate of water through the turbine, the head of the power plant, the power rating of the turbine/pump, and of the generator/motor (Luo et al., 2014; Hosseini et al., 2008).

The most simple and usual PHS system is the pump as turbine (PaT) system. It consists of one upper, one lower reservoir, and a reversible pump-turbine (RPT) placed in a cavern at a lower elevation than the lowest water regulation of the lower reservoir, and can work both as a turbine and as a pump. The RPT is connected to an electrical invertible generator(motor-generator) that can work as both a generator and as a motor.(Amirante et al., 2016) According to the European Association for Storage of Energy EASE (2022), PHS is the most mature energy storage concept with respect to total installed capacity and storage volume worldwide. It is thus assumed in most literature that all costs remain constant in the future.

The main drawbacks of PHS is the size of the system itself and location requirements. PHS requires vast land areas for the reservoirs and a lot of infrastructure for the dam, and the system is often located far from consumption points. This yields high construction costs and long construction time in comparison to other energy storage technologies. PHS also has a big environmental impact, especially during the construction of the reservoirs, as it affects the aquatic ecosystem, wildlife and land vegetation in the area of the reservoirs (Diawuo et al., 2022).

There are however positive sides of PHS having large reservoirs. They can store more energy and are therefore more resilient against seasonal variability such as dry seasons in comparison to smaller reservoirs. This also allows for seasonal storage, meaning energy stored in rainy seasons or low-demand seasons can be used weeks/months later in dry or high-demand seasons (Blakers et al., 2021). Other benefits of PHS are high efficiency and long lifetime.

PHS takes up large land areas and requires an altitude difference between two bodies of water. This makes it such that only some areas in the world are suitable for PHS. In Europe mostly Switzerland, Austria, Germany, Spain, and Portugal are being focused on for potential new builds (EASE, 2022). EU projections suggest that 4 GW of new PHS will be deployed by 2030. However, the expansion mostly consists of upgrades to existing hydro power plants (Quaranta et al., 2022)

### 2.1.2. Compressed air energy storage

Compressed air energy storage (CAES) is a storage system that stores energy as compressed air in a reservoir. The reservoir can either be an underground cavern (usually a salt cavern) or an above-ground tank. When storing energy, CAES uses electric energy to run a reversible motor/generator to pump air into the reservoir, and can later release the pressurized air to run a turbine to create electric energy (Luo et al., 2014). The temperature of the air rises when the pressure rises, meaning the air can get higher than 600 °C when being pumped into the storage reservoir, and a cooler is needed at the inlet. Consequently, the air cools down when it is being released as pressure drops and heat needs to be supplied to the air before entering the turbine (EASE, 2022). There are two main ways of handling the temperatures at the inlet and outlet, namely with the technologies diabatic compressed air energy storage (D-CAES) and adiabatic compressed air energy storage (A-CAES).

D-CAES uses the combustion of natural gas or fuel to heat the air on the way out and does not take advantage of the hot air at the inlet. A-CAES stores the heat that the air produces when being pumped into the cavern in a Thermal Energy Storage system (TES), and uses the stored heat to heat up the air when being released. This makes the A-CAES system more efficient than the D-CAES as less heat goes to waste. A-CAES also has the benefit of not having to import external fuels such as natural gas for combustion. D-CAES is a mature technology and has been around for a long time, although according to EASE (2022) and King et al. (2021), there were only a handful D-CAES plants in operation. A-CAES systems have for a while struggled to find their way into the market, but over the last ten years several projects have been commissioned around the world and a couple of projects are now commercially active (King et al., 2021).

The main drawback of the large CAES systems is that they require geological formations, preferably salt caverns. This means that CAES systems are only suitable in areas where available salt caverns exist. Consequently, possible salt cavern capacities in each country can be accounted for when modeling CAES. Another drawback concerning the D-CAES is that it uses fossil fuels, which makes it more expensive, and raises concerns about emissions (Amirante et al., 2016).

The positive side of CAES is that it is a matured and tested technology in D-CAES, giving potential for A-CAES to take its place in the future. Another positive is that, it is relativly cheap according to literature, in the sense of energy capacity. In GENeSYS-MOD, the CAES technology is assumed to be A-CAES, but with a slight increase in efficiency in the first years.

### 2.1.3. Battery Energy Storage Systems

The most commonly used energy storage technology today is rechargeable battery systems. It is used both in industry and in the daily life of most people. Battery energy storage systems (BESS) are rechargeable battery systems that store electrical energy as chemical energy, and can convert the energy bidirectionally between chemical and electrical energy (Luo et al., 2014). In terms of large-scale energy system modeling, the most interesting types of batteries are the ones suitable for large-scale energy storage. There are several types of batteries suitable for large-scale energy storage, including lead–acid, nickel–cadmium, sodium–sulfur, lithium-ion, and flow batteries (Poullikkas, 2013), the two latter is discussed further in this study. All BESS consists of electrochemical cells connected in series and parallel to provide the desired voltage and current output, and different types of cells differ in suitable applications. Some of the main benefits of BESS for large-scale energy storage are the flexibility of location and the short construction time, usually within 12 months. The BESS can be located wherever is most beneficial, either inside a building or out on a field with low environmental impact. The most limiting factor for BESS to be used in large-scale energy storage to date is the high maintenance and operating cost, for mobile applications however, the size to stored energy is the limiting factor (Luo et al., 2014; Poullikkas, 2013).

BESS used for energy application has typically only one discharge cycle per day which can happen over several intervals and usually in periods of hours. The charging periods can be over longer periods depending on the application and the fluctuation in electricity need or electricity price. For power applications, the charging and discharge periods of BESS are usually seconds to minutes and can have up to multiple cycles per day (Poullikkas, 2013). GENeSYS-MOD models BESS for energy applications and it is therefore assumed in this study that the BESS has one storage cycle per day, meaning that if the day starts with a storage level of zero the day ends with a storage level of zero.

**Lithium-ion batteries**

Over the last decades lithium-ion (Li-Ion) batteries have become one of the most well-known battery types to the average person after its penetration into the market of portable consumer electronics. Li-Ion batteries have become the frontier of energy storage in the market today and have an important role within high power applications, both within hybrid and electric vehicle applications, and within stationary grid storage (Amirante et al., 2016; Poullikkas, 2013). It is a technology with high efficiency (up to 97%), fast response time (within milliseconds), and one of the highest energy densities out of the commercially available battery storage technologies today (100-265 Wh/kg or 250-670 Wh/L) (Amirante et al., 2016; CEI, 2020). This is what makes it such a great contender for mobile applications such as hybrid and electric vehicles. It has also been shown to be well-suited for stationary grid-scale applications, with projects showing its ability for frequency regulations and its ability to support the variability of wind farms (Luo et al., 2014). In addition, the cost of Li-Ion batteries has experienced a rapid decrease since 2013 falling from 732 USD per kilowatt hour (kWh) $/kWh to 141$/kWh in 2023 (O'Dea, 2023). The cost reduction is according to Ziegler et al. (2021) mostly driven by public and private research and development (R&D), which has led to advancements in the chemistry and materials science of the electrochemical cells of the Li-Ion batteries. With a proven ability to perform ancillary services and coupling with vRES combined with a reduction in cost, the Li-Ion stationary battery storage market has grown to a value of $19.7 billion in Germany in 2022 and is expected to grow to $94 billion in 2032 (Gupta and Gupta, 2023).

In recent times however, the cost of Li-Ion batteries has seen an increase in cost, with 2022 cost being up to 151$/kWh (O'Dea, 2023). According to IEA (2023a) the price of lithium had nearly doubled as of January 2023 in comparison to the beginning of 2022. The reason is an increase in demand for essential minerals and metals needed to produce the batteries in combination with disrupted supply chains due to the war in Ukraine and geopolitical repercussions (IEA, 2023a).

**Reduction–oxidation flow batteries**

Redox flow batteries (RFB) normally consists of two electrolyte solutions stored in separate tanks. These solutions, which contain different reduction–oxidation (redox)-active species, flow through a stack of electrochemical cells. Each cell consists of an anode and a cathode separated by an ion-permeable membrane Poullikkas (2013). Based on this unique operating design with the electrolyte solutions separated in two tanks it has the ability to decouple power and energy. The power rating of the RFB is dependent on the size of the electrodes, while the energy capacity is dependent on the concentration and the volume of the electrolyte solution. Another advantage resulting from the separation of the electrolytes is that it also limits the rate of self-discharge of the battery (Luo et al., 2014). Another feature of RFB that differs from other battery types such as Li-Ion is that the lifetime is not influenced by Depth of Discharge (DoD). Meaning that many types of RFB can discharge to 0% battery level. In comparison, Li-Ion batteries usually have a max DoD of 80% and can never discharge lower than 20% without it affecting the health and lifetime of the battery (Amirante et al., 2016; Murden, 2023). Dependent on the type of RFB the volumetric energy density ranges from 45–90 W h/l (Amirante et al., 2016), can have a response time faster than 0.001 s (Luo et al., 2014), and can reach efficiencies up to 86% (Sánchez-Díez et al., 2021). Having a lower energy efficiency and energy density than Li-Ion makes RFB less suitable for mobile applications, but it is still a prime candidate for stationary storage applications, and can for some applications, be cost-competitive. It is especially suited for applications with longer charge and discharge times, meaning it can be a good option to Li-Ion within large-scale energy applications. As mentioned earlier Li-Ion batteries have in recent times had an increase in cost, due to the limited availability of lithium, giving an opening for RFB in the stationary battery storage market (Murden, 2023).

Many types of RFB are mature technologies and are already commercialized. Some cost reduction is expected as there are efforts looking at improving components and the efficiency of the systems. Vanadium redox flow batteries (VRFB) are currently the leading type of RFB, and is the most successful both in terms of performance and market share. However, an increase in demand for vanadium has become the limiting factor for VRFB, and alternative chemistries are also being researched to further decrease costs (Sánchez-Díez et al., 2021).

### 2.1.4. Battery Electric Vehicles and Vehicle-to-Grid

Battery electric vehicles (BEVs), also known as electric vehicles (EVs), are fully electric vehicles with an electric motor and a rechargeable battery pack. Electric vehicles has lately had huge success in the car market, seeing an exponential growth in sales. In 2022 14% of all new cars sold were electric, with China being the biggest market and accounts for around 60% of the sales world wide. Europe is the second biggest marked with 25% of the market, and more than 20% of new cars sold in Europe in 2022 were electric. The increase in sales are expected to increase further, with share of sales worldwide reaching 35% in 2030, based purely on existing policies according to IEA (2023b). This number could realistically also be higher by 2030, as battery manufacturer has announced a production capacity more than sufficient to meet the demand of 35% in 2030 (IEA, 2023b).

Another technology related to electric vehicles that has gained popularity within research is V2G. V2G is the concept of allowing the battery of an electric vehicle bidirectional charging, meaning the car is not only consuming energy from the grid but also discharging to the grid, given that the car is parked and connected to the grid with a bidirectional charging cable (SHI et al., 2018). The BEVs can in that way work in the same way as conventional BESS, and provide the same type of services to the grid. The difference between a utility-scale battery park, and BEVs performing V2G is the distribution of the BEVs. The consumption and supply of the BEVs is distributed throughout the grid in places where people live, relinquishing the need for an extensive transmission grid. It can also serve a purpose during power outages, serving as a local backup generators for the nearby distribution grid (Mastoi et al., 2023).

## 2.2. The cost of energy storage in energy modeling

In this section two ways of modeling storage cost is put forth. LCOS and a decoupled capital cost of storage method.

### 2.2.1. Levelized Cost of Storage

LCOS is defined as the total cost over the lifetime of a storage system divided by the accumulated energy delivered by the system over its lifetime. The unit of LCOS is often given in euros per kilowatt-hour or megawatt-hour[€/kWh or €/MWh] (Schmidt et al., 2019). The use of the unit cost per energy works well for systems with an energy application, however, as mentioned in section 2.1.3, when talking about storage systems for power applications, it might be more reasonable to have an LCOS measured in cost per power capacity, i.e. euro per kilowatt [€/kW] (Bistline et al., 2020). LCOS is in that way comparable to the more commonly known levelized cost of electricity (LCOE) which is the same calculation for electricity generation technologies. Another way to look at LCOS is that it reflects the revenue needed per energy unit discharged from the storage system for the investment to have a net present value (NPV) of zero. There are various types of LCOS concepts, such as levelized cost of stored energy, and levelized cost of delivery, both describe cost calculations that include different costs or different energy accumulations as the names suggest. While the levelized cost of stored energy does not account for the discharge efficiency and the discharge cost of the unit, the levelized cost of delivery does, and is the more common approach. It is therefore important to notice what methodology or concept is being used when gathering data and calculating LCOS to use in energy system modeling (Schmidt et al., 2019).

LCOS has many purposes, it allows for direct comparisons between different energy storage technologies and gives a metric of how economically attractive each technology is. Investors and policymakers can use LCOS as a pointer to make informed decisions or further calculations on the profitability of investments. It can also be used in energy system modeling as a way of accounting for the costs of the different energy storage technologies by setting it as the variable cost of the technology. In short, LCOS is a simplification of the cost, and for actual investment or policy decisions, further analysis is necessary. Either way LCOS has its merit and provides a convenient statistic of the current and future price of energy storage technologies (Bistline et al., 2020).

### 2.2.2. Decoupled Capital Cost of Storage

Another way of representing the cost of energy storage in energy system modeling, is through endogenously determining the energy-to-power ratio by decoupling energy capacity costs and power capacity costs Bistline et al. (2020). This cost structure is similar to how normal energy-producing technologies usually are represented, with capital expenditure (CapEx), fixed operating expenditure (OpEx), and variable OpEx. The difference in comparison to normal energy-producing technologies is that energy storage has an energy storage component as well as a power component, meaning there are two components to the capital cost. One part of the capital cost concerns energy storage capacity, and is given in cost per energy storage capacity, and the other concerns the power cost, and is given in cost per power capacity. Using PHS as an example; the energy capacity cost would concern the cost of the upper reservoir that stores the energy, whilst the power capacity cost concerns the rest of the system, tunnels, turbine/pump, generator/motor, and outlet (Viswanathan et al., 2022).

# 3. Methodology

In this study, the effects of a new cost structure of storage in the Global Energy System Model (GENeSYS-MOD) is being presented. The new cost structure is based on separating storage investment cost into two independent investment, that are the cost of storage size (energy capacity) and grid link (power capacity). The following sections introduce GENeSYS-MOD in general with its framework, as well as describing changes made to the model.

## 3.1. Model description

The analysis conducted in this study is based on the energy system model GENeSYS-MOD, originally developed, and initially published in 2017 by Löffler et al. (2017)[1]. GENeSYS-MOD builds upon the foundation of the Open Source Energy Modelling System (OSeMOSYS) while introducing new functionalities and features to enable more comprehensive investigations into long-term energy system transition pathways. The model builds on mathematical optimization, with the objective of minimizing the net present cost of a given energy system over the chosen modeling period. The energy system model is designed to mirror the evolving, interconnected landscape of future energy systems, characterized by greater sector coupling and electrification. GENeSYS-MOD facilitates simultaneous decision-making across various sectors, including electricity, heat, industry, and transportation, optimizing choices related to investments, energy generation, and distribution. The structural layout of GENeSYS-MOD is represented in Figure 1.

[1] For further information on GENeSYS-MOD including a documentation, quick-start guide, and a sample data set, the reader is referred to: https://git.tu-berlin.de/genesysmod/genesys-mod-public

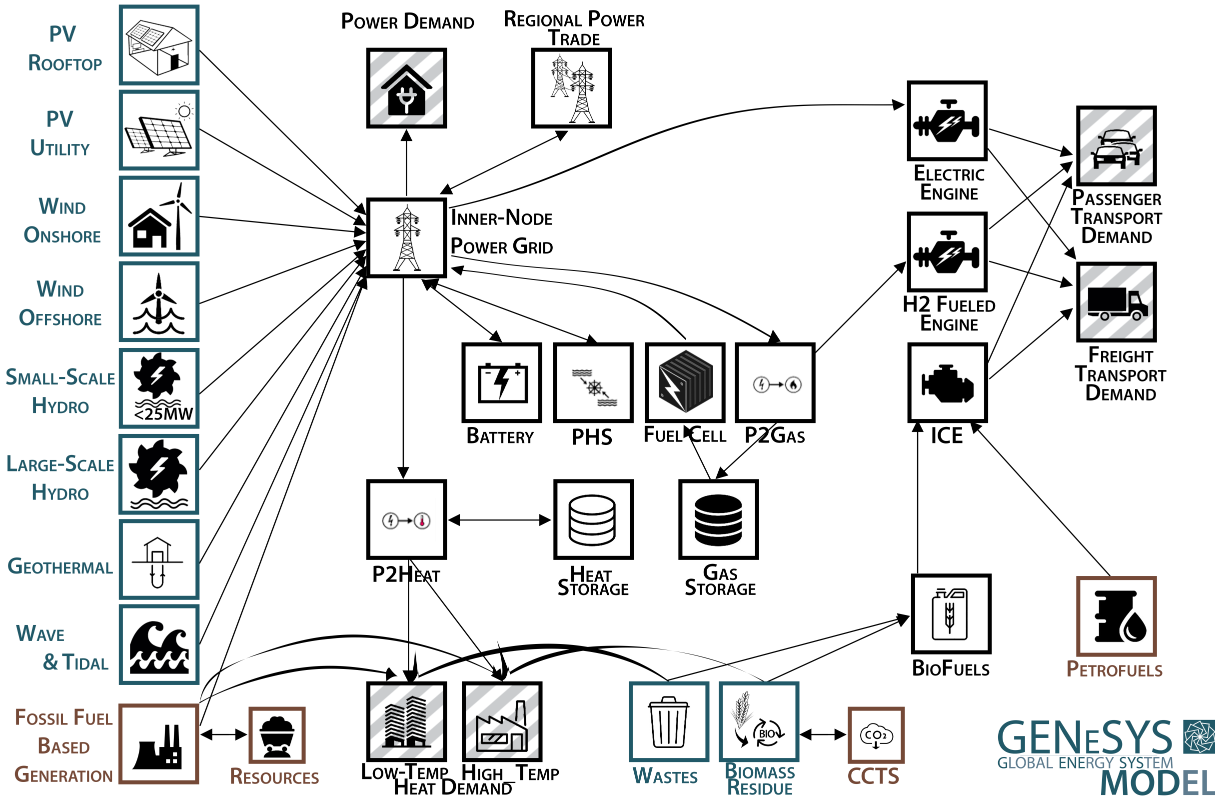


**Figure 1: The model structure of GENeSYS-MOD. (Löffler et al., 2022)**

The basis for the work in this study is a model based on previous iterations of GENeSYS-MOD, with the model setup based on the European model developed in *openENTRANCE* which is a project from Horizon 2020. The European model used as base case, is a model made as part of an open modeling platform with the intention to analyze different possible pathways of the European energy system into a low-carbon system (Auer et al., 2021; Hainsch et al., 2022). The model offers several different scenarios/pathways, but this study uses the *Techno Friendly* scenario, which is a pathway from 2018 to 2050. The base year in this study is 2018 and the model is allowed investment decisions with 5-years steps starting from 2025 (i.e. 2018, 2025, 2030...). The time disaggregation is defined by the user, and is based on the reduced time-series principle. The reduced time-series only accounts for every *nth* hour, where *n* is the number of hours in each timestep, and rescales the values to the original series. In this study $n = 122$ is used. This reduces computational complexity at the cost of lower temporal resolution. With the reduced times-series method the intraseasonal patterns are included, but extreme values might not be accounted for. Further model splits the European energy system into 30 different regions, with mainland EU-25, Norway, Switzerland, UK, Turkey, and a comined Balkan region.

## 3.2. Energy storage in GENeSYS-MOD

The implementation of storages in GENeSYS-MOD is a modified version of the implementation in OSeMOSYS. The difference from OSeMOSYS to GENeSYS-MOD is that GENeSYS-MOD allows for an endogenous calculation of storage capacities. That means that energy storage capacity is a variable that the model decides, but with a fixed Energy-Power-Ratio (EPR) exogenously given as a parameter for each storage technology. The power rating results from the EPR and the amount of energy storage capacity invested in for each technology (Löffler et al., 2017). The cost of storage in GENeSYS-MOD is modeled in a decoupled way, meaning each technology is separated into grid link and the actual energy storage. The grid link is defined as a so-called *dummy-technologies* and is included in the set of technologies, while the storage itself is defined in a separate set called storage. The dummy-technology has two modes of operation, mode of operation 1 is the charging mode with power from the grid as input and power to the storage as output, mode of operation 2 is the discharging and takes power from the storage as input and has power to the grid as output.

Eight different storage technologies are included in GENeSYS-MOD, four electricity storage systems, two thermal storage systems, and two gas storage systems. The electricity storages included are PHS, Battery Li-Ion, Battery redox, and CAES. The thermal storages included are low-heat residential and low-heat industrial storage systems. The gas storage systems included are methane gas storage and hydrogen storage. All the storage technologies in the model take input values for operation lifetimes, maximal and minimal charge ratios, and costs. For this study, only the electricity storage systems were analyzed in depth.

The cost of the electricity storage systems in GENeSYS-MOD have in previous iterations, and in the base model for this study, used an LCOS approach with exogenously specified charge and discharge durations, i.e energy to power ratio. Included input costs in the model were LCOS as variable cost given in [M€/PJ], and a fixed yearly cost given in [M€/GW]. The capital cost of energy and power capacity were kept at arbitrarily low values, as the LCOS accounts for the capital cost.

## 3.3. Changes to GENeSYS-MOD

As mentioned in Section 1.2.2 two models have been developed named the Capex model and the V2G model. The section below introduces the changes made to the two models in comparison to the base model.

### 3.3.1. Capex model

The cost structure of storage in GENeSYS-MOD has in the previous iteration been based on LCOS, as mentioned in the previous section 3.2. The main changes made for this study were to decouple the capital cost of storage into energy capacity cost and power capacity cost, put in other terms, the cost of energy capacity and the cost of power capacity. This allows the model to endogenously determine the energy-to-power ratio (Bistline et al., 2020). The change in cost structure makes the previous cost assumptions for storage obsolete and a literature review has been performed to better reflect the costs of each storage technology in all the decision years. The new cost input includes capital cost of power capacity, variable cost, fixed annual cost, and capital cost of energy capcaity. A wide range of literature has been reviewed regarding the cost, including Viswanathan et al. (2022), Breyer et al. (2017), Centre et al. (2014), Amirante et al. (2016), Luo et al. (2014), Zakeri and Syri (2015), and The Danish Energy Agency (2020). A final selection of costs from 2018 to 2050 and their sources can be seen in Table 1, 2, 3, and 4 in section 4.1.

Another change compared to the original model is the scaling of the capital cost of storage based on the chosen timestep and the consequent hour steps used in the simulations. The hour steps being the amount of hours moved forward in the day since the last step. A step size of $n = 122$ is used, which amounts to five days and two hours, making the hour step equal to 2. The scaling equation can be seen in Equation 1.

$$CapitalCostStorage_{rsy} = CapitalCostStorage_{rsy} * \frac{hour\_steps * 8760}{timestep * 365 * 24} \tag{1}$$

Where $CapitalCostStorage_{rsy}$ is the energy capacity cost of storage technology *s*, in region *r*, in year *y*. *Timestep* is the step size chosen for the simulation, and *hour_steps* is the amount of hours moved forward within the day from one step to another. The reason for the scaling is that energy storage is heavily dependent on the fluctuations in energy demand and supply and the subsequent fluctuation in the energy price. Energy storage is used optimally when it can buy electricity cheaply and sell it later at a higher price. The difference between the selling price and buying price has to be bigger than the marginal cost of the storage technology, and preferably also bigger than its LCOS, to have a willingness to charge and discharge the storage unit. As a reduced time series is used in the model the storage technology sees less of the fluctuations throughout the year and energy storage stands hence as a less profitable asset. Equation 1 makes up for the lost fluctuations in the market by lowering the capital cost of all the storage technologies based on the amount of reduced hours used in the simulation.

### 3.3.2. V2G model

The second part of this study is a continuation of the changes made in section 3.3.1 above. Meaning it uses the same cost structure and data. The new changes are based on a study from Hainsch (2023), where the structural implementation of BEVs was changed in the model. Previously the BEVs in the model had no implementation of energy storage, and electricity used to power the BEVs had to be produced at the same time as it was used, similar to how overhead-powered trains work. Hainsch (2023) made the change such that all BEVs have a storage unit that have to be charged, for later to provide the electricity for the BEVs to drive. In this model, the new changes are only< implemented for passenger BEVs, meaning cars and buses, but not freight transport as in (Hainsch, 2023). The specific storage unit for the BEVs are introduced by implementing a storage unit, S_BEV, and a power capacity unit, D_BEV, with two modes of operation. Mode of operation 1 allows the storage to charge electricity from the grid, and mode of operation 2 allows that energy to be exclusively dispatched to the BEVs for driving. The costs for both S_BEV and D_BEV are assumed to be accounted for in the cost of the car in the model, and are hence set to arbitrarily low values.

Furthermore more, a new function has been introduced to the model from the year 2030. The new function is the method previously introduced as V2G, which allows the storage unit of the cars, not only to provide electricity for driving, but also to discharge electricity back to the grid, the same way as conventional battery storages. The way it is implemented is by introducing a new storage technology called S_BEV_V2G, coupled with a power capacity unit D_BEV_V2G with three modes of operation. The two first modes of operation works exactly as for the previously mentioned D_BEV, whilst mode of operation 3 allows for the storage unit to discharge electricity back to the grid. The V2G storage unit is created separately from the normal BEVs storage unit to be able to control the rate of V2G implementation, and to be able to set costs related to the battery and charging component of the V2G cars. The implementation rate of V2G is set as a percentage of the amount of BEVs in the model and is described in Equations 2 and 3.

$$\begin{aligned} NewCapacity_{yt_1r} &\leq NewCapacity_{yt_2r} * V2GPercent * 1.1 \\ NewCapacity_{yt_1r} &\geq NewCapacity_{yt_2r} * V2GPercent * 0.9 \\ \text{for } t_1 = \text{D\_BEV\_V2G}&,\ t_2 = \text{D\_BEV}, \text{ and } y \geq 2030 \end{aligned} \tag{2}$$

$$\begin{aligned} NewStorageCapacity_{s_1yr} &\leq NewStorageCapacity_{s_2yr} * V2GPercent * 1.1 \\ NewStorageCapacity_{s_1yr} &\geq NewStorageCapacity_{s_2yr} * V2GPercent * 0.9 \\ \text{for } s_1 = \text{S\_BEV\_V2G}&,\ s_2 = \text{S\_BEV}, \text{ and } y \geq 2030 \end{aligned} \tag{3}$$

Equations 2 and 3 describe the implementation rate of V2G as a percentage of BEVs in the model from the year 2030 and onward. *NewCapacity* is a variable describing the amount of new power capacity invested in for the respective technology *t*, in the year *y*, in region *r*, and is given in GW. *NewStorageCapacity* is a variable describing the amount of new energy storage capacity invested in for the respective storage technology *s*, in year *y*, in region *r*, and is given in PJ. *V2GPercent* is a parameter given endogenously to control how big share of the battery electric vehicle (BEV) market V2G cars have.

V2G is only allowed in the model from the year 2030. There is no equation limiting the investment in the technology before 2030, but an equation limiting the rate of activity of mode of operation 3 for D_BEV_V2G (discharging to the grid) is implemented for the year before 2030. This is done to ensure that the function only becomes available in the intended start year.

Figure 2 below shows an updated version of the model structure from section 3.1(See Figure 1). The changes in the updated model structure is the battery pack which acts as a median between the power grid and the electric engine. The batterypack now also has bidirectional features with options of charging back to the grid.

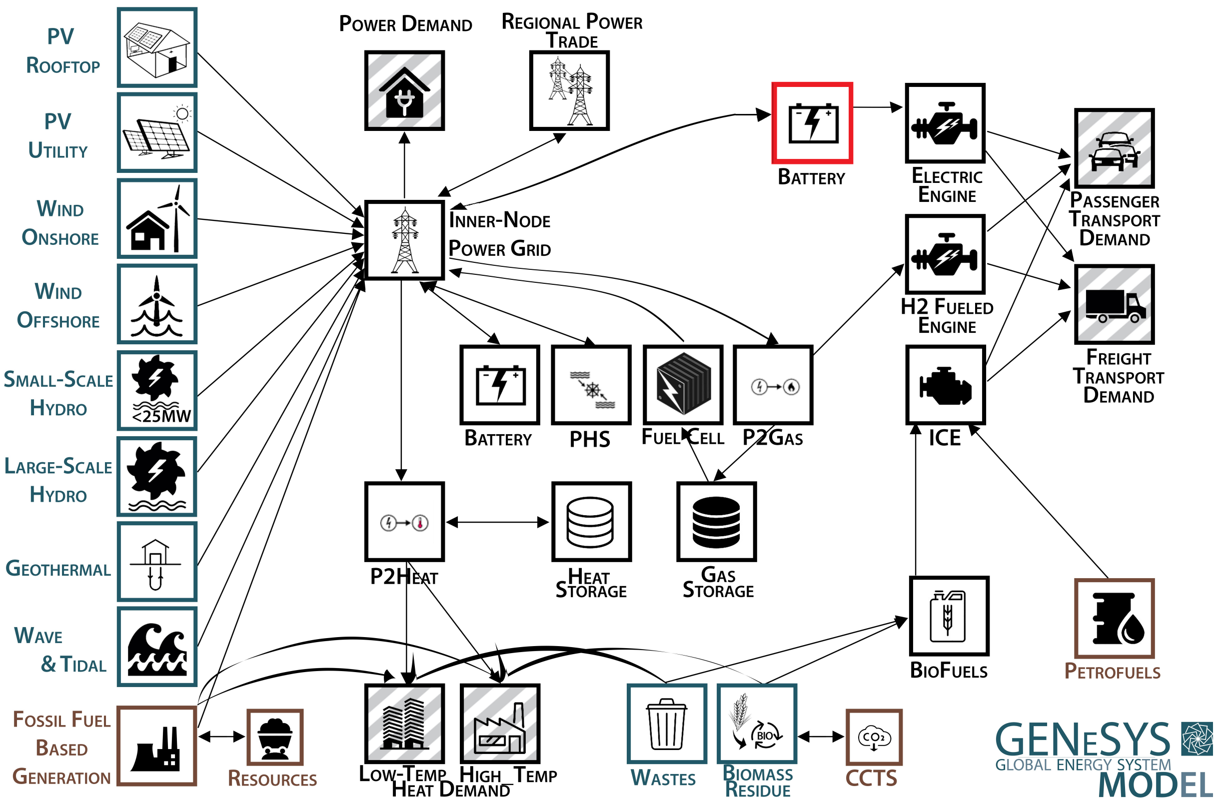


**Figure 2: The updated verison of the model structure of GENeSYS-MOD after the implementation of V2G. The new implementation of battery storage between the grid and the electric engine can be seen in red. (Löffler et al., 2022)**

The model now has the opportunity to invest in as much power capacity as the model deems optimal, without any correlation to how many cars there actually are in the model. To limit this for the vehicles participating in the V2G-scheme, an equation that correlates the rate of activity of charging and discharging of the V2G battery pack is introduced. The equation can be seen in Equations 4 and 5.

$$\begin{aligned} RateOfActivity_{y,l,t_1,m,r} &\leq TotalCapacityAnnual_{yt_2r} * PowerFactor * ChargerCapacity \\ &\text{for } t_1 = \text{D\_BEV\_V2G},\ t_2 = \text{PSNG\_Road\_BEV},\ m = 1, \text{ and } y \geq 2030 \end{aligned} \tag{4}$$

$$\begin{aligned} RateOfActivity_{y,l,t_1,m,r} &\leq TotalCapacityAnnual_{yt_2r} * PowerFactor * ChargerCapacity \\ &\text{for } t_1 = \text{D\_BEV\_V2G},\ t_2 = \text{PSNG\_Road\_BEV},\ m = 3, \text{ and } y \geq 2030 \end{aligned} \tag{5}$$

Where $RateOfActivity_{yltmr}$ is the actual power output/input in year *y*, in hour *l*, of technology *t*, in mode of operation *m*, in region *r*, and is given in GW. $TotalCapacityAnnual_{ytr}$ is the total power capacity in year y, of technology t, in region r and is given in GW. PowerFacor is a correction factor given in [number of actual cars/$GW - modeled$] and ChargerCapacity is an exogenous parameter describing the power capacity of the car charger cable given in GW. Although the model sees $TotalCapacityAnnual_{ytr}$ as given in gigawatts, it represents, in this case, the amount of battery electric vehicles in the model and can be thought of as the amount of cars in the model, scaled by a factor. The *PowerFactor* introduced in Equations 4 and 5 is a correction factor, to allow for the use of real numbers for the *ChargerCapacity* parameter. The *PowerFactor* is found by dividing the amount of actual BEVs by the residual capacity of cars in the model for that same year. For this case, Germany in the base year of 2018 was used to set this factor, with 53 861 BEVs in Germany (Carlier, 2023), and 58.6 GW residual capacity in the model the PowerFactor ended up at 919.1 [number of actual cars/$GW - modeled$].

**Further equations**

With the implementation of Equations 4 and 5, the power capacity of the charger cable was limited to the number of cars in the model, but the energy capacity of the car battery is still not limited to the number of cars in the model. There are at least two ways this can be implemented in the model. One way is by locking the investment of energy capacity (S_BEV and S_BEV_V2G) to the number of cars in the model $TotalCapacityAnnual_{ytr}$ similarly to how it is done for the charger capacity. The second way is to lock the investment of energy capacity (S_BEV and S_BEV_V2G) to the number of passenger kilometers the BEV-fleet produces. A similar multiplication factor such as the previously mentioned *PowerFactor* from Equations 4 and 5 has to be implemented in the second way, based on a number of parameters such as the average amount of people in a car, average kilometers each car drives each year, and battery size. Both methods were implemented and tested but resulted in simulation errors and did not make it to the final version of the model.

# 4. Data and analysis assumptions

## 4.1. Data

Gathering cost data has been an integral part of the changes made to model in this study. In general, when looking at cost data of technologies there are some thing to keep in mind. First of all the date of the published cost data. Some technologies like Li-Ion has, as mentioned in 2.1.3, gone through a rapid decrease in cost over the last decade, and older cost estimations and forecasts might be outdated. On the other hand, technologies like PHS, which has been around for a longer time and is considered a well matured technology, is not as sensitive for the time of publication. Another factor is the geographical location of the published data as political, economical and geopolitical differences can make an impact on the cost of the different technologies. That include labor cost, transportation cost, supply chain and resource availability, available expertise, and land availability.

The main difference made from the previous iterations of GENeSYS-MOD is the introduction of a decoupled capital cost of storage. The energy component of the capital cost, or energy capacity cost, is given in cost per energy [M€/PJ]. The power capacity component of the capital cost, or grid-link cost, is given in cost per installed power [M€/GW]. There is limited data available and only some studies and databases provide a break down of the different cost components.

| | 2018 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Energy cost [M€/PJ] | 16 163 | 16 163 | 16 163 | 16 163 | 16 163 | 16 163 | 16 163 | 16 163 |
| Grid-link cost [M€/GW] | 1 424 | 1 424 | 1 424 | 1 424 | 1 424 | 1 424 | 1 424 | 1 424 |
| Variable O&M [M€/PJ] | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 |
| Fixed O&M [M€/GW/year] | 15.59 | 15.59 | 15.59 | 15.59 | 15.59 | 15.59 | 15.59 | 15.59 |
| Technical lifetime [years] | 60 | 60 | 60 | 60 | 60 | 60 | 60 | 60 |

**Table 1: Pumped hydro storage cost and lifetime[2]**

The data given for PHS in Table 1 are gathered from Viswanathan et al. (2022) and Luo et al. (2014) and is based on a 10h, 1000MW system with 10GWh storage. The 10h, 1000MW system is the most optimistic option presented in Viswanathan et al. (2022), as it has the lowest specific costs.

[2] Note. The data for Energy Cost, Grid-link cost, Fixed O&M, and Technical lifetime are from Viswanathan et al. (2022). Viswanathan et al. (2022) assumes no cost delevelopment from 2022 to 2030, hence it is assumed no cost development to 2050. The data for Variable O&M are from Luo et al. (2014) and it is assumed no cost reduction. A currency exchange rate of 1€ = USD 1.1 is assumed.

The energy cost includes reservoir construction costs and infrastructure costs. The grid-link cost includes powerhouse construction costs, infrastructure costs, contingency fees, and the costs of the electro-mechanical system (turbine/pump and generator/motor or PaT system as referred to in section 2.1.1).

Out of the seven cost related studies reviewed for cost data, the cost values for energy cost ranged from 1263 M€/PJ to 25 255 M€/PJ, grid-link cost ranged from 455 M€/GW to 4091 M€/GW according to Amirante et al. (2016) and Luo et al. (2014) which had the highest and lower estimated costs out of the reviewed studies. One of the challenging parts when modeling PHS and looking at PHS capital cost data is to know if the cost are intended for a completely new power plant or if it is intended for a reconstruction of existing power plants. The data used in this study is intended for a completely new power plants, but as mentioned earlier in section 2.1.1, it is more likely that future PHS projects in Europe are reconstruction projects.

One thing to notice in Table 1, is that the data stays constant over all the years. This is something that is consistent within the literature, and it is assumed that there is no significant cost development towards 2050.

In this study it is assumed that the potential for PHS in Europe is saturated, meaning there is no potential for new PHS storage expansion, and the model is limited to the existing residual capacity with the option for grid link expansion. This deems the Energy cost redundant as it is not allowed to invest in energy capacity expansion, however, it allows for variations of the model to be made in the future to include expansion.

| | 2018 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Energy cost [M€/PJ] | 1 460 | 1 460 | 1 460 | 1 460 | 1 460 | 1 460 | 1 460 | 1 460 |
| Grid-link cost [M€/GW] | 965 | 965 | 965 | 965 | 965 | 965 | 965 | 965 |
| Variable O&M [M€/PJ] | 0.68 | 0.68 | 0.68 | 0.68 | 0.68 | 0.68 | 0.68 | 0.68 |
| Fixed O&M [M€/GW/year] | 9.13 | 9.13 | 9.13 | 9.13 | 9.13 | 9.13 | 9.13 | 9.13 |
| Technical lifetime [years] | 60 | 60 | 60 | 60 | 60 | 60 | 60 | 60 |

**Table 2: CAES cost and lifetime[3]**

[3] Note. The data for Energy Cost, Grid-link cost, Fixed O&M, and Technical lifetime are from Viswanathan et al. (2022). Viswanathan et al. (2022) assumes no cost delevelopment from 2022 to 2030, hence it is assumed no cost development to 2050. The data for Variable O&M are from The Danish Energy Agency (2020) and for values not given linear interpolation has been used. A currency exchange rate of 1€ = USD 1.1 is assumed.

The data given for CAES in Table 2 are gathered from Viswanathan et al. (2022) and The Danish Energy Agency (2020) and is based on a 100h, 1000MW system with 100GWh storage. Similar to the what is done for the PHS, the largest most optimistic system with the lowest cost was chosen. This approach might be optimistic, as only one CAES project of similar size existed as of 2021 according to King et al. (2021). The energy cost includes the cavern storage costs. The grid-link cost includes cost of turbine, compressor, balance of plant (BOP), and engineering, procurement, and construction (EPC) managment costs. From the reviewed literature the cost values for energy cost ranged from 505 M€/PJ to 30 305 M€/PJ, grid-link cost ranged from 364 M€/GW to 1364 M€/GW according to Amirante et al. (2016) and Luo et al. (2014) which had the highest and lower estimated costs out of the reviewed studies.

Similar to the data given for PHS, the data stays constant over all the years, and no significant cost or technology development is assumed. This is consistent with what Viswanathan et al. (2022) assumes. Dependent on the year of the study this might differ, databases based on older studies such as The Danish Energy Agency (2020) assumes that D-CAES is the dominant technology until somewhere between 2020 and 2030. However The Danish Energy Agency (2020) bases this on CAES studies from 2011-2012 and it is hence assumed in this study that A-CAES already is the dominant technology and that there are no significant cost development towards 2050.

| | 2018 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Energy cost [M€/PJ] | 116 111 | 64 444 | 51 944 | 39 444 | 32 777 | 26 111 | 23 472 | 20 833 |
| Grid-link cost [M€/GW] | 290 | 270 | 215 | 160 | 130 | 100 | 80 | 60 |
| Variable O&M [M€/PJ] | 0.58 | 0.56 | 0.53 | 0.50 | 0.49 | 0.47 | 0.46 | 0.44 |
| Fixed O&M [M€/GW/year] | 6.90 | 6.57 | 6.24 | 5.91 | 5.75 | 5.59 | 5.42 | 5.26 |
| Technical lifetime [years] | 15 | 20 | 22.5 | 25 | 27.5 | 30 | 30 | 30 |

**Table 3: Lithium-Ion battery cost and lifetime[4]**

The data given for Li-Ion in Table 3 are gathered from The Danish Energy Agency (2020) and Zakeri and Syri (2015), and is based on a utility-scale lithium-ion nickel Manganese Cobalt (NMC) battery system with various power and energy ratings based on the year. The energy cost includes the battery pack cost, construction cost, and power cable costs. The grid-link cost includes the power conversion system (PCS) cost, and assumes inverter replacement costs every 10 years. From the reviewed data

[4] Note. The data for Energy Cost, Grid-link cost, Variable O&M, and Technical lifetime are from The Danish Energy Agency (2020) and for values not given linear interpolation has been used. The data for Fixed O&M are from Zakeri and Syri (2015) and the same cost reduction rate as the Variable O&M is assumed.

energy cost in 2018 ranged from 88 391 M€/PJ to 959 673 M€/PJ, and grid-link cost in 2018 ranged from 96[5]M€/GW to 3636 M€/GW according to Viswanathan et al. (2022), Amirante et al. (2016), and Luo et al. (2014) which had the lowest and highest estimated costs out of the reviewed studies. The older study in Amirante et al. (2016), provides a wide range in the cost, giving the highest and loswest estimated cost, while the newer study from Viswanathan et al. (2022) in general shows a lower cost, especially in grid-link cost. It can be seen in Table 3 that the technology development is expected to be exceptionally high compared to the other technologies. The capital costs in 2050 are expected to drop to one-fifth of the cost in 2018, as well as a doubling in lifetime. This is the consensus in the literature, and both the cost and lifetime of Li-Ion are expected to improve according to all the reviewed articles in this study.

| | 2018 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Energy cost [M€/PJ] | 177 778 | 138 889 | 75 000 | 69 444 | 73 611 | 72 222 | 70 833 | 69 444 |
| Grid-link cost [M€/GW] | 450 | 410 | 330 | 330 | 330 | 330 | 330 | 330 |
| Variable O&M [M€/PJ] | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 |
| Fixed O&M [M€/GW/year] | 2.00 | 2.00 | 1.75 | 1.50 | 1.50 | 1.50 | 1.50 | 1.50 |
| Technical lifetime [years] | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |

**Table 4: Redox-flow-batteries cost and lifetime[6]**

The data given for redox-flow-batteries in Table 4 are gathered from The Danish Energy Agency (2020) and is based on a 4 hour, 0.5 megawatt (MW) Vanadium Redox Flow Battery (VRFB) system with 2 megawatt hours (MWh) storage. VRFB is the market leading and most mature RFB as mentioned in 2.1.3 and is therefore used as basis for the RFB data.

Out of the seven cost related studies reviewed, the cost values for energy cost ranged from 37 882 M€/PJ to 252 545 M€/PJ, grid-link cost ranged from 450 M€/GW to 7775 M€/GW according to The Danish Energy Agency (2020) and Luo et al. (2014) which had the highest and lower estimated costs in 2018 out of the reviewed studies. The Danish Energy Agency (2020) reports a relatively high cost of energy capacity, but in return the lowest cost of grid-link and a higher technology development than the other studies. This seems to be a trend, where The Danish Energy Agency (2020) reports higher costs for energy capacity relative to the other studies, while they report a lower cost of grid-link

[5] The lowest value for grid-link cost of 96 M€/GW was provided by Viswanathan et al. (2022) which is a study from 2022 and not 2018, but is only a third of the next lowest cost given by The Danish Energy Agency (2020) for 2018

[6] Note. All the data are from The Danish Energy Agency (2020) and for values not given, linear interpolation has been used.

and higher degree of technology development, in comparison to other studies. When that is said the cost range of the energy capacity is big in 2018 with the highest value reporting more than 6.6 times higher than the lowest value.

| | 2018 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| Energy cost [M€/PJ] | 833 | 833 | 694 | 556 | 486 | 417 | 375 | 333 |
| Variable O&M [M€/PJ] | 8.33e-6 | 8.33e-6 | 6.94e-6 | 5.56e-6 | 4.86e-6 | 4.17e-6 | 3.75e-6 | 3.33e-6 |
| Fixed O&M [M€/GW/year] | 6.00e-8 | 6.00e-8 | 5.00e-8 | 4.00e-8 | 3.50e-8 | 3.00e-8 | 2.70e-8 | 2.40e-8 |
| Technical lifetime [years] | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Table 5: $H_2$-gas cavern storage cost and lifetime[7]**

Cost data for $H_2$ is included in Table 5 as it is used in the sensitivity analysis. One thing to note is that Grid-link cost are not included. The reason is that $H_2$-gas cannot be directly fed into the grid, and other costs such as transportation and use in an electrolyzer or for direct $H_2$ applications reflects the grid-link costs we see in the other storage technologies.

## 4.2. Vehicle-to-Grid Data

The data gathered for the V2G part of the study includes charger cost, charging capacity per car, battery size per car, driving patterns, and charge level. All data except driving pattern data can be seen in Table 6.

| | **Charger cable CapEx** | **Charger-capacity per-car** | **Charge / Discharge Efficiency** | **Battery size per car** | **Minimum charge level** |
|---|---|---|---|---|---|
| **Data** | 22-115 €/kW | 4 - 22 kW | 95 % | 60 kWh | 20 % |
| **Source** | Kempton and Dhanju (2006) and Huber et al. (2021a) | Mojumder et al. (2022) | Hainsch (2023) | Abdelbaky et al. (2020) | Straub et al. (2023) |

**Table 6: V2G data**

The charger cable CapEx, Grid-link cost for comparison to the other energy storage technologies, varies from 22 €/kW to 115 €/kW coming from three different sources (Huber et al., 2021a; Kempton and

[7] Note. All the data are from The Danish Energy Agency (2020) and for values not given, linear interpolation has been used.

Dhanju, 2006; Huber et al., 2021b). The lower cost of 22 €/kW is being used in this study. This can be seen as optimistic as V2G is not a mature technology yet, and estimated costs is closer to 115 €/kW with current prices. However lower values can be found in literature, and as V2G is being implemented in 2030 in this study, and studies suggests that the future price might be drastically lower than current prices (Huber et al., 2021a). The cost of energy capacity expansion (S_BEV_V2G) is assumed to be implemented in the cost of the car and is hence set to an arbitrarily low value as described for the BEVs in section 3.3.2. The model used in this study is a derivation of (Hainsch, 2023) and the charge/discharge efficiency of 95% used is the same as in (Hainsch, 2023) for both BEVs and for V2G. The battery pack is assumed to be an average of 60kWh in 2030, and is likely to increase towards 2050 (Abdelbaky et al., 2020). However, there are no equations limiting this in the model as described in 3.3.2. It is also assumed a minimum charge level of 20%, but is a restriction that is only assumed for the cars participating in the V2G scheme (Straub et al., 2023).

The study from Straub et al. (2023), which is a V2G study based in Berlin, has set a state of charge (SOC) target at 90% which must be reached before a vehicle leaves for a trip. A similar constraint inspired by Straub et al. (2023) has been set in this study which states that the battery park has to reach a SOC of 90% before the start of the morning. A study of the German car fleet and the probability of when cars are driving from Kölbl et al. (2013) suggest that cars start driving between 06:00 and 07:00 reaching a maximum probability at 07:00. With the study from Kölbl et al. (2013) in mind, the morning start is set to 06:00, meaning that the SOC of the V2G car fleet has to be at 90% each time the model reaches 06:00. Based on the probability of driving from Kölbl et al. (2013) and the time of use of public chargers in Noussan and Neirotti (2020), it can be seen that most cars are being driven in the time span 06:00-10:00 and 15:00-22:00 with a slight dip in cars driving between those times (10:00 - 15:00). It can also be seen that most cars are parked in the evening and night, that is after 22:00 until 06:00 the next morning. Based on the driving patterns observed in Kölbl et al. (2013) and Noussan and Neirotti (2020) the day can be categorized into three categories:

- Peak 06:00 - 10:00 and 15:00 - 22:00
- Midday 10:00 - 15:00
- Night 22:00 - 06:00

Peak represents the time of day when driving is most likely to take place, midday represents the time of day when some cars are likely to drive, and night represents the time of day when the least amount of cars are expected to drive. This categorization is further used in the scenarios which can be seen in Section 4.3.2.

## 4.3. Sensitivity analysis and Scenarios

This section is separated into two parts similarly to how the whole study is separated in two. Namely into a sensitivity analysis on the Capex model, and a scenario analysis on the V2G model.

### 4.3.1. Sensitivity in the Capex model

The objective of the work on the Capex model is to observe the behavioral changes of the model with the implementation of the new cost structure. Not only to observe the changes, but analyse if the new cost structure serves as an improvement to the previously used LCOS structure. Five separate sensitivities were tested on the model and can be seen in Table 7

| | Parameter | Default | Min | Max | Increment |
|---|---|---|---|---|---|
| **$H_2$ Import prices** | The price of importing $H_2$ from outside Europe | 100% | 50% | 200% | 25% |
| **Carbon price** | Emission cost | 100% | 50% | 200% | 25% |
| **CapEx power** | CapEx of storage grid-link [M€/GW] | 100% | 50% | 200% | 25% |
| **CapEx Energy** | CapEx of energy storage capacity [M€/PJ] | 100% | 50% | 200% | 25% |
| **$H_2$ Storage cost** | CapEx of $H_2$ storage capacity [M€/PJ] | 100% | 50% | 200% | 25% |
| **vRES integration** | vRES minimum integration rate in 2030 | 0% | 50% | 80% | 10% |

**Table 7: Sensitivities on the Capex model**

The sensitivities serve multiple purposes. It makes it possible to see any structural flaws in the cost structure by observing if the results behave in a realistic or at least plausible manner with the changes in the input parameters. It also allows to observe how robust of a position energy storage has in the model, and how uncertainty in the input parameters affects the model. The parameters used are expected to be some of the key performance indicators (KPIs) of energy storage investment, and is chosen there after. $H_2$ import price can be seen as a key performance indicator (KPI) as it is a competing provider of flexibility. Carbon price might be a KPI as it affects the cost of technologies such as gas and coal power plants, which usually provide flexibility. The CapEx of the energy technologies are usually considered one of the biggest obstacles for its breakthrough in the market, and is hence an interesting parameter to study. The difference in the importance of energy capacity cost and power capacity cost also provides valuable information into which cost component has the biggest impact. Lastly, an integration of vRES comes with a higher need for flexibility and the rationality of the model can hence be analyzed from the sensitivity. The sensitivities is compared to a model run at default value which in Table 7 is referred to as 100% for all price/cost parameters, and 0% for the minimum vRES integration rate parameter. All the default cost values can be seen in Table 8.

| Parameter | 2018 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|
| **$H_2$ Import prices [M€/PJ]** | 99 | 50 | 35 | 29 | 23 | 17 | 13.3 | 10.4 |
| **Carbon price [M€/Megatonnes]** | 15.06 | 30 | 325 | 577.86 | 830.71 | 1184.71 | 1492.54 | 1800 |
| **$H_2$ Storage cost [M€/PJ]** | 833 | 833 | 694 | 556 | 486 | 417 | 375 | 333 |

**Table 8: Default values of the sensitivity parameters[8]**

All the price/cost sensitivities are implemented in the same way, which is simply to multiply the input parameter by the sensitivity factor. The minimum vRES integration sensitivity is however implemented in a different way, and only affect the model from the year 2030. The minimum vRES is restricted in three equations, one starting in the year 2030, one in 2040 and one in 2050. The minimum integration rate is chosen for 2030 as a percentage of total annual power production, and is subsequently increased by 10% in 2040, and 20% in 2050 by the two following equations. That means that if the minimum integration rate is set to 70% in 2030, it has to be a minimum of 80% in 2040 and 90% in 2050. A special case occurs in the maximum sensitivity analyzed (see Table 7) where the minimum integration rate is set to 80% in 2030, which gives 90% in 2040, and 100% in 2050. To avoid modeling issues by forcing the model to 100% vRES in 2050, the limit is set to 99% for that particular analysis. The method of implementation for the year 2030 can be seen in Equation 6.

$$\begin{aligned} \sum_{r}\sum_{t\in vRES} ProductionByTechnologyAnnual_{ytfr} >= \\ \sum_{r}\sum_{t} ProductionByTechnologyAnnual_{ytfr} * vRES\_percentage \\ \text{for } f = \text{Power and } y >= 2030 \end{aligned} \tag{6}$$

[8] Note. Default values for CapEx Energy and CapEx Power are not included as it is technology technology-dependent. Both the $H_2$ import price and the carbon price follows the Techno Friendly scenario of openENTRANCE used in previous iterations of GENeSYS-MOD (Löffler et al., 2022)

Where $ProductionByTechnologyAnnual_{ytfr}$ is the total annual production of fuel *f*, by technology *t*, in year *y*, and region *r*. vRES is a set of all vRES technologies that produce electricity, and *vRES_percentage* is the input parameter which describing the minimum integration rate.

### 4.3.2. Scenario analysis V2G model

The scenario analysis of the V2G model is split into four separate scenarios with 9 sensitivities each. The scenarios defines at what times of the day the V2G-cars are allowed to charge and discharge to the grid, while the sensitivites defines the amount of cars participating in the V2G scheme. The four scenarios defined are:

- Free (Free charging)
- Night (Only V2G during night)
- Night-Midday (Only V2G during midday and night)
- Weekend (Only V2G during midday and night, but free charging on the weekend)

*Free* is the least restricting scenario and has free charging and discharging, meaning the model can choose to charge, discharge or drive the V2G cars at any point in time. *Night* is the most restricted scenario where the V2G cars are limited to only charge and discharge at night, meaning from 22:00-06:00, but is still free to drive at any point in time. The scenario *Night-Midday* is restricted to charging and discharging at night and midday, which is from 10:00 - 15:00 and 22:00-06:00, but is free to drive at all times. The last scenario is called *Weekend*, and is a scenario mix of *Night-Midday* and *Free*, it is limited like *Night-Midday* in weekdays, but is free to charge, discharge, and drive at all times on the weekends. Weekends are defined as Saturday and Sunday and weekdays are defined as Monday - Friday.

The scenarios are based on the data describing driving patterns given in Section 4.2. Peak driving hours which are defined as 06:00-10:00 and 15:00-22:00 are the most restricted in the scenarios. While at night, which is the time of day when the least amount of cars are driving, is always available for V2G.

The sensitivities used for the scenarios are V2G participation rate, or V2G market share. The participation rate is set as a percentage of normal BEVs in the model, and the total BEV market is hence BEV + BEV_V2G. That gives that at 100% integration of V2G, the amount of V2G is equal to the amount of normal BEVs, meaning V2G has 50% of the market and normal BEVs has 50% of the market. The sensitivity analysis starts at 10% and goes up to 90%, with a 10% increment, and is inspired by Straub et al. (2023). The sensitivity also includes a 10% margin, meaning at 10% participation rate of V2G, it is between 9% and 11%, and at 90% participation rate it is between 81% and 99%.

The sensitivities serve as an uncertainty as the actual market participation of V2G in the future is uncertain. In combination with the scenarios, the sensitivities may also help validate the need for restrictions by showcasing the result of too much restriction or too little restriction as the amount of V2G cars increases.

# 5. Results

## 5.1. Capex model sensitivites

### 5.1.1. General findings

The Capex model is compared against the NoChanges model, where the NoChanges model is the European model that was developed in the openENTRANCE project (See section 3.1) and has been used as a basis for the work in this study. The general findings presented in the Figures 3, 4, and 5 below, displays the differences between the Capex model and the Nochanges model.

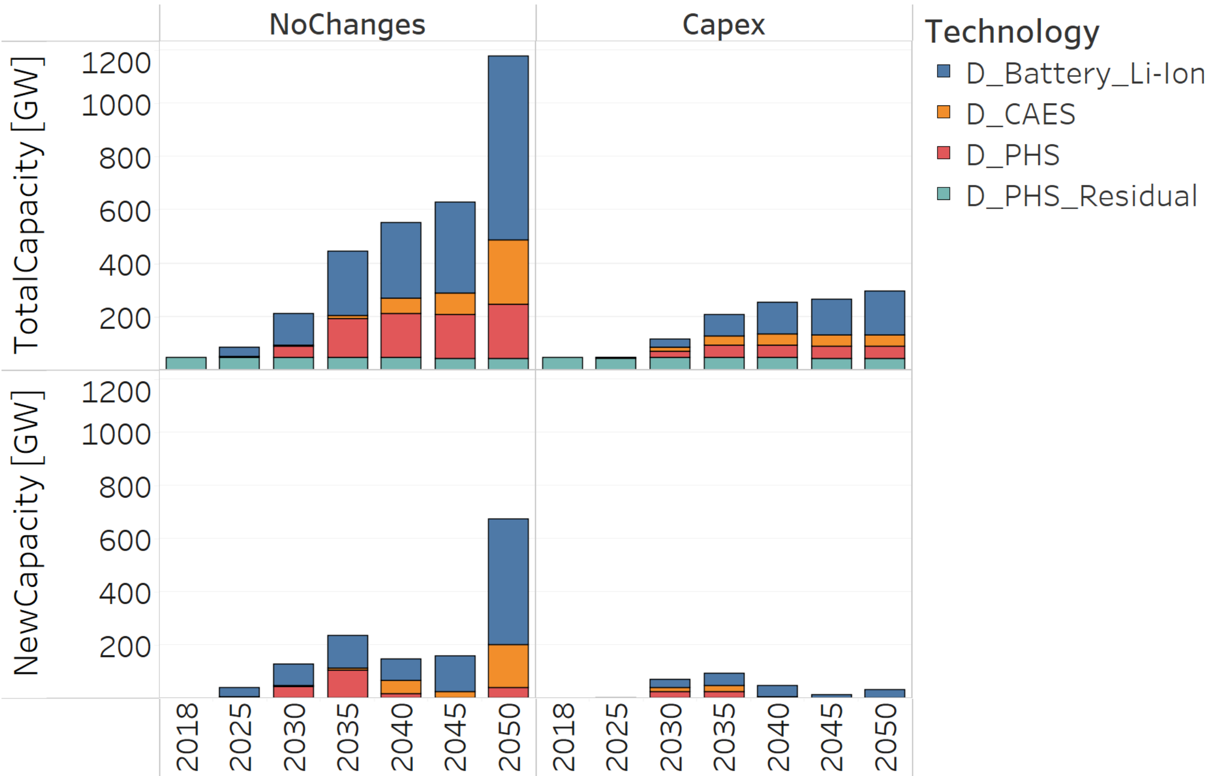


**Figure 3: New and total grid-link capacity of electric storage technologies in all regions in the NoChanges and Capex model**

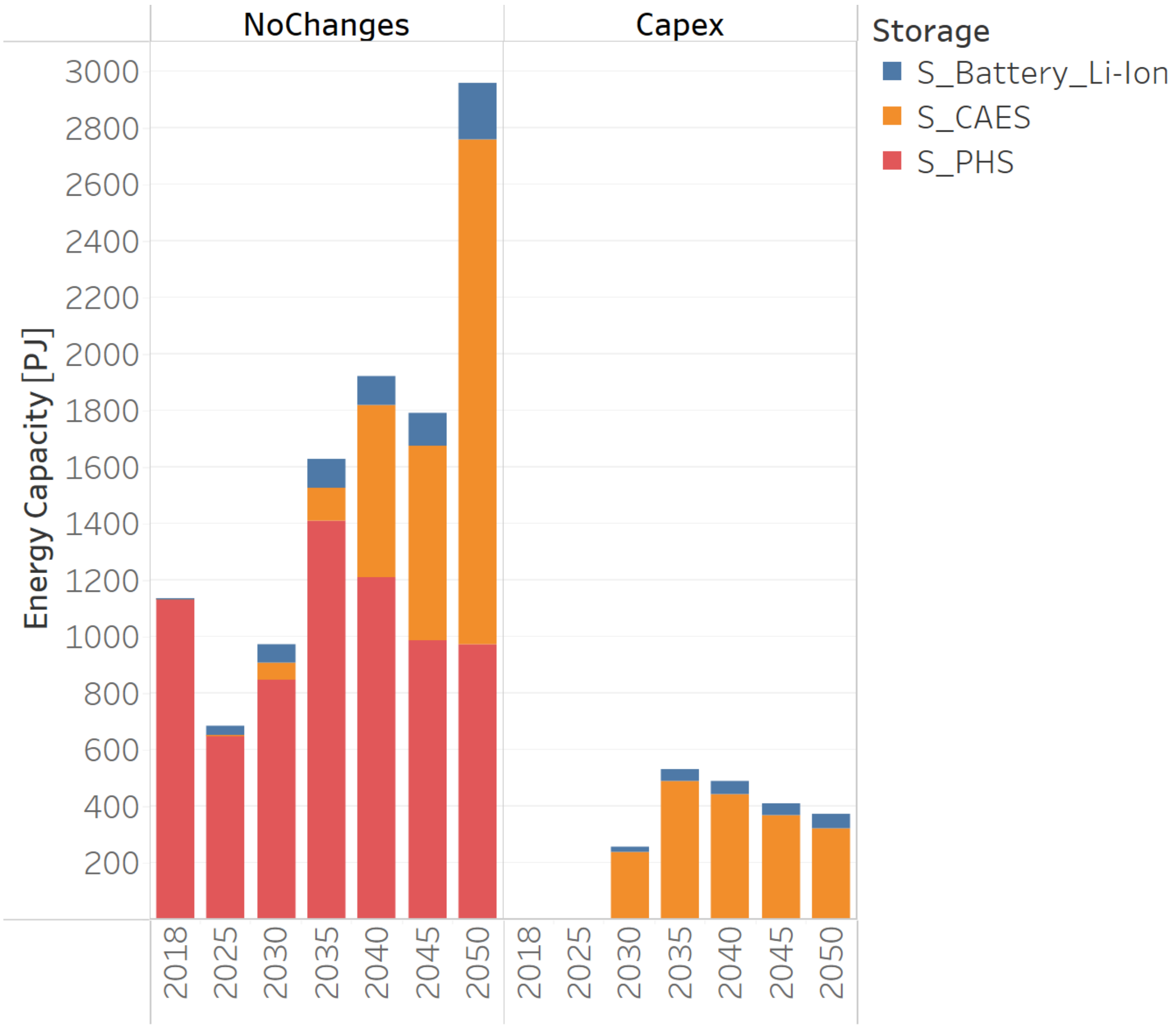


**Figure 4: New energy storage capacity of all electric storage technologies in all regions in the NoChanges and Capex model**

Figure 3 shows the total and new power capacity of electricity storage for all the decision years summed over all regions in the Capex and NoChanges model. Figure 4 shows the new energy capacity of electricity storage for all the decision years summed over all regions in the Capex and NoChanges model. It is clear to see in both Figure 3 and 4 that the total amount of both energy storage capacity and power capacity has decreased in the Capex model compared to the NoChanges model. Both models tends to invest into battery Li-Ion for power capacity, and CAES for energy capacity. The NoChanges model also invest in PHS for energy capacity, but this technology was limited in the Capex model. The Capex model has a moderate and steady increase in the total energy and power capacity starting in 2025, while the energy capacity flattens out as new capacity investments decreases after 2035. This is in contrast to the NoChanges model where the investment in both energy and power capacity has a sharp upward trend. One peculiar thing to notice is that the NoChanges model invest into a lot of energy storage capacity in PHS before 2030, but no power capacity before 2030, but rather utilizes the residual capacity.

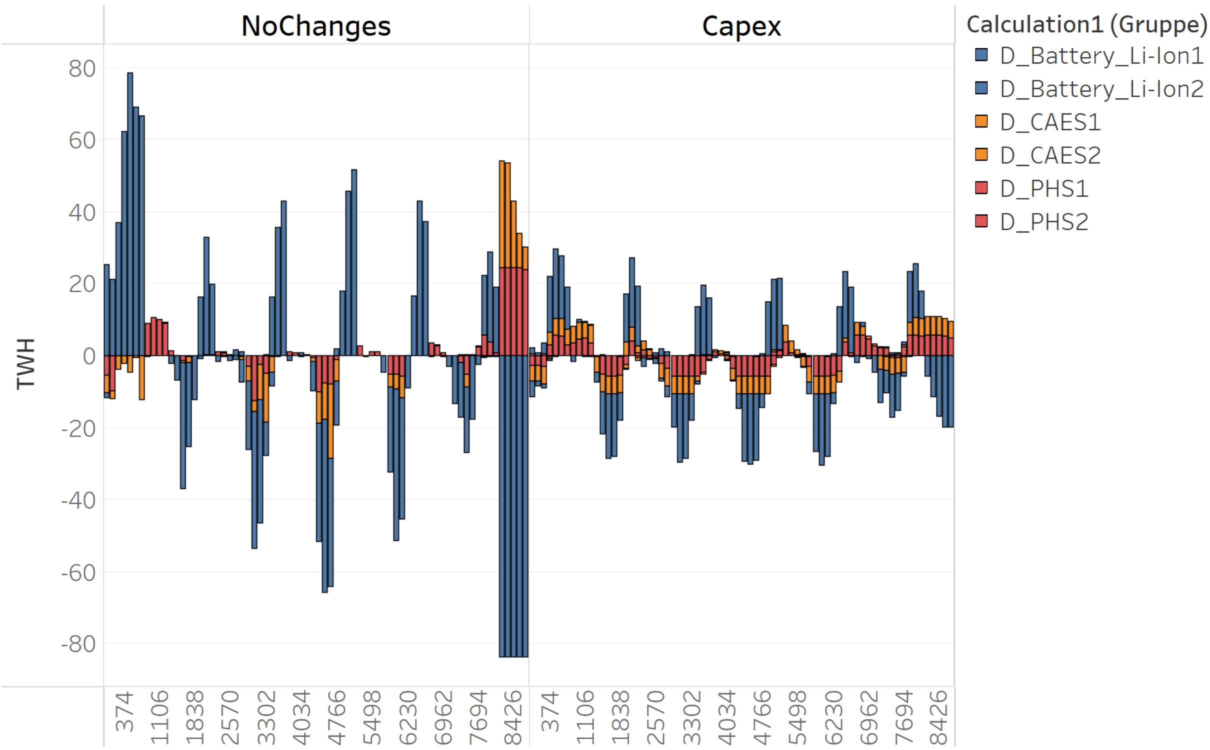


**Figure 5: Aggregated dispatch of all regions of electric storage in 2050 in the NoChanges and Capex model. The x-axis shows the hour of the year, and the y-axis shows energy output in that hour. Positive numbers indicates discharging to the grid and negative numbers indicate charging from the grid.**

As previously described in Section 3.1 the time step of the simulations are 122 hours. The aggregated dispatch of electricity from energy storage across all regions in each time step is represented as columns in Figure 5, where positive numbers represents discharge to the grid, and negative numbers represents charging from the grid. Each column represents one time step. The amount of days represented in Figure 5 can be calculated with Equation 7, which in our case is equal to 6 days. The amount of days can also be seen in Figure 5, by counting the day cycles of charging during the day and discharging during the evening.

$$\text{Number of days represented in a year} = \frac{hourstep * 8760\frac{h}{y}}{timestep * 24\frac{h}{d}} = \frac{2h * 8760\frac{h}{y}}{122h * 24\frac{h}{d}} \approx 6\frac{d}{y} \tag{7}$$

A daily discharge and charge cycle of battery Li-Ion can be seen, with charging during the day, when the sun is shining and there is high production of solar PV, and discharging during the evening when demand is high but renewable production is low. PHS and CAES also has a tendency to charge during times of high solar PV production, but a more seasonal dispatch can be seen. Charging of PHS and CAES occurs more in the middle of the year, which is in the summer when the demand is lower, and renewable energy sources such as solar PV have a higher production. Discharging of PHS and CAES occurs more in the beginning and end of the year which are the colder winter months, with less sunlight and solar PV production. The nature of the technologies seems to be equal across the two model, with similar charging and discharging patterns, but there is one thing that sticks out in the NoChanges model. The thing that sticks out in the NoChanges model is the spike in discharging at the beginning of the year and the spike in charging and discharging at the end of the year. The spiking phenomena will be discussed further in the *Discussion*.

### 5.1.2. $H_2$ Import price sensitivity

The $H_2$ import price sensitivity is analyzed to see its effect on electricity storage investment. Both hydrogen and electricity storage serve as flexibility for the grid. Hydrogen can be used in industrial heating, transportation and to feed electricity to the grid with the help of fuel cells. Figure 6 the amount of H2 imported in the different sensitivities.

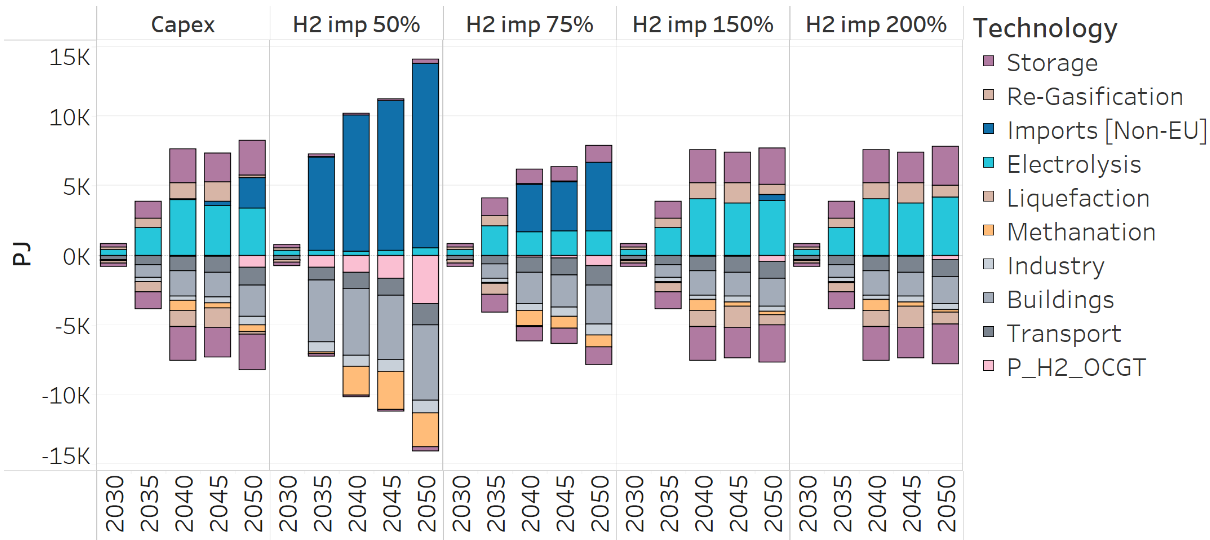


**Figure 6: Hydrogen production and consumption in the Capex model and with hydrogen import price at 50%, 75%, 150% and 200% of base price.**

The amount of $H_2$ imported increases with a lower import price, and decreases with a higher import price as expected. From Figure 6 it can be seen that a threshold price for no more import is somewhere between 150% and 200% in the model, as there is some import at 150% and no import at 200%. Close to 100% of all $H_2$ is imported at an import price of 50% of the base price. Since the import is flexible and on-demand, $H_2$-storage becomes less important as import increases. The Capex model only imports in the years 2045 and 2050, at 50% it import from 2035, at 75% from 2040, and at 175% it only imports in 2050.


**Figure 7: New energy storage capacity of all electric storages in all regions in the Capex model and with hydrogen import price at 50%, 75%, 150% and 200% of base price.**

In comparison to the Capex model, at 175% and 200% import cost there is a slight increase in the new energy storage capacity in years 2045 and 2050, which are the years where the Capex model imported $H_2$. At 50% import price we see a slight decrease in energy storage capacity, while at 75% import price we unexpectedly see a slight increase in energy storage capacity (See Figure 7).

### 5.1.3. Carbon price sensitivity

Carbon price is an instrument to put a cost on GHG emissions, and is often thought of as an important driving factor for the integration of less carbon-intensive energy sources. Wind and solar power, which are vRES, are expected to take a big role in the transition to low-carbon electricity production and are expected to have an increasingly important role in the energy sector as the carbon price increases. Figure 8 shows the total amount of $CO_2$ emissions per sector for the sensitivities analyzed.

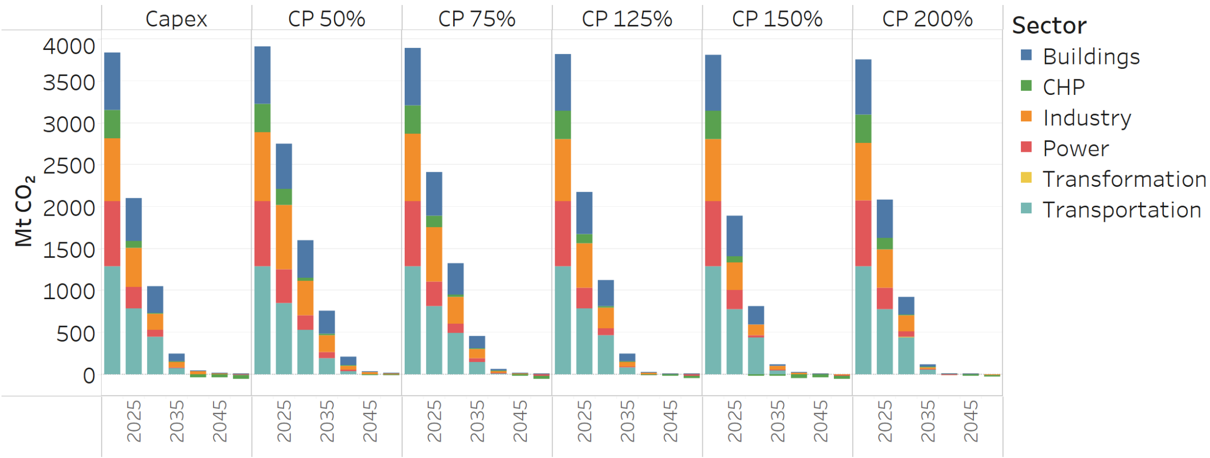


**Figure 8: Emissions per sector in Mt $CO_2$ for all years in sensitivity 50%, 75%, 125%, 150%, and 200%. (CP: Carbon price)**

Figure 8 shows a slight decrease in total emissions for all years as the carbon price increases. For the year 2018 it ranges from 3915 Mt $CO_2$ to 3756 Mt $CO_2$ in the *CP 50%* case and *CP 200%* case respectively. In all sensitivities, including the Capex model, the carbon emissions fall rapidly toward zero, and emissions are more or less halving every 5 years.

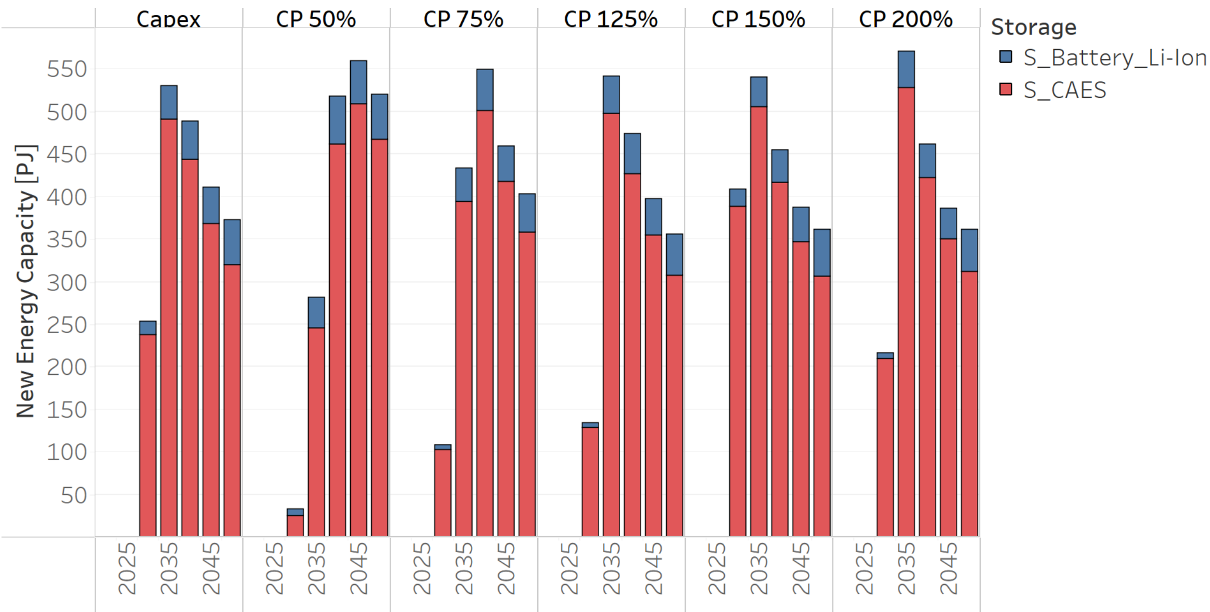


**Figure 9: New energy storage capacity in PJ for all years in all sensitivities. Only electricity storage is included.(CP: Carbon price)**

Figure 9 shows the new energy storage capacity investment in each year for all sensitivities. It is hard to see a correlation between carbon price and new storage capacity. It seems to increase investment in later years for *CP 50%*, have a slightly lower investment for *CP 75%* and *CP 125%*, and then an increased investment in *CP 150%* and *CP 200%*.

### 5.1.4. Power capacity CapEx sensitivity

The cost of power capacity, referred to as the cost of grid-link in this study, plays a big role in the cost-effectiveness of storage technologies. In this analysis capital cost of storage power capacity is tried as a sensitivity, ranging from 50% to 200% of its base value as shown in Figure 10 and 11 below.

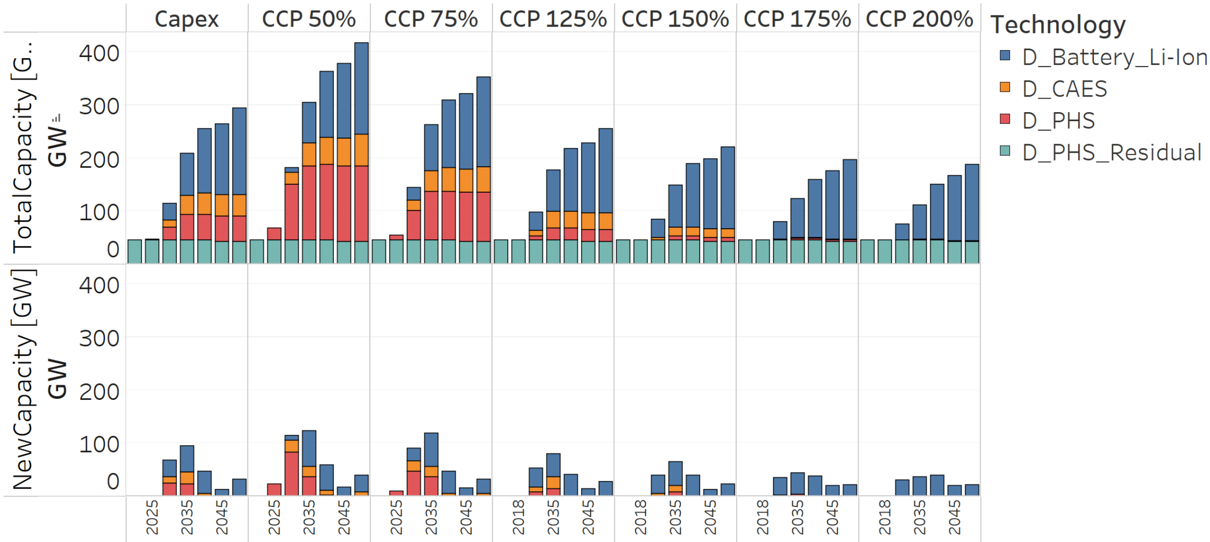


**Figure 10: New and total grid-link capacity of electric storage technologies in all regions and for all sensitivities (The sensitivities are named CCP for Capital cost power).**

As expected the total amount of grid-link capacity decreases with the rising capital cost of grid-link as seen in Figure 10. PHS and CAES seems to be the first technologies to fall out, while Li-Ion decreases much more gradually with only a 20% decrease from *CCP 50%* to *CCP 200%*.

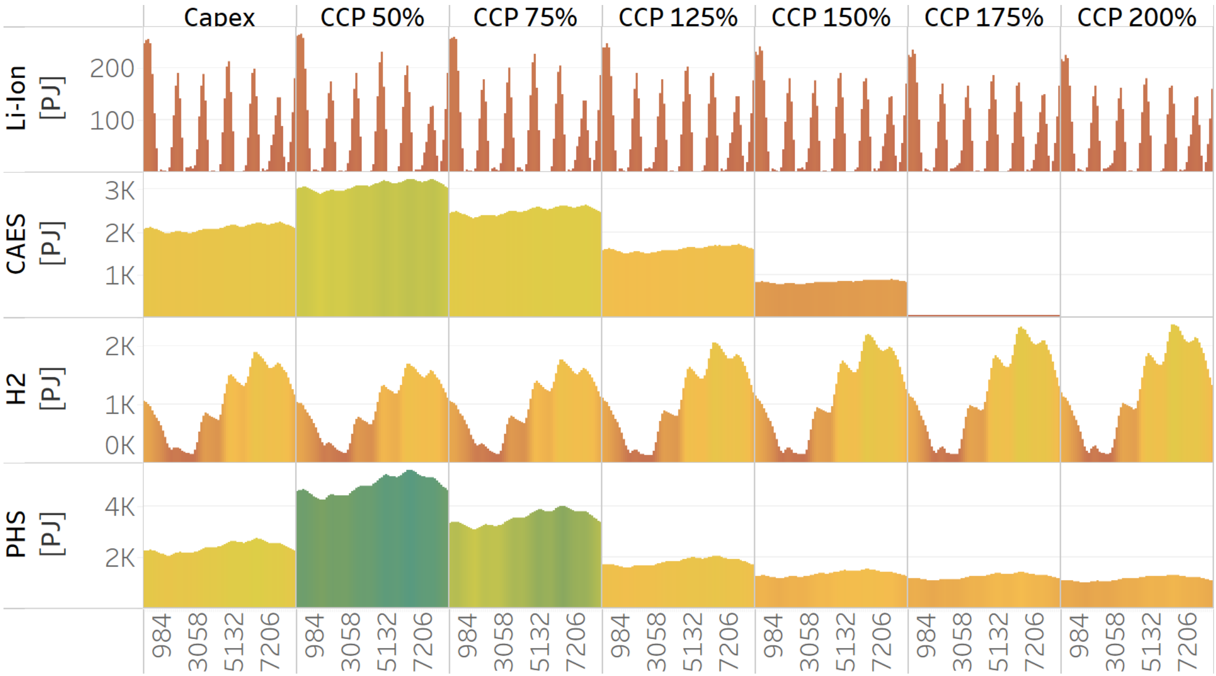


**Figure 11: Storage level over the year 2050 of all electric storage technologies and $H_2$ for all sensitivities (The sensitivities are named CCP for Capital cost power). The x-axis is showing the hour of the year.**

Figure 11 shows the storage levels of all electric storage technologies and H2-storage in PJ over the year 2050. Battery Li-Ion seems to have a daily cycle where it charges during the day when the sun is shining and discharges completely before the next day. CAES, $H_2$, and PHS seem to cover seasonal storage to a bigger degree, having both daily cycles but also seasonal cycles with charging during spring and summer, and discharging more during winter. The total amount of CAES drops towards zero with the increasing sensitivity, PHS decreases till its residual values, while Li-Ion only decreases slightly. $H_2$ however increases as the other technologies become less cost-effective. $H_2$-storage is not directly affected by the capital cost of grid-link as it is not connected to the electric grid, and output capacity cost is set to an arbitrarily low value.

### 5.1.5. Energy capacity CapEx sensitivity

In this section the capital cost of energy storage capacity is analysed. The sensitivities ranges from 50% to 200% as a percentage of the base capital cost in the Capex model. Only the sensitivities at 50%, 150% and 200% is shown for better visualization.

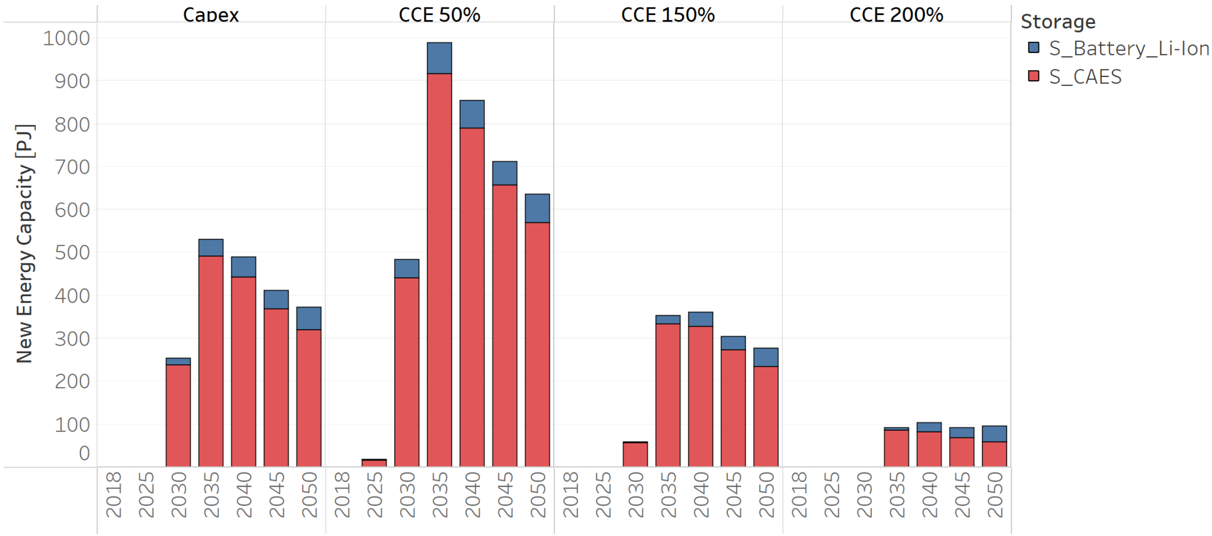


**Figure 12: New energy storage capacity in PJ for all years in sensitivities 50%, 150%, 200% and in the Capex model. Only electricity storage is included.(CCE: Capital Cost Energy)**

It is clear to see in Figure 12 that new energy capacity decreases with an increasing capital cost. CAES decreases faster than Li-Ion. In the year 2050 in *CCE 200%* the amount of CAES is 90% lower in comparison *CCE 50%*, while Li-Ion sees a 50% decrease in the same year for the two sensitivities.

A similar decrease can be seen for the grid-link capacity, but it stabilizes on a set total capacity. CAES decreases quickest, while LI-Ion decreases more gradually. PHS grid-link however actually increases with the decreasing CAES grid-link (See Appendix A Figure 27. It can also be seen that $H_2$ gets a bigger role in the system as electricity storage becomes more expensive (See Appendix A Figure 28).

### 5.1.6. $H_2$ storage CapEx sensitivity

In this section, a sensitivity on $H_2$ storage capacity CapEx is being analyzed. Figure 13 displays the amount of new $H_2$ storage capacity for each year in the Capex model and with the sensitivity at 50% and 200%.

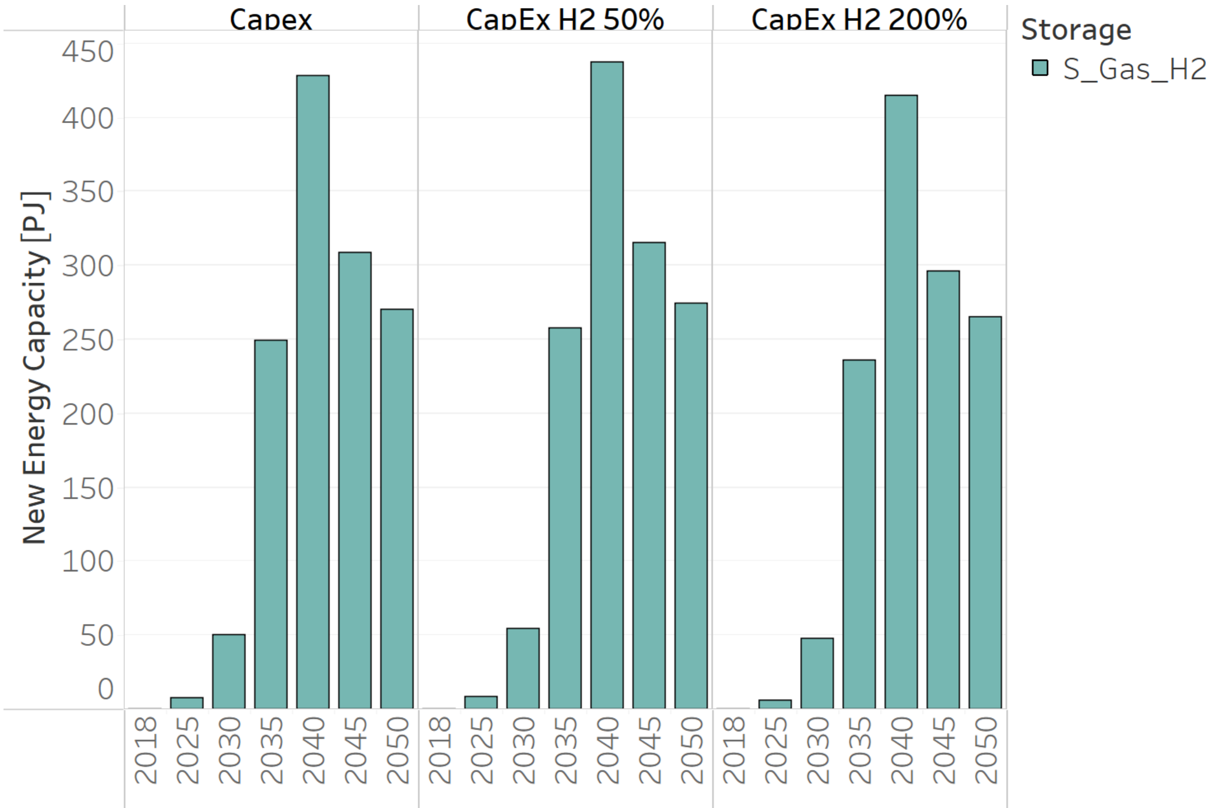


**Figure 13: New energy storage capacity of $H_2$-storage in all regions in the Capex model and H2-storage price at 50% and 200% of base price.**

In Figure 13 it can be seen that there are only slight differences in $H_2$ storage capacity, even between the lowest and highest sensitivity of 50% and 200% respectively. The storage capacity is slightly higher with 10 PJ more storage at 50% than the Capex model and at 200% it is slightly lower with 12 PJ. $H_2$ storage capacity is the variable that is affected most by this sensitivity, and the rest of the variables see little to no change as a result of the small change in $H_2$-storage investment.

### 5.1.7. vRES integration rate sensitivity

The profitability of energy storage heavily relies on the integration rate of vRES. vRES produce cheap energy, but is not controllable and the production is weather dependent. Energy storage can take advantage of the variability by charging when the supply surpasses the demand, and later discharge when the supply of vRES is lower. In this section the effect of a minimum integration rate of vRES is introduced as a sensitivity parameter. The method for how the sensitivity is implemented is based on Equation 6 and explained in the same section 4.3.1. Figure 14 and 15 below compares the different sensitives to the Capex model.

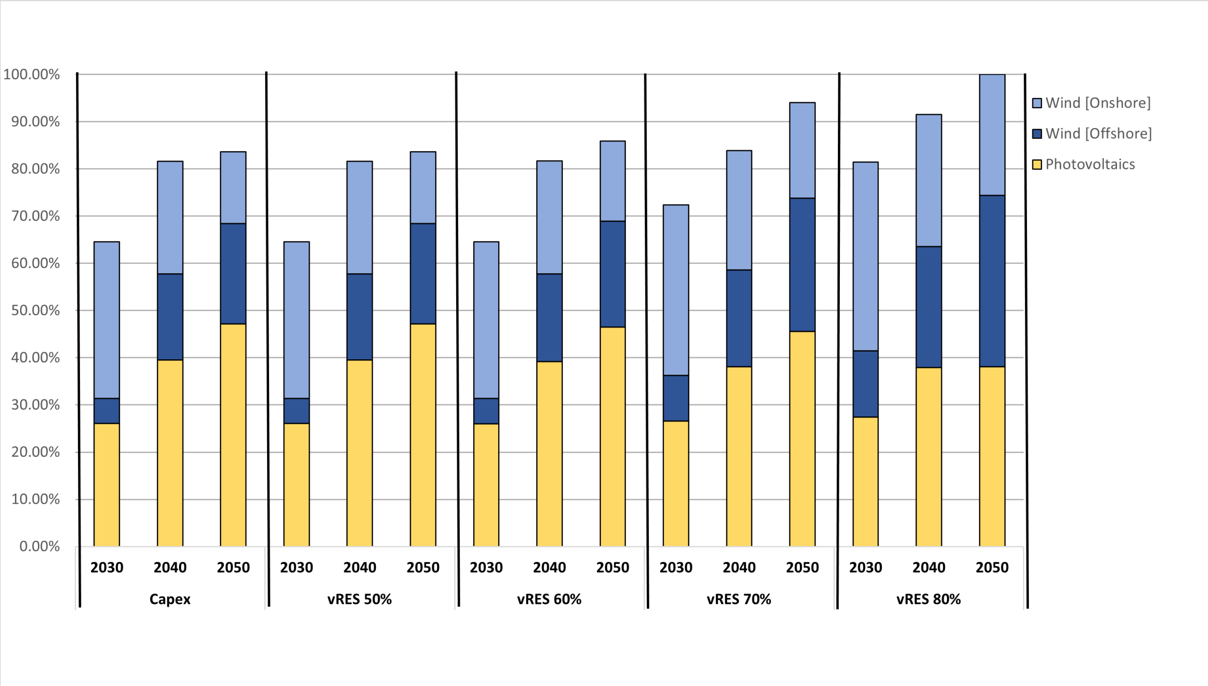


**Figure 14: Amount of electricity produced by vRES represented as a percentage of all electricity produced that year. The years 2030, 2040 and 2050 are represented for all sensitivities.**

Figure 14 displays the effect the sensitivities has on the percentage of electricity produced by vRES. An interesting thing to notice is that in the Capex model, vRES already covers over 60% in 2030 and over 80% in 2040 and 2050. This renders the *vRES 50%* sensitivity restriction redundant, and the results are exactly the same. One would think that the sensitivity *vRES 60%* would be redundant as well as the Capex model already is above the limit in all years, but a slight increase in vRES production can be seen in the year 2050, going from 83.6% in the Capex model to 85.9% in the *vRES 60%* sensitivity. In the sensitivities *vRES 70%* and *vRES 80%* we see an increase in the percentage of electricity produced by vRES compared to the Capex model in line with the restrictions.

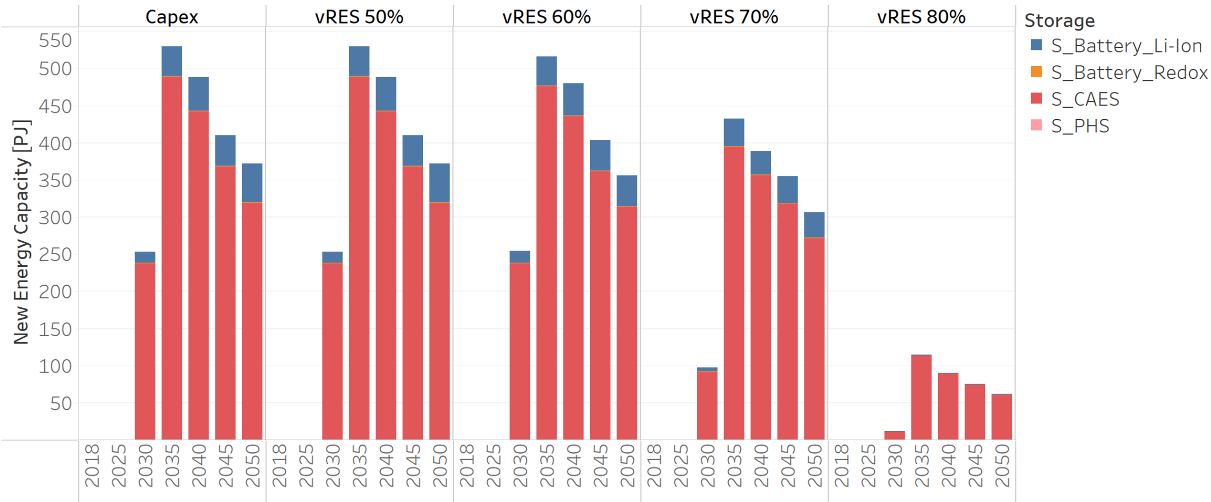


**Figure 15: New energy storage capacity in PJ for all years in all sensitivities. Only electricity storage is included.**

Figure 15 displays the amount of new energy storage capacity investment in all sensitivities. It is clear to see that investment in electricity storage technology decreases with the increasing percentage of vRES production. This can at first seem counter intuitive, but the reason is that a higher percentage of electricity has to be produced by vRES and hence limits the possibility of electricity output by the storage technologies. This in turn reduces the investment in electricity storage technologies.

Hydrogen and biomass become more prevalent With the decreasing output possibility for electricity storage technologies. Hydrogen gets a bigger role in industrial heating, and an increase in hydrogen storage becomes apparent in the model. Although hydrogen now plays a bigger role in industrial heating, it still has a small part of the market in comparison to direct electricity heating (See Appendix A Figure 29). Biomass sees a decrease in industrial heating with the increase in vRES, but biomass has an increase in the market of passenger transport, specifically within bio-fueled cars (See Appendix A Figure 30).

Another thing that changes in *vRES 70%* and *vRES 80%* is that heat storage actually gets invested in as electricity produced by vRES closes in on 100%. But the capacity is rather small compared to the electricity storage with a maximum of of 1.2 PJ of new investment in 2040 in *vRES 80%*.

## 5.2. V2G scenarios

### 5.2.1. General findings

The general findings presented in this section is a comparison between the Capex model, which stands as a base case, and *Free 10* and *Free 90*. *Free 10* and *90* are scenario results from the scenario *Free* described in section 4.3.2. Both *Free 10* and *90* are compared to the Capex model to be able to display if the variation between the Capex model and the V2G model is dependent on the integration rate of V2G. The results presented in this section is to get an overview of what changes between the Capex model and the V2G model, and the scenarios of the V2G model is presented in the next sections. In the Figures 16, 17, and 18 below, the amount of electricity storage technologies and vRES in the Capex model and in the V2G model is displayed.

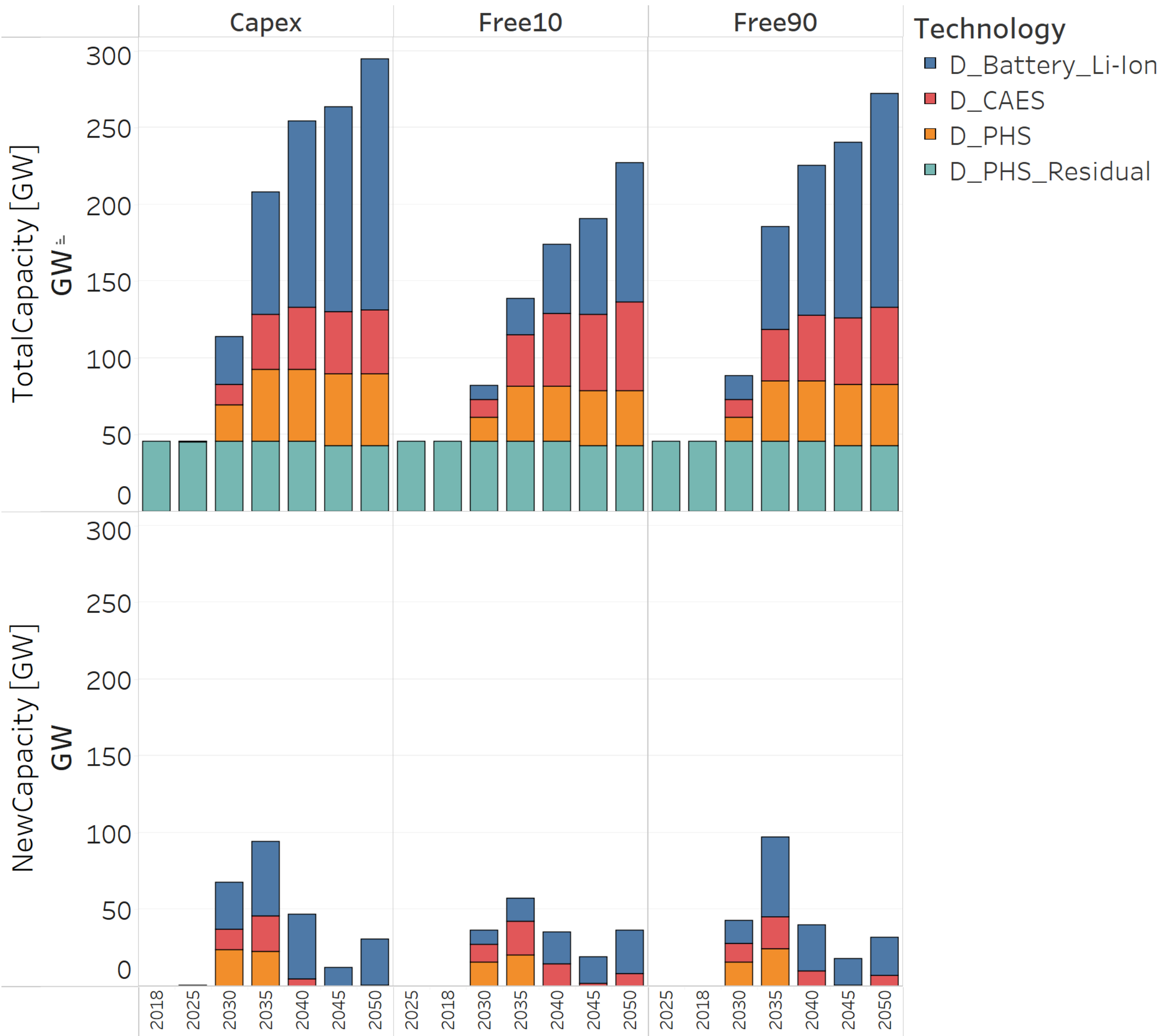


**Figure 16: New and total storage grid-link capacity in GW for all years comparing the Capex model to the V2G model scenario Free 10 and 90. Only electricity storage is included.**

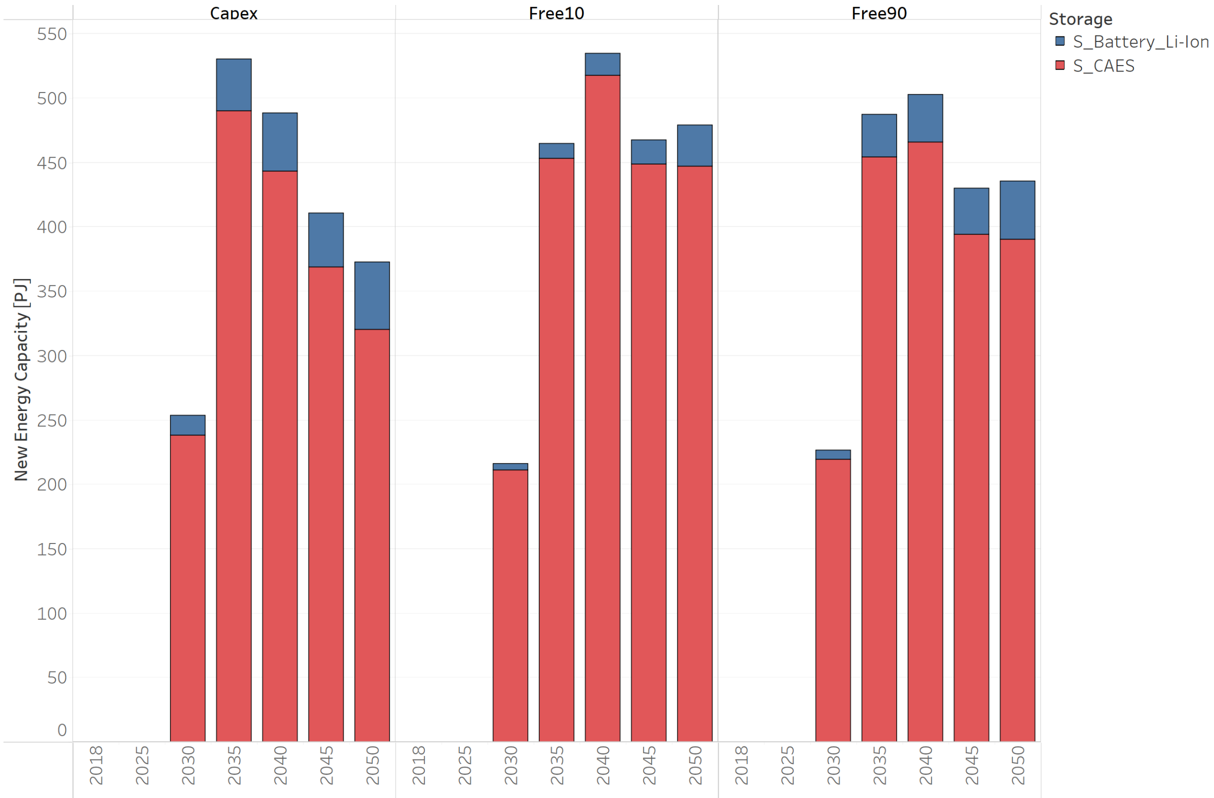


**Figure 17: New energy storage capacity in PJ for all years comparing the Capex model to the V2G model scenario Free 10 and 90. Only electricity storage is included.**

Figure 16 shows that the total amount of electric energy storage grid-link decreases with the integration of battery storage for BEVs, but that it is dependent on the V2G participation rate. The amount of PHS and Li-Ion grid-link decreases, and CAES grid-link increases for both *Free 10* and *Free 90* in comparison to the Capex model. The amount decreases more at lower V2G participation rates. One reason for the increase in grid-link with a higher V2G participation rate might be that at higher participation of V2G more V2G-cars has to be driving as there are less normal BEVs, this is illustrated in Figure 32 in appendix A.

Figure 17 however, displays another picture than Figure 16. The amount of new energy storage capacity invested in actually increases in the V2G model in comparison to the Capex model, and a negative correlation between V2G participation rate and energy storage capacity can be seen. The amount of CAES energy storage capacity increases in both the V2G scenarios compared to the Capex model. Li-Ion energy capacity however decreases in the V2G scenarios, and is lower for a lower participation rate.

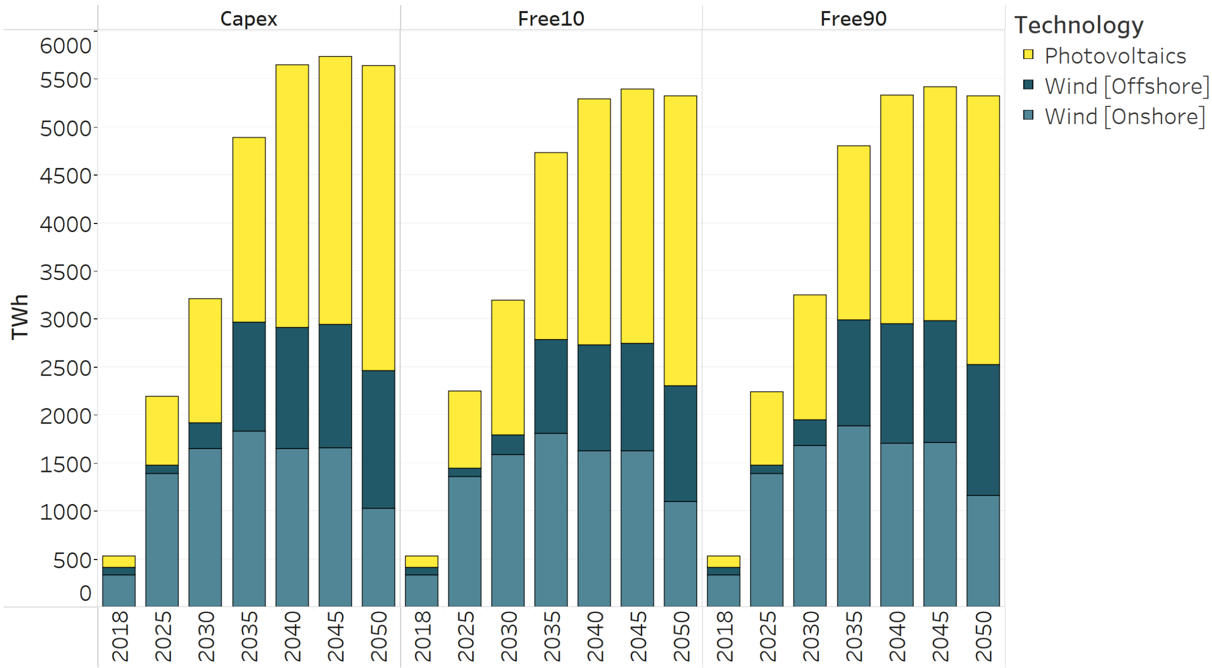


**Figure 18: Energy production by vRES in TWh for all years comparing the Capex model to the V2G model scenario Free 10 and 90.**

The amount of vRES is lower in the V2G model compared to the Capex model, but does not seem to be dependent on V2G participation rate as seen in Figure 18. The investment in photovoltaics decreases the most followed by offshore wind, while onshore wind actually increases.

### 5.2.2. Scenario comparison

In the section all the scenarios is compared at the 50% scenario, meaning that V2G has between 31% and 35% of the market depending on the models willingness to invest. *Free* is the scenario where the model freely decides when the V2G cars charge and discharges to the grid. *Night* is the scenario where charging and discharging to the grid only is allowed at night. *Night_ Midday* is the scenario where charging and discharging to the grid only is allowed at night and during midday. And *Weekend* is the same as *Night_ Midday*, but on the weekends (Saturday and Sunday) it can charge and discharge freely again.

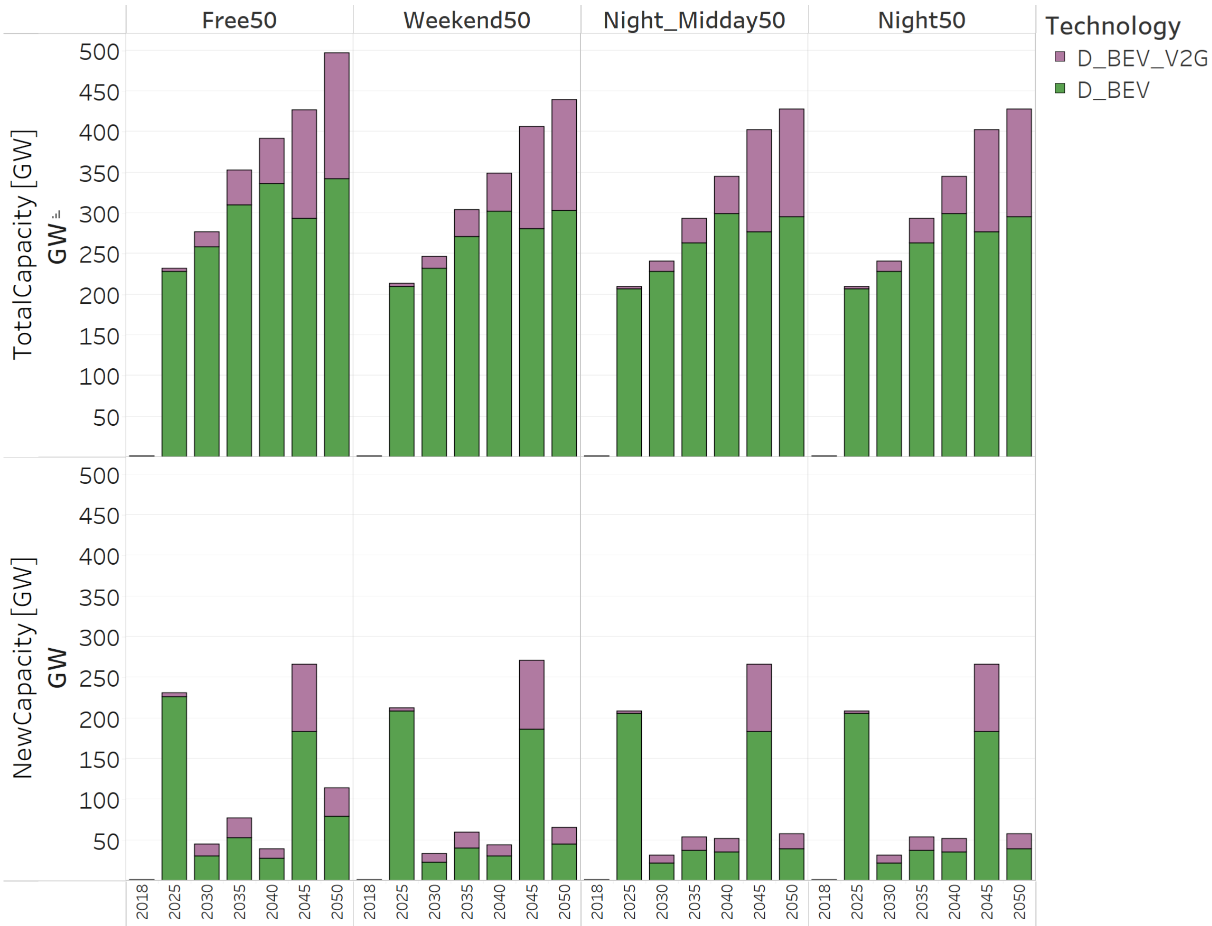


**Figure 19:** New and total charger cable capacity of the BEVs given in GW for all years comparing the four scenarios Free, Weekend, Nigh_Midday, and Night sorted after model charging strictness.

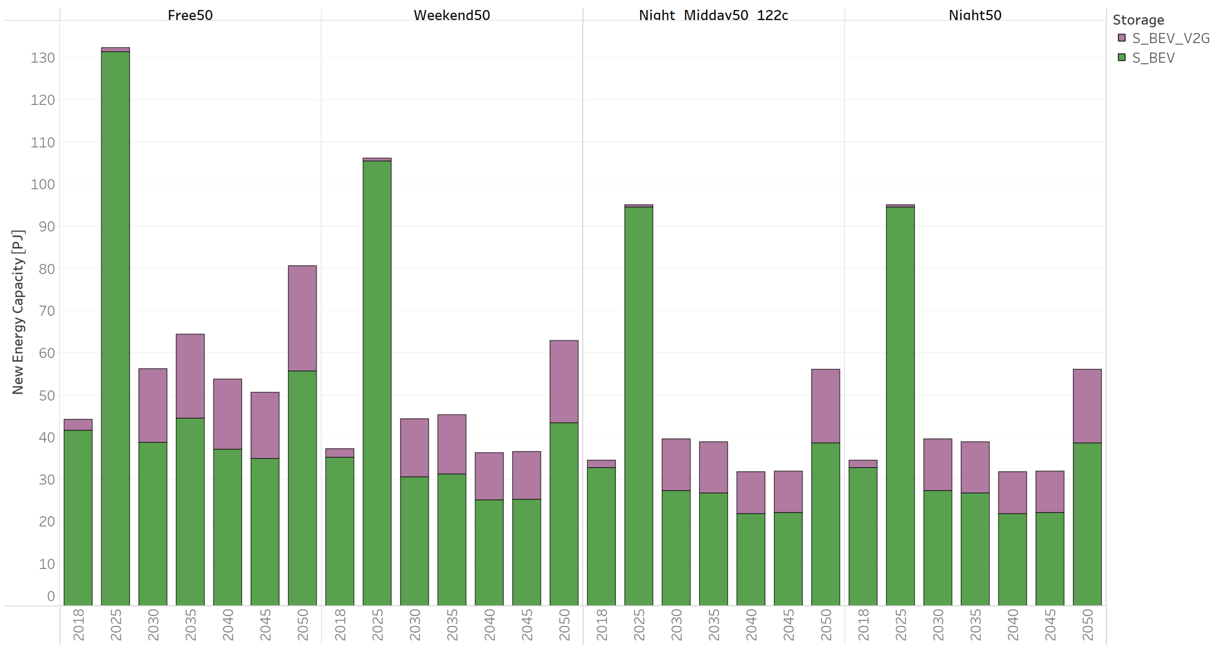


**Figure 20:** New energy storage capacity of the BEVs in PJ for all years comparing the four scenarios Free, Weekend, Night_Midday, and Night sorted after model charging strictness.

Figure 19 and 20 displays the investment into power capacity and energy storage capacity in the V2G-cars for all decision years across the four scenarios. The amount invested decreases with the strictness of V2G in the model, *Free* invest in the most and *Night* invests in the least amount of both power and energy capacity. One thing to notice is that both the scenarios *Night_ Midday* and *Night* invest in an equal amount of capacity, both for energy and power capacity. Another thing to notice is that the model already invests in 2018 and 2025, all though the cars are restricted from charging and discharging before the year 2030.

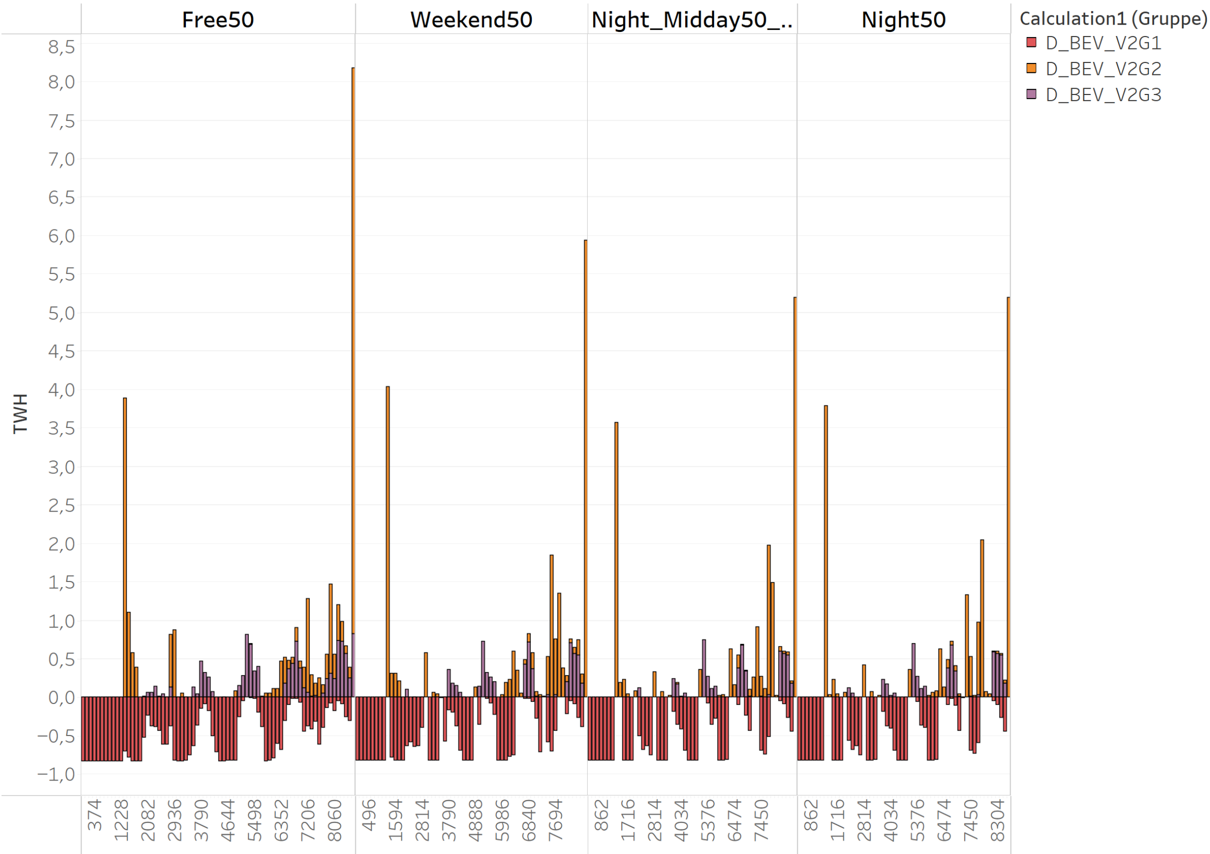


**Figure 21: V2G dispatch over the year 2050 given in TWh comparing the four scenarios Free, Weekend, Night_Midday, and Night. D_BEV_V2G1,2,3 represents mode of operation 1, 2 and 3. Mode 1 is charging, mode 2 is driving, and mode 3 is the V2G function discharging back to the grid**

In Figure 21 the V2G-cars split between mode of operation 1, 2 and 3 is displayed. Mode of operation 1 in red is charging and is always negative, mode of operation 2 in orange is driving and is always positive and mode of operation 3 in purple is discharging back to the grid and is also always positive. In all scenarios, we can see that the model drives the cars in bursts over the year, especially in the least restricted scenarios. In the most restricted scenarios there is some degree of daily driving, but bursts in driving is also seen here at the beginning and end of the year. In all scenarios it seems like the patterns tends towards a more daily pattern the later in the year it is. All model scenarios start the year by charging the battery pack, and through out the year a somewhat daily charging pattern can be seen. The max charging is also limited by a sharp line seen at -0.8 TWh, this comes from Equation 4 and Equation 5 which restricts the charging and discharging activity to the charger cable size of 22kW (see Table 6). Discharging to the grid with the V2G functionality (mode of operation 3) is mostly taken advantage of in the least restricted scenarios, and a daily discharge pattern can be seen throughout the year, and becomes more prevalent later in the year.

### 5.2.3. Scenario sensitivities

The results over the sensitivities shows similar trends across the scenarios. This section hence aggregates all scenarios and analyses how the sensitivities affects them.

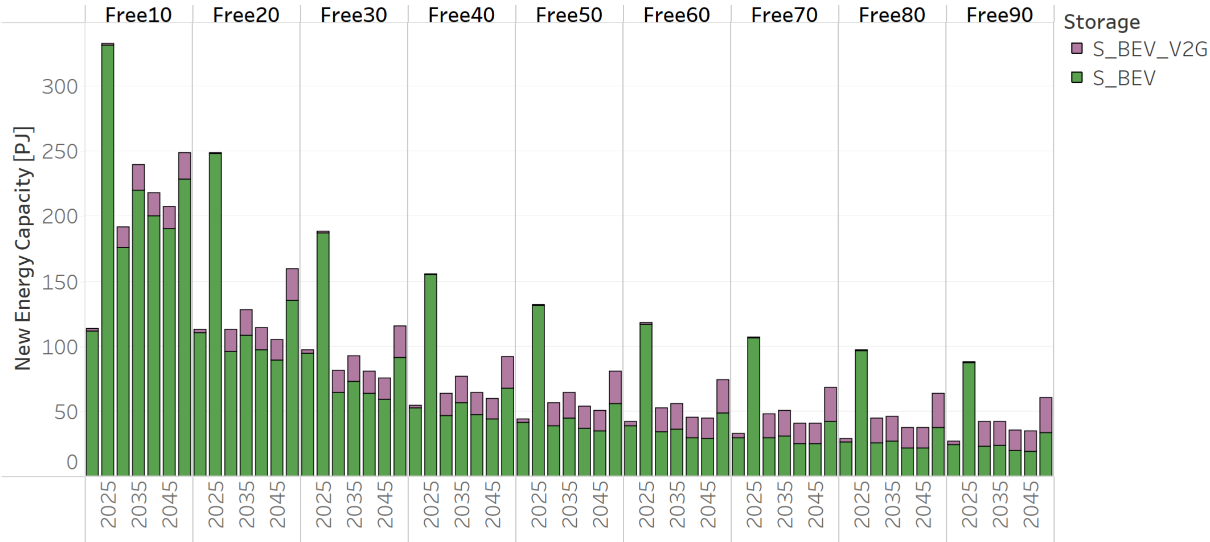


**Figure 22: New energy storage capacity of the BEVs in PJ for all years comparing all sensitivities in the scenario Free.**

In Figure 22 the new energy storage capacity can be seen for normal BEVs and V2G-cars across all decision years and all sensitivities in the scenario *Free*. A clear decreasing trend in total new energy capacity can be seen with the increasing V2G participation rate. One thing to notice is that the capacity of S_BEV_V2G actually does not decrease, but rather increases with the increasing participation rate, while S_BEV decreases. However, while S_BEV decreases by 85% from *Free 10* to *Free 90*, S_BEV_V2G only increases with 30%. This means that the model actually does not invest in much new V2G to take a bigger share of the market, but rather decreases the amount of normal BEVs until V2G has the share of the market given by the restrictions. This trend can be seen across all the scenarios and can also be seen to some degree within charger cable capacity as is shown in Figure 23.

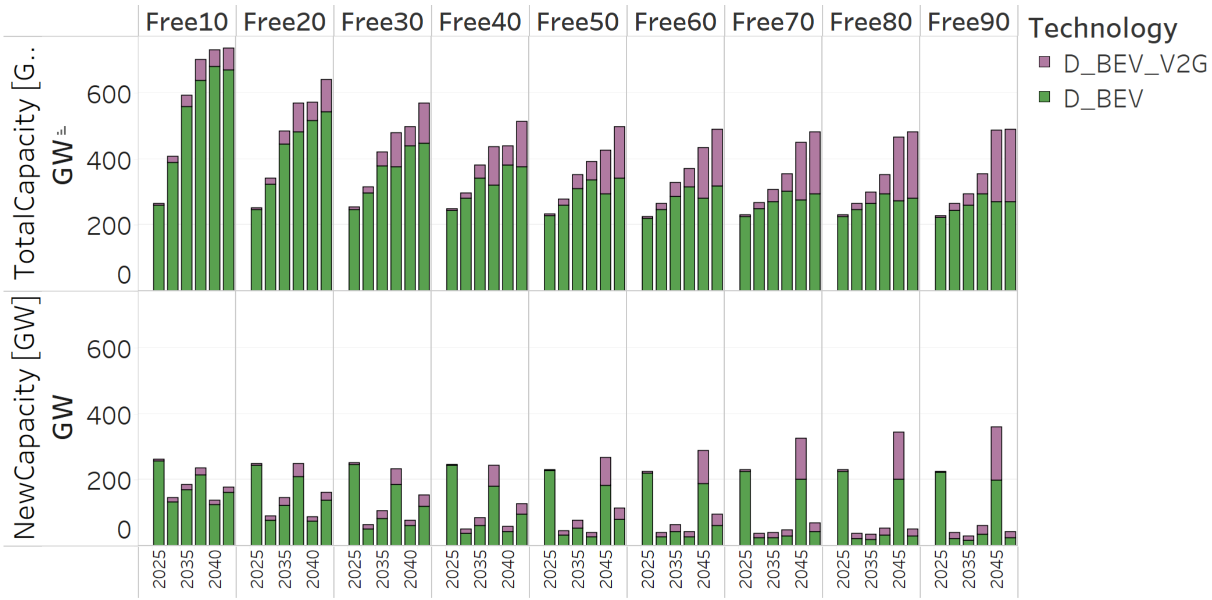


**Figure 23: New and total charger cable capacity of the BEVs given in GW for all years and across all sensitivities for the scenario Free.**

The D_BEV and D_BEV_V2G technologies does not only represent the output and input capacity of the battery, but also the driving output capacity. Figure 23 shows that the investment in power capacity of the BEV-fleet decreases with an increasing V2G participation rate, but stagnates at a certain level. The reason for the stagnation may be that the BEVs needs sufficient driving output capacity to be able to meet their driving demand, but other factors might play in as well. Similarly to the new energy capacity in Figure 22, D_BEV decreases while D_BEV_V2G increases with an increasing V2G participation rate.

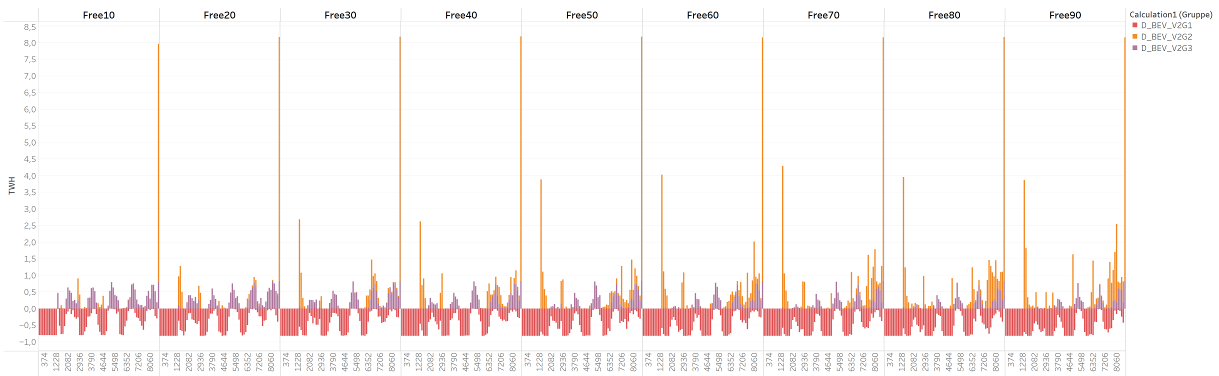


**Figure 24: V2G dispatch over the year 2050 given in TWh with hours of the year on the x-axis. Comparing all sensitivities of the scenario Free. D_BEV_V2G1,2,3 represents mode of operation 1, 2 and 3. Mode 1 is charging (in red), mode 2 is driving (in orange), and mode 3 is the V2G function discharging back to the grid (in purple)**

Figure 24 displays the V2G dispatch of all sensitivities between 10% and 90% for the scenario *Free*. In general a trend towards more driving and less discharging to the grid can be seen with the increase in

V2G participation, where driving is represented in orange and dischagring is represented in purple in Figure 21. An increase in the number of burst of driving aswell as an increased magnitude of the burst peaks can also be seen with the increase in V2G participation rate. With the increase in bursts a lower degree of daily patterns can be seen, and a trend towards brutal charging in the fist half of the year and consecutively discharge and driving at the end of the year can be seen.

Additional results shows that the amount of $H_2$-storage increases slightly with a an increasing V2G participation rate (See appendix A Figure 33). Residential heat storage also increases with an increased amount of V2G participation rate, but reaches a top and decreases again for the 80% and 90% sensitivities (See appendix A Figure 34). Lastly the amount of new energy storage in electricity storage technologies (CAES and Li-Ion) decreases in total with an increasing V2G participation rate. CAES which has the bulk of the storage capacity decreases while Li-Ion increases slightly (See appendix A Figure 35).

# 6. Discussion

In this study two energy system models has been developed based on the existing energy system modeling framework of GENeSYS-MOD which is developed by Löffler et al. (2017) and derives from the OSeMOSYS-framework. The first model, referred to in this study as the *Capex model*, is developed based on the European energy system model that was developed under the openENTRANCE project (see section 3) and changes the cost structure of the energy storage in the model from a LCOS approach to a decoupled CapEx approach. The second model, referred to in this study as the *V2G model*, is a continuation of the *Capex model*, but the method of which BEVs consume electricity from the grid is changed. Firstly by implementing a battery-pack between the BEVs and the grid, forcing the model to charge the BEVs before they can drive, and is based on the work of Hainsch (2023), and secondly, by implementing the V2G functionality where BEVs are allowed to discharge back to the grid, and hence be used as conventional batteries.

## 6.1. The Capex Model versus LCOS

In previous iterations of GENeSYS-MOD, an LCOS structure has been used for modeling the cost of energy storage technologies, meaning that the Capital cost of storage has been equal to zero in the model, while the variable costs has accounted for the full cost of the energy storage systems. In the Capex model a decoupled capital cost of storage structure has been implemented. The decoupled capital structure cost divides the capital cost into, capital cost of energy capacity, and capital cost of power capacity, as well as having a fixed yearly cost and a variable cost per unit of energy delivered back to the grid. Both method is shown to have its advantages and disadvantages.

The LCOS approach allows for a convenient way of comparing the cost of the different technologies, and is easier to use when generalizing the cost for multiple regions and countries. LCOS usually requires less time for data gathering as only one cost metric has to be accounted for, and scientific literature offers future forecasted values for LCOS for several technologies. Some technologies are more suited for using LCOS, that is especially technologies that differ in price across projects, and technologies that more easily can be generalised across regions. That is often technologies that are less dependent on geographical locations, and have a similar supply chain cost and project cost, independent of location. A good exampled for such technologies are utility scale battery energy storage, such as Li-Ion-batteries and redox flow batteries. Both Li-Ion and redox flow batteries are location-dependent, with variations in cost dependent on supply chain availability of material, and labor cost, but to a lesser degree than systems such as PHS and CAES, that heavily rely on geological and topological formations. The LCOS approach is also often modeled with an exogenously given fixed E2P-ratio, which also can be thought of as the duration of the storage system, or the time the storage system uses to go from a SOC of 100% to a SOC of 0% while discharging at its maximum power rating. The LCOS structure also has its merits, and a realistic or common E2P-ratio can be defined, whereas an endogenous E2P-ratio can induce unrealistic E2P-ratios if the model sees it as economically more efficient.

The decoupled CapEx approach with an endogenously determined E2P-ratio, that is used in the Capex model, provides a more detailed view of the cost elements of the energy storage technologies than the LCOS approach. The more detailed view of the cost elements also allows for a more detailed comparison of the energy storage technologies. The capital cost of energy and power, the variable cost, and the fixed cost can be compared across technologies. This can be useful in several instances. For example, when analyzing a system, or region, that has problems managing its short term variations in supply and demand and is in need of more balancing power, the power capacity cost might be of a higher interest. While in a system with longer-term variabilities, where a big quantity of energy has to be moved from one time to another, the energy capacity cost might be of a higher interest. Both the energy and power capacity need is however interconnected, but indications of which technologies are more economically efficient in specific cases can be analysed in more detailed with the decoupled CapEx approach, which can be useful. As mentioned previously, the LCOS approach is more suitable for technologies that are less location dependent, as it is more generalising than the CapEx approach. The CapEx approach allows for more detailed differences in costs across different regions. For example cost of labor can more easily be manipulated to fit the region by increasing or decreasing the more labor-intensive cost elements, and cost of material can be specified for each region as different cost element requires different materials. This can however make data gathering more tedious as it allows for a higher level of detail, and updating the costs from year to year when using the model can become more challenging than with a LCOS approach, as there are more parameters to account for.

In general the decoupled CapEx approach does make technology comparison more complex, and it can be harder to get a good understanding of the total cost of a energy storage system. However, in energy system modeling, it might not be as important to get a good understanding of the total cost. As the model is built to optimize on minimum cost, and by analysing the results of the model an overview and comparison of the technologies can be achieved.

### 6.1.1. Capex model results

A decrease in investment in both energy capacity and power capacity can be seen in the Capex model compared to the NoChanges model (see Figure 3 and 4). The reason for the decrease is the implementation of capital expenditures in the Capex model. In the previously used NoChanges model, which uses an LCOS approach, the CapEx is set to an arbitrarily low value. The model has no incentive to limit its investment in a model without capital cost, as the technology investment zero, this can in turn result in unrealistically high investments, as displayed in the results, section 5.1.1. The NoChanges model invests in new energy capacity for PHS as seen in Figure 4, this comes from a modeling mistake as the model was not supposed to be allowed to invest in PHS energy capacity. However, it does not take away from the result that the NoChanges model invests in higher amounts of both energy capacity and power capacity than the Capex model, and the total energy capacity in the NoChanges model is higher even if the PHS capacity is subtracted.

Another difference between the NoChanges and Capex models is the dispatch pattern of the energy storage technologies. In the NoChanges model, the charging and discharging peaks are higher in magnitude and over shorter duration, taking advantage of the ability to invest in high power and energy capacity, the storage technologies can charge more energy over a shorter period of time. The NoChanges model also tends towards charging the Li-Ion intensely at the start of the year, for then to discharge it intensely at the end of the year. PHS and CAES can also be seen discharging at a unrealistically high rates at the end of the year. This may be for two reasons. The first reason is that the model has invested unnecessarily high amounts of power capacity, as the capital cost is close to zero. The second reason is that the energy storage technologies has to be energy neutral across the year, that means that every storage technology in the model has to have the same amount of energy stored at the end of the year as it had at the beginning of the year. This restriction allows the model to start the year with energy already stored, but to compensate, it has to be back at the same level at the end of the year. This restriction is however in the Capex model as well, and the same intense charging/discharging at the beginning and end of the year cannot be seen in the Capex model.

Both the Capex model and the NoChanges model agrees on which technology is suited for energy capacity and longer term storage, and which technology is suited for power capacity to supplying a more short term flexibility. PHS, CAES, and $H_2$-storage seems to be the preferred choice for energy capacity, and the storage level time series, and the dispatch time series, shows that they supply over seasonal variation throughout the year. Charging is mostly seen during summer days when solar PV has high production, while discharging is seen more during winter. The results does not come as a surprise, as the energy capacity cost also reflects that PHS and CAES are cheaper than the alternatives in Li-Ion and RFB (see section 4.1). Literature also agrees that PHS and CAES are good options for bulk energy storage, and the literature review (section 2) describes PHS to preferably have large reservoirs, and the CAES to have large underground salt caverns. On the other hand the models seems to prefer battery technologies for power capacity and short term flexibility, especially Li-Ion batteries. The Li-Ion batteries out competes RFB with a lower capital cost of energy and power, and a higher degree of technology development through lower future prices and a longer future lifetime. Both battery types has a lower cost of power capacity than PHS andCAES, but as previously mentioned, has a higher cost of energy capacity, which makes them more suitable for the short term supply of power through out the day. It is reflected in the model results with a higher investment in power capacity of Li-Ion, as well as a daily charge/discharge cycles with a higher power input/output than PHS and CAES provides (see Figure 5). This also holds true with how literature views the applications of BESS. In section 2.1.3 of the literature review it is described how battery storage systems usually have one discharge cycle per day, with duration depending on its application (grid stabilizing in the ancillary market or energy management through arbitrage), which showcases that BESS works better in short term energy storage with higher power capacities.

The sensitivity analysis on the Capex model was implemented for several reasons. First to observe if there were any structural flaws in the new cost structure, causing the results to behave unexpectedly or in an unrealistic manner. Another reason was to see how robust of a position energy storage has in the model, or to see which parameters that has a big impact on the results. This helps to get a better understanding of which parameters need a high degree of accuracy, and which parameters that can allow a higher degree of uncertainty.

The $H_2$-import price sensitivity results were mostly consistent with the expected results. Import increased with lower price and decreased with a higher price. Investments into electricity storage was expected to have a positive correlation with the $H_2$-import price, expecting a flexibility vacuum at high import prices and a somewhat lower willingness to invest in energy storages at lower import prices, as flexibility would to a higher degree be covered by $H_2$. The results paint a somewhat different picture, with lower investment in electricity storage at 50% sensitivity, but suddenly higher at 75% sensitivity, and a more or less unchanged investment at the sensitivities higher than 100%. This does have an explanation and the model is consistence with rationality. In Figure 6 it can be seen that hydrogen import actually does not play a big role in the Capex model, and the model only imports $H_2$ in the years 2045 and 2050. It can also be seen that $H_2$-consumption does not increases in any sensitivity except for 50% sensitivity, meaning that $H_2$ does not cover any more flexibility at any of the other sensitivities (including 75%) than in the base case. This means that the expected flexibility vacuum never occurs at sensitivities higher than 100%. A possible reason for the sudden increase in investment at 75% sensitivity might be that electrolysis decreases as $H_2$-import increases. Electrolysis prefers to operate at times of cheap electricity meaning that electrolysis coincide with energy storage charging. As electrolysis decreases a market for more energy storage occurs as the available cheap energy at times of high solar PV production increases, and hence an increase in energy storage investment can be seen in the 75% sensitivity. The reason the same increase is seen at 50% sensitivity is the increased

H2 consumption in the model which supplies flexibility. The results also tells us that the model is not particularly sensitive to variations in the $H_2$-import price, but that there is a threshold at around 75% of the forecasted price, where the model does become sensitive to the import price.

Carbon price sensitivity did not provide a lot of information on the models consistency within energy storage, and no clear pattern could be observed in the results regarding the electric storage technologies. However, a clear pattern could be seen in total emissions and fuel use in industry. Overall emissions had a slight, but clear downwards trend with an increasing carbon price. Industry had a quicker transition towards less emitting fuels, starting by phasing out coal and oil by implementing more fossil gas, to later replace the fossil gas with direct electric heating and biomass (see Appendix A, Figure 25). vRES integration decreases with a low carbon price which is expected, and increases gradually with the increase in carbon price, just up until *CP 200%*. At 200% sensitivity the investment in vRES actually decreases, the reasons seems to be that since most industry and consumption has transitioned to more energy efficient methods, such as direct electric heating, the total need for energy is lower in the system (see appendix A, Figure 26). This shows that the model, in general, is to some degree sensitive to the carbon price, and differences in investment can be seen across different carbon prices. However, the sensitivity is not high, and it is first at bigger variations that big differences occur in the model.

Capital cost of power capacity sensitivity is consistent with what is expected from reality. A decrease in energy storage can be seen with an increased power capacity cost, which is to be expected. Li-Ion is the only electricity storage technology to remain at higher cost sensitivities, the reason being that there are no other technologies that are cost efficient enough to compete with daily flexibility that Li-Ion provides. This means that there are no replacements for Li-Ion. Battery Li-Ion also has, at default value, a relatively low cost of power capacity and is hence less impacted than the other technologies by the percentage sensitivity. Contrary to the power capacity intensive electricity storage that is Li-Ion, CAES which is more energy capacity intensive, has a replacement in $H_2$ storage and dispatchable production technologies such as burning biomass or fossil gas, which can account for the seasonal variabilities. There is also residual capacity of PHS that handles some of the seasonal variability, relieving the need for additional investment in technologies such as CAES. The capital cost of energy sensitivity builds further on the fact that battery Li-Ion has a strong position in the model. At lower sensitivities it increases more than CAES, and at higher sensitivities it decreases less than CAES. The higher increase for Li-Ion at lower cost also comes from that the capital cost of energy already is multiple times more expensive than CAES, making the percentage sensitivities play in its favor. Similarly to the trend in the power capacity CapEx sensitivity, $H_2$ takes over for CAESs seasonal flexibility, while Li-Ion still provides most of the daily flexibility. The model shows a high degree of sensitivity for both energy and power CapEx of the energy storage technologies. Li-Ion is not as affected, but the longer term energy storage technologies are affected, and a quicker transition to $H_2$ is seen at higher prices.

The $H_2$ storage sensitivity provided the results with the least amount of variations. The results where more or less unaffected by the capital cost of $H_2$. This shows two things, first that $H_2$ storage has a strong position in the model, and set at a certain value almost regardless of price. Secondly, the $H_2$ storage price sensitivity is exceptionally low. In the model it can be allowed to miss the correct value of the H2 storage price without much change in results. However, the cost of H2 storage is from the default value relatively low compared to the other technologies, which might be the reason for the low variation in the sensitivities.

Lastly the vRES results where also less interesting from an energy storage perspective, but interesting in the sense of energy system modelling and simulation. The goal of the sensitivity was to see how investments in energy storage was affected by the integration rate of vRES. But something that was forgotten to be considered was that the electric energy storage technologies contributes to the total power output, which contradicts the implementation method of minimum vRES in the system. The minimum vRES was implemented by limiting *ProductionByTechnologyAnnual* which includes the contribution from energy storage technologies. In this way, the energy storage technologies was limited by the equation that was suppose to only limit the conventional power producing technologies. For future sensitivity analyses this has to be accounted for, either by excluding energy storage technologies from *ProductionByTechnologyAnnual* in the equation, by subtracting the contribution of the energy storage technologies from the right side of the equation (see Equation 6), or lastly by using a variable that does not account for the energy storage technologies when calculating annual power production.

## 6.2. V2G model results

The general differences between the Capex model and the V2G model represented in the general finding (section 5.2.1) gives an overview of what changes when BEVs are model with batteries, as well as a short intro to how the V2G participation rate affects the model results. In general the thing that sticks out in the new model is the reduced need for BESS such as Li-Ion. In the V2G model the electric vehicles has the flexibility to optimize when it is charging the car, rather than the complete inflexibility of using energy when driving with a given driving demand. This new flexibility relieves the system of some of the energy demand at high demand periods and moves it to lower demand periods, reducing the need for the daily flexibility that Li-Ion provides. This reduction in need for Li-Ion in the V2G model can be seen decreasing at higher V2G participation rates (see Figure 16 for a comparison with 10% versus 90% participation rate). The reason for this might be because the V2G cares provides a similar service to the grid as regular Li-Ion battery parks, and that the V2G-cars are, at higher V2G participation rates, more preoccupied with driving rather than utilizing the V2G function, opening for Li-Ion to take a bigger market share again.

This charging flexibility given in the model, where the model optimizes charging, is not completely realistic, as consumer charging patterns are not completely flexible. But it showcases a perfect scenario and that the model behaves rationally with the new implementations. Further changes that is seen is that the model invest in more BEVs and produces more passenger kilometers with BEVs than the Capex model. This induces a model that uses more energy, and an increased investment in energy capacity can be seen in technologies such as CAES and PHS, in comparison to the Capex model.

One peculiar thing to notice in the V2G model is that the total investment in vRES decreases compared to the Capex model, solar PV and offshore wind decreases while onshore wind increases. It is hard to pin point exactly why this occurs, but two probable reasons is; one, that the system is more power based and hence more energy efficient, making it a less energy demanding system, or two, that most of the BEVs charges during the night, shifting the power demand away from the day when solar PV is not producing, and onshore wind has a higher production. The second reasoning is to some degree true, especially for higher V2G participation rate, but the BEVs mostly charges when the solar PV is producing at lower V2G participation rate.

The results shown in the scenario comparison is seems rational, and the model behaves mostly as expected. There are lower investments in BEVs in the stricter scenarios, and the model reduces the amount of energy spent on the V2G function rather than driving, which is logical as the model is forced to produce some amounts of personal kilometers, while the V2G function acts purely as a flexibility option in the model. It is preferred that the model would output more personal kilometers, from the V2G participating BEVs, with a daily pattern, as this would have been more realistic. To do this, introducing more restrictions or locking the charging or driving patterns to a time series might be an idea for further work. Another unexpected result in all the scenarios, is the investment in V2G energy and power capacity before the year 2030. The model is restricted from charging and discharging the V2G cars before the year 2030, and so it does not seem rational to invest before the year 2030. The reason for this is still uncertain, and further investigation with variations in restrictions would be necessary to find the reason. Another peculiar thing that occurs in all the scenarios is the prolonged charging at the beginning of the year, and the sudden burst of driving at the beginning and end of the year. The reason for the prolonged charging at the beginning of the year might be because of a restriction that forces the V2G-participating cars to be at 90% SOC at 06:00 every morning. This was a restriction based on Straub et al. (2023) which states that the V2G cars should be at 90% before a trip, the reasoning being that most cars start driving in the morning between 06:00 and 07:00 (see section 4.2), but it might have been a stretch to force this upon the whole BEV-fleet at the same time. The restriction might also be the reason for the bursts in driving, as the model only sees it reasonable to drive when there is sufficient time to recharge the batteries for the next 06:00 occurrence in the model.

Further results shows that a higher V2G participation rate gives lower total BEV investment. This means that it is only economically efficient to invest in a certain amount of V2G cars at the current price. The price is constant in the model, and there are few good sources forecasting future V2G prices. Another thing to notice is that the D_BEV and D_BEV_V2G technologies does not only represent the charging cable, but also the ability to output personal kilometers through driving. A better implementation could have been to separate these technologies into two technologies, one that charges the battery and allows the V2G battery to discharge to the grid, and another that only outputs driving. The time series in Figure 24 shows that an increase in V2G participation rate increases the amount, and magnitude, of the driving bursts. This could, as mentioned previously, be caused by the forced 90% charge at 06:00, but either way a driving pattern time series, or charging pattern time series would probably remove the bursts and give a more realistic representation of the BEV-fleet.

## 6.3. Limitations

### 6.3.1. PHS

Not allowing for PHS energy capacity expansion is a simplification, and as mentioned in 2.1.1, EU projections suggest 4GW of new PHS being deployed by 2030. It is also mentioned in 2.1.1 that new projects mostly consist of upgrades to existing hydro power plants justifying the simplification. For further work, some energy capacity expansion could be considered, and a method of re-purposing the existing hydro power plants in the model to PHS should also be considered, as this seems to be a more realistic approach, at least within Europe. This requires however a lot of new implementation, but might be worth diving into especially if modeling countries or regions with high amounts of existing hydro power or hydro power potential.

### 6.3.2. Time steps

The reduced time series of 122 stands as a limitation, and a higher time resolution would greatly benefit energy storage in the model, as it would be easier to take advantages of the fluctuations in the electricity price. The limitation stands despite the re-scaling of the costs (see Equation 1) which justifies some of the missed data of the skipped hours. The constraint forcing the SOC of the V2G cars to be at 90% by 06:00 does not work as well with the reduced time series as hoped, and the sudden bursts in driving seen in the model would most likely disappear at a higher time resolution. At the same time, the model does not reach 06:00 as many times a year, meaning that the constraint does not have the same impact as it would if every hour was accounted for.

### 6.3.3. V2G battery size

In section 3.3.2, an equation that limits the energy storage capacity of the V2G participating cars to the amount of cars in the model is described. This equation did however, not make it into the final version of the model, even though several different approaches was tested. The results of the model with the equations limiting the energy storage capacity, only invested in the bare minimum of BEVs needed in the model and the BEVs was barely used in the end results. The size of the battery pack was assumed to be 60 kWh on average in 2030, but higher values are expected towards 2050 and can already be seen available in the market. However as the model does not account for the battery size of each car, and the restriction was not included, the model can invest in higher amount of car battery storage than we would expect to see realistically.

### 6.3.4. V2G charger cost

It is assumed that a V2G bidirectional charger, including inverter, costs 22 €/kW in the model. This is quite optimistic in comparison to current prices, and the study referred to suggesting the cost of 22 €/kW (Kempton and Dhanju, 2006) is from the year 2006, and inflation is not accounted for. However the V2G function is not implemented before the year 2030, and it is expected that the technology develops towards 2030, both increasing charging/discharging capacity, and a decrease in cost is expected (Huber et al., 2021a). It might therefor be reasonable to assume 22 €/kW, but it is surrounded by uncertainty as there is no clear consensus in the literature. Further technology development could have been implemented, but then again either assumptions have to be made, or single source studies with their own assumptions has to be considered.

### 6.3.5. BEV charging/driving profile

As mentioned previously in the discussion (see section 6.2), either a BEV charging profile or BEV driving profile could be implemented induce more realistic charging and driving results. In this study a set of scenarios introducing time based restrictions for when the cars are allowed to charge and discharge to the grid was implemented. This could in itself be a good idea, but the implementation was somewhat flawed. The restrictions implemented in the V2G scenarios are unrealistic in the sense that none of the V2G cars are allowed to charge and discharge at specific times. A more realistic approach would be to limit the charging capacity by some factor instead of limiting them to zero in specific times. This limiting factor could be implemented with the help of a "cars plugged in" profile, showing the amount of cars plugged to the grid as a percentage of all cars (similar to capacity factor often used for vRES). The scenarios that have been implemented in this study does still serve a purpose. For instance it does show, and builds the groundwork for, how to implement a simple way to restrict or limit V2G cars in a realistic way.

# 7. Conclusions

This last section summarizes the findings of the two models developed in this study and further research directions the models can be used in. The first model named the Capex model presents a structural change in how energy storage is modeled within GENeSYS-MOD, from an LCOS structure to a decoupled CapEx structure. The second model named V2G model builds upon the Capex model and introduces a storage mechanism for the electric cars in the model, and allows the model to both charge the batteries of the cars, but also for the cars to discharge back to the grid with a V2G function.

## 7.1. Capex model

The first research question of the Capex model, and the biggest change seen in the Capex model, is the change in energy storage investment. As the model now has a overnight cost of investing in both energy and power capacity, a decrease in investment in both capacities in comparison to when the model used an LCOS approach. The new capacity can be thought to be more rational, as the model previously had no direct incentive to limit its investment in power and energy capacity. This rationality also unfolds itself in the dispatch of the energy storage technologies. The Capex model displays a logical daily dispatch cycle with seasonal variability that depends on the production of cheap renewable energy. The sensitivities tested in $H_2$-import price, carbon price, power capacity cost, energy capacity cost, $H_2$ storage cost, and vRES participation rate, showcased that the willingness to invest in energy storage primarily depends on the capital cost of both energy capacity and power capacity, while the other sensitivities displayed marginal differences in energy storage investment. This effect works both ways, and investment in other technologies, and other behaviours of the model was not influenced in any major way by the new cost structure of the Capex model.

### 7.1.1. Furter work - Capex model

The Capex model presents a good option to the LCOS approach. It allows for a more precise view on the optimal investment in energy storage, as well as a more realistic energy storage dispatch within the model. However with a CapEx approach, more data is needed in the model, and the accuracy of the data can seem to be more important. Further work on a model of Europe could look at implementing different costs across different regions, as CapEx costs can differ depending on location. Another single element in the model that would benefit from more research is PHS. In this research PHS was limited to no new reservoirs, but in reality, new plants are being built within Europe, and conventional hydro power plants are being transformed into PHS. A function allowing hydro power plants to be transformed into PHS would add an interesting dimension to the model.

## 7.2. V2G model

The V2G model imposes two big changes in the investment decisions of the model. Firstly the model increases its investment into electric cars (see Figure 36), as the new modeling approach, where the electric cars have battery storage, makes the cars more flexible in terms of when they charge. The other investment that changes is the investment in energy storage power capacity. The flexibility introduced to the electric cars lowers the need for day-to-day flexibility and the total power capacity of the energy storage decreases, especially within Li-Ion. However, as the transportation sector now electrifies at a quicker rate the need for electric energy in the system increases, and the total energy capacity of the energy storage increases with the new modeling approach.

The V2G participation rate and the allowed charging/discharging patterns of the BEV-fleet plays a major role on the system as a whole. An increased V2G participation rate increases the total system cost giving that the model prefers to not invest into the V2G charging cables a cost of 22 €/kW, but prefers to rather invest in Li-Ion batteries for short term energy storage. It can be seen that the total amount of BEVs in the model decreases, and the investment in Li-Ion increases, with an increasing V2G participation rate. This can be seen even when the model is allowed to freely optimize when to charge, discharge, and drive the electric cars. Restricting the charging/discharging pattern of the BEVs does make the BEVs less attractive to invest in, but make the dispatch of the BEVs tend towards a more realistic charge, discharge and driving pattern.

### 7.2.1. Further work - V2G model

Allowing electric vehicles the flexibility of charging at different times than when they are driving, can give a more realistic understanding of the impact of an increased amount of electric cars in the energy system. However, this needs to be implemented with care, as real-world charging patterns does not follow optimality, but rather human behavior. The same can be said for V2G, and it can be seen in this study that it is important to establish limitations for charging and discharging of the BEVs to get realistic results. Further research into charging patterns of electric vehicle users, and its flexibility, would allow for a better understanding of how V2G, and an increased amount of BEVs, can affect the energy system in the future. For V2G-optimization purposes, more research in the cost of V2G equipment. and its technology development, would benefit the results. The model does however set a playing field for approaches of limiting and implementing V2G in energy system modeling, and allows for direct implementation in further studies.

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# A. Appendix: Additional results

## A1. Carbon price sensitivity

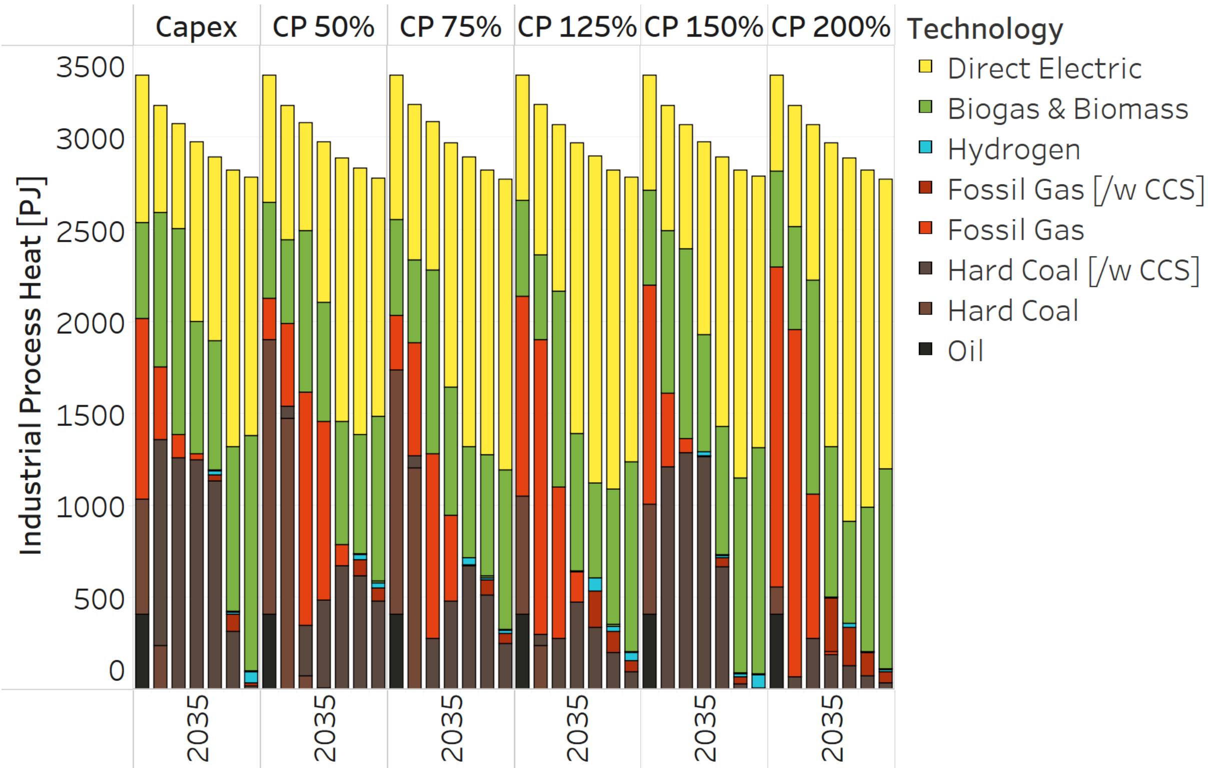


Figure 25: Industrial heating in carbon price sensitivities.

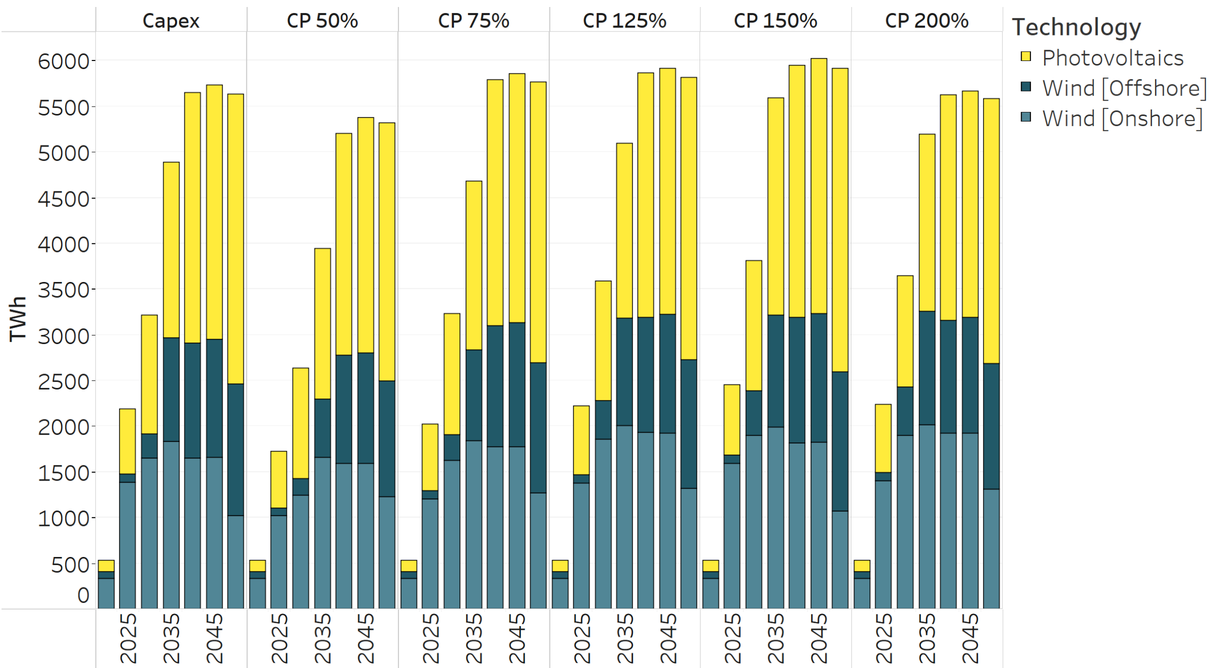


Figure 26: vRES integration in the carbon price sensitivities.

## A1. Capital cost of energy storage capacity sensitivity

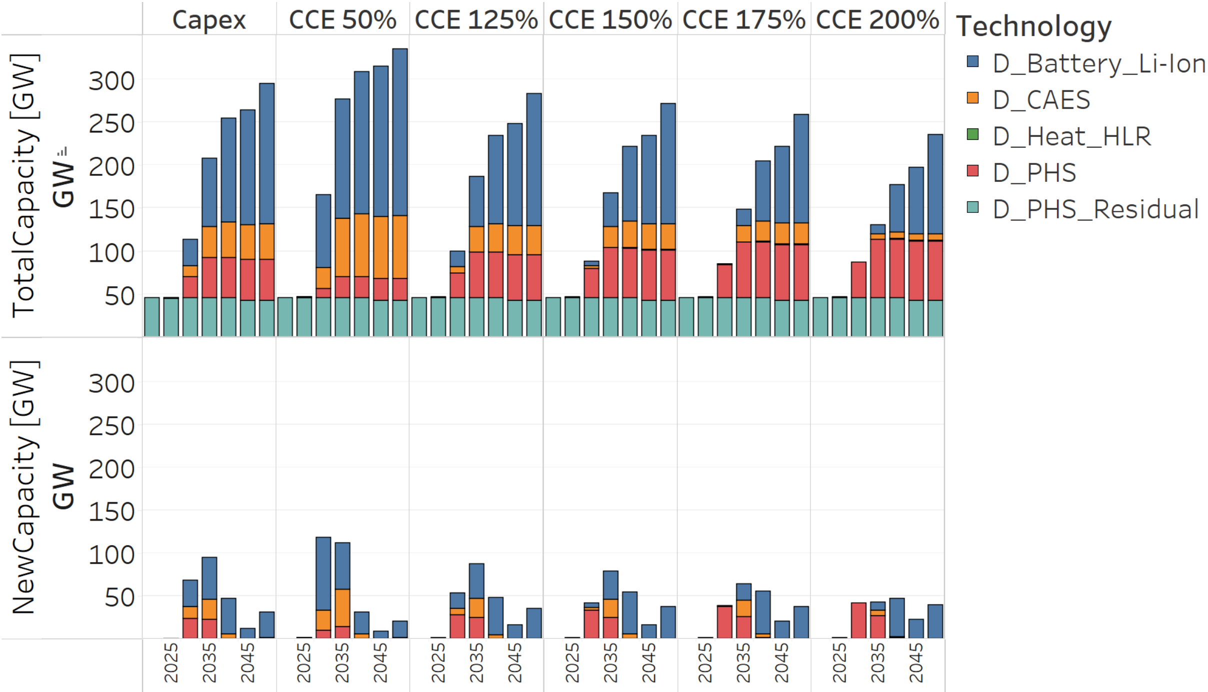


**Figure 27: New and total grid-link capacity of electric storage technologies in all regions and for all sensitivities (CCE: Capital Cost Energy).**

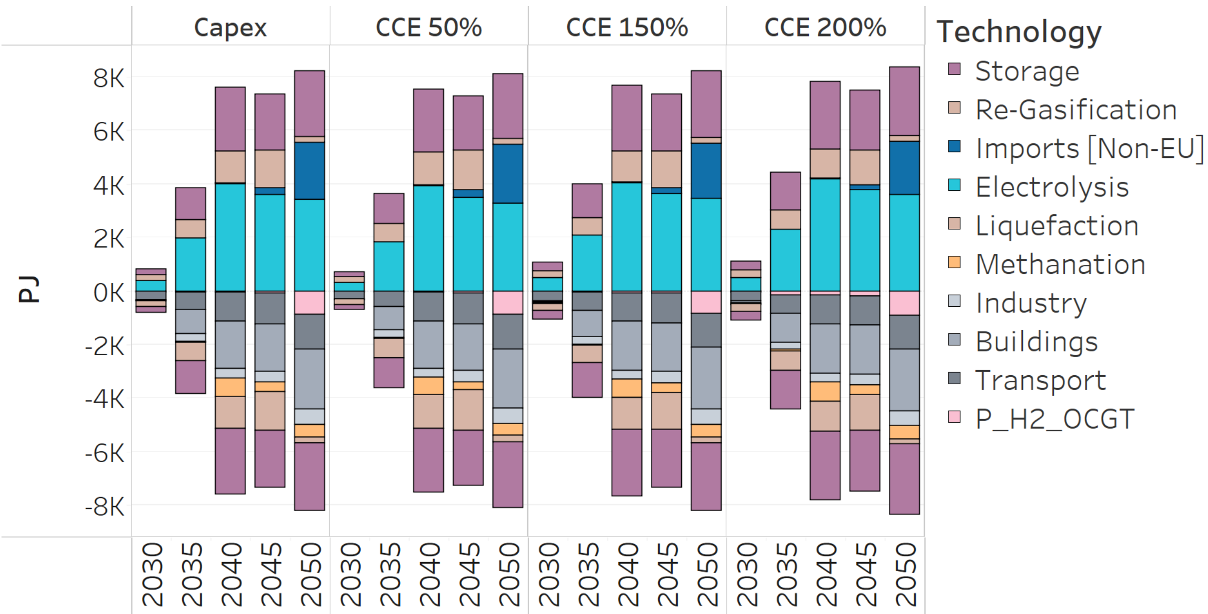


**Figure 28: Hydrogen production and consumption in capital cost of storage energy capacity senstivities**

## A1. vRES sensitivity

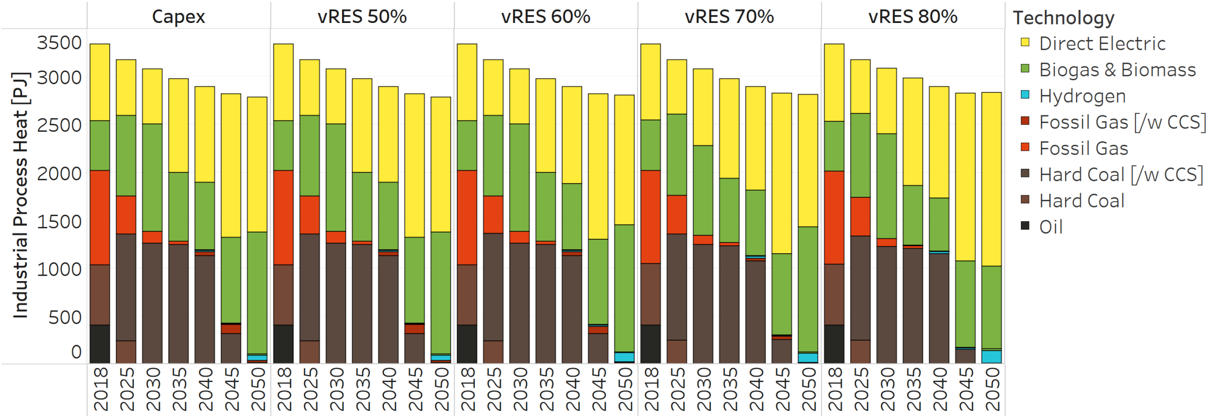


**Figure 29: Industrial heating in vRES sensitivities**

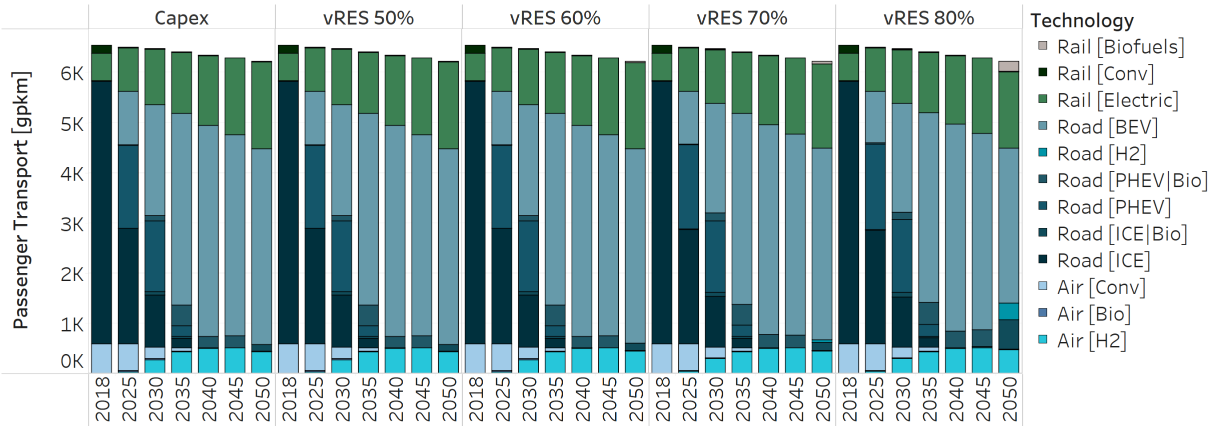


**Figure 30: Transportation sector in vRES sensitivities**

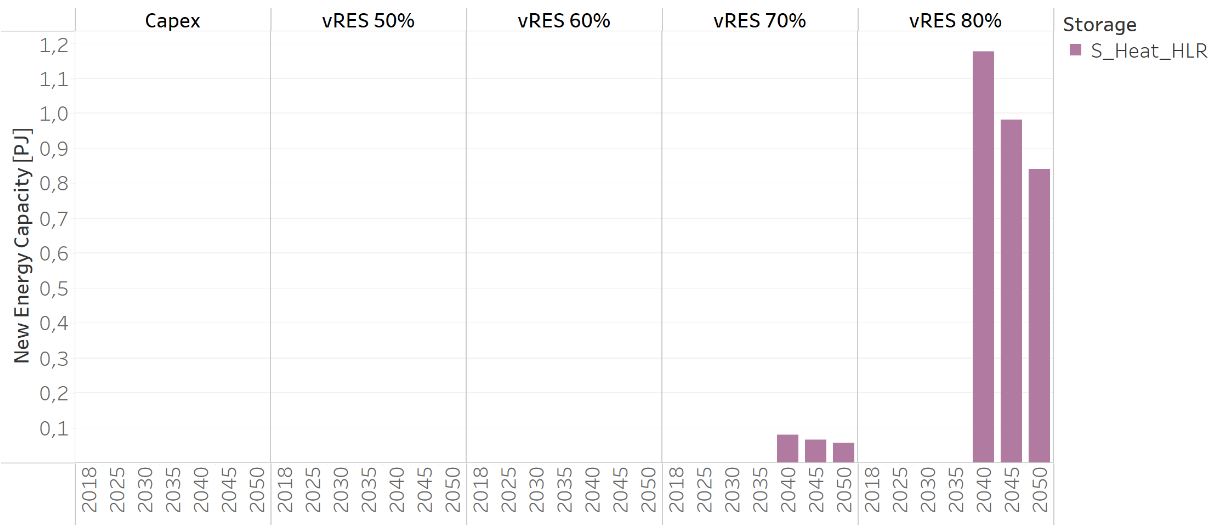


**Figure 31: Residential Heat storage in vRES sensitivities**

## A1. V2G General

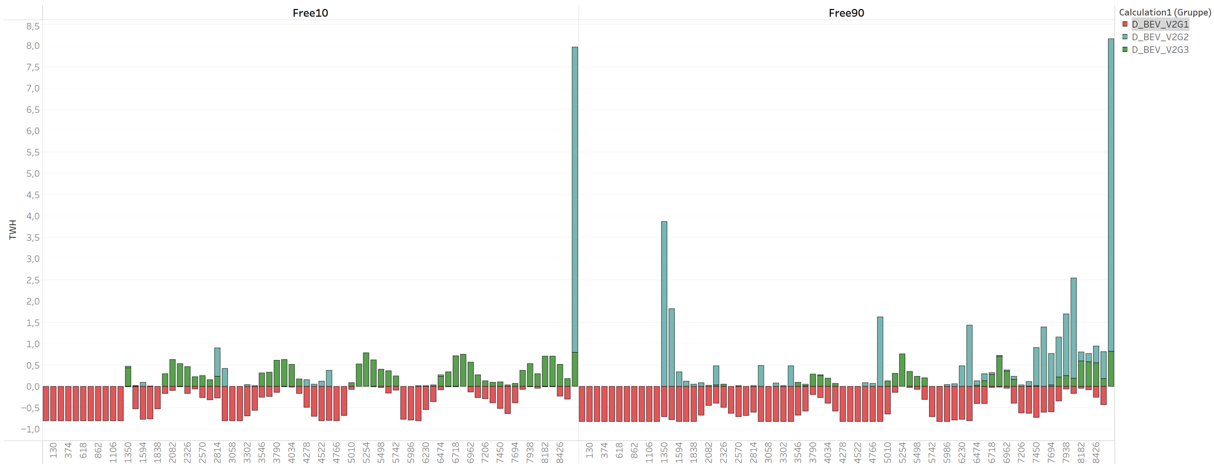


**Figure 32: V2G battery dispatch in the year 2050. D_BEV_V2G1,2,3 represents mode of operation 1, 2 and 3. Mode 1 is charging, mode 2 is driving and mode 3 is the V2G function discharging back to the grid**

## A1. V2G Sensitivities

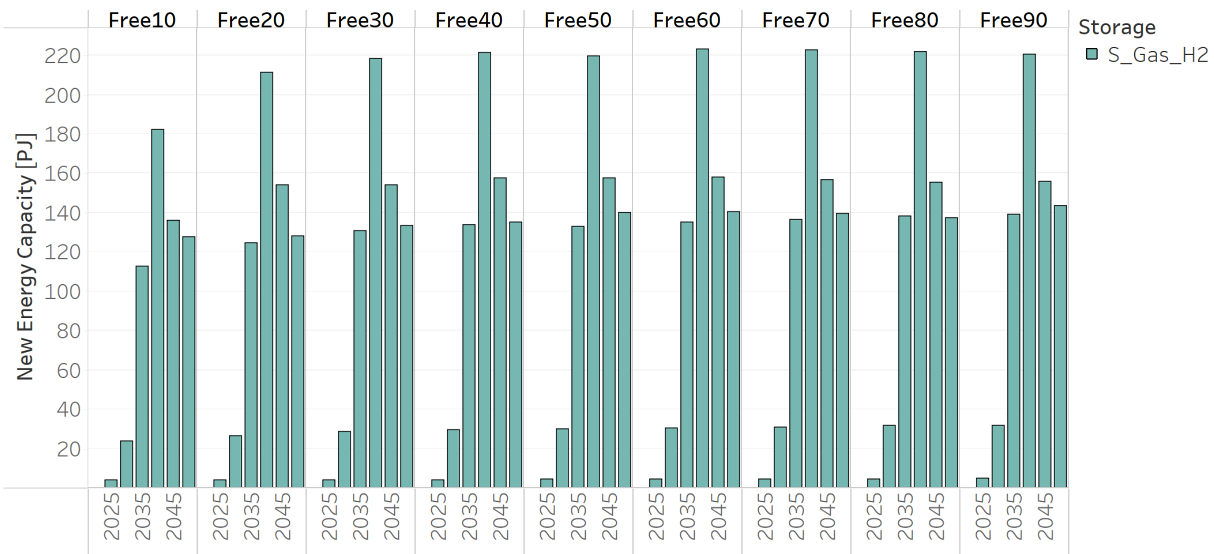


**Figure 33: New hydrogen storage capacity in V2G sensitivities**

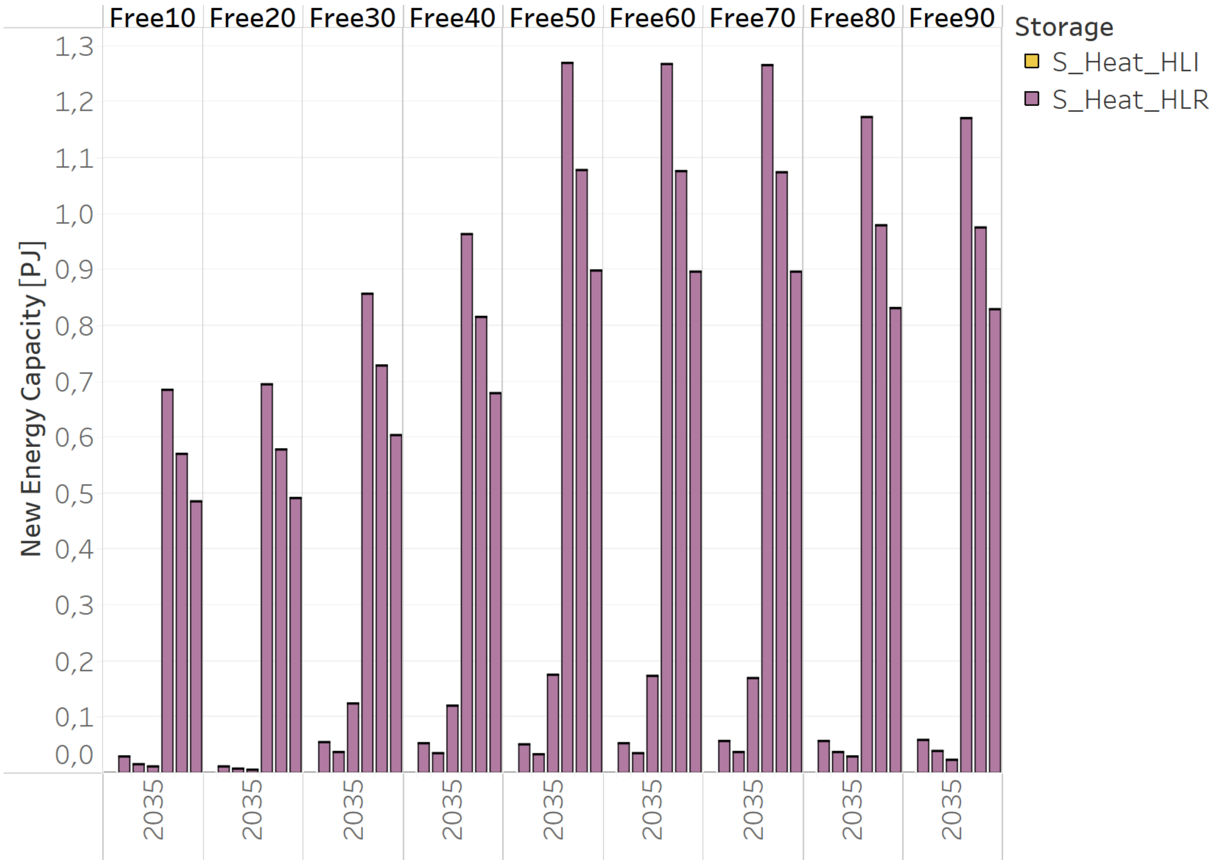


**Figure 34: Residential Heat storage in V2G sensitivities**

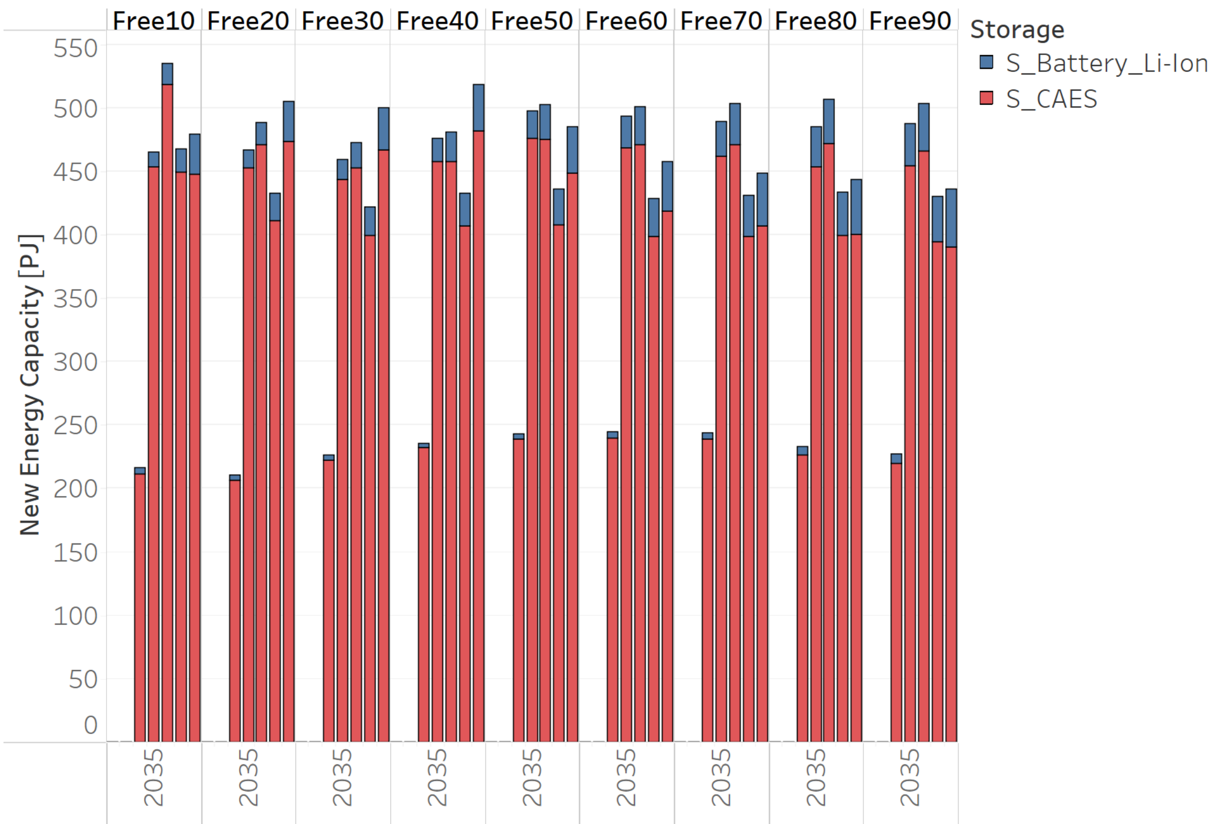


**Figure 35: New energy storage capacity in electricity storage technologies in V2G sensitivities**

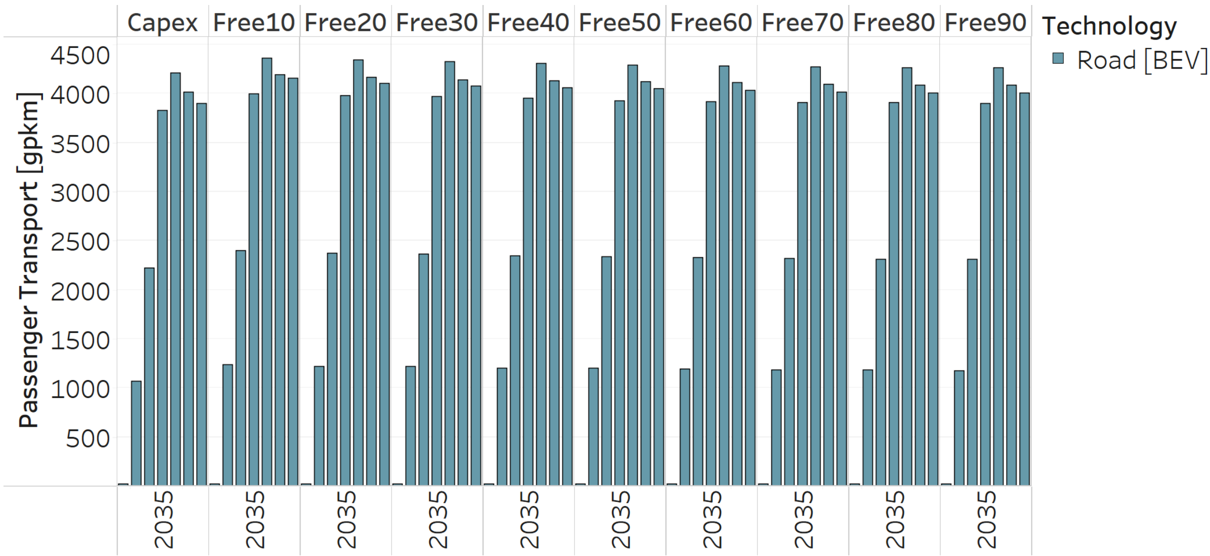


**Figure 36: BEVs across the V2G sensitivities, scenario Free**

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