Economic prospects of electricity storage systems

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Kurzfassung

Durch die zunehmende Stromerzeugung aus variablen erneuerbaren Energiequellen wie Wind und Photovoltaik, wird auch die Diskussion um zusätzliche kurz- und langfristige Speicherkapazitäten verstärkt geführt. Die vielversprechendsten Optionen für die langfristige Speicherung des erneuerbaren Überschusses sind Pumpspeicherkraftwerke, Power-to-Gas (PtG)-Wasserstoff- und Power-to-Gas- Methan Anlagen. Des Weiteren sind Batteriespeicher als Kurzzeitspeicher eine besonders vielversprechende Option, insbesondere als dezentrale stationäre Batteriespeicher gekoppelt mit Photovoltaikanlagen, aber auch in Form von Elektrofahrzeugen zur Speicherung des Überschusses aus dezentral erzeugter erneuerbarer Energie.
Hauptziel dieser Arbeit ist es, die Kosten und zukünftigen Marktchancen dieser verschiedenen Speicher zu analysieren. Dazu werden Berechnungen zu den Speicherkosten bis zum Jahr 2040 durchgeführt und die zuvor aufgeführten Speicheroptionen miteinander verglichen. Darüber hinaus wird in drei Anwendungsfällen mit Hilfe eines linearen Optimierungsmodells und der Methode des internen Zinsfußes untersucht, wie weit die spezifischen Investitionskosten für Batteriespeicher sinken müssten, um wirtschaftlich betrieben werden zu können. Um die Auswirkungen der wichtigsten Parameter wie Strompreis oder Einspeisevergütung bewerten zu können, wird zudem eine Sensitivitätsanalyse durchgeführt. Darüber hinaus wird eine Methode vorgestellt, die es erlaubt, den Verbrauch sowie die Park- und Ladezeiten von Elektrofahrzeugen, die für unterschiedliche Fahrzwecke eingesetzt werden, zu modellieren. Diese Modellierung ermöglicht eine nachgelagerte Betrachtung optimaler Lade- und Laststeuerungspotentiale. Der Schwerpunkt dieser Analyse liegt in der Betrachtung des motorisierten Individualverkehrs. Die Unterschiede in den Last- und Fahrprofilen beziehungsweise Weglängen für Wochentage sowie für Samstage, Sonn- und Feiertage im Allgemeinen werden aufgezeigt. Eine anschließende Analyse der kostenoptimalen Beladung zeigt dann die Potenziale der Nutzung des dezentralen Photovoltaik Überschusses in Elektrofahrzeugen.
Die wichtigste Schlussfolgerung ist, dass die Wirtschaftlichkeit sowohl von Langzeit- als auch Kurzzeitspeichern nur schwer erreichbar ist. Für alle am Strommarkt partizipierenden Speichertechnologien wird es auch zukünftig schwierig werden, auf den Großhandelsmärkten zu konkurrieren. Aber auch dezentrale Batteriespeicher können, trotz der deutlich höheren Endkundenstrompreise, auch zukünftig nur schwer wirtschaftlich betrieben werden. Das Kernproblem praktisch aller Kategorien von marktbasierten Speichersystemen sind die geringen Volllaststunden. Neue Speicherkapazitäten sollten daher nur koordiniert gebaut werden und auch nur dann, wenn auch der Überschuss aus Erneuerbaren deutlich steigt.
Für dezentrale Batteriespeicher lässt sich schlussfolgern, dass die Batteriespeicherkosten je nach Kombination der Kapazitäten von Photovoltaik, Batteriespeicher und in Bezug auf das Lastprofil um mindestens 85% sinken müssten um eine bestimmte vordefinierte Rendite zu erzielen. Je mehr unterschiedliche Lastprofile direkt mit Photovoltaikstrom gedeckt werden können, z.B. in einem Mehrfamilienhaus oder liegenschaftsübergreifend, desto weniger Strom muss gespeichert werden. Dadurch wird die Auslastung und der Nutzen des Batteriespeichers geringer und somit müssten die spezifischen Investitionskosten noch weiter sinken.
Elektrofahrzeuge können je nach Größe der PV-Anlage und des Lastprofils nur bedingt als dezentrale Speicher dienen, da die Parkzeiten insbesondere bei Einfamilienhäusern nicht direkt mit der PV-Erzeugung korrelieren und auch der Verbrauch nicht hoch genug ist, um genügend PV-Strom der eigenen PV-Anlage zu speichern. Abhilfe könnte hier geschaffen werden, indem der selbsterzeugte PV-Strom auch auswärts in das Fahrzeug geladen werden kann und somit zumindest der Energieanteil des Strompreises eingespart werden kann.

Abstract

Increasing electricity generation from variable renewable energy sources, such as wind and solar, has led to interest in additional short-term and long-term storage capacities. The most promising options for long-term storage of the renewable surplus are pumped hydro storage power plants, power-to-gas (PtG) hydrogen and power-to-gas methane plants. In addition, battery storage systems are a particularly promising option as short-term storage, especially as decentralised stationary battery storage coupled with photovoltaic systems, but also in the form of electric vehicles to store the decentralised renewable electricity surplus.

The core objective of this thesis is to investigate the costs and future market prospects of these different electricity storage options. For this purpose, calculations on storage costs up to 2040 are conducted and the previously listed storage options are compared to each other. In addition, the level to which the specific investment costs of battery storage needs to decrease in order to be economically viable is assessed. Three different use cases are analysed using a linear optimisation model and the method of the internal rate of return: Battery storage in single-family buildings, in multi-apartment buildings and in cross-building utilisation. In order to be able to evaluate the impact of the most important parameters such as electricity price or feed-in remuneration a sensitivity analysis is carried out.

Furthermore, a method is presented that allows the consumption as well as the parking and charging times of different vehicles and driving purposes to be modelled and thus also the possibility of storing the decentralised photovoltaic surplus. The focus of this analysis lies in the assessment of motorised private transport, which makes it possible to outline future charging and load control potentials in a subsequent analysis. The differences in demand and driving profiles for weekdays as well as for Saturdays, Sundays and holidays in general is outlined. Furthermore, the modelling considers the length distribution of the individual trips per trip purpose and different start times. A subsequent evaluation using an optimisation model then reveals the potential for electric vehicles to utilise decentralised photovoltaic surplus.

The major conclusion is that the economic prospects of storage are not very bright. For all market-based storage technologies it will become hard to compete in the wholesale electricity markets and for decentralised (battery) systems it will be hard to compete with the end users' electricity price. The core problem of virtually all categories of market-based storage systems are low full-load hours. However, any new storage capacity should be constructed only in a coordinated way and if there is a clear sign for new excess production, in this case from variable renewables. In addition, for hydrogen and methane there could be better economic prospects in the transport sector due to both higher energy price levels as well as a general lack of low carbon fuel alternatives.

For decentralised battery storage, it can be concluded that, depending on the combination of capacities of photovoltaics, battery storage and in relation to the load profile, the battery storage costs would have to drop by at least 85% in order to generate a certain predefined return over a depreciation period of 25 years. The more different load profiles can be covered directly with photovoltaic electricity, e.g. in a multi-apartment building or across buildings, the less electricity needs to be stored and this reduces the benefit and the utilisation of the battery storage and therefore the specific investment costs must further decrease. Depending on the size of the PV system and the load profile, electric vehicles can only serve as decentralised storage to a limited extent, as the parking times do not correlate directly with PV generation, especially in the case of single-family buildings, and consumption is also not high enough to store enough PV electricity.

Contents

1 Introduction

1.1 Motivation

The European Commission has set ambitious targets to increase the share of electricity from renewable energy sources (RES). In recent years especially electricity generation from variable sources, such as wind and solar, has increased remarkably, see Figure 1.1. This figure shows that between 1990 and 2020 in the EU-27 “new” RES, excluding hydro, grew from less than 1% to about 20%, mainly from wind and photovoltaics (PV). As seen in 2020, wind and PV represent more than two third of the “new” RES. In addition to the use of ground-mounted- and agricultural PV, building-integrated and building-mounted photovoltaic systems will play a major role. Since additional land sealing should be avoided, these systems offer a great opportunity, especially in new buildings, but also in renovations, to optimally use the already built-up and existing surface potential. In addition, the electricity generated should be consumed as locally or regionally as possible in order to use the capacities efficiently, relieve the distribution grids and reduce the resulting transportation losses.

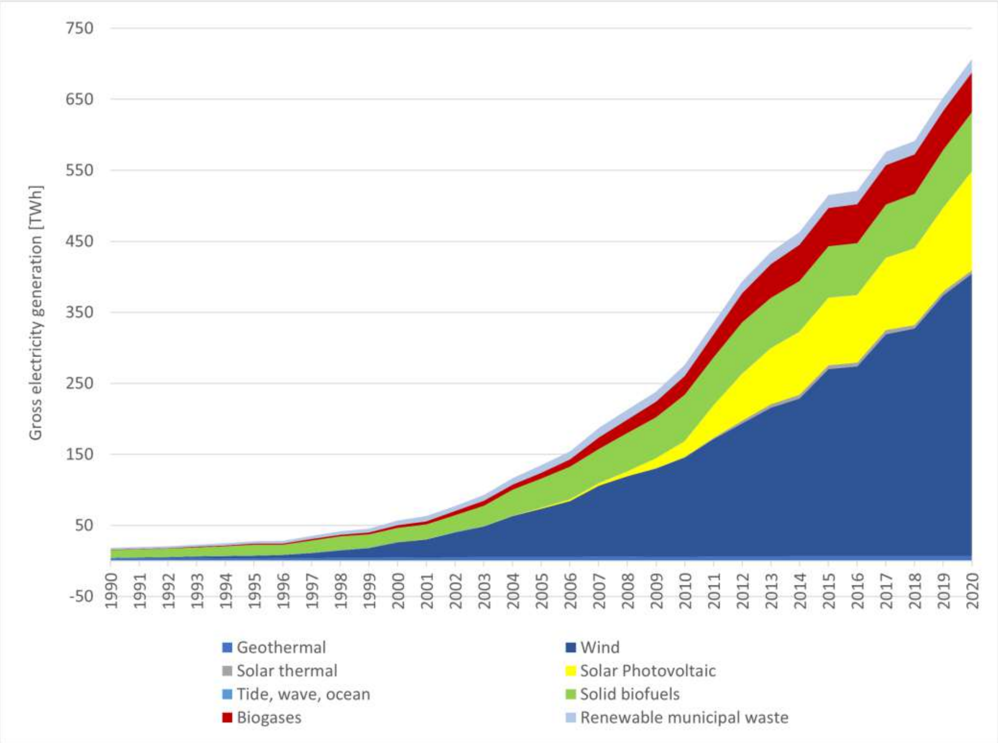


Figure 1.1: Development of electricity from ‘new’ renewables (excluding hydro) in EU-27 between 1990 and 2020, in TWh (Source: EUROSTAT).

The variability caused by the expansion of these new renewable resources, however, leads to new challenges in terms of security of supply, flexibility and predictability. To match supply with demand and to even out the intermittency of renewable supply, energy storage could be a key component in the integration of renewable energy, compare Figure 1.2.

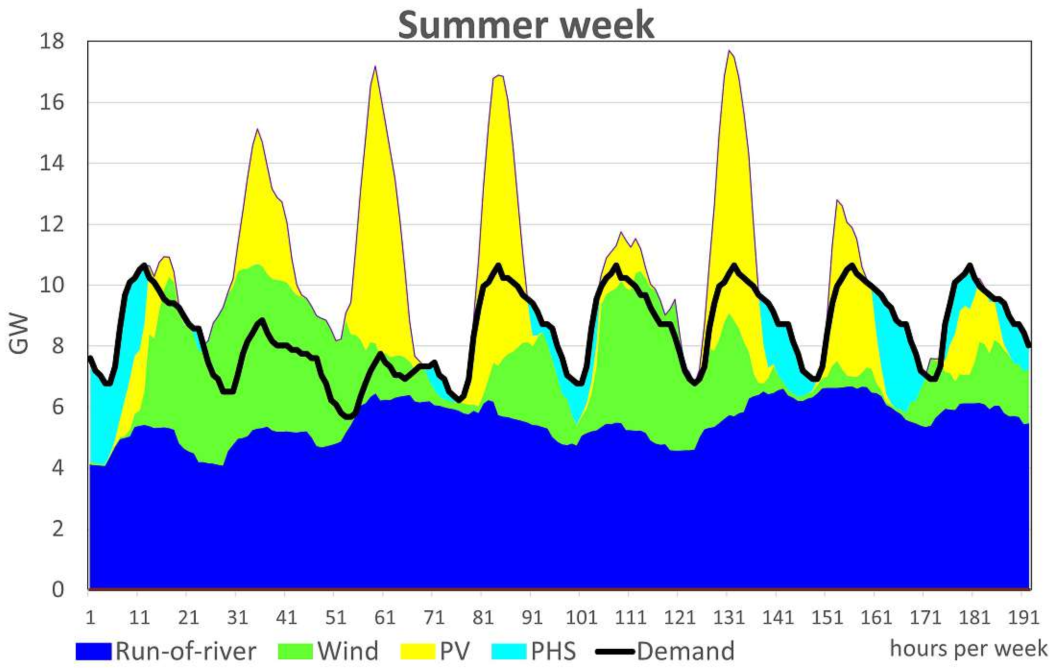


Figure 1.2: Electricity generation from variable RES and load over a week (modeling example for Austria 2030).

It could play a crucial role in the transition towards a sustainable energy system by enhancing the reliability, flexibility and security of the European energy supply. The potential position of energy storage in the future energy industry could be particularly significant, given the ambitious targets for the development and deployment of renewable energy. Especially, in Germany calls for large new capacities have been launched, see Management (2015) and BVES/DIHK (2017). Already in 2010, the EU addressed this topic and published a corresponding work on the potential of storage(Comission, 2011). For a broader market penetration of storage systems their economic performance is most important. As in principle many different storage options exist, see e.g.Sterner and Stadler (2014), the first challenge simply is to compare the costs of different types of storage to identify the most cost-effective option, see e.g. the analysis in Jülch (2016) and Schmidt et al. (2019). From an economists point of view the value of storage results from an opportunity for arbitrage. Purchasing electricity at times of low prices and to sell it when the price is high. Hence, this so-called price spread along with the full-load hours (FLH) are the major criteria for the economic performance of storage (Sioshansi, 2010; Ehlers, 2011).
It is important to note that balancing supply and demand has been a major challenge since the beginning of the electricity system. Historically, however, this has been slightly more straightforward with fossil-fuelled and very flexible peaking power plants and smaller amounts of new renewables. With increasing renewable capacity and the objective to fully decarbonise the energy system, fossil peak load power plants can only be operated with renewable gas and the flexibility has to be provided e.g. by storage [1]. Furthermore, it must be noted that storage is not the only flexibility option. It competes with grid expansion, load management and other

[1]Other options for decarbonising fossil generation such as Carbon Capture and Storage (CCS) or Carbon Capture and Utilisation (CCU) and using it to produce e.g. synthetic fuels are also possibilities.

options such as sector coupling, i.e. the integrated assessment of the electricity, heat and transport sectors (Ajanovic, Hiesl, and Haas, 2020). From the perspective of a long-term economic assessment, the possible storage options must therefore be considered simultaneously with other flexibility options. As can be seen in Figure 1.2, the variability due to photovoltaics and wind is significantly higher and generation can also vary strongly on an hourly basis, while for run-of-river power plants the variability, which also has to be balanced, is significantly lower and the time constants are also significantly longer. In addition, Figure 1.2 and Figure 1.3 show the situation with the corresponding capacities of renewables in Austria. In other countries, these graphs could look significantly different. Due to the seasonality of renewable generation and the resulting differences in individual months, see Figure 1.3, the need for long-term electricity storage options is of particular importance (Ajanovic and Haas, 2019).

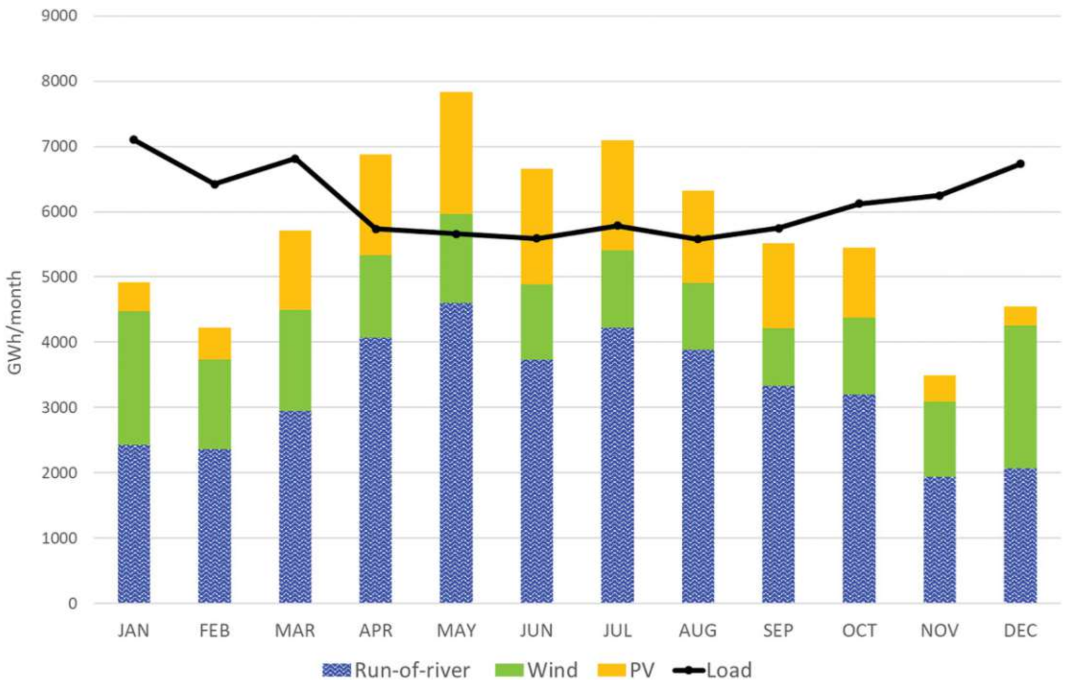


Figure 1.3: Distribution of electricity generation from variable RES as PV, wind and run-of-river hydro power as well as load (demand) over the months of an average year for Austria, Source: Ajanovic, Hiesl, and Haas (2020)

The integration of larger amounts of variable RES into the electricity system and how to balance seasonality is currently the focus of analyses. Since the early days of electricity systems, pumped hydro storage has played the largest role in balancing supply and demand. Currently, about 99% of all electricity storage is pumped hydro storage, see Ajanovic, Hiesl, and Haas (2020), Deane, Ó Gallachóir, and McKeogh (2010) and Fu, Remo, and Margolis (2018). Although Deane, Ó Gallachóir, and McKeogh (2010) is already ten years old, it is important, because it provides the best overview of pumped storage power plants in the literature. Fu, Remo, and Margolis (2018) is a more recent work that focuses on batteries. However, seasonal balancing is only possible to a limited extent with pumped hydro storage. The most promising solution for storage and seasonal balancing is via PtG based storage solutions, see also Figure 1.7. Renewably generated gas is produced e.g. via electrolysis and can then be stored for longer periods of time and used when renewable electricity is scarce. The economic viability of electricity storage for variable renewable energy sources is analysed by Zerrahn, W.-P. Schill, and Kemfert (2018). They question whether storage limits the expansion of renewables and find that the need for storage is significantly lower than is often claimed in the literature. They conclude that electrical storage is unlikely to limit the transition to renewables.

The expansion of new renewable energies, especially photovoltaics, is not limited to large-scale systems, but is also of particular importance in a decentralised manner, thus transforming former consumers into prosumers who generate and consume their own electricity. Therefore, aside from the above mentioned arbitrage approach, there might also be the opportunity of own use of the stored electricity “behind the meter”, e.g. in a household, at a farm, in a super market or in an office building (Ajanovic, Hiesl, and Haas, 2020). Behind-the-meter battery storage systems as well as battery storage in electric vehicles could be used to significantly increase the share of self-consumption. As can be seen in Figure 1.4, the worldwide installed capacity behind the meter has expanded substantially in recent years, with lithium batteries being the dominant technology in this segment (IEA, 2022).

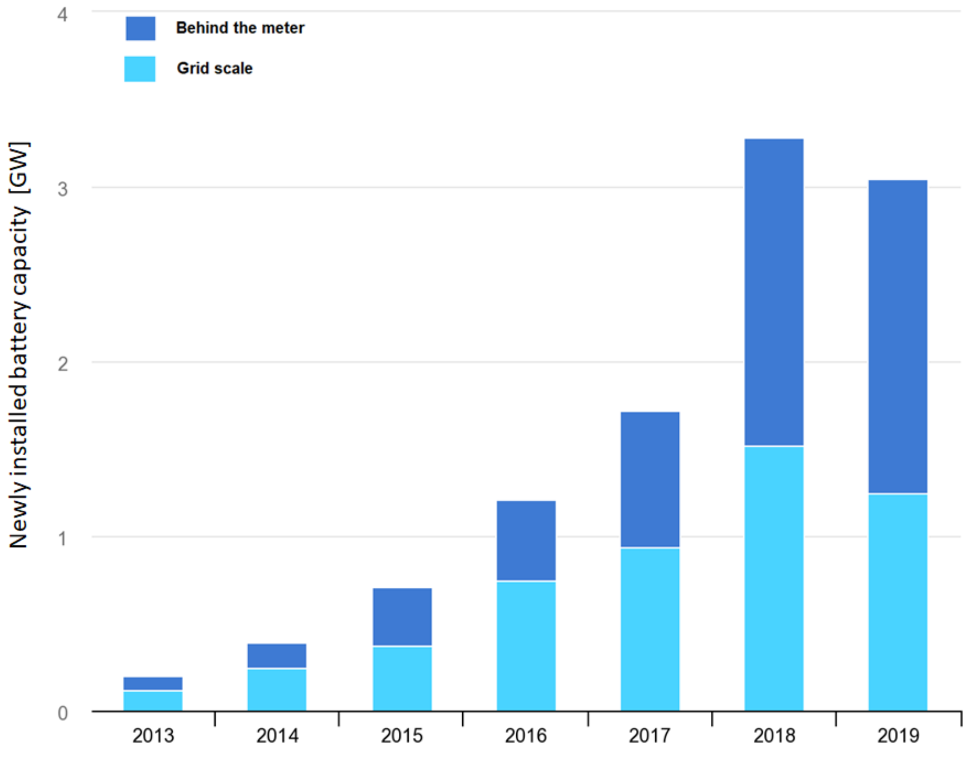


Figure 1.4: Newly installed battery capacity grid scale and behind the meter [GW], Source: IEA, 2022

In this case, storage costs compete with the end users’ electricity price and show a positive economic performance if storage costs are lower than electricity costs including all fees and

taxes but excluding fixed costs. However, the large expansion of decentralised photovoltaics leads to the fact that with the currently prevailing grid tariffs, which are largely based on kWh, the fixed costs of the electricity grids are increasingly paid by those who do not (or cannot) operate their own PV system, as PV owner purchase less electricity from the grid and therefore also pay less grid fees. For this reason, there will have to be further changes in the tariff structure in order to distribute the costs in a way that is fair to those who cause them and to secure the necessary investments in the electricity grids. This also means that the grid tariffs will tend to develop in the direction of capacity or fixed pricing, and this must also be taken into account in future analyses. Due to new EU-regulations like the Directive on common rules for the internal market in electricity ((EU) 2019/944), see Comission (2019) as well as the revised Renewable Energy Directive (2018/2001/EU), compare European (2018) it is now also possible not only to supply single-family buildings with self-generated photovoltaic electricity, but also to include tenants of multi-apartement buildings and to supply entire blocks or regions and merge them into energy communities. The Directive on common rules for the internal market in electricity ((EU) 2019/944) therefore addresses new regulations that allow consumers to actively participate in all markets, individually or in the context of citizen energy communities, whether through generation, consumption, sharing or sale of electricity, or through the provision of flexibility services with demand response and storage, see Comission (2022).
In addition, the revised Renewable Energy Directive (2018/2001/EU) aims to strengthen the role of renewable energy self-consumers and renewable energy communities, thereby increasing the acceptance of renewable energy and making citizens drivers of the energy transition. EU countries should therefore ensure that they can participate on an equal footing with large participants in the available support schemes (Comission, 2022). In smart and sustainable energy systems of the future there are much more opportunities to place storage than in the conventional system of the past (H. Lund et al., 2016; Ajanovic, Hiesl, and Haas, 2020; V. W.-P. Schill, Zerrahn, and Kemfert, 2018). A major reason is that in future the one-way system of the past will be replaced by kind of a bi-directional system where much more flexibility options in the whole electricity system will be used including also prosumers and prosumagers. Especially for prosumers with a photovoltaic system in single-family buildings, multi-apartment buildings but also across buildings, the question arises of how they deal with their surplus. As already mentioned, the adapted EU regulations now make it possible to distribute and store decentralised renewable energy more easily to residents of multi-party buildings, but also across property boundaries. Two of the storage options of particular interest in this context are stationary battery storage "behind the meter" and battery storage in electric vehicles. Even if electric vehicles are not always available for charging, they can be considered as storage mass in the system and, through intelligent charging, increase the share of renewable electricity used in electric vehicles and reduce the additional capacity required by the electricity grid. The advantage of storage using electric mobility is quite simply that no additional storage costs are incurred, as these are already included in the vehicle. As pointed out in Figure 1.4, behind the meter battery capacity expanded significantly in recent years but also e-mobility is now experiencing an upturn, especially in the sector of passenger light duty vehicles see Figure 1.5 and 1.6.

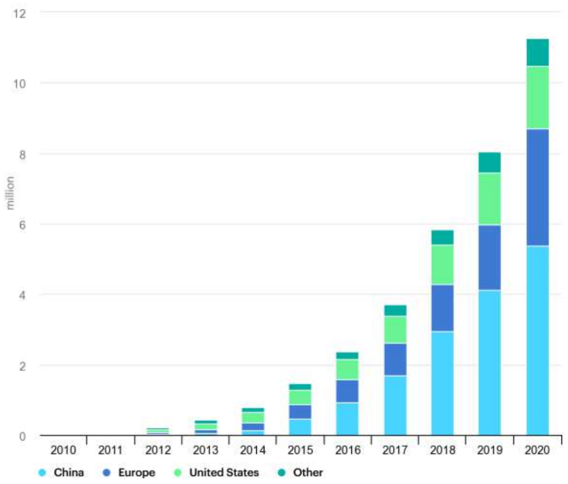


Figure 1.5: Global electric vehicle stock by region, 2010-2020
Source: IEA, 2021b

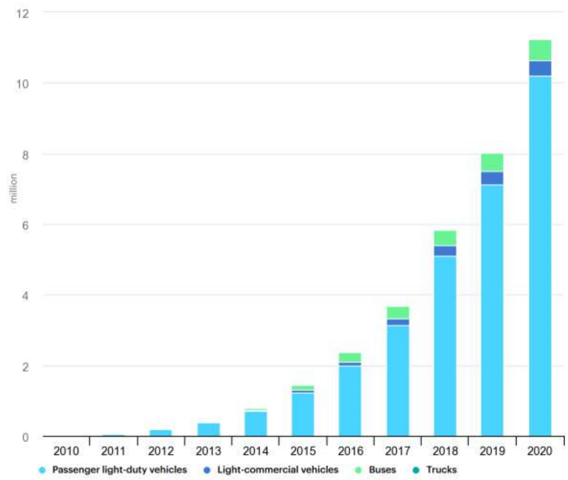


Figure 1.6: Global electric vehicle stock by transport mode, 2010-2020
Source: IEA, 2021a

While in the EU-27, in 2010 only 700 electric vehicles were newly registered, this figure increased to 550,000 vehicles in 2019. However, this still only represents a 3.5% market share of newly registered passenger cars of which about 2% were battery electric vehicles (BEV) and 1% were plug-in hybrid electric vehicles (PHEV). The frontrunners in new registrations are Norway with 56% electric vehicles as measured by total newly registered vehicles, followed by the Netherlands with 18.53% and Iceland with 16.06%. Austria is in the middle of all EU countries with 3.43% of newly registered electric vehicles (EEA, 2021). Regardless of current growth rates, a study by Eberhard and Steger-Vonmetz (2019) outlines that, by 2050, the entire vehicle fleet in Austria will be electric. The boom in electric mobility also means a boom in the battery industry, which is one of the reasons why the cost of battery storage in electric vehicles continues to go down, great learning effects are to be achieved and this also has an impact on the investment costs of stationary battery storage, as both are mainly based on lithium technologies (Kittner et al., 2020; Weiss, Zerfass, and Helmers, 2019). If the global 12 million electric vehicles with an average assumed battery capacity of 40 kWh are taken into account, this means an additional storage capacity of about 480 GWh, with a strong upward trend. This storage capacity could be used, at least partially, to store the surplus of renewable energies in the decentralised segment of single-family buildings, multi-party buildings or even office buildings, instead of being fed into the grid. However, the systemic use of this storage capacity would also require business models for aggregators that can bring the entire resulting or available storage capacity to the market. Figure 1.6 points out, that the registered vehicles are mainly passenger light-duty vehicles, which are mainly operated by private individuals. This means that the largest shares of mobile storage are primarily located in the decentralised, private sector. If we now consider this, as well as the decentralised battery storage, at the household level, the electric vehicle could, on the one hand, store the surplus of a PV system and thus lead to savings in operation of the electric vehicle or, by feeding it back to the building, also partly cover the electricity demand of the household. However, this requires a method for estimating the actual demand profile and charging availability of individual transport at different levels of detail and a high-resolution time scale. Only when this data is available, the optimal charging of the electric vehicle can be simulated and optimised under different constraints (e.g. grid restrictions, optimisation of charging according to renewable generation), which is also the aim of this work.

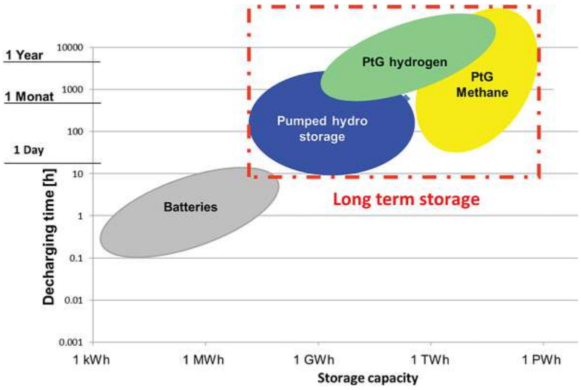


Figure 1.7: Typical storage times of various storage technologies dependent of installed storage capacity. Source: (Ajanovic, Hiesl, and Haas, 2020; Haas and Ajanovic, 2013; Ajanovic and Haas, 2014)

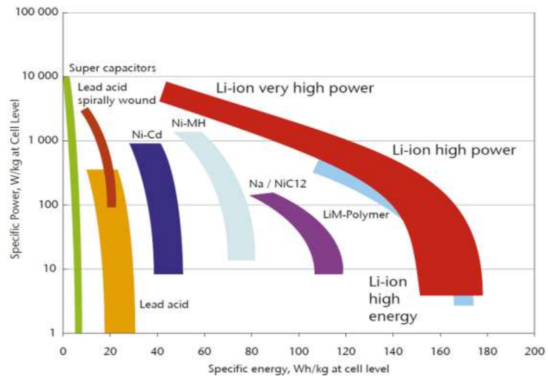


Figure 1.8: Specific power in W/kg as a function of specific energy in Wh/kg of Supercapacitors as well as various types of batteries from Lead acid to Li-ion
Source: IEA, 2021a

As already stated, renewable energy systems with a high share of fluctuating generation need both short-term and long-term flexibility and storage can be part of this flexibility solution. However, the economic viability of both decentralised storage and centralised long-term storage and the future outlook is uncertain, so this thesis will take a closer look. The long-term storage systems analysed in this paper are pumped hydro storage, power to gas (PtG) hydrogen and PtG methane, see Figure 1.8. Long-term storage systems have a large capacity and can also maintain this capacity over a long period of one year or more. In contrast, the second focus of this work is on different applications of battery storage, which represent short-term storage. Short-term storage systems are used to store small amounts of energy over a period of a few hours to days. The currently dominant technology, lithium-based battery storage, has favourable characteristics in terms of specific energy- and power density, depending on the area of application, see Figure 1.6. Due to this characteristic, lithium based storage systems are used in electric vehicles as well as in decentralised home storage systems.

1.2 Core objective

The core objective of this dissertation is the comprehensive analysis of the economic efficiency of different long-term storage systems in the market environment. In addition short-term storage systems in the form of decentralised stationary battery storage systems in the household environment as well as battery storage systems in privately used electric vehicles are analysed. The following research questions are answered in this thesis:

- **Research question 1:** Can PHS, PtG Ch4 and PtG H2 as well as decentralised battery storage operate economically in their respective (market) environments and how will this change by 2040? Derived from this results the question of what the decisive parameters for the economic viability of the storage technologies are.
  This question is answered by calculating the costs per kWh of stored energy of the

different technologies and varying the full load hours. The costs of storage are then compared with the possible revenues on the spot market (PHS, PtG CH4, PtG H2) on the one hand and the household electricity prices (battery storage) on the other.

- **Research question 2:** What is the decentralised PV-storage potential in Austria and how can it be estimated?
  For this purpose, a methodology is presented on how the PV potential on buildings can be calculated, compared to the expansion targets in Austria and the storage potential estimated using a typical share of self-consumption.

- **Research question 3:** Which investment costs should be expected for a decentralised battery storage system in different use cases (single-family house, multi-party building, use of the storage system across buildings) and taking into account an expected return on investment? Research questions derived from these results are then to what extent the specific investment costs would have to decrease compared to today's investment costs and which parameters most influence this result.
  In order to answer these questions, a linear PV storage optimisation model is developed, which aims to minimise the electricity purchase costs. Different load profiles, electricity prices, feed-in remuneration as well as PV generation and storage capacities serve as input parameters. With the help of a modified version of the Internal Rate of Return (IRR), the necessary investment costs are calculated.

- **Research question 4:** To what extent can electric vehicles also utilise the decentralised PV surplus and what savings result from storing the surplus in an electric vehicle?
  To address this question, stochastic load and charging profiles are modelled. A distinction is made between workdays and Sundays and public holidays and path lengths for eight different driving purposes. As a result, an averaged load profile is then created. This load profile is then integrated into the previously developed optimisation model to guarantee cost-optimal charging in two different scenarios and to analyse the resulting savings through the use of PV electricity in electric vehicles.

The central analyses in this thesis are essentially based on three papers and on their core objectives to answer the research questions before. For reasons of readability, these are not further cited directly or indirectly.

1. Hiesl, Ajanovic, and Haas (2020) - On current and future economics of electricity storage

   The core objective of this paper is to analyse the costs and to investigate the current and future market prospects of storage for electricity. Short-term battery storage as well as long-term storage options such as pumped hydro storages, and PtG technologies such as hydrogen (H_2) and methane (CH_4) are analysed from an economic point of view. A derived objective is to compare the costs of different storage types depending on likely full-load hours, storage efficiency and electricity prices.
   The major new contributions of this paper are:

   a. It serves as a primer on the economics of storage;
   b. It provides a very comprehensive survey and literature review;
   c. It considers all different economic perspectives of central and decentralised storage;

d. It analyses all relevant storage technologies;

e. In addition, the economic future perspectives for these technologies considering the long-term learning effects regarding the investment costs of the investigated technologies are analysed.

2. Hiesl, Ramsebner, and Haas (2022) - Economic viability of decentralized battery storage systems for single-family buildings up to cross-building utilization

   The core objective of this work is the economic evaluation of decentralised battery storage systems that are installed in different constellations to increase the self-consumption of prosumers, and thus also to minimise the electricity purchase costs from the grid. The prosumers question of "how much" a storage system may actually cost in order to meet certain economic expectations will be addressed in the following analyses. The situation in single-family buildings, multi-property buildings as well as across properties is addressed, since different scales and different legal frameworks come into play here. For this purpose, the difference in cash flow of a pure PV system compared to a PV storage solution with a given annual return is evaluated and the maximum possible investment costs are calculated via a linear optimisation model, with the aim of minimizing the costs for electricity purchase, and a subsequent economic evaluation via the internal rate of return method. These investment costs are then compared to actual investment costs and necessary future cost reductions are analysed.
   The major new contribution of this paper to the topic of the economic viability of battery storage is to show exactly under which framework conditions (electricity price, feed-in remuneration, given rate of return) which investment costs may arise for a battery storage system in different use cases in addition to a photovoltaic system. So precisely the answer to the question of the prosumer "how much" a battery storage system may cost in order to generate a certain rate of return. In addition, to the authors' knowledge, no work has yet analysed how far the investment costs of battery storage systems would have to drop in order to be operated profitably under different conditions. The analysis in this paper is intended to provide prosumers with an indication of whether battery storage is cost-effective and a sense of the extent to which investment costs need to fall in order for an investment to be considered reasonable.

3. Hiesl, Ramsebner, and Haas (2021) - Modelling stochastic electricity demand of electric vehicles based on traffic surveys - The case of Austria

   This paper shows a method for estimating the actual demand profile of individual traffic at various detail levels. To provide optimal solutions for the interaction of EVs with the electricity grid it is important to design effective charging strategies.
   The core objective of this paper is to model driving patterns and electricity demand profiles of (future) electric mobility based on a survey on current mobility behaviour in Austria. Typical starting times, path lengths and trip purposes are considered. It also takes into account the differences in mobility behaviour between weekdays and Saturdays and Sundays. The main contribution of this paper lies in the transparent and straightforward modelling of load profiles, the easy calibration for different mobility behaviour, based on traffic surveys and in the high time resolution of the load profiles as a quarter of an hour. The proposed methodology makes it possible to generate demand

patterns for individual vehicles, different driving purposes but also for an aggregated average demand pattern including all driving purposes, which are scalable according to the share of EV's in a region or in a whole country, in this paper, demonstrated by the example of Austria. Furthermore, different regional parameters can be applied to analyse demand patterns in different seasons or to distinguish between urban and rural areas. In addition, various distributions of routes and travel times within the driving purposes, as well as the mix of driving purposes on weekdays and weekends are taken into account. By focusing on individual vehicles and driving purposes, a holistic bottom-up analysis can be carried out on an aggregated level.

1.3 Structure of the thesis

The dissertation is structured as follows. In Chapter two, a systemic overview of the economic efficiency of the storage technologies already mentioned in the introduction is given. Both long-term storage (pumped hydro, PtG methane, PtG H_2) and battery storage are analysed individually and compared with each other. The key parameters for economic viability are elaborated and also an outlook for the development of investment costs through technological learning until 2040 and thereby also on economic viability is given.
Chapter three shows the basic decentralised storage potential. The expansion targets for photovoltaics are put into context with the actual expansion rates and the decentralised PV storage potential in buildings is estimated. In addition, the modelling of the important components such as photovoltaics and battery storage will be discussed in more detail. The formulation of the optimisation model for the cost-optimal operation of decentralised storage forms the end of this chapter.
Chapter four focuses on the economic efficiency of decentralised battery home storage. Building on the findings in Chapter two, the question is answered of how the investment costs of battery storage systems would have to develop in different use cases in single-family buildings, multi-party buildings and for use across buildings in order to be operated in an economical manner under certain parameters. The methodology used for the linear optimisation model as well as the economic evaluation by the method of the internal rate of return are presented and the results for each use case are presented and interpreted.
Chapter five rounds off the analysis of decentralised mobile battery storage in the form of electric vehicles. It specifically addresses the stochastic modelling of driving profiles to estimate the driving and parking times for eight different driving purposes and thus the availability of the mobile storage. Based on this modeling of the load profile of the electric mobility, an optimisation is carried out to identify the additional savings through the use of the electric vehicle as storage for the PV surplus and to increase the economic efficiency of the overall system.
Chapter six concludes the thesis with a summary and interpretation and discussion of the results.

2 Economics of electricity storage - a systemic perspective

In general, economic research on electricity storage is still very limited. However, it has increased in recent years (Baumann, R. Schuster, and Moser, 2013; Geske and Green, 2020; Giulietti et al., 2018; Green and Vasilakos, 2012; López Prol and W.-P. Schill, 2021; Parra et al., 2017; Sauer et al., 2012; W.-P. Schill and Kemfert, 2011; W.-P. Schill and Zerrahn, 2018; Schmidt et al., 2019; Sioshansi et al., 2009; Sioshansi, 2011; Sterner and Stadler, 2019). Based on data from the literature and own investigations, the following sections compare the storage costs between different long-term storage systems such as pumped hydro, PtG hydrogen, PtG methane and short-term storage systems such as batteries. For this purpose, the method of calculating the storage costs and the input parameters such as investment costs, full-load hours, operation and maintenance (O&M) costs as well as the market environment are presented. In addition, an outlook on future storage costs is given.

2.1 Method of approach, technical and economic parameters of selected storage systems

The method of approach is based on cost calculation of different electricity storage technologies, see Ajanovic, Hiesl, and Haas (2020), Ajanovic and Haas (2018), Ajanovic (2008) and Haas and Ajanovic (2013). In the following equation it is described how the storage cost C_{STO} are calculated:

$$C_{STO} = \frac{\frac{IC * C.R.F + C_{O\&M}}{T} + C_E}{\eta_{STO}} \tag{2.1}$$

with

$$\begin{aligned}
C_{STO} &= \text{Cost of storing a kWh of electricity e.g. in a pumped hydro storage or a battery } [\frac{€}{kWh}] \\
IC &= \text{Investment costs of a storage } [€] \\
C.R.F. &= \text{Capital recovery factor } [\frac{1}{a}] \\
C_{O\&M} &= \text{Operation and maintenance costs } [\frac{€}{a}] \\
T &= \text{Full-load hours } [\frac{h}{a}] \\
C_E &= \text{Costs of electricity } [\frac{€}{kWh}] \\
\eta_{STO} &= \text{Efficiency of storage}
\end{aligned}$$

Equation 2.1 shows the cost of storing one kWh for newly built plants also including fixed costs. Equation 2.2 shows the definition of the C.R.F. and how it is calculated depending on the depreciation time (see Table 2.2) and the interest rate (assumed 5%).

$$C.R.F = \frac{z * (1+z)^n}{(1+z)^n - 1} \tag{2.2}$$

with

$$n = \text{Depreciation time [a]}$$

$$z = \text{Interest rate (in decimal points, e.g. 0.05)}$$

The interest rate of 5% is thus roughly in the middle of the range as also outlined in Haas, Ajanovic, et al. (2021) while Matute, Yusta, and Correas (2019) also outline an interest rate of 5%. In principle, however, the interest rate can vary depending on the type of investment, the investment risk and the composition of equity and debt capital, see also Roth et al. (2021). Even though Roth et al. (2021) does not directly deal with the financing of storage, the range of possible values is nevertheless shown. For better comparability, however, the same interest rate was used for the calculation of all technologies presented here. In addition, the influence of the interest rate is analysed in more detail in the sensitivity analysis in Chapter 4. Table 2.1 provides a summary of the assumptions for the technical parameters used in the following investigations, and Table 2.2 documents the numbers applied in the economic analysis.

Table 2.1: Summary of assumptions for the technical parameters (Source: all numbers are from own investigations, based on the year 2018 for efficiencies, efficiencies for storing electricity, no reverse transformation)

Type of storage	Capacity		Efficiency	Full-load hours
	(MW)	(kWh)		(h/a)
PHS	350		0.82	2000
PtG-H2 centralised	10		0.7	2000
PtG-CH4 centralised	10		0.56	2000
Battery small	0.0025	5	0.88	500
Battery medium	0.015	30	0.9	700
Battery large	0.5	1000	0.92	900

Table 2.2: Summary of assumptions for the economic analysis (Source: All costs of 2018, own investigations)

Type of storage	Investment costs		O&M costs	Depreciation
	(€/kW)	(€/kWh)	(€/(kW a)	(a)
PHS	1200		5	30
PtG-H2 centralised	1550		25	20
PtG-CH4 centralised	2600		35	20
Battery small	2400[1]	1200	20	12
Battery medium	1880[1]	940	15	12
Battery large	1120[1]	560	10	12

[1] calculated from $(\frac{€}{kWh})$ assuming 0.5 kW/kWh

In order to be able to estimate future investment costs and the economic feasibility of different storage technologies, the method of technological learning (TL) is applied. TL can be quantified by so-called experience or learning rates (McDonald and Schrattenholzer, 2001; Wene, 2000; Wiesenthal et al., 2012). Equation 2.3 is used to describe such a relationship using a learning rate b:

$$IC_{New}(x_t) = IC(x_{t0}) * (\frac{x_t}{x_{t_0}})^{-b} \tag{2.3}$$

with

$IC_{New}(x_t)$ = Investment costs of the technology at time t [€]
$IC(x_{t_0})$ = Investment costs of the technology at time t_0 [€]
x = Cumulated produced quantity of a specific storage type at time t and t_0
b = Learning rate

The method of technological learning is used in section 2.3 when calculating the economic perspective up to the year 2040.

2.2 Economics of selected storage systems and market parameters

The total costs of storing electricity for different storage technologies (as of 2018) in new plants or devices and the amounts of capital costs, O&M costs, and energy costs, are depicted in Figure 2.1.

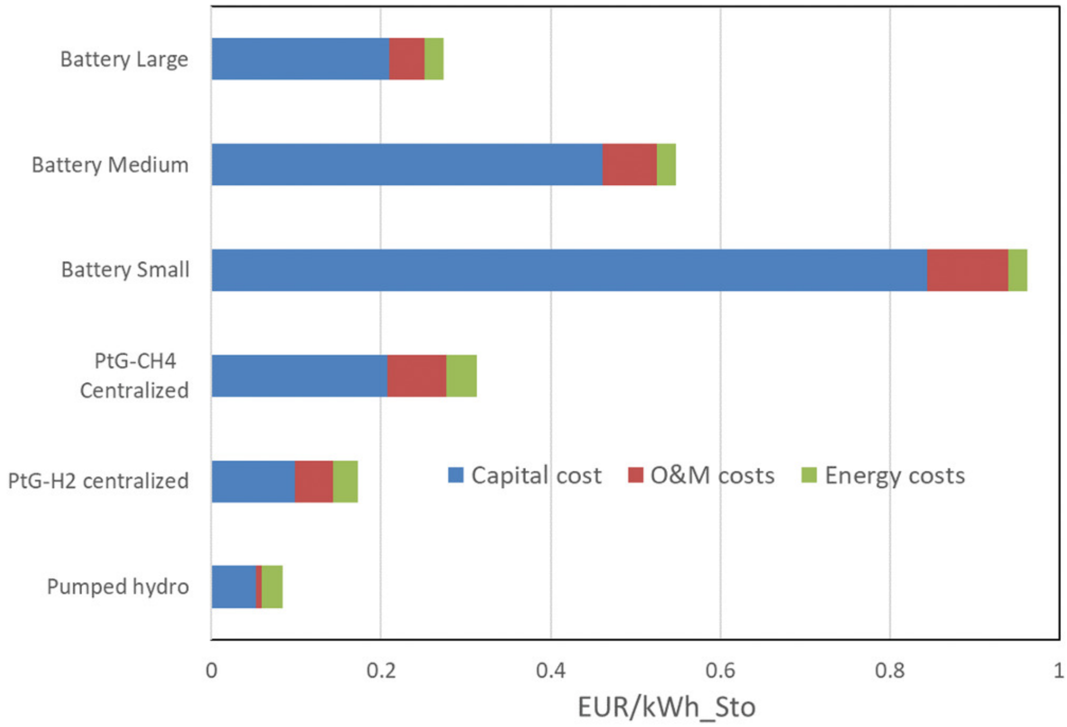


Figure 2.1: Costs of storing electricity for different technologies (as of 2018) for newly constructed plants including storage efficiency and the corresponding amounts of capital costs, O&M costs, and energy costs: Source: own calculation & illustration

It can be clearly seen that there is a huge range of total costs – between 0.08 €/kWh and almost 1 €/kWh and in addition, quite different shares of capital, energy, and O&M costs. Whether a market-oriented storage is economically feasible decides the so-called price spread in the electricity market and the number of overall operating hours, the full-load hours[2]. The

[2]This analysis does not address how the application of e.g. pumped hydro storage plants for balancing services would affect the economics of the storage system.

importance of full-load hours for the economic feasibility of storage facilities has already been discussed (Ajanovic, Hiesl, and Haas, 2020; Ajanovic and Haas, 2019; Ajanovic and Haas, 2018; Ajanovic, 2008). Along with the issue of the price spread this is the Alpha and Omega in every discussion on the future prospects of centralised storage as a market-based option from an economic point-of-view.Figure 2.2 depicts the sensitivity of the capital costs on FLH per year. For example, at 500 h/a capital costs are four times higher than at 2000 h/a.

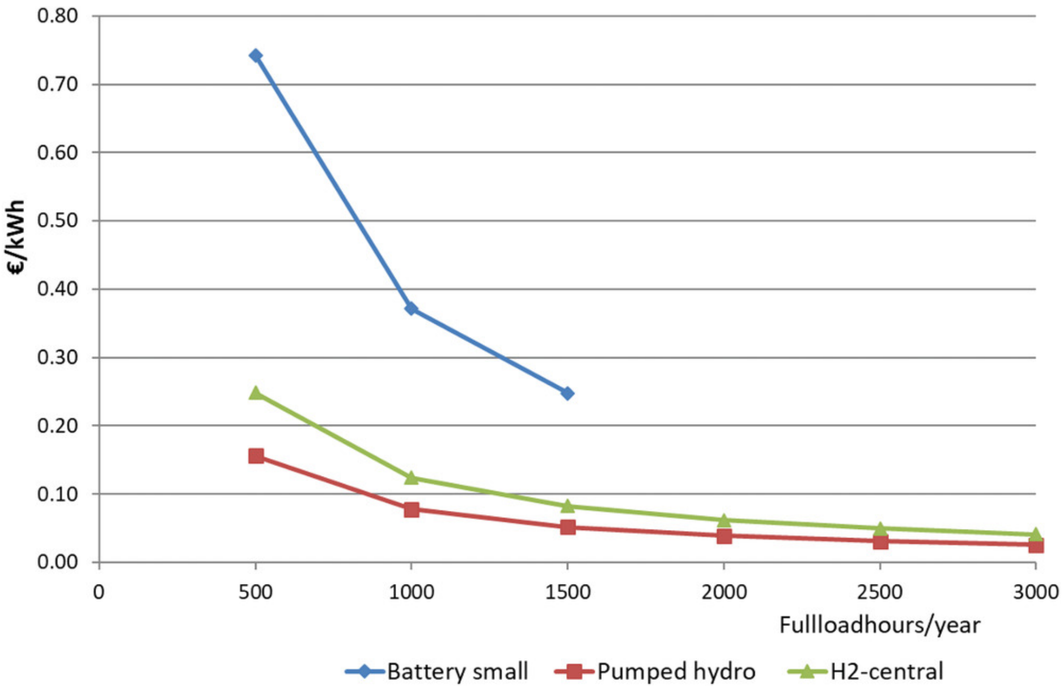


Figure 2.2: Costs of storing electricity for selected technologies depending on the full-load hours per year

The most important results of our investigations are as follows: the first major problem of the economics of storages is low FLH (see Figure 2.2). Currently, about 2000 hours per year is considered to be the minimum to operate the storage facilities economically.

As Figure 2.2 shows costs at current price spreads of about 0.03–0.06 €/kWh in the Western European day-ahead markets (range between 2010 and 2020) for 2000 FLH no new plant for any type of storage is economically attractive.

A second reason for limited attractiveness of long-term storages are competition with demand response options, demand-side management, and grid extension. Moreover, decentralised battery storages might also compete. The costs of the latter will not decline significantly faster but they will compete on end-user price level, which is (and will remain) remarkably higher.

An additional reason for the unfavorable economic conditions of long-term storage is the "self-cannibalism" of storages in electricity markets. This means that every additional storage has lower FLH then the one before and, in addition reduces the price spread and, thus, its own economic performance (Ehlers, 2011). In this section, the economics of storage are analysed more in detail. The economic analysis essentially focuses on three technologies: pumped hydro storage plants, hydrogen as market-based storage systems and batteries as an example of decentralised installation to increase self-consumption in households.

As already explained above from the storage operators point of view in a market, the objective is to maximise profit, that is to say the difference between revenues and costs. While the revenues simply result from the sum of the products ‘price times quantity sold’, the costs are more complex and encompass all terms of Equation 2.1.

From a battery storage operator’s point of view, the objective is also to maximise profit, but it will now be calculated in a different way: The revenues are simply the product of own-used electricity times and the end user’s electricity price, the costs encompass the capital as well as the operation and maintenance costs.

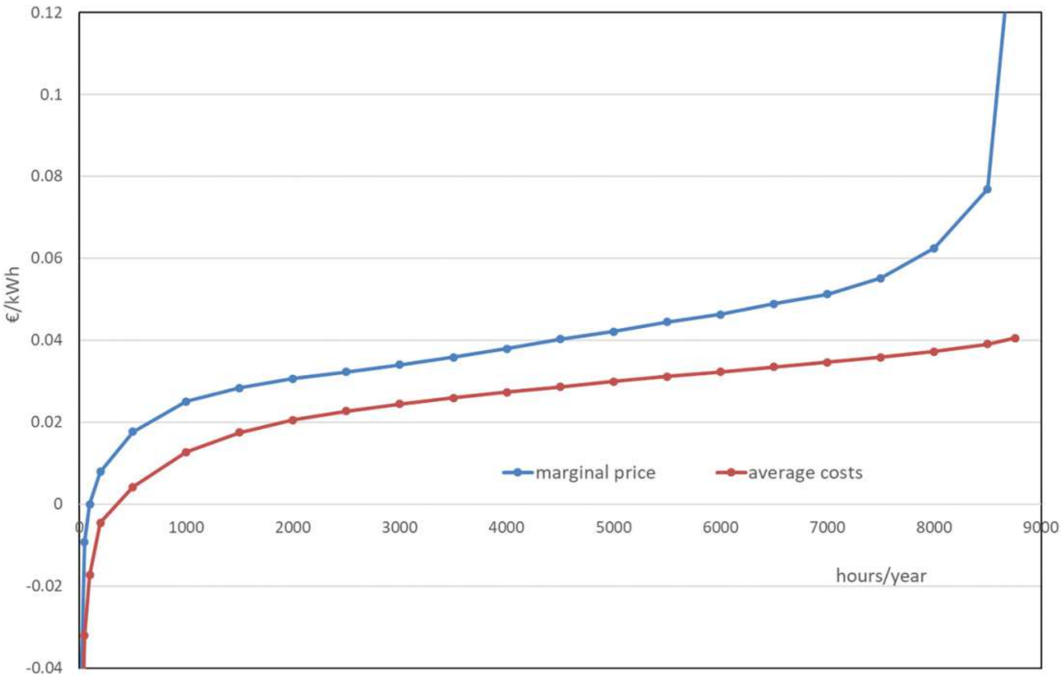


Figure 2.3: Classified frequency of hourly marginal and average prices of electricity in the joint Austrian-German wholesale electricity market over a year for the example of the average of 2016 and 2017

As seen from Equation 2.1, the costs of electricity are an important parameter for calculating the total storage costs. In this context, and also used for the following calculations, Figure 2.3) shows the classified frequency of hourly marginal and average prices for electricity in Austria and Germany for the annual average of 2016 and 2017. The marginal prices represent the actual prices on the day-ahead market, and the average prices show the average of the prices below a certain number of FLH. It can be seen that, for example, the average electricity price is about 0.02 €/kWh for about 2000 FLH (Figure 2.2)) used for the further calculations.

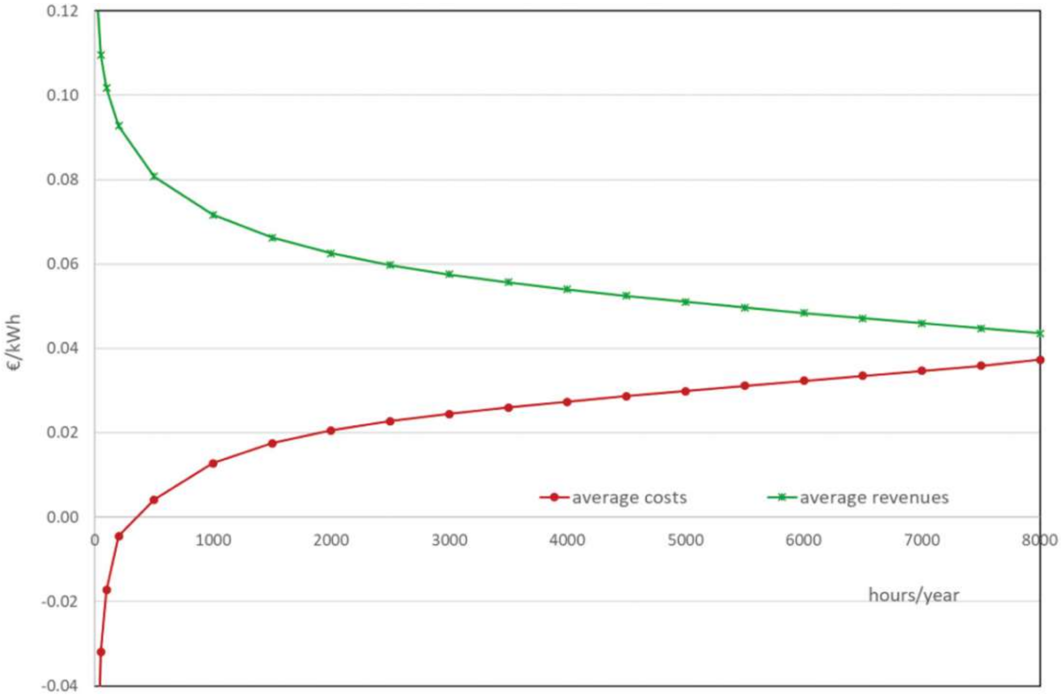


Figure 2.4: Costs and revenues (average prices of electricity in the joint Austrian–German wholesale electricity market over a year for the example of the average of 2016 and 2017) in an electricity market if there are no storage losses

Derived from Figure 2.2, in Figure 2.4 the average costs and also the revenues (average prices of electricity in the wholesale electricity market over a year for the example of the average of 2016 and 2017) in the Austrian–German electricity market are shown, not considering storage losses.

2.2.1 Pumped hydro storage

The most widely used type of storage for electricity is pumped hydro storage (PHS). However, in recent years their economic performance has become challenged due to new market conditions caused mainly by the increases in wind and photovoltaic generation. In addition, a discussion on grid fees has emerged. In some European countries PHS has to pay for using the grid, whereas in others such as Austria they do not. This issue is shortly analysed below.

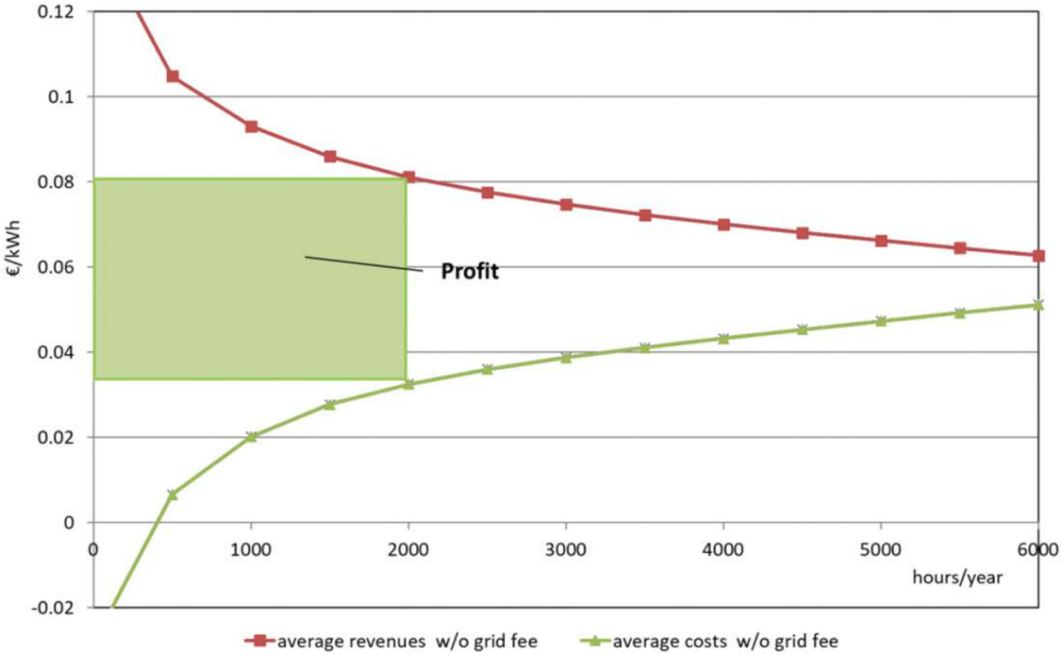


Figure 2.5: Costs of existing hydro storage depending on the annual full-load hours without a grid fee

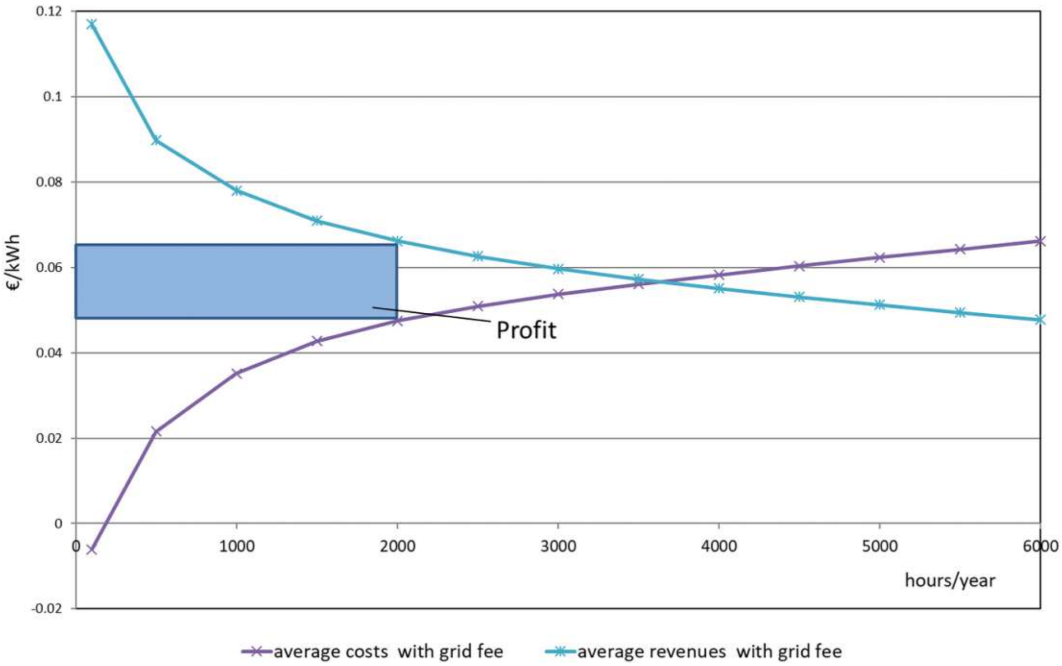


Figure 2.6: Costs of existing hydro storage depending on annual full-load hours with a grid fee

In Figure 2.5 and 2.6 the costs of PHS, depending on the annual FLH with and without a grid fee, are depicted (electricity costs as shown in Figure 2.3). It can be seen clearly that only without grid fees they can be operated at reasonable number of FLH per year. Figure 2.5 shows the possible total profit without grid fees at 2000 FLH per year whereas in Figure 2.6 the possible profit is shown for a hypothetical grid fee of 0.015 €/kWh. The total costs of new pumped hydro storage without grid fee are shown in Figure 2.7 depending on the annual FLH. The major finding from this figure is that if there is no grid fee, these storage could be economically between about 2500 and 4500 FLH. In this range the average revenues from selling electricity from hydro storage are in about the same range as the total costs consisting of the capital, O&M, and the energy costs.

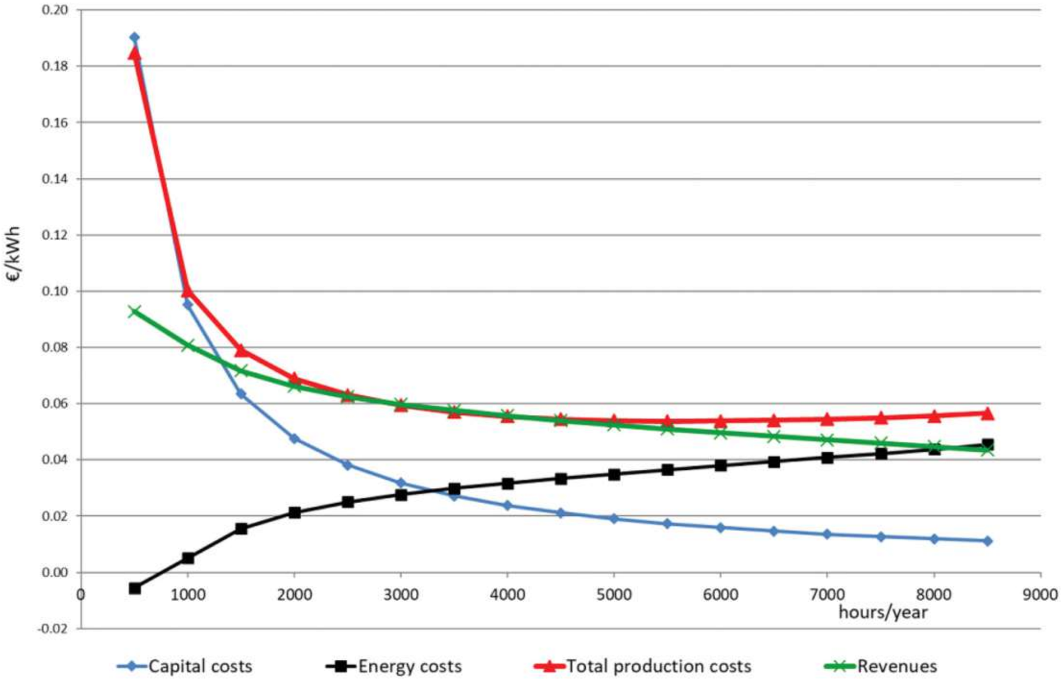


Figure 2.7: Total costs and revenues of new pumped hydro storage depending on the full-load hours per year

2.2.2 Hydrogen as storage

Hydrogen can be used as an energy carrier, as well as a storage for excess electricity from RES. It can be produced by electrolyses and used as long-term electricity storage. Today, mainly small systems with capacities below 500 kW are in operation. However, there are already plans for constructing plants with capacity of 10 MW and beyond (May, Davidson, and Monahov, 2018). This would reduce the specific hydrogen generation costs remarkably, mainly because of economies-of-scale. However, there are also some challenges in choosing the right location for the electrolyser. Since electrolysis also generates a non-negligible amount of heat, it should be ensured that this heat can also be used for efficient utilisation. Another limiting technical factor is the possibility of dynamic use of the electrolyser with fluctuating generation such as PV and wind.
Finally, it is important to find an optimal balance between investment costs of electrolyser (depending on the plant size) and possible full-load-hours per year. As an example, Figure 2.8 shows the cost of hydrogen generation from a large centralised electrolyser system (including the costs of hydrogen storage) depending on the full-load-hours and the costs of electricity

used, according to Figure 2.3 and Table 2.2. Acceptable low costs of hydrogen of about 0.08–0.09 €/kWh could be reached only from about 4000 FLH per year upwards.

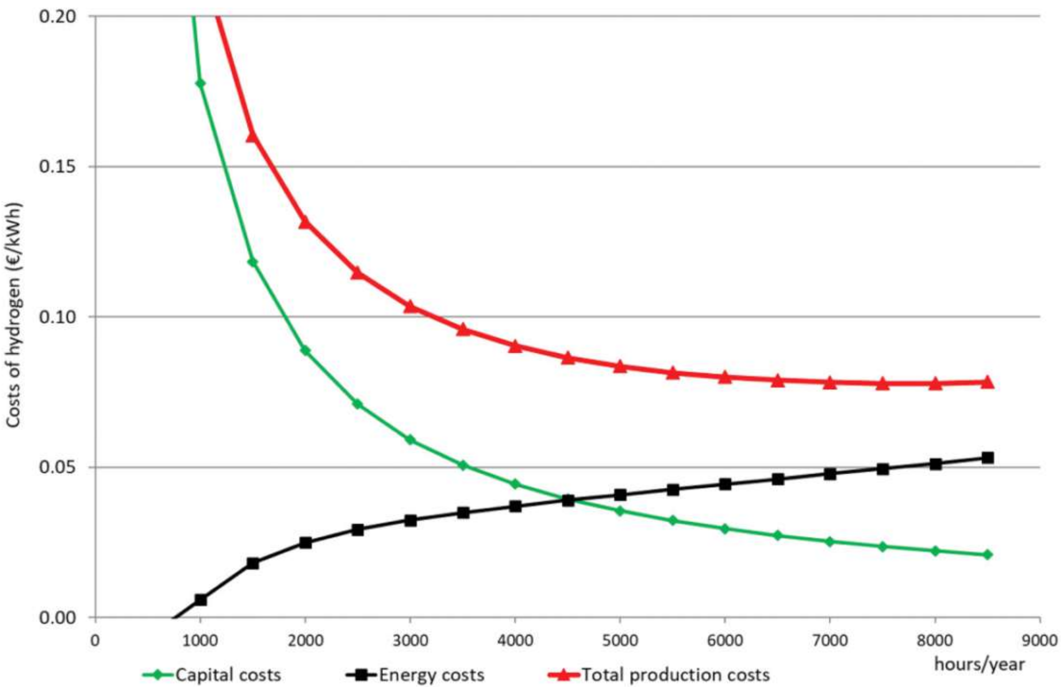


Figure 2.8: The cost of hydrogen from a large electrolyser system (10 MW_{Ele}) depending on the number of full-load hours

2.2.3 Battery storage

As already outlined in the previous sections, decentralised battery storage might also play a role in a future electricity system. Their costs will not decline significantly faster than those of long-term storage but they will compete on end-user price level which is (and will remain) remarkably higher.

Different applications naturally require different types of storage. Looking at the worldwide expansion of storage capacity, one thing in particular becomes clear. Lithium-based technologies dominate the storage market, excluding pumped storage technologies. With a share of 88% of worldwide expansion, lithium-based technologies were clearly in the lead. Basically, there are many different battery types with different cell types, but as it can be seen from Figure 2.9, only a few have played an important role in recent years. These technologies are as follows:

- Lithium-based batteries
- Lead-acid batteries
- Flow batteries
- Sodium sulfur batteries

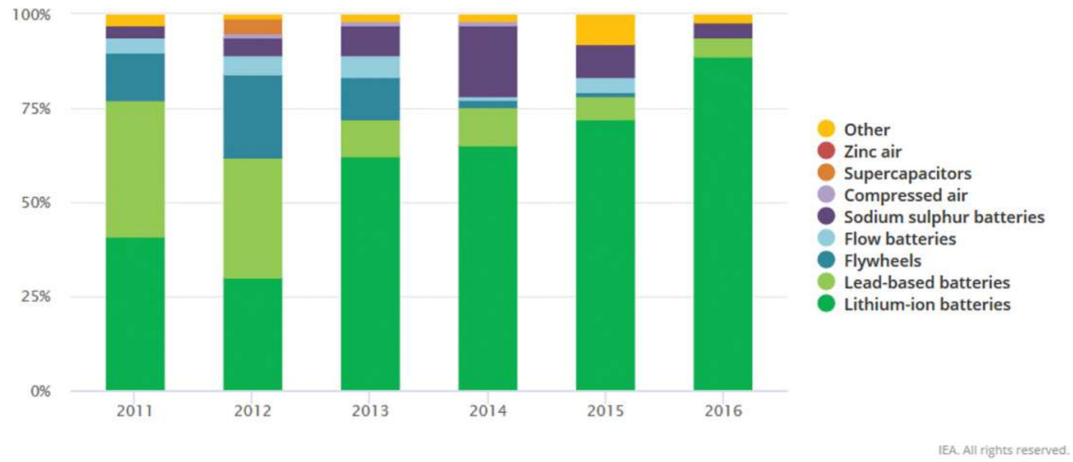


Figure 2.9: Technology mix in percent in new storage installations per year from 2011 to 2016 excluding pumped hydro. Source: Munuera and Alberto, 2019

Most decentralised stationary battery storage systems are either lead-based or lithium-based systems, but lithium-based systems clearly dominate 'behind the meter' as well.

The lead acid battery is one of the most proven and widely used battery in many applications. This battery is known as a classic car battery and most uninterruptible power supply (UPS) systems are still based on this cell type. Lead-acid batteries are inexpensive, but also have low cycle stability, especially at high discharge depths. This fact, as well as the fact that lithium-based batteries have significantly higher energy and power densities, has also made them interesting for the prosumer market in recent years (Mitchel and Waters, 2017).

Of specific interest is the development of the storage costs over time. Especially for batteries in the last decade significant cost reductions has been achieved as seen from Figure 2.10. Driven by the construction of immense capacities for battery manufacturing facilities for e-mobility, prices have fallen significantly, especially for battery modules.

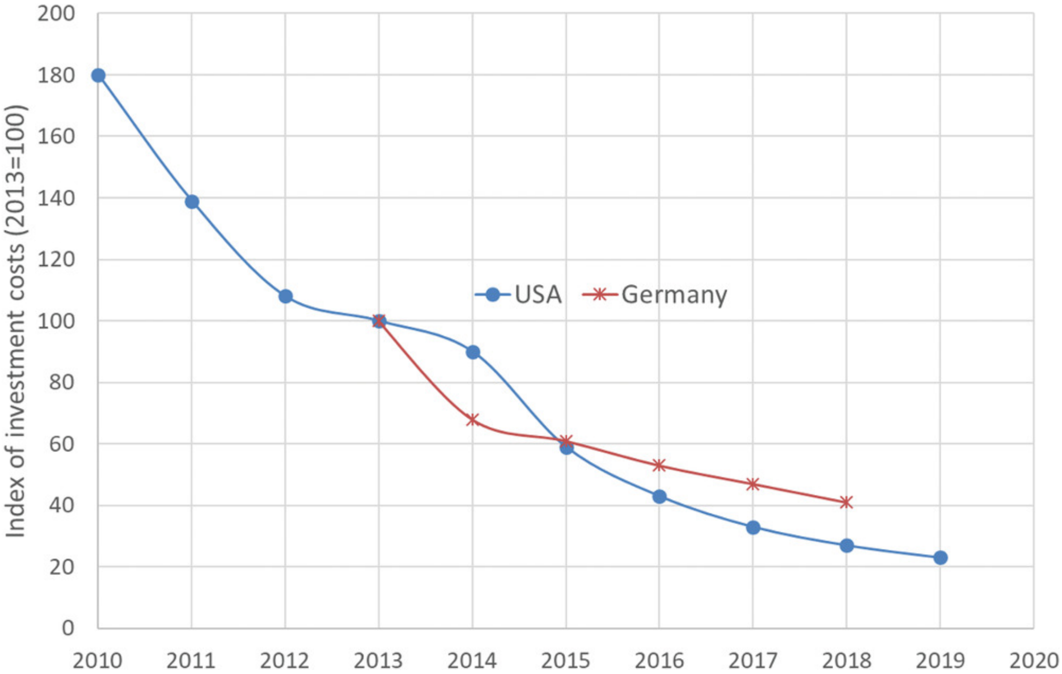


Figure 2.10: Recent developments of battery investment costs in Germany and the USA (EES 2019 and Bloomberg 2019)

Even if electric mobility can certainly be considered as a major driver or enabler for battery storage systems in general, developments in storage costs in the automotive sector cannot always be transferred one-to-one to stationary operation. It strongly depends on what is directly considered in the costs (cells, packaging, charge control, thermal management, installation, inverter, etc.) and what is left out (OECD/IEA, 2011; EASE/EERA, 2013). Looking at the average end-user costs of AC-coupled lithium batteries in recent years for the German-Austrian market, it can clearly be seen – see Figure 2.11 – that battery storage costs have fallen significantly, especially in the area of typical sizes for single-family buildings and smaller properties with an energetically optimal battery capacity between 1 and 7 kWh. This is exactly in line with the findings that capacities behind the meter have been expanded in recent years (EV, 2019).

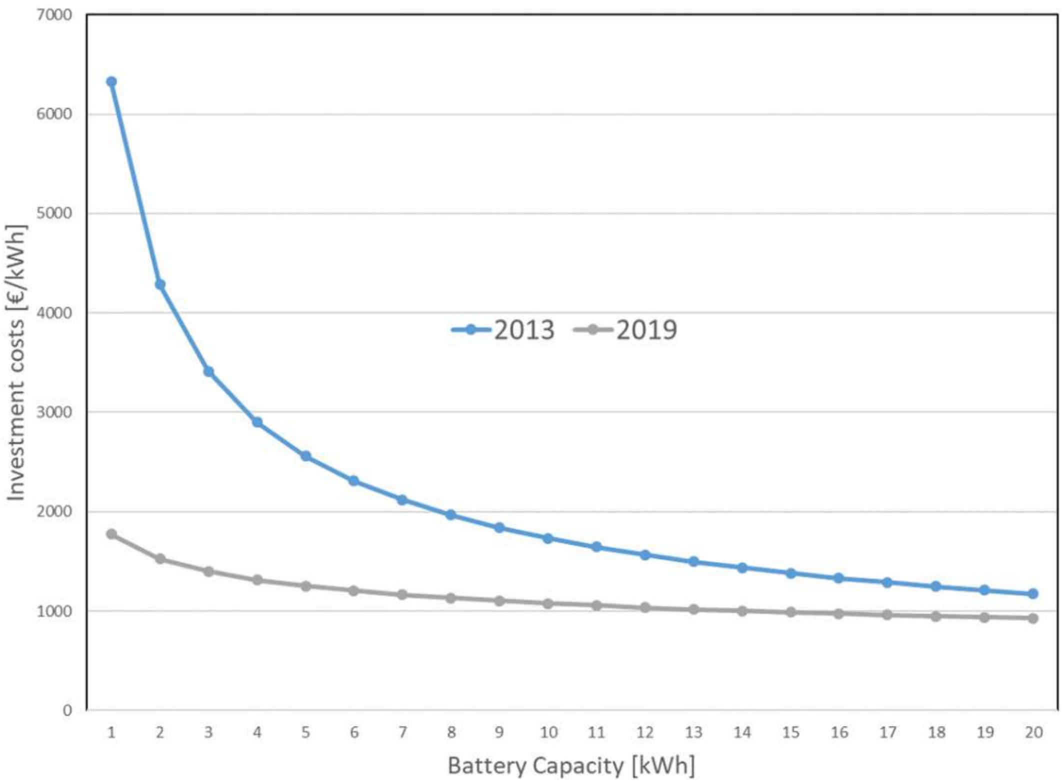


Figure 2.11: Economies-of-scale of battery storage for 2013 versus 2019 (Source: Own calculations, data based on C.A.R.M.E.N EV, 2019

This large cost degression in the area of typical household capacities (Figure 2.11) can be attributed primarily to the fact that demand in decentralised battery storage systems has increased sharply in recent years and competition has developed between different manufacturers. This is also the area with the most available data points. The demand for storage solutions from 15 kWh upwards is unlikely to be as large, so that the number of system solutions on offer is also no longer as large and therefore the cost degression is hardly noticeable.

2.3 Economic perspective until 2040

The current economic performance of all investigated storage options shows that they are hardly competitive, see the situation in 2018 in Figure 2.2. However, for most storage technologies – except pumped hydro – in the next decades remarkable reductions in investment costs are expected mainly due to technological learning (TL), compare Section 2.3. Therefore the prospects of different storage types in the next decades up to 2040 are analysed. Figure 2.12 depicts the possible development of investment costs of different long-term storage options for electricity compared to batteries, with average learning rates of 20% (V. W.-P. Schill, Zerrahn, and Kemfert, 2018). The quantities for the different technologies are modeled based on work conducted by the International Energy Agency (Agency and Economic Co-operation and Development, 2000).

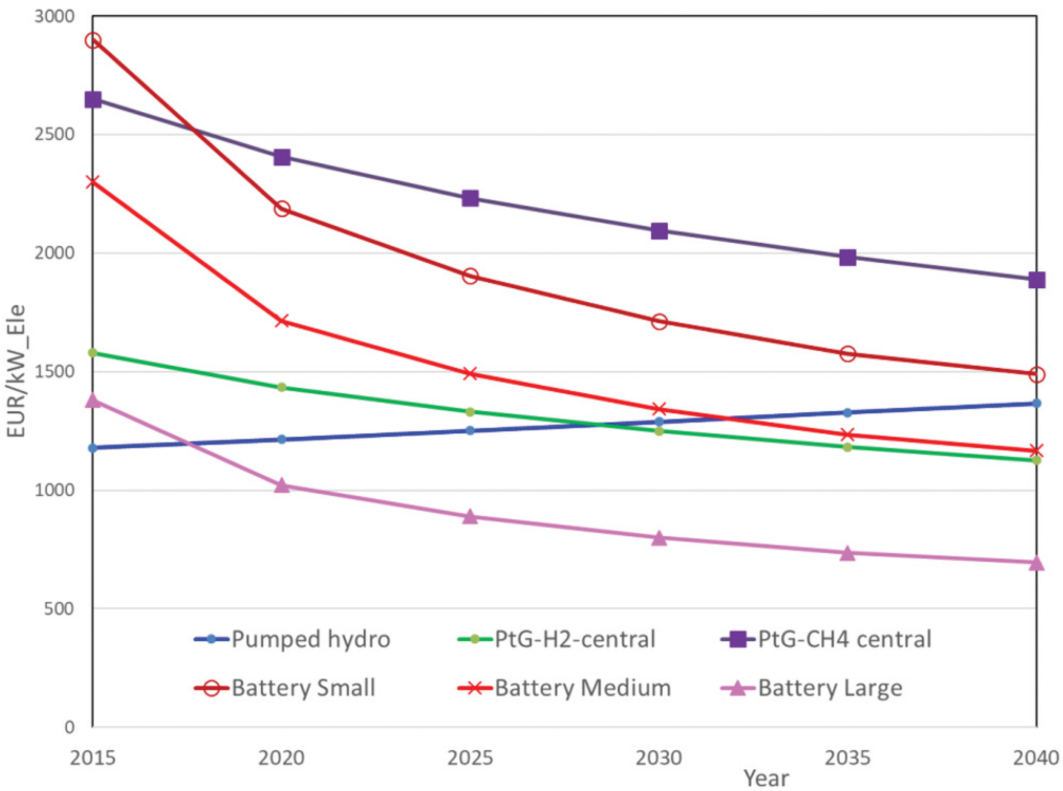


Figure 2.12: Future perspectives of the investment cost development for different long-term storage types compared to batteries up to 2040 (with learning rates of 20% except for pumped hydro).

As can be seen from Figure 2.12 in the period up to 2040 it is to be expected that the investment costs of the PtG technologies will fall, mainly due to learning effects. For pumped hydro storage further TL is not considered, because their costs are more likely to continue to rise, mainly due to the lack of sites with reasonable costs and increasing lack of acceptance.

Applying this learning rate to electrolysers and methane plants their investment costs will decrease by about 30%, applying it to batteries they will even half. The major reason for this difference is that larger quantities x (Equation 2.3) are expected to be deployed for batteries in shorter time frames.

In the last 10 years the price spreads in the Western European day-ahead markets has been between about 0.03 and 0.06 €/kWh for 2000 FLH per year.

Regarding the storage costs of pumped hydro and batteries respectively the production costs of hydrogen and methane by 2040 under favorable learning conditions (20% learning rates) and the costs of hydrogen and methane for 2000 FLH per year will be between 0.08 €/kWh and 0.13 €/kWh. For the same number of FLH the price spread will be at the utmost about 0.10 €/kWh. This explains why it will become hard for storage to compete in day-ahead or intraday electricity markets.

Regarding batteries competing with end user prices: as said they compete with end user electricity prices (except the large ones which are likely to be implemented at grid level) which are currently on average about 0.20 €/kWh in Europe, the highest being in Germany and Denmark with about 0.30 €/kWh. As seen from Figure 2.13, in these cases it will be difficult for batteries to compete.

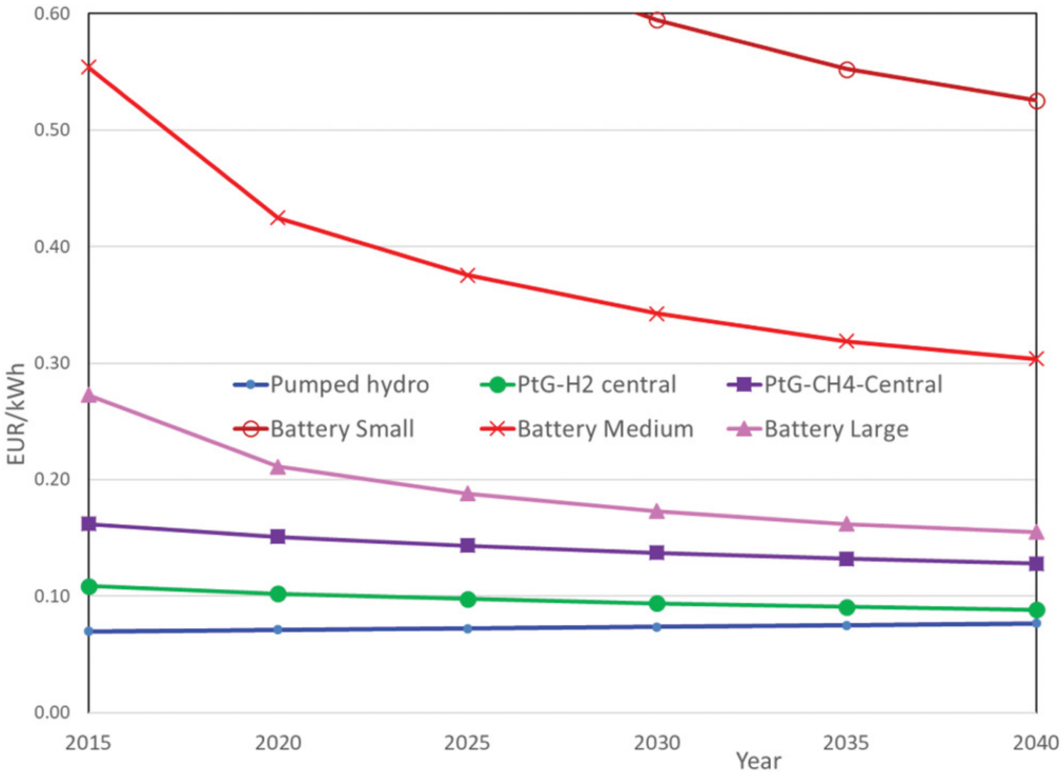


Figure 2.13: Development of the storage costs of several technologies for long-term storage of electricity vs batteries over time up to 2040 (full-load hours as documented in Table 2.1).

3 Decentralised PV-storage potentials in Austria & basic model framework

The following chapters of this thesis will now take a closer look at the situation of decentralised photovoltaic generation and the associated possibility of storing the surplus via stationary battery storage as well as via electric mobility. In particular, the situation in Austria will be discussed, as the legal framework for the handling of self-consumption and storage in single-family buildings, multi-apartment buildings and also across buildings is different in each EU country.
Furthermore, in the next sections, the calculation and modelling of the decentralised photovoltaic output, the linear PV-storage optimisation model, which answers the question of the cost-optimal operation of the decentralised battery storage as well as the cost-optimal charging of the electric vehicles, will be discussed in more detail. In addition, the basic characteristics of the battery storage modelling and its characteristics are discussed.

3.1 PV expansion potential on buildings

In order to achieve the climate targets, especially in the electricity sector, enormous efforts are necessary by 2030. In Austria, the expansion of renewable energies is defined by the Renewable Energy Expansion Act (EAG), compare Österreich (2022). It foresees an expansion of 27 TWh of generation by 2030, with 11 TWh coming from photovoltaics only. If the past rate of capacity addition is analysed, it becomes clear that the rate of expansion needs to be accelerated significantly, see Figure3.1.

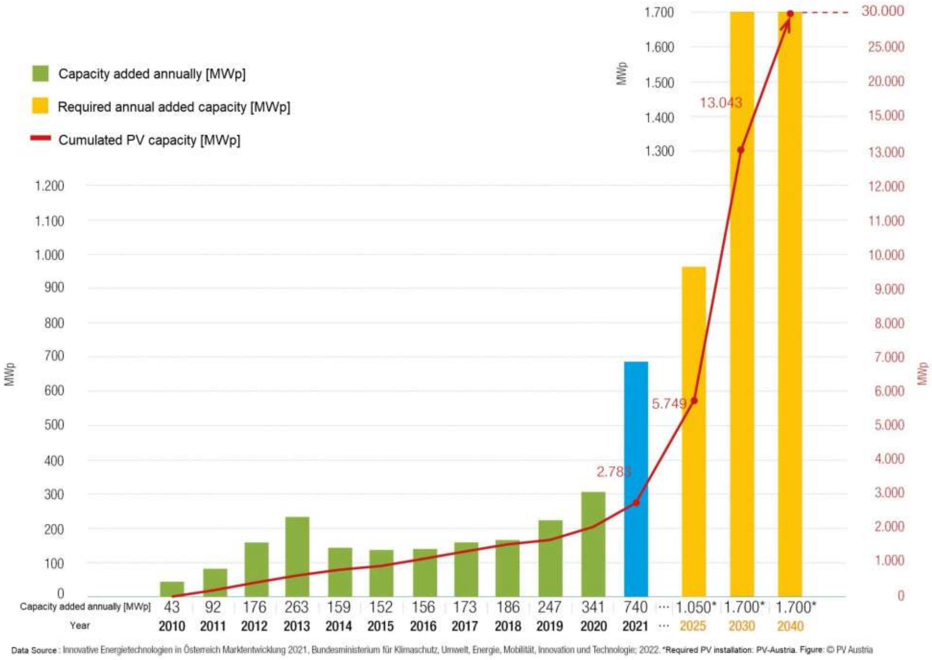


Figure 3.1: Annual and necessary PV capacity additions in Austria [MWp]. Source: PV-Austria

Part of this will have to be achieved by decentralised PV systems, either on buildings or integrated into buildings, in order to avoid additional land sealing and to consume the electricity where it is generated. An approach to estimate the potential of photovoltaics on buildings was developed by the International Energy Agency (IEA) (Gutschner et al., 2002). This approach calculates the potential area for photovoltaics on roofs and facades based on a ground area of one square metre. Architectural limitations as well as restrictions due to shading and unsuitable surfaces are considered, see Table 3.1.

Table 3.1: Calculation of PV surface potentials on buildings

	Roof		Facade
Ground floor area	1 m²	Basic BIPV potential in relative terms	1 m²
Gross area	1.2 m²	Ratio 'gross area/ground floor area'	1.5 m²
	60%	Suitable building envelope parts taking into account construction, historical and shading elements, including vandalism factor	20%
Architecturally suitable area	0.72 m²	Ratio 'architecturally suitable area / ground floor area'	0.3 m²
	55%	Suitable building envelope parts taking into account sufficient solar yield	50%
Solar yield and architecturally suitable area	0.3 m²	Ratio ``solar architecturally suitable area / ground floor area'' (utilisation factor)	0.15 m²

One square metre of floor area therefore results in a potential roof area of 0.3 m^2 and in a potential of 0.15 m^2 for façades.
To calculate the photovoltaic potential on Austrian buildings, an available per capita building ground area of 42 m^2 was applied (Gutschner et al., 2002). The total area potential was then estimated using the data of the total population of 8.9 million (Austria, 2022). Based on an average PV efficiency of 15% and an average irradiation of 1000 W/m^2, the following capacity and generation potentials are calculated, see Table 3.2. The calculation of the average PV output is shown again graphically, see Figure 3.2:

Figure 3.2: Determination of BIPV potential

The total available surface potential according to this method of calculation is about 206 km^2. The overall potential for photovoltaic generation on roofs and facades in Austria thus amounts to around 30.84 TWh. If one compares this figure with the 11 TWh expansion target by 2030, this figure could be achieved with about one third of all available surfaces. In reality, however, this will be difficult to implement in the next few years, as many surfaces are difficult to access, not all of them can be connected by the grid operator and, for example, unanimity must be reached in multi-party buildings. In other words, the dependence on private owners is relatively high. Therefore, a mix of ground-mounted photovoltaic systems and photovoltaic systems on buildings will be needed in the future. Assuming a rate of self-consumption (without storage, applicable mainly to average households) of 30%, this would result in about 21.6 TWh, which can either simply be fed into the grid, or traded or stored directly.

Table 3.2: Calculation of PV surface potentials on buildings

	Rooftop	Facade	Total
PV surface potential [km²]	150	56	206
PV capacity potential [MWp]	22,428	8,410	30,838
PV generation potential [TWh]	22.43	8.41	30.84
Assumed self-consumption [TWh]	6.73	2.52	9.25
Available for storage, trading, feed-in [TWh]	15.70	5.89	21.59

The estimation of the future photovoltaic potential may have to be adjusted slightly, as we can expect less ground are per inhabitant and, on the other hand, higher buildings will have to be built due to increasing land sealing. Therefore, the ratio of roof to facade areas will also shift to some extent. In principle, however, this estimate is a good indication of the development of photovoltaic potential on buildings. In addition to the expansion of PV, the infrastructure must also be prepared for the massive expansion of renewable energy, especially photovoltaics, as other neighbouring countries such as the Czech Republic and Germany will also massively expand PV. However, this also means that in times of PV surplus, it is not always possible to export and the surplus must then either be stored, curtailed or used in other sectors via sector coupling.

3.2 Modelling photovoltaic output

To determine the share of electricity that can be stored, the amount of energy generated by photovoltaics must first be calculated. In order to be able to determine the rate of self-consumption and the rate of self-sufficiency with high temporal resolution, both the load profile and the photovoltaic generation data must be available in the same resolution. In the following chapters, a temporal resolution of a quarter of an hour is used, which is why the PV output data are also generated in this temporal resolution.
Based on measured data of global horizontal irradiation and ambient temperature of the year 2010, the PV-generation is, depending on direction, installation angle and location, calculated. The global horizontal irradiation is defined in Equation 3.4

$$G_h = G_{bh} + G_{dh} \tag{3.4}$$

where G_{bh} is defined as direct horizontal irradiation and G_{dh} is defined as diffuse horizontal irradiation. With the degree of clarity $k_{th} = \frac{G_h}{G_{TOA}}$, whereby G_h and G_{TOA} are the global horizontal irradiation and the extraterrestrial irradiation (top of atmosphere), the segmentation into diffuse- and direct irradiation is done as outlined in Erbs, Klein, and Duffie (1982), compare Equation 3.5 to Equation 3.7

$$G_{dh} = G_h * (1 - 0.09 * k_{th}) \ for \ k_{th} \leq 0.22 \tag{3.5}$$

$$G_{dh} = G_h * (0.9511 - 0.1604 * k_{th} + 4.388 * k_{th}^2 - 16.638 * k_{th}^3 * 12.336 * k_{th}^4) \ for \ 0.22 \leq k_{th} \leq 0.8 \tag{3.6}$$

$$G_{dh} = G_h * 0.165 \ for \ k_{th} \leq 0.8 \tag{3.7}$$

The irradiation at any angle is calculated by an isotropic diffuse radiation model specified in Liu and Jordan (1960) and which is not further discussed here. Basically, direct, diffuse and also reflected irradiation on the inclined surface are considered.
The power-output of the photovoltaic modules is then derived with the help of a model revised by Huld et al. (2010) which only depends on the in-plane irradiance G_{mod} and the module temperature, see Equation 3.8 and Equation 3.9:

$$P(G, T_{mod}) = P_{stc} * \frac{G_{mod}}{G_{stc}} * \eta_{rel}(G', T') \tag{3.8}$$

P_{STC} is the power output at standard test conditions ($G_{STC} = 1000 \frac{W}{m^2}$ and $T_{STC} = 25°C$). The relative efficiency is calculated as:

$$\eta_{rel}(G', T') = 1 + k_1 * ln(G') + k_2 * (ln(G'))^2 + T' * (k_3 + k_4 * ln(G') + k_5 * (ln(G))^2) + k_6 * T'^2 \tag{3.9}$$

G' and T' are normalised parameters to STC Values: $G' = \frac{G_{mod}}{G_{STC}}$, $T' = T_{mod} - T_{STC}$. The parameters k_1 to k_6 are technological parameters from different module types. The module temperature can be estimated from the ambient temperature: $T_{mod} = T_a + c * G_{mod}$ whereby c is the temperature coefficient and depends on the way the modules are mounted, compare Huld et al. (2010) and Skoplaki and Palyvos (2009).

3.3 Modelling battery parameters for the use as decentralised or mobile storage

Due to the simple modular expandability, battery storage systems are a good solution for decentralised use. In recent years, lithium-based battery storage systems have become the most popular choice for decentralised use, compare Hiesl, Ajanovic, and Haas (2020) , also due to the increasing market caused by e-mobility. Lithium batteries can be charged and discharged with an efficiency of about 95%, which corresponds to an overall efficiency of about 90%. This efficiency level is also assumed for the following analyses, compare Dufo-López and Bernal-Agustín (2015) and Hameer and van Niekerk (2015).

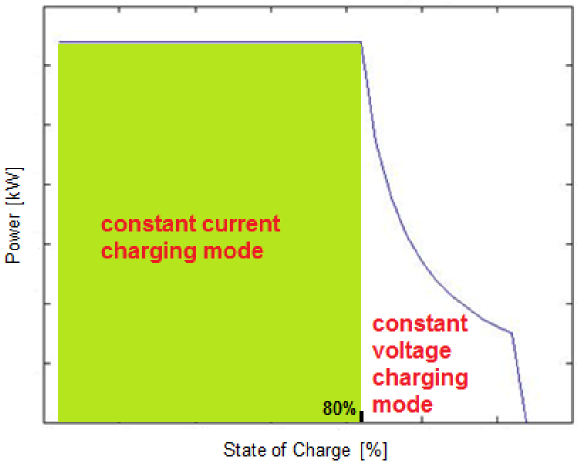


Figure 3.3: Typical charging strategy of a Lithium battery

A. Schuster (2008) points out that lithium batteries are mainly charged with an IUa charging strategy: First, the battery is charged with constant current until the state of charge reaches the value of 80%. Secondly, the battery is charged with constant voltage until the state of charge reaches 100%, see Figure 3.3. Due to the minimal change in cell voltage in the first phase, the charging power can also be assumed to be constant. The charging power can be different for different buildings and for different types of integration like alternating current (AC) or direct current (DC) or even for the use in electric vehicles. This charging curve is also assumed in the model to obtain a charging curve as realistic as possible. Battery storage systems differ in terms of maximum charging power, depth of discharge, cycle stability, efficiency and the integration into the electricity system, see EV (2019). One of the most important parameters besides the efficiency of the storage unit is the depth of discharge (DoD) and the correlation between DoD and the number of full cycles. Basically, the deeper a storage system is discharged, the fewer full cycles (cycle of full discharge and charge) the battery storage system can complete and the sooner it has to be replaced.

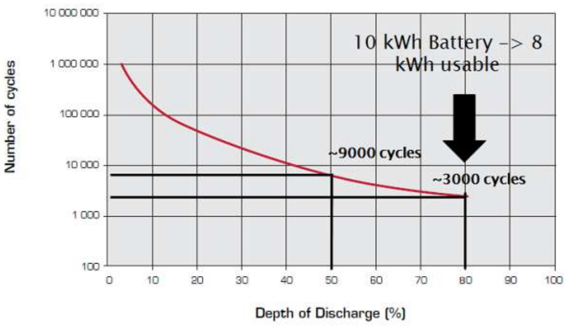


Figure 3.4: Cycle life of a Lithium Battery
Source: Datasheet Saft Intensium Flex, www.saftbatteries.com

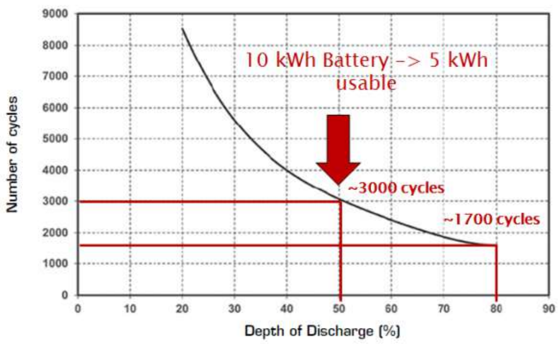


Figure 3.5: Cycle life of a Lead Battery
Source: Datasheet Hoppecke OPzV solar.power, www.hoppecke.de

Figure 3.4 and Figure 3.5 show the cycle life of exemplary lithium and lead batteries. A depth of discharge of 80% means, that at every time at least 20% of the gross capacity is left in the battery. Therefore the useful capacity is 80% of the gross capacity. If one compares Figure 3.4 and Figure 3.5 it can be concluded that lithium batteries last much longer than lead batteries assuming the same depth of discharge. The two figures point out that a decreasing depth of discharge leads to more load cycles before the end of the life of the battery has reached. For this reason batteries should not be fully discharged to extend their cycle lifetime.

3.4 Linear optimisation model for cost-optimal utilisation of stationary as well as mobile battery storage

In this section, the formal framework for the calculation of the PV-output, self-consumption and self-sufficiency will be explained.

To calculate the economic efficiency of the battery storage, a linear optimisation model was developed in Matlab using the YALMIP toolbox and the Gurobi solver, with the aim of minimising the costs of purchasing electricity for different load profiles. The optimisation model thereby performs calculations with a temporal resolution of a quarter of an hour. This is a model that optimises the utilisation of the PV-storage combination. It does not optimise the PV-storage system in the sense of an expansion model that calculates the optimal capacities based on the investment costs and the load profile. Instead, different PV-storage capacities are simulated.
The objective function, see Equation 3.10, is defined as follows:

$$\begin{aligned} min \sum_t (q_t{}^{grid_{battery}} + q_t{}^{grid_{demand}}) * c_t{}^{electricitypurchase} \\ -(q_t{}^{PV-feed-in} + q_t{}^{battery-feed-in}) * p_t{}^{feed-inremuneration} \end{aligned} \tag{3.10}$$

with

$$\begin{aligned} q_t{}^{grid_{battery}} &= \text{Stored electricity from the grid [kWh]} \\ q_t{}^{grid_{demand}} &= \text{Supply of the load profile from the electricity grid [kWh]} \end{aligned}$$

$$\begin{aligned}
{c_t}^{electricitypurchase} &= \text{Electricity price [c/kWh]} \\
{q_t}^{PV-feed-in} &= \text{Direct feed-in to the grid [kWh]} \\
{q_t}^{battery-feed-in} &= \text{Feed-in from the battery to the grid [kWh]} \\
{p_t}^{feed-in-remuneration} &= \text{Feed-in remuneration [c/kWh]}
\end{aligned}$$

In Equation 3.10, the electricity price and the feed-in remuneration are specified. All other terms are independent variables and are optimised using the objective function.
The most important constraints of the optimisation model are outlined in Equation 3.11 to Equation 3.15:

Demand:

$$ {q_t}^{demand} = {q_t}^{grid_{demand}} + {q_t}^{PV_{demand}} + {q_t}^{battery_{demand}} \tag{3.11}$$

Storage:

$$\begin{aligned}
{q_t}^{charge} &= ({q_t}^{PV_{battery}} + {q_t}^{grid_{battery}}) * \eta^{charge} && (3.12) \\
{q_t}^{discharge} &= \frac{-{q_t}^{battery_{demand}} - {q_t}^{battery_{feed-in}}}{\eta^{discharge}} && (3.13) \\
StorageLevel_t &= StorageLevel_{t-1} + {q_t}^{charge} + {q_t}^{discharge} && (3.14)
\end{aligned}$$

PV generation:

$$ {q_t}^{PV-generation} = {q_t}^{PV_{battery}} + {q_t}^{PV_{demand}} + {q_t}^{PV-feed-in} \tag{3.15}$$

with

$$\begin{aligned}
{q_t}^{demand} &= \text{Demand of the load profile [kWh]} \\
{q_t}^{PV_{demand}} &= \text{Supply of the demand by PV [kWh]} \\
{q_t}^{battery_{demand}} &= \text{Supply of the demand by the battery [kWh]} \\
{q_t}^{charge} &= \text{Charging power [kWh]} \\
\eta^{charge} &= \text{Charging efficiency [kWh]} \\
{q_t}^{PV_{battery}} &= \text{Stored electricity from the PV [kWh]} \\
{q_t}^{discharge} &= \text{Discharge power [kWh]} \\
\eta^{discharge} &= \text{Discharge efficiency [kWh]} \\
StorageLevel &= \text{State of charge [kWh]} \\
{q_t}^{PV-generation} &= \text{Photovoltaic generation [kWh]}
\end{aligned}$$

This optimisation function, by minimising the costs of grid consumption, thus has the effect of maximising the self-consumption of the photovoltaic system at constant tariffs.
The rate of self-consumption as well as the rate of self-sufficiency are defined in Equation 3.16 and Equation 3.17

$$ Q_{self-consumption} = \sum \frac{{q_t}^{self-consumption}}{q_t^{PV-generation}} \tag{3.16}$$

$$Q_{self-sufficiency} = \sum \frac{q_t^{self-consumption}}{q_t^{electricitydemand}} \tag{3.17}$$

with

$Q_{self-consumption}$ = Rate of self-consumption
$q_t^{self-consumption}$ = Share of photovoltaic generation that can be used to cover the load profile [kWh]
$q_t^{PV-generation}$ = Photovoltaic generation [kWh]
$Q_{self-sufficiency}$ = Rate of self-sufficiency
$q_t^{electricitydemand}$ = Load profile [kWh]

The rate of self-consumption and the rate of self-sufficiency are strongly related to the storage capacity. On the one hand, if the capacity of the battery storage is too small, only a small part of the load profile can be covered by the battery. On the other hand, the battery can not be fully discharged in summertimes if the capacity is too large and the additional capacity is useless.

The basic structure of the optimisation model is shown in Figure 3.6.

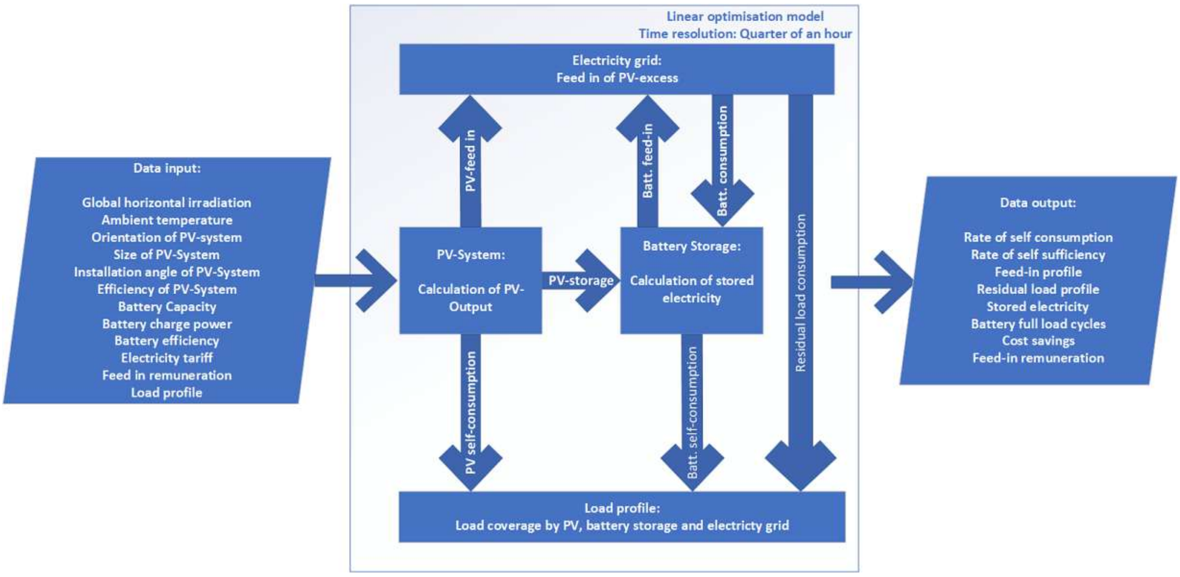


Figure 3.6: Structure of the optimisation model

Taking into account real global horizontal irradiance data from Vienna in 2010, the direct, diffuse and reflected irradiance on any inclined surface is calculated according to the isotropic diffuse irradiance model, whereby the degree of clarity is considered. Based on this irradiation, the power output of the photovoltaic modules is determined, including the location, the orientation, the installation angle and the ambient temperature, and serves as input for the optimisation model. Further input parameters for the optimisation model are the capacity of the PV system, the capacity and efficiency as well as the charging curve of the battery storage as well as the electricity price, tariff structure and feed-in remuneration. Miscellaneous load profiles can also be fed into the optimisation model. The optimisation model then calculates a cost-minimum solution to cover the load profile via the PV system, the battery storage and the electricity grid. In principle, the optimisation model is given the option of charging the storage from the grid and feeding electricity back to the grid. However, this is only relevant for variable tariffs, as with a flat tariff it is always more cost-efficient to either feed in directly or to cover the load profile directly from the grid due to the storage losses. The output parameters of the optimisation model are the energy flows between the PV system, the battery storage, the electricity grid and the load profile and, derived from this, the rate of self-consumption, the rate of self-sufficiency, the self-consumption savings and the feed-in revenues as well as the costs of purchasing electricity from the grid.

The optimisation model is then applied for single-family buildings, multi-apartment buildings as well as for cross-building optimisation in Section 4. Due to the different sizes of PV and battery storage and the differences in the load profiles, where a certain pooling effect is expected especially for multi-apartment buildings as well as for cross-building solutions, differences in self-consumption as well as in self-sufficiency should become apparent, which then also has an impact on the maximum possible investment costs of battery storage.

In Section 5, the stationary battery storage in the optimisation model is replaced by a battery in the electric vehicle. This battery storage then mainly supplies the load profile of the electric vehicle and only in a scenario where feeding back into the building is also possible, also the load profile of the building. When and during which time the storage unit is available for charging via PV or from the grid is indicated by the charging vectors, which show the parking times of the electric vehicle. The maximum charging power also differs insofar as it is assumed that the consumption profile can be covered at any time and thus the maximum discharge power is based on the maximum of the demand profile. The maximum charging power is based on typical specifications for household connections as well as public wallboxes. However, the objective function remains the same, namely the cost-optimised coverage of both load profiles (single family building and electric vehicle) via PV, grid and battery storage.

4 Economics of electricity storage - decentralised battery storage systems

As already discussed in Section 2, the economic viability of battery storage is difficult to achieve. In this section, the current state of the art in the literature on the economic evaluation of battery storage systems is reviewed in more detail in order to subsequently answer the question of how much a battery storage system should cost in different use cases in order to be operated economically. For this purpose, the general methodology of the economic evaluation via the internal rate of return and the input parameters are explained in more detail. Subsequently, the three use-cases of single-family buildings, multi-apartment buildings and cross-building use of the battery storage system are analysed.

4.1 State of the art

As already outlined in the introduction, battery storage is a practical solution to store the surplus of decentralised photovoltaic systems and thus also to increase self-consumption or to relieve the electricity grid, e.g. through peak shaving or load shifting in general. Due to the huge photovoltaic boom in recent years, the topic of decentralised storage is also intensively discussed in the literature. The spectrum ranges from the economic efficiency of storage in single-family buildings to office buildings, taking into account different types of tariffs, the performance of components and the provision of ancillary services. Initially, it were still lead batteries that were considered for the analysis. In the meantime, however, lithium-based batteries dominate. A general outlook on the economic evaluation of storage and its future prospects in the electricity market and also its value for the society is presented by Haas, Kemfert, et al. (2022) and Ajanovic, Hiesl, and Haas (2020). After a comprehensive literature review and simulations, Hoppmann et al. (2014) conclude that decentralised battery storage can already be operated profitably in 2014. However, only lead-acid batteries are considered in this study and not lithium-ion batteries, as in this thesis. Lead-acid batteries have significantly lower investment costs, but need to be replaced more often and have significantly lower efficiency. The study is only representative to a limited extent for this work, but it shows the technological change that has taken place in the last eight years. In different regions, the profitability of battery storage systems varies significantly. In Broughton, Nyer, and Ybarra (2021) the economics of battery storage systems in California are analyzed and it is concluded that the economic benefit is hardly justifiable but can make sense for security of supply. The same finding was made by Chaianong et al. (2020) and Khezri, Mahmoudi, and Haque (2020), who analysed the economic viability of PV-storage systems in Thailand and Australia. Dietrich and Weber (2018) state that the net present values of most of the PV-battery configurations are very low and therefore households will invest into standalone PV installations instead. The paper by Förstl et al. (2020) focuses on regional differences, through use cases in Germany and Australia, as well as through different operating strategies such as maximisation of self-consumption, feed-in damping and mixed integer programming with the objective function of minimising electricity costs. On the one hand, the authors conclude that battery storage cannot be operated economically under the assumptions made and, on the other hand, that there are indeed differences in battery lifetime with the various operating strategies. Feed-in damping appears to be the most advantageous for battery life. O'Shaughnessy et al. (2018) combine dispatchable load components as well as batteries and conclude that load shifting through domestic hot water as well as smart AC units are much

more profitable than battery storage systems due to their high investment costs.
McLaren et al. (2019) find that investment costs and electricity tariffs are the primary drivers of economic viability, while building load size is the most important factor in determining solar-plus-storage size in commercial buildings. In contrast, Han, Garrison, and Hug (2022) conclude that in Switzerland for some user groups PV-storage systems are already profitable and will become more profitable until 2050, while the optimal size of the battery system increases. In Tervo et al. (2018), the economic viability of PV storage systems is assessed using three different locations in the United States via the method of levelized costs of electricity (LCOE). Battery storage is presented as an alternative to net metering or bidirectional metering and to increase self-consumption. The authors conclude that under optimal dimensioning and assumed retail electricity prices, PV storage systems are indeed economically viable. The electricity production costs are between \$0.11/kWh and \$0.15/kWh, which is slightly below the procurement costs. The greatest sensitivity in the economic viability is the investment costs of both PV and storage systems, as well as the use of the Investment Tax Credit, which was included here. ITC reduces the tax burden in the first year of operation, which can even lead to an economic profit in the most favourable case. A similar approach was taken by Barzegkar-Ntovom et al. (2020). In this paper, however, the levelised costs of use are calculated (i.e. no feed-in to the electricity grid, pure self-consumption) and compared to the retail electricity price for different household types and sizes of PV storage systems and six different countries in Europe (Cyprus, France, Greece, Italy, Portugal, Spain). The authors conclude that grid parity cannot be achieved under the current framework conditions in the countries without reducing the costs of the components and therefore battery storage systems aren't an economic solution. The two papers by Förstl et al. (2020) and Mishra et al. (2020) deal with the degradation of battery storage under different operating conditions and different technologies while Faraji, Ketabi, and Hashemi-Dezaki (2020) also includes the costs due to the full load cycles of the battery. Angenendt et al. (2018) analysed forecast-based operation strategies and conclude, that this strategy is able to increase battery lifetime, decrease curtailment and therefore also decrease costs by up to 12%. The paper by Mishra et al. (2020) concludes that time-of-use tariffs have a negative impact on the battery life due to the higher depth of discharge (DoD) and the higher state of charge (SOC). In addition, when operating as a backup, it is advised not to leave the battery 100% fully charged. Furthermore, lower temperatures as well as overdimensioning and the associated lower DoD rate have a favourable effect on the service life. The degradation of the battery storage is also depicted in the current paper using a simple, linear model of the decrease in capacity per cycle. Several papers deal with ancillary services like voltage or frequency regulation, power quality as well as peak load shaving and battery storage systems in smart systems, see Georgakarakos, Mayfield, and Hathway (2018), Leadbetter and Swan (2012), Maeyaert, Vandevelde, and Döring (2020) and von Appen and Braun (2018). These papers analyse different aspects of ancillary services and conclude that while battery storage can provide such services, it can only be operated profitably under certain scenarios and battery life can also suffer, and that regulatory frameworks and incentives need to be put in place. As can be seen from the review of the literature, there are many different opportunities, and the topics analysed in the field of battery storage are very diverse. A majority of the papers conclude that lithium-based battery storage is currently still not economically viable. However, it is assumed that the costs will be significantly reduced in the next few years and that battery storage can play a major role in the integration of renewable energies (Hiesl, Ajanovic, and Haas, 2020). In order to be able to provide services for the electricity grid, however, sufficient

regulatory framework conditions still need to be created.

4.2 Method and data input

For reasons of readability, this thesis distinguishes in the units between €/kWh and c/kWh and $€/kWh_{storage}$. The first two are used for electricity prices and feed-in remuneration. The latter for the investment costs of the battery storage.

4.2.1 Retail electricity price & feed-in remuneration

Two of the most important parameters for assessing the economic viability of battery storage systems, apart from the investment costs, are the electricity price and the feed-in remuneration. The electricity price composition as well as the level of electricity prices vary significantly in Europe, therefore it is not possible to extrapolate per se from the electricity price to the economic efficiency of battery storage systems. Figure 4.1 shows the level of retail electricity prices for average households in the range between 2500 kWh and 5000 kWh electricity consumption per year.

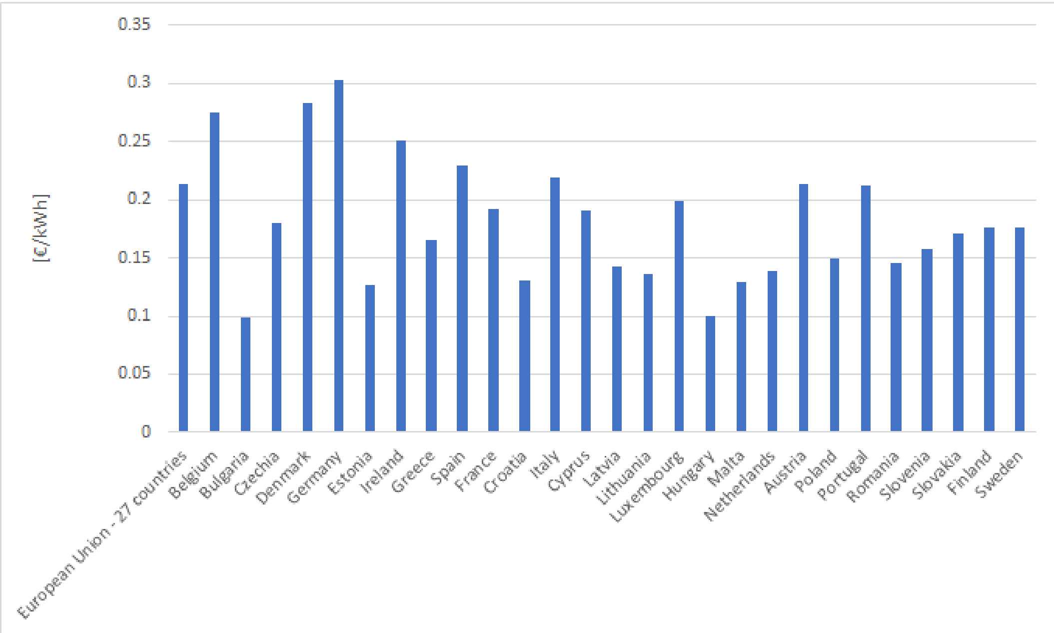


Figure 4.1: Retail electricity price in EU 27 member states in 2020, Data source: Eurostat

The strong increase in electricity prices in the last months of 2021 and in the first quarter of 2022 is not directly considered in this thesis, but the sensitivity analysis addresses the question of how a change in the electricity price level affects the economic viability of battery storage. As can be seen in Figure 4.1, electricity prices in Europe vary between 10 c/kWh and 30 c/kWh.

The level of the electricity price does not necessarily reflect the share of the electricity price that can actually be used to evaluate the savings from self-consumption by the battery storage system. Depending on the country, there are different regulations and not all components of the electricity price, such as fixed and capacity-related components of the grid tariffs as well as taxes and other fixed levies, can be included in the economic evaluation of self-consumed PV electricity. In some countries there are fixed and capacity-related components, e.g. in the grid tariff, which cannot be considered [3] In this work, it is assumed that the applied electricity price only includes the components that can also be used to calculate the savings from self-consumption.

In this work, the electricity price is assumed to be 15 c/kWh in the baseline scenario. Flat tariffs are currently still the predominant tariff structure, although more and more flexible tariffs are also being offered. For the following analyses, constant electricity prices and non-dynamic tariffs are assumed.

In Austria, for example, the feed-in remuneration, i.e. the remuneration paid by an energy supplier for the purchase of surplus PV electricity, has been 3-7 c/kWh in recent years. In other countries, the feed-in remuneration can be higher or lower, but will tend to be based on the current market value of the PV electricity. The variation of the feed-in remuneration is also considered in the sensitivity analysis, whereas subsidies are not taken into account.

The parameters for the economic calculation are summarised in Table 4.1:

Table 4.1: Electricity Price & Feed-in remuneration

Parameter	**Value**
Electricity price	15 c/kWh
Tariff structure	Flat tariff
Feed-in remuneration	6 c/kWh

4.2.2 Battery parameters

In the following analysis, a maximum charging power of 10 kW and a maximum possible depth of discharge of 80% is assumed. This means that 80% of the gross capacity can actually be used for photovoltaic surplus storage. Cycling stability is assumed to have a realistic value of 3000 in this analysis. The definition of cycle lifetime is assumed to be reached when the battery storage can only provide 80% of its original capacity.

Table 4.2: Battery parameters

Parameter	**Value**
Charge & discharge efficiency	95%
Maximum charge/discharge power	10 kW
Depth of Discharge (DoD)	80%
Number of full-load cycles	3000

The cost of a battery storage system has also dropped significantly in recent years, as outlined in Hiesl, Ajanovic, and Haas (2020). In 2022, the average specific investment costs for a 1 kWh storage unit are around 1300 $€/kWh_{battery}$ and for a 10 kWh storage around 1000 $€/kWh_{battery}$. As can be seen from Figure 4.2, the specific costs are decreasing, especially in the segment up to 10 kWh. The cost degression flattens out significantly thereafter and, especially for large storage units above 100 kWh, the specific costs drop only slightly.

[3] .

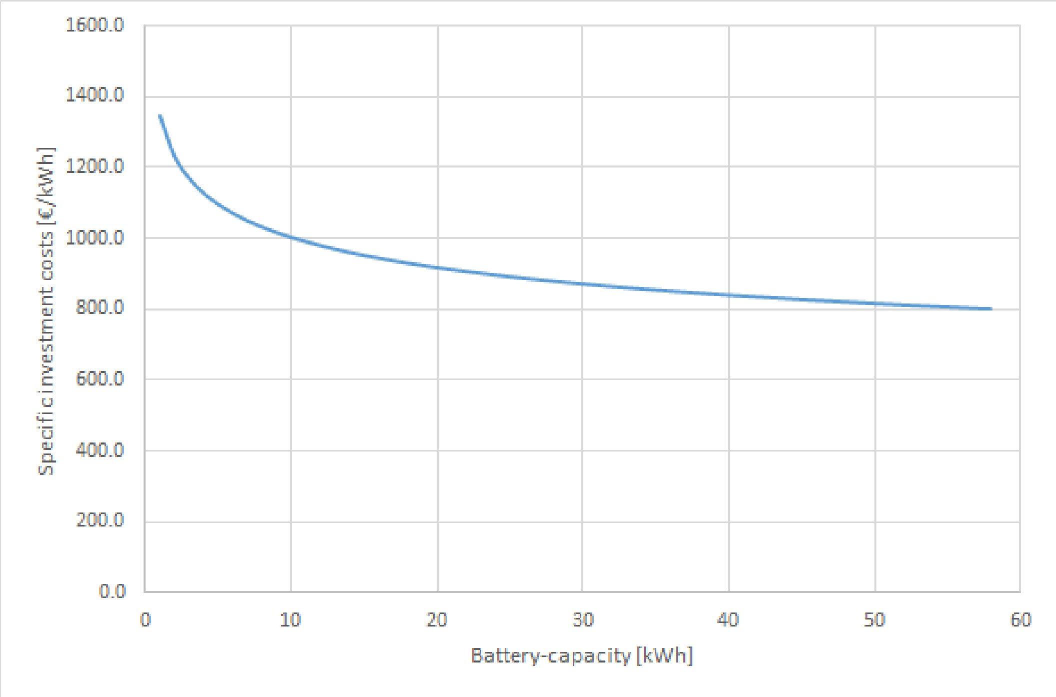


Figure 4.2: Specific investment costs for lithium based batteries in 2022, w/o VAT [$€/kWh_{battery}$]
Data source: C.A.R.M.E.N EV

4.2.3 Economic calculation

The method of the internal rate of return (IRR) is used in this thesis to evaluate the economic viability of a battery storage system. The IRR is a discount rate at which the net present value (NPV) becomes exactly zero within the calculation period. This implies that the investment costs are exactly equal to the discounted cash flow, see Equation 4.18.

$$NPV = -I_0 + \sum_{t=1}^{T} \frac{C_t}{(1+IRR)^t} = 0 \tag{4.18}$$

with

$$\begin{aligned} NPV &= \text{Net present value [€]} \\ I_0 &= \text{Initial investment costs [€]} \\ C_t &= \text{Cash flow at time t [€]} \\ IRR &= \text{Internal rate of return} \\ T &= \text{Calculation period [a])} \end{aligned}$$

The method of the internal rate of return also has some limitations. For example, the internal rate of return provides no information about the absolute level of the return. Therefore, projects with the same depreciation time and similar parameters must always be compared.

In addition, it may occur that the IRR does not exist at all or has a complex value and therefore not only the IRR but also, for example, the NPV should be used as a criterion when comparing different projects. In this thesis, however, the same parameters such as the depreciation time are assumed and only the amount of cash flow changes. In addition, in this work the IRR is preset and the investment costs are derived from it. In general, the higher the internal rate of return, the more profitable an investment is. The internal rate of return can be used for investments of different types so investments or projects can be evaluated on the same basis. When comparing investment options with similar parameters, the investment with the highest internal rate of return is considered the most economically viable. In principle, the weighted average cost of capital (WACC) is the benchmark for the IRR. The weighted average cost of capital is thereby composed of the cost of equity and the cost of debt and is weighted according to its share, see Haas, Ajanovic, et al. (2021). If the internal rate of return is higher than the weighted cost of capital, the investment in a battery storage system is considered economically viable. The aim of the economic analysis is to quantify the additional benefit of the battery storage system compared to a pure photovoltaic system and to calculate the maximum investment costs of such a battery storage system, taking into account a given internal rate of return, whereby additional savings due to increased self-consumption as well as the replacement of the battery storage system after the cycle life or, if reached first, the calendaric life are taken into account.

To identify the maximum additional investment costs of battery systems to be profitable, compared to a standalone PV-system, for households as well as for multi-apartment buildings and across-buildings, the calculation is done as shown in Equation 4.19 to Equation 4.21

$$NPV = -I_{Battery_{tot}} + \sum_{t=1}^{T} \frac{\Delta C_t}{(1+IRR)^t} = 0 \tag{4.19}$$

$$I_{Battery_{tot}} = \sum_{t=1}^{T} \frac{\Delta C_t}{(1+IRR)^t} \tag{4.20}$$

$$I_{Battery} = \frac{I_{Battery_{tot}}}{1 + 0.7 * (1+IRR)^{-t_c}} \tag{4.21}$$

with

NPV = Net present value [€]
$I_{Battery_{tot}}$ = Overall investment costs (initial + rebuy) [€]
$I_{Battery}$ = Maximum additional investment costs at given IRR [€]
ΔC_t = Difference cash flow with battery storage and without battery storage [€]
IRR = Internal rate of return
t_c = Year of the battery storage replacement [a]
T = Calculation period [a]

In order to calculate the maximum possible investment costs, including the additional investment in a battery storage system during the calculation period, Equation 4.18 is slightly transformed. Equation 4.19 is similar to Equation 4.18 with the exception that only the difference of the cash flow with and without battery storage (ΔC_t) is used. Equation 4.20 is now transformed so that the discounted cash flow is equal to the total investment costs (initial + rebuy). The additional costs of the rebuy are assumed to be only 70% of today's costs, regardless of the time of the additional investment. These additional investment costs are discounted depending on the timing of the investment and are then considered in Equation 4.21, where the maximum additional investment costs are calculated. The calculation period is assumed to be 25 years, as this also corresponds to the lifetime of the photovoltaic system. As mentioned before, ΔC_t is the difference in cash flows (cost savings + feed-in revenue - operation and maintenance (O&M) costs) in year t with and without battery. If there is an additional stationary battery storage, the changed cash-flow due to increased self-consumption and decreased feed-in revenues has to be considered. Here, C_t strongly depends on the amount of self-consumed PV electricity ($q_t^{self-consumption}$), household electricity prices ($c_t^{electricitypurchase}$), feed-in remuneration ($p_t^{feed-in}$) and the amount of PV electricity fed into the grid ($q_t^{feed-in}$).

$$C_t = q_t^{self-consumption} * c_t^{electricity-purchase} + q_t^{feed-in} * p_t^{feedin} - O\&M_t \tag{4.22}$$

Table 4.3 points out the parameters for the economic evaluation of the baseline scenario:

Table 4.3: Economic parameters baseline scenario

Parameter	**Value**
Electricity costs	15 c/kWh
Feed-in remuneration	6 c/kWh
IRR	5%
Rebuy date	13a
Cost of rebuy	70% of actual costs
Calculation period	25a

4.3 Battery storage in single-family buildings

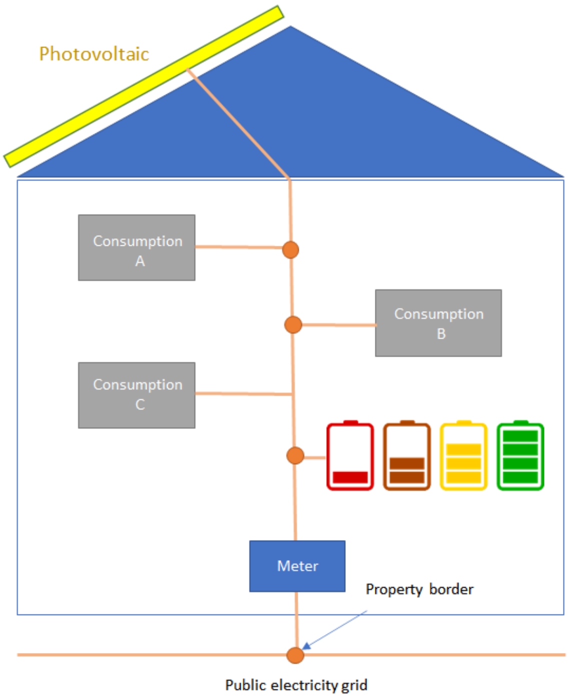


Figure 4.3: Schematic configuration in a single-family building

The situation for single-family houses is shown in Figure 4.3. A rooftop photovoltaic system is installed with a southern orientation and an installation angle of 30°. This is the energetically optimal orientation for maximum photovoltaic energy production in the geographical location of Central Europe. The battery storage system is additionally installed in the building as a wallbox either directly connected to the photovoltaic system using the inverter of the PV system or as a dedicated system with its own inverter for coupling with the AC system of the building. The photovoltaic system as well as the battery storage can then supply various appliances in the building with PV electricity. An average electricity consumption of 4000 kWh/a is used for both the energy and the economic calculation, and the standardised H0 load profile is accordingly scaled.

The standardised H0 load profile represents an average load profile over a large number of households. The disadvantage of using a standardised H0 load profile is that peak loads of individual households are lost or compensated by other households. On the other hand, it represents an average household and is therefore also used for the calculation in this work. Figure 4.4 shows the H0 load profile for an exemplary summer week.

Both temperature data and irradiation are used from the year 2010, as this year represents an average weather year. The summary of the parameters used is shown in Table 4.4, all other parameters are applied as outlined in the previous chapters.

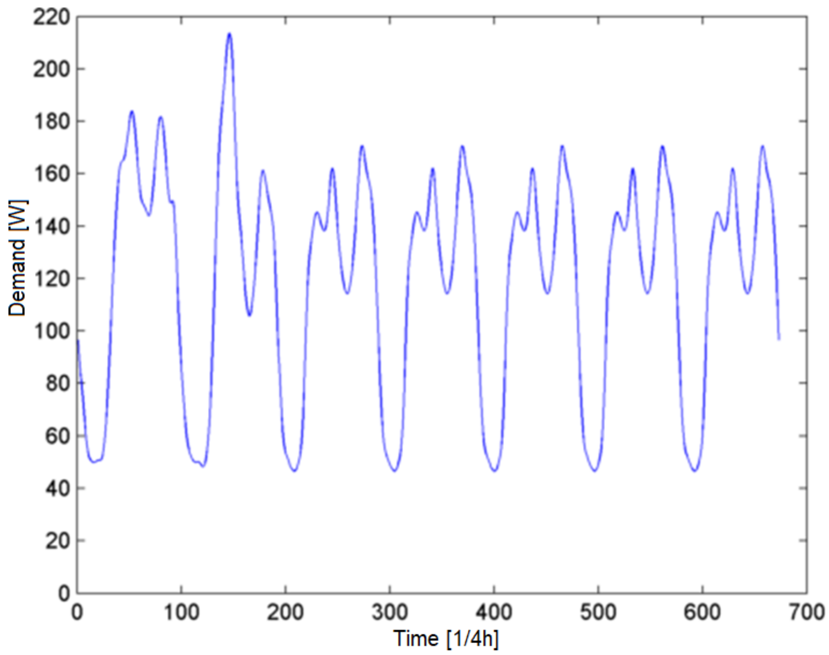


Figure 4.4: Load profile H0 summer week. Exemplary scaled with 1000 kWh/a [W]

Table 4.4: Parameters for single-family buildings

Parameter	Value
PV-System	
Orientation	south
Installation angle	30°
Size	1 - 14 kWp
Battery System	
Charge/Discharge Power	10kW
Size	0 - 14 kWh
Load profile	
Type of profile	Standardised H0
Consumption	4000 kWh/a

4.3.1 Energetic calculation

The energy calculation of the rate of self-consumption as well as the rate of self-sufficiency for a single-family building was calculated using a standardised H0 load profile and results are presented in Figure 4.5 and Figure 4.6.

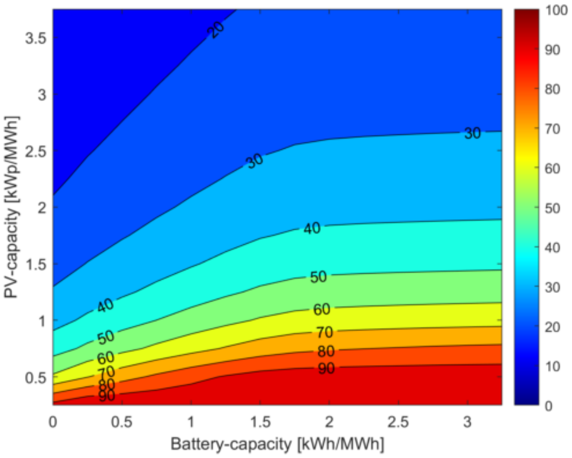


Figure 4.5: Rate of self-consumption for different combinations of PV-capacity and battery-capacity related to an annual consumption of 1000 kWh/year [%]

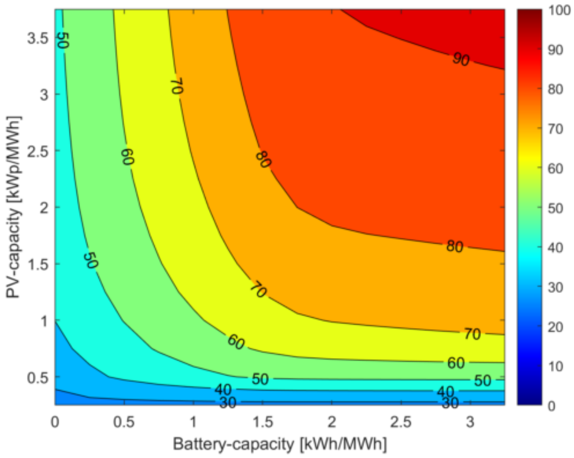


Figure 4.6: Rate of self-sufficiency for different combinations of PV-capacity and battery-capacity related to an annual consumption of 1000 kWh/year [%]

Different combinations of battery storage and photovoltaic system sizes are considered. Both the capacity of the photovoltaic system and the battery storage are related to an annual consumption of 1000 kWh/a. This makes it illustrative insofar as it is relatively easy to estimate the rate of self-consumption as well as the rate of self-sufficiency for a known electricity consumption. With an annual electricity consumption of 5000 kWh/a and an installed PV size of 5 kWp, this means a specific PV output of 1 kWp/MWh. This configuration provides a rate of self-consumption of just over 36% and a rate of self-sufficiency of 40%. If a battery storage system with a capacity of 5 kWh is also installed, which corresponds to a specific capacity of 1 kWh/MWh, the rate of self-consumption increases to about 54% and the degree of self-sufficiency rises to about 59%, i.e. 41% of the electricity consumption still has to be purchased from the grid. A specific battery capacity of more than 1.5 kWh/MWh results in only minor advantages in terms of self-consumption. Self-sufficiency also increases significantly less from this battery capacity, as the storage system can no longer be fully discharged at night. Levels of self-sufficiency over 90% can only be achieved with very large specific PV outputs of over 3.5 kWp/MWh and large specific battery sizes of over 2.5 kWh/MWh. In this range, however, the rate of self-consumption is relatively low and large amounts of electricity must be fed into the grid or curtailed.

In principle, it is possible to estimate the share of self-consumption and the rate of self-sufficiency of an average household on the basis of the annual consumption from Figure 4.5 and Figure 4.6. For individual households, however, this can of course also deviate due to the deviating load profile, because it depends on which appliances are used, which load peaks occur and when these load peaks occur.

4.3.2 Economic calculation

As already pointed out in Section 4.2.3, the method of the internal rate of return is used, whereby the internal rate of return is specified, a cash flow is calculated from own consumption and feed-in as well as the annual operation and maintenance costs, and the resulting maximum investment costs of a battery storage system are derived. As the delta of the cash flow with battery and without battery is applied, see Section 4.2.3, only the additional investment costs of the battery systems are analysed and not the investment costs of the combined PV-storage system. These costs are then compared to the actual costs in order to analyse necessary cost reductions.

4.3.2.1 Baseline scenario

The baseline scenario is the initial reference point for the following calculations and sensitivity analyses with regard to electricity price, feed-in tariff, expected annual return and lifetime of the battery storage. The parameters for the baseline scenario are presented in the section below as a recapitulation. An electricity price of 15 c/kWh and a feed-in remuneration of 6 c/kWh are assumed. In addition, a real rate of return of 5% per year is assumed for the calculation of investment costs. A change of the battery storage, after the end of the lifetime of the initial battery storage, is assumed in the middle of the calculation period of 25 years. This is also plausible insofar as the battery storage in a household typically performs about 250-300 full load cycles per year at a depth of discharge of 80% in a typical configuration. Assuming a cycle stability of 3000 full load cycles lifetime, this means a replacement approximately in the middle of the calculation period. The parameters of the calculation are summarised in Table 4.3.

Figure 4.7 and Figure 4.8 show the results of the calculations for the H0 load profile graphically. In Figure 4.8, only selected combinations of PV and storage capacity have been outlined for the sake of visual clarity.

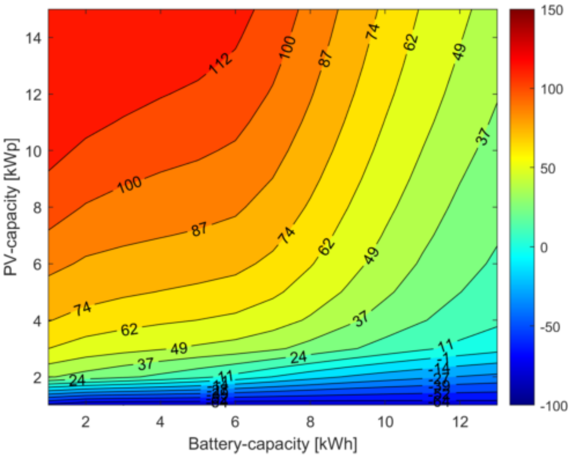


Figure 4.7: Maximum additional investment costs for different PV and battery capacities, single-family building [€/$kWh_{battery}$]

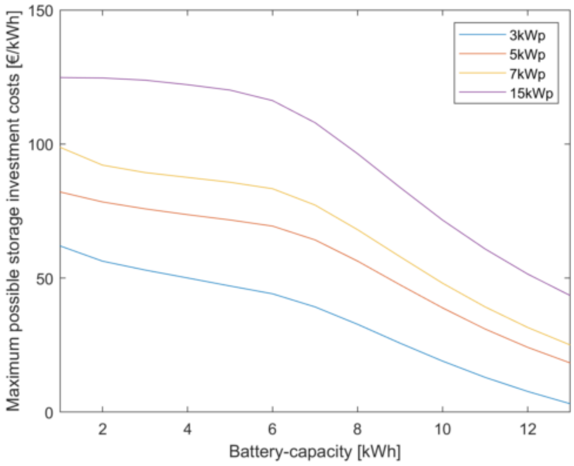


Figure 4.8: Maximum additional investment costs for for selected PV and battery capacities, single-family building [€/$kWh_{battery}$]

From Figure 4.7 it can be deduced, that the calculated specific investment costs of the battery storage range between 120 €/$kWh_{battery}$ and -75 €/$kWh_{battery}$, depending on the size of the battery storage and the PV system. For small PV systems, where self-consumption is already high, the additional benefit of the battery storage is non-existent. In this segment, the additional investment costs are correspondingly also negative, as the operational costs exceed the additional benefit. The maximum specific investment costs may occur where large photovoltaic systems are combined with small battery storage systems. The additional benefit of the battery storage is highest there, as a large surplus prevails and the storage is thus best utilised. In addition, Figure 4.8 illustrates a slight downward bend at around 6-7 kWh battery capacity. This is the range in which an additional kWh of battery storage only brings a small additional benefit in terms of increasing self-consumption, compare Figure 4.5.

If the calculated investment costs are compared with the actual investment costs of a battery storage system pointed out in Figure 4.2, it becomes clear that the investment costs still have to decrease significantly in order to be economically viable.

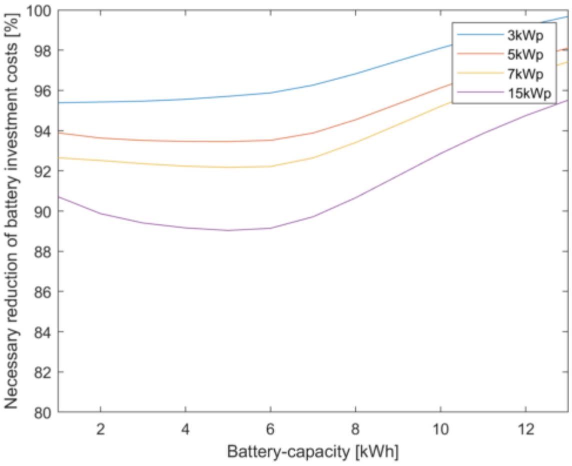


Figure 4.9: Necessary cost reduction compared to investment costs in 2022 [%]

As depicted in Figure 4.9, the necessary cost reduction ranges from about 89% for a 15 kWp PV system and a 6 kWh battery storage to about 99% for a 3 kWp PV system and a 13 kWh battery storage. This result demonstrates that, under the assumptions made, battery storage is still far too expensive and must either be subsidised, or other additional uses for battery storage must be found in addition to the pure increase in self-consumption.

4.3.2.2 Sensitivity analysis

The baseline scenario shows that a battery storage system is not economically viable compared to actual investment costs. How the economic viability and the associated investment costs develop if the input parameters are varied will be discussed in the following chapter. In doing so, electricity prices, feed-in remuneration, expected annual returns and the lifetime of the battery are varied and the effects on the additional investment costs are analysed.
For reasons of clarity of the sensitivity analysis, only a typical combination of PV and battery storage capacity is considered. The initial parameters are summarised in Table 4.5:

Table 4.5: Parameter sensitivity analysis

Parameter	Value
PV-capacity	5 kWp
Battery capacity	7 kWh
Electricity price	15 c/kWh
Feed-in remuneration	6 c/kWh
IRR	5%
Battery lifetime	13a
Variation of Parameters	-50% to +50%

The results of the sensitivity analysis are presented in Figure 4.10.

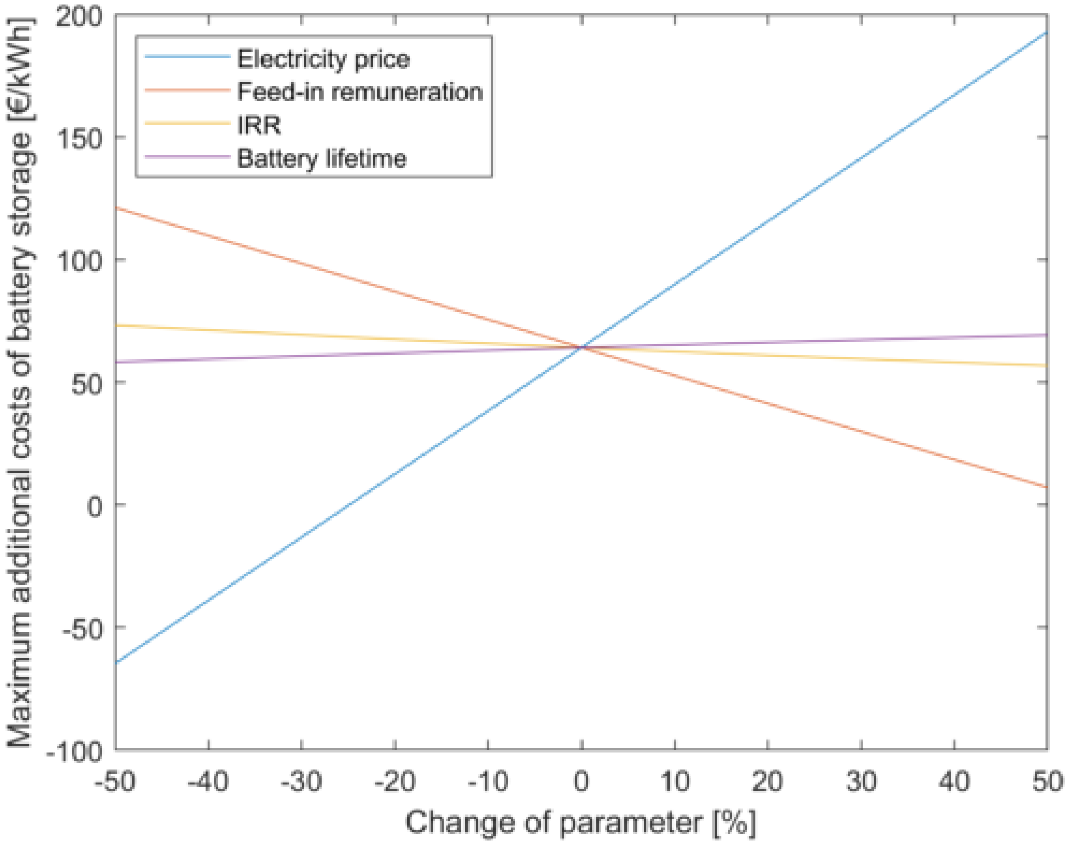


Figure 4.10: Sensitivity analysis for additional storage investment costs [$€/kWh_{battery}$]

The sensitivity analysis was conducted in such a way that one parameter was adjusted at a time, while all other parameters were kept constant. Figure 4.10 clearly illustrates that the electricity price has the greatest influence on the maximum additional investment costs. When varying the parameters by +-50%, the electricity price shows the largest gradient. The feed-in remuneration impacts the economic viability of the battery storage system the second most, compared to the case without battery storage. The expected annual return and the lifetime of the battery storage system play a subordinate role in the sensitivity analysis. Figure 4.10 reveals that halving the electricity price to 7.5 c/kWh would make the battery storage system obsolete. The additional investment costs are clearly negative in this scenario. The significantly lower amount of self-consumption savings from battery storage compared to the pure PV system means that battery storage should cost nothing in the optimised self-consumption setting and that the operating costs exceed the resulting benefits. An increase in the electricity price by 50% to 22.5 c/kWh leads to a significant increase in the maximum possible investment costs of the battery storage system compared to the initial value. The maximum possible investment costs increase from about 64 $€/kWh_{battery}$ to just under 200 $€/kWh_{battery}$ for the previously specified configuration. Although an increase in the electricity price has a positive effect on the possible specific investment costs of the battery storage system, these would nevertheless have to fall by 82% in order to be operated economically.

An increase in the feed-in remuneration has a negative impact on the economic viability and thus also on the maximum possible investment costs. The increase in the feed-in remuneration

makes the feed-in economically more attractive and since more electricity is fed into the grid with a pure photovoltaic system, the cash flow increases significantly more than with the PV-storage combination. The higher the feed-in tariff in relation to the electricity price, the lower the maximum possible investment costs can be. An increase of the feed-in remuneration to 9 c/kWh leads to maximum possible investment costs of only just under 7 $€/kWh_{battery}$, while a halving to 3 c/kWh would mean investment costs of about 120 $€/kWh_{battery}$.
The analysis of the expected annual return (IRR) shows a slightly lower impact on the result. The examined range varies from 2.5% to 7.5% expected annual return over a calculation period of 25 years. Increasing the expected rate of return decreases the additional investment costs of the battery storage from about 64 $€/kWh_{battery}$ to about 57 $€/kWh_{battery}$. Decreasing the interest rate leads to an increase of the investment costs to 73 $€/kWh_{battery}$. The analysis of the sensitivity of the battery storage lifetime is of the same order of magnitude, but in the opposite direction. In the baseline scenario, it is assumed that the battery storage needs to be replaced in the middle of the calculation period. An earlier replacement, i.e. after 6.5 years, leads to a slight reduction of the possible investment costs to 58 $€/kWh_{battery}$, a later replacement after 19.5 years leads to additional investment costs of 69 $€/kWh_{battery}$.

4.4 Battery storage in multi-apartment buildings

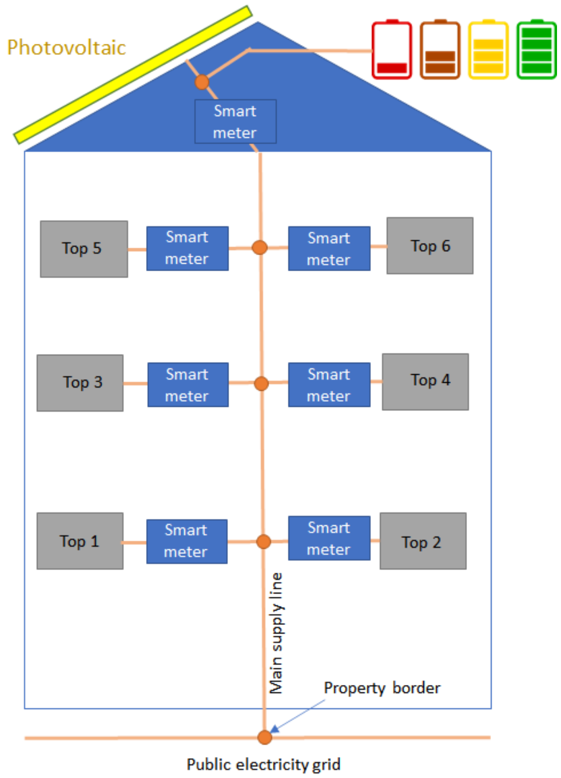


Figure 4.11: Schematic configuration in a multi-apartment building

The situation in multi-apartment buildings is shown in Figure 4.11. As with single-family houses, a rooftop photovoltaic system with a southern orientation and an installation angle of 30° is simulated. Since the legal/regulatory framework for the distribution of PV electricity within the building is implemented differently in each country, this work specifically addresses the situation in Austria. A photovoltaic system may (even in urban, densely built-up areas where roof/building areas are directly adjacent to each other) only be physically connected to one multi-apartment building or to one main electrical line if there are several main lines in a building. The participating beneficiaries in the PV system then do not have to pay grid fees for the self-generated and used electricity in the building and are therefore clearly favoured. The same applies to a battery storage system if it is only used for one building. The situation is different if it is to be used across-buildings, see section 4.5.

In order to participate in such a shared generation system, however, several contracts are necessary to ensure correct calculation and allocation of the energetic shares by the grid

operator.
The calibration of the simulation model for multi-apartment buildings can be found in Table 4.6. Since the actual distribution in the building is simulated here, this is not performed using individual H0 profiles due to the simultaneity, but instead calculated with measured load profiles. For this purpose, 10 household profiles were stochastically selected from a pool of over 70 measured (anonymous) household load profiles, which are used in this use-case and which are scaled with different annual electricity consumptions.

Table 4.6: Parameters for multi-apartment buildings

Parameter	Value
PV-System	
Orientation	south
Installation angle	30°
Size	1 - 41 kWp
Battery System	
Charge/Discharge Power	10kW
Size	0 - 51 kWh
Load profile	
Type of profile	measured household
Overall consumption	20,000 kWh

4.4.1 Energetic calculation

The distribution of photovoltaic electricity within the building depends on the chosen method. In Austria, both a static and a dynamic distribution scheme can be chosen. The dynamic distribution key, on the one hand, which has a temporal resolution of a quarter of an hour, is based on the actual consumption at time t of a participating household in relation to the sum of the consumption of all participating households at time t. The static distribution key, on the other hand, is determined in advance and is based, for example, on the investment sum of the individual households and can only be changed by contractual agreement. If, for example, another household joins or a household leaves, the distribution key must be redefined. The static key at the same time provides the advantage of simple allocation, but also the disadvantage that within the building, the unused share of one participant cannot be used by another. With the dynamic model, however, this is possible. As a result, the rate of self-consumption within the building is also significantly higher. The disadvantage is the more complicated accounting. In the following calculations, the battery storage is also integrated into the dynamic key and thus all participants are given the opportunity to store their respective surpluses. The dynamic distribution within the building is calculated as in equation 4.23:

$$PV_{Top_n}(t) = PV_{generation}(t) * \frac{Load_{Top_n}(t)}{\sum_{n=1}^{N} Load_{Top_n}(t)} \tag{4.23}$$

with

$PV_{Top_n}(t)$ = Share of PV generation at time t of a participating household (kWh)

$$\begin{aligned} PV_{generation}(t) &= \text{PV generation at time t (kWh)} \\ Load_{Top_n}(t) &= \text{Load of a participating household at time t (kWh)} \\ N &= \text{Number of participating households (1)} \end{aligned}$$

Figure 4.12 and Figure 4.13 show the rate of self-consumption as well as the rate of self-sufficiency for multi-apartment buildings related to a yearly electricity consumption of 1 MWh/a.

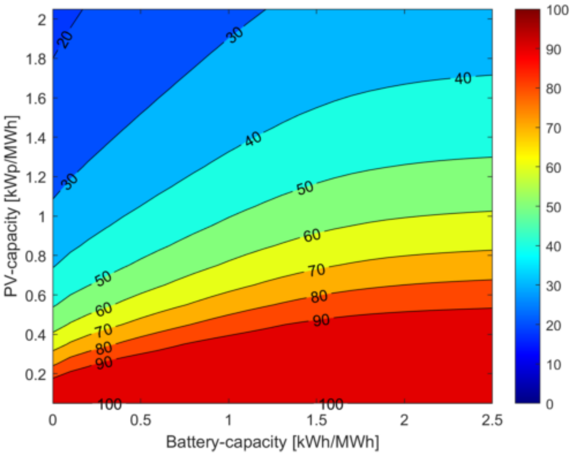


Figure 4.12: Rate of self-consumption for different combinations of PV-capacity and battery-capacity related to an annual consumption of 1000 kWh/year, multi-apartment building [%]

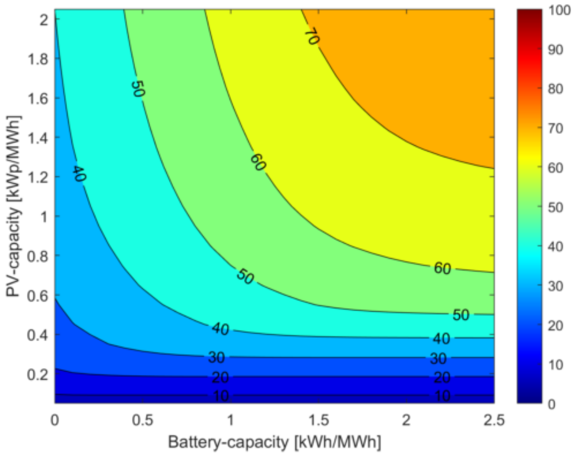


Figure 4.13: Rate of self-sufficiency for different combinations of PV-capacity and battery-capacity related to an annual consumption of 1000 kWh/year, multi-apartment building [%]

Due to the dynamic distribution of the photovoltaic electricity generated, a large amount can also be used directly in the building. With a total consumption of 20,000 kWh in the building and a photovoltaic output of 20 kWp, this results in a rate of self-consumption of about 33%. This rate of self-consumption results for 10 different measured household load profiles, scaled with an annual consumption of 1000 kWh/a to 4000 kWh/a with an average electricity consumption of 2000 kWh/a across all profiles. The rate of self-sufficiency within this configuration is around 34%. If a battery storage with a gross capacity of 20 kWh is installed, the rate of self-consumption increases to about 50% and the rate of self-sufficiency to about 54%. However, the rate of self-consumption and the rate of self-sufficiency also depend on the composition of the load profiles. If there is a high daytime consumption in the building, this can increasingly be covered by the PV system. Many different load profiles also lead to an increase in the share of self-consumption. Especially if there are not only residential apartments in the building, but possibly also a commercial business or a charging station for electric vehicles is integrated into the dynamic distribution key.

4.4.2 Economic calculation

As with a single-family building, the following sections illustrate the economic efficiency of a battery storage system in various scenarios for multi-apartment buildings. The parameters for the economic evaluation are also identical and can be taken from Table 4.3. However, the increased electricity consumption in the building as well as the larger area suitable for PV installation are specifically addressed and therefore larger combinations of PV and battery storage systems are analysed and compared to the current investment costs.

4.4.2.1 Baseline scenario

In the baseline scenario, an electricity price of 15 c/kWh, a feed-in remuneration of 6 c/kWh and an expected annual return of 5% per year are again assumed. The analysis of the full load cycles has shown that due to the different capacity ratios of the battery storage and the PV system as well as the total annual consumption, a similar behaviour with regard to the number of cycles is shown and therefore it is also assumed that the battery storage must also be replaced in the middle of the calculation period for multi-apartment buildings.

Figure 4.14 and Figure 4.15 show the results of the calculations for an overall annual electricity consumption of 20.000 kWh. The sizes of PV systems and battery storage systems shown here account for the change in space available and are also intended to represent the conditions and dimensions exemplarily. With a typical size of 5-7m²/kWp, a 40 kWp photovoltaic system would already require between 200 and 280 m² of roof space. Realistically, the typical usable roof area of a multi-apartment building (considering all distances that must be maintained, e.g. from chimneys and property boundaries) is around 100 m², which corresponds to a PV capacity between 14 and 20 kWp.

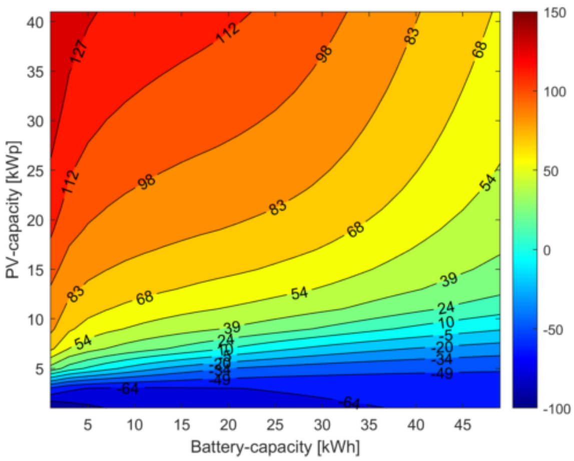


Figure 4.14: Maximum additional investment costs for multi-apartment buildings for different PV and battery capacities and an annual consumption of 20,000 kWh/a [€/$kWh_{battery}$]

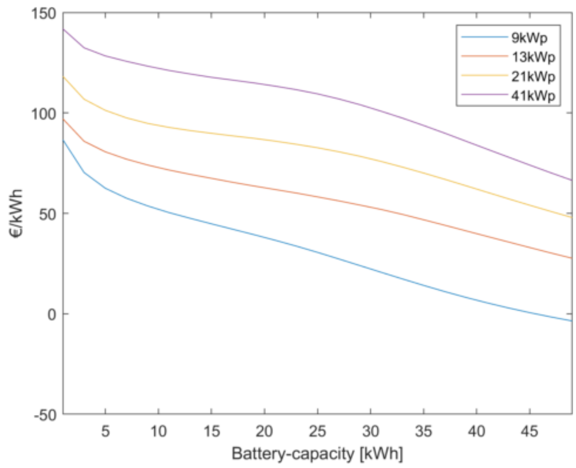


Figure 4.15: Maximum additional investment costs for multi-apartment buildings for selected PV and battery capacities and an annual consumption of 20,000 kWh/a [€/$kWh_{battery}$]

In the baseline scenario, the maximum possible investment costs are between about 140 €/$kWh_{battery}$ and -75 €/$kWh_{battery}$. The range is roughly the same as for single-family building, but the scale has changed significantly here. Additional costs of 140 €/$kWh_{battery}$ apply here for a 1 kWh storage unit for a PV size of 41 kWp, whereas for a single-family building additional costs of 120 €/$kWh_{battery}$ may occur for 15 kWp and a 1 kWh storage unit. Figure 4.15 shows a slight downward bend at a capacity of 30 kWh, which corresponds to 1.5 kWh/MWh. Especially for smaller systems below 5 kWp, where self-consumption is already significantly above 80 percent, additional investment costs are hardly reasonable.

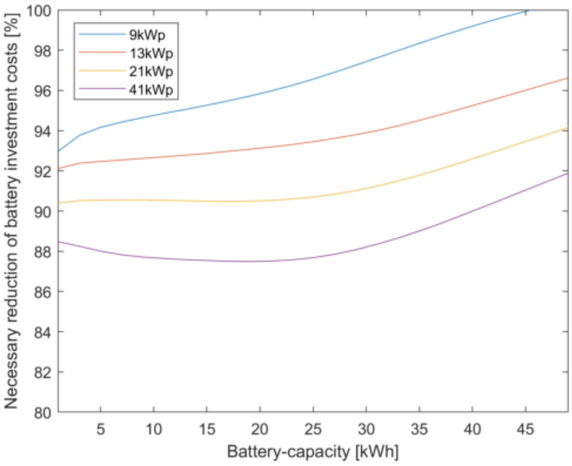


Figure 4.16: Necessary cost reduction compared to investment costs in 2022, multi-apartment building [%]

As Figure 4.16 depicts, the necessary cost reduction ranges from about 88% for a 41 kWp PV-system and a 20 kWh battery storage to over 100% for a 9 kWp PV-system and with a battery storage capacity of 45kWh or above. This result demonstrates that the investment costs for battery storage under the assumptions made are clearly too high even for multi-apartment buildings. Among typical capacities, battery storage may even cost less than for single-family buildings.

The primary reason lies in the distribution scheme and in the different load profiles that can be covered. The more different load profiles with different daily consumptions can be supplied, the higher the self-consumption share even without storage. With an optimal distribution key, as assumed here, the maximum possible share can be consumed directly and a much smaller share must be fed into the grid or stored.

4.4.2.2 Sensitivity analysis

As with single-family buildings, the following chapter analyses the effects of a change in the level of the electricity price, the feed-in tariff, the expected return and the lifetime of the battery. The initial parameters for the analysis are outlined in Table 4.7

Table 4.7: Parameter sensitivity analysis multi-apartment building

Parameter	Value
PV-capacity	15 kWp
Battery capacity	30 kWh
Electricity price	15 c/kWh
Feed-in remuneration	6 c/kWh
IRR	5%
Battery lifetime	13a
Variation of Parameters	-50% to +50%

The basic characteristics of the sensitivity analysis are, as expected, similar to those for single-family buildings, see Figure 4.17. The amount of additional costs has slightly decreased, mainly due to the optimal distribution of electricity within the building and the coverage of different load profiles. An increase in the electricity price by 50% results in additional potential investment costs of about 176 $€/kWh_{battery}$ compared to about 200 $€/kWh_{battery}$ for single-family buildings, whereas a reduction by 50% means negative investment costs of about -53 $€/kWh_{battery}$, compared to about -60 $€/kWh_{battery}$. Similar results can be derived for the analysis of the feed-in tariff, the expected annual return as well as for the lifetime of the battery. An increase in the feed-in tariff also has a negative impact on the economic efficiency and thus also on the maximum possible investment costs. An increase in the feed-in tariff to 9 c/kWh leads to maximum possible investment costs of about 11 $€/kWh_{battery}$, while a halving to 3 c/kWh would mean investment costs of about 113 $€/kWh_{battery}$. The analysis of the expected annual return (IRR) also shows a lower impact on the result here. An increase in the expected return reduces the additional investment costs of the battery storage from about 62 $€/kWh_{battery}$ to about 55 $€/kWh_{battery}$, a reduction in the interest rate leads to an increase in investment costs to 70 $€/kWh_{battery}$. The analysis of the sensitivity of the lifetime of the battery storage is roughly in the same order of magnitude, but in the opposite direction. An earlier replacement, i.e. after 6.5 years, leads to a slight reduction of the potential investment costs to 56 $€/kWh_{battery}$, a later replacement after 19.5 years leads to additional investment costs of 66 $€/kWh_{battery}$.

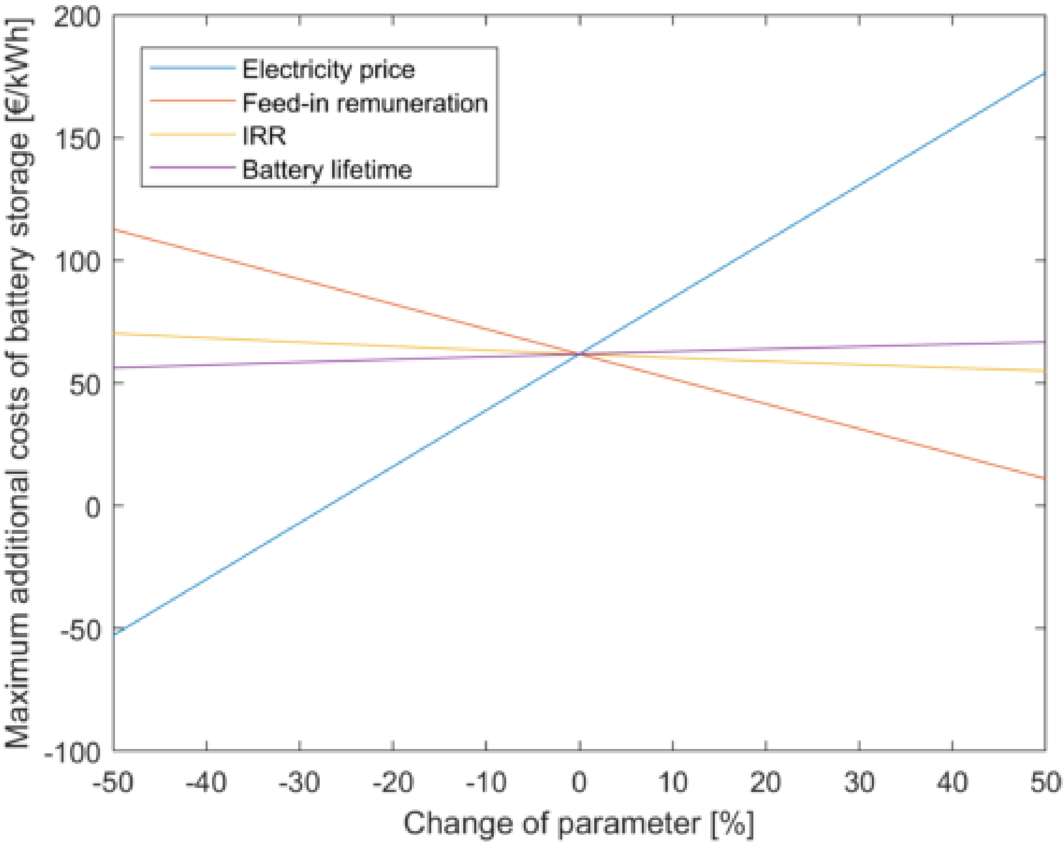


Figure 4.17: Sensitivity analysis for additional storage investment costs in a multi-apartment building [$€/kWh_{battery}$]

4.5 Cross-building storage utilisation

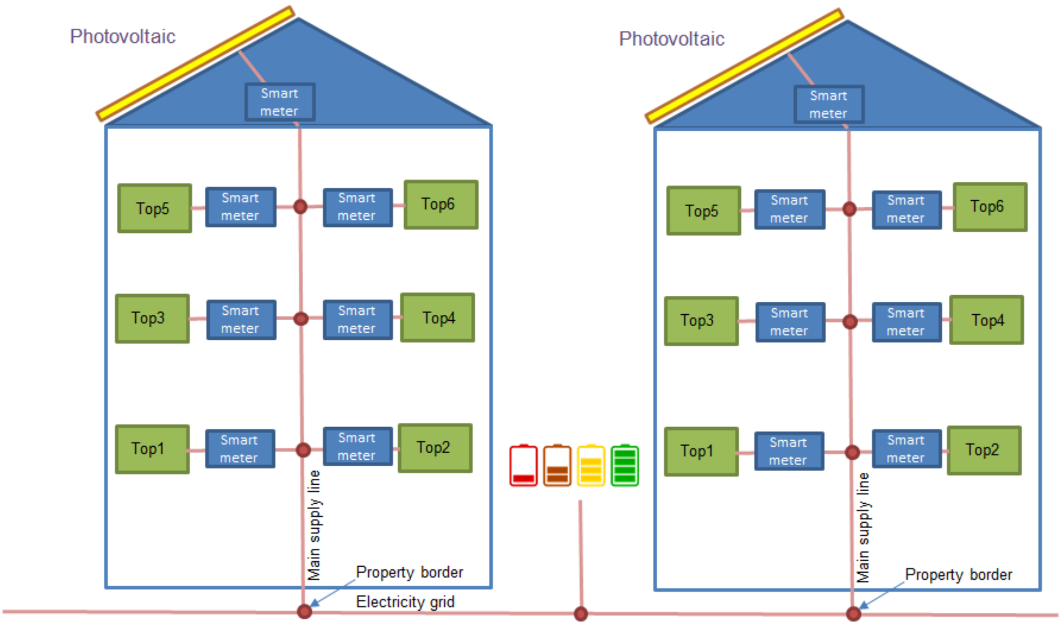


Figure 4.18: Schematic configuration of cross-building energy sharing

An extension of the scenarios already analysed results from the use of battery storage across buildings. In this case, the development of the economic efficiency and the additional maximum investment costs is assessed, if the system boundaries were extended to several buildings. Figure 4.18 shows the cross-building use of photovoltaic electricity and battery storage. Battery storage can be used across-buildings to store surplus electricity from one or more photovoltaic systems or other renewable energy systems. For instance, only one photovoltaic system can be installed on a building and cover part of the consumption of both buildings directly or via a battery storage system. This can be a good option, for example, if no photovoltaic system can be installed on the second building due to shading. In the same way, it can also make sense for several differently oriented systems to supply several buildings and for the surplus to be stored and used, for example, at night. The cross-building use poses some challenges, especially with regard to integration and billing. In principle, the decentrally generated photovoltaic electricity can also be used via the public grid through energy communities, whereby grid fees are incurred for that part of the electricity. However, the previous scenarios have already shown that economic viability is difficult to achieve. Additional grid fees would also be incurred for storing the electricity and consumption from the storage facility if it is connected to the public grid. Therefore, it is important to ensure that the battery storage system does not have to be connected to the public grid.
In Austria, the grid infrastructure is divided into seven grid levels representing different voltage levels. Grid level 1 is the extra-high voltage or transmission grid, whereas grid level 7 represents the low-voltage level, where private households, agricultural farms and small businesses are located. Large-scale industry and also large consumers are often located on grid level 3. The price differentiation of the grid charges results from the principle of "cost rollover", i.e. the total costs are passed on proportionally from the highest to the lowest grid

level. This regulation leads to higher grid charges for households and other small consumers (agriculture and small businesses) at the lowest level, as they not only contribute to the financing of the grid level they use in each case, but also have to pay a share of the grid charges of all preceding grid levels. Therefore, the higher the grid level, the lower the average grid charge to be paid per kWh (Plank and Doan, 2019). In Austria, a reduction of grid fees is provided for renewable energy communities depending on the regional expansion and the grid level used. A distinction is made between local renewable energy communities and regional energy communities. Local energy communities may only use grid levels six and seven, which includes the local low-voltage grid including the transformer station. Regional energy communities can also use the medium-voltage grid, i.e. grid level five and the medium-voltage busbar in the transformer station located on grid level four, compare Cejka, Frieden, and Kitzmüller (2021) and Energiegemeinschaften (2022).
Different concessions apply to local and regional communities:

- Local area: The energy prices for the grid usage charge in local EEGs are reduced by 57 % compared to standard grid charges.
- Regional area: The energy prices for the grid usage charge in regional EEGs are reduced by 28 % for users on grid levels six and seven, and by 64 % on grid levels four and five.

The scenario was extended by adding ten more measured load profiles and bringing the total consumption of the buildings to about 40,000 KWh. To account for the increased total consumption, the PV and battery storage capacities were also adjusted.
Table 4.8 summarises the parameters for cross-building storage utilisation.

Table 4.8: Parameters for cross-building storage utilisation

Parameter	Value
PV-System	
Orientation	south
Installation angle	30°
Size	1 - 81 kWp
Battery System	
Charge/Discharge Power	10kW
Size	0 - 101 kWh
Load profile	
Type of profile	measured household
Overall consumption	40,000 kWh

4.5.1 Energetic calculation

The energetic calculation is based on a total electricity consumption of 40,000 kWh per year and 20 different measured, randomly selected household load profiles. As can be seen in Figure 4.19 and Figure 4.20, the different compositions of the load profiles result in marginal differences for the share of self-consumption and the rate of self-sufficiency for PV systems up to a size of 1 kWp/MWh and a battery storage of 1.5 kWh/MWh compared to multi-apartment buildings in Figure 4.12 and Figure 4.13. Only above these values deviations can be observed. In multi-apartment buildings, rates of self-sufficiency of over 70% are already achieved with significantly smaller capacities. Basically, two reasons attribute to this effect. On the one hand, the level of self-sufficiency is already slightly higher for a building-wide calculation compared to a multi-apartment building, even without a storage system, which is why the additional benefit of the storage system increases to a smaller extent. On the other hand, due to the supply of twice as many different measured load profiles and the simultaneity of the load profile peaks, not all peaks can be covered by the battery storage. For this purpose, the charging and discharging capacities would have to be adjusted, which would also lead to higher investment costs for the storage.

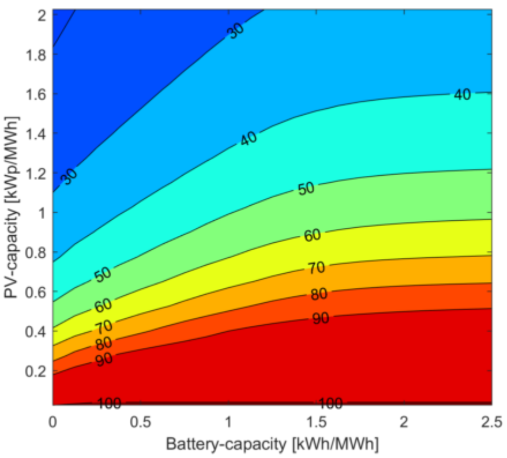


Figure 4.19: Rate of self-consumption for different combinations of PV-capacity and battery-capacity related to an annual consumption of 1000 kWh/year, cross-building utilisation [%]

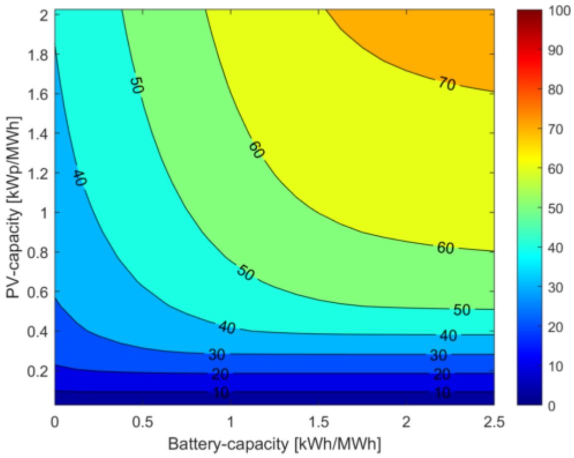


Figure 4.20: Rate of self-sufficiency for different combinations of PV-capacity and battery-capacity related to an annual consumption of 1000 kWh/year, cross-building utilisation [%]

Without storage, the self-consumption share at 1 kWp/MWh, which would correspond to a 40 kWp system in this case, is about 32%. With a correspondingly smaller system of only 0.5 kWp/MWh, i.e. 20 kWp, the rate of self-consumption is already over 52%, even without storage. If we assume that two (Wilhelminian style) buildings in Vienna have suitable rooftop areas of about 100 m² each and assume an area of 5m² per kWp, a 40 kWp system is a realistic size. An additional storage unit with a size of 1.5 kWh/MWh, corresponding to 60 kWh, increases the self-consumption to approximately 85%. An increase of just over 30 percentage points. Basically, it can be stated that a battery storage size of 1.5 kWh/MWh for the supply of different household load profiles can be considered ideal in this use case, at least in terms of energy supply.

4.5.2 Economic calculation

As shown in the energy performance assessment, the relative changes in terms of self-consumption and self-sufficiency are only relatively small in some areas compared to multi-apartment buildings. How the different capacities of PV and battery storage affect the additional investment costs is analysed in the following sections.

4.5.2.1 Baseline scenario

Figure 4.21 and Figure 4.22 show the results for an overall annual electricity consumption of 40,000 kWh, PV-capacities between 1 and 81 kWp and storage capacities between 5 and 100 kWh.

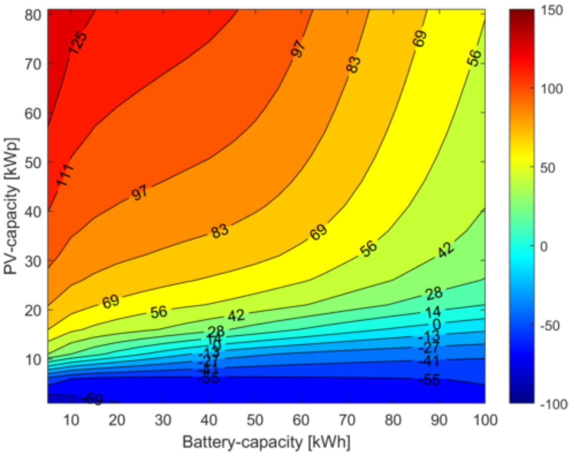


Figure 4.21: Maximum additional investment costs for cross-building utilisation for different PV and battery capacities and an annual consumption of 40,000 kWh/a [$€/kWh_{battery}$]

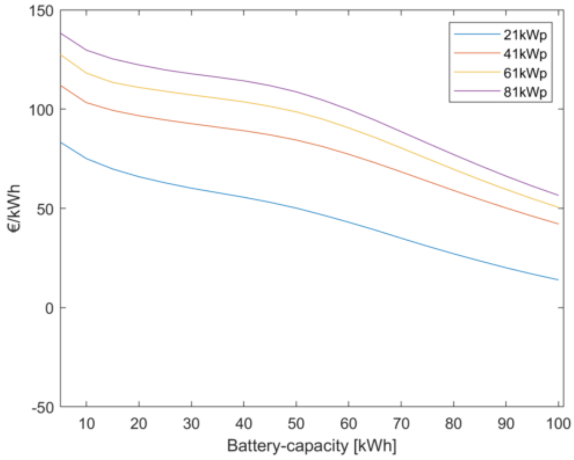


Figure 4.22: Maximum additional investment costs cross-building utilisation for selected PV and battery capacities and an annual consumption of 40,000 kWh/a [$€/kWh_{battery}$]

As can be seen in the previous use cases, the additional costs depend heavily on the dimensioning of the systems in relation to the yearly electricity consumption. Since the dimensions are different in each use case and different load profiles are used, comparability is not that easy. However, if the investment costs for a 41 kWp system are compared in the case of a multi-apartment building, Figure 4.15, and in the case of a cross-building electricity exchange, Figure 4.22, it becomes clear that in the latter scenario the costs for the battery storage system must be lower for the same size. The reason for the lower costs is the already increased self-consumption due to the different load profiles and the higher yearly total consumption. As a result, the additional benefit of the battery storage system decreases. This becomes also apparent in Figure 4.23 and Figure 4.16, where the respective necessary reduction of the specific investment costs is shown in comparison to the current battery storage costs.

In general, the same order of magnitude can be seen for all three use cases and for the respective realistically feasible capacity combination of PV and battery storage. However, if we compare the same sizes of PV and battery storage as before, the investment costs must decrease further to guarantee the same economic performance if the PV electricity is also distributed or sold to tenants/owners in multi-apartment buildings and if electricity is exchanged between buildings. In the case of cross-property use of the battery storage via the public grid, grid fees for storage or consumption from the storage would also have to be included, which is not the case in this analysis. If these were also taken into account, the investment costs would have to be reduced even further.

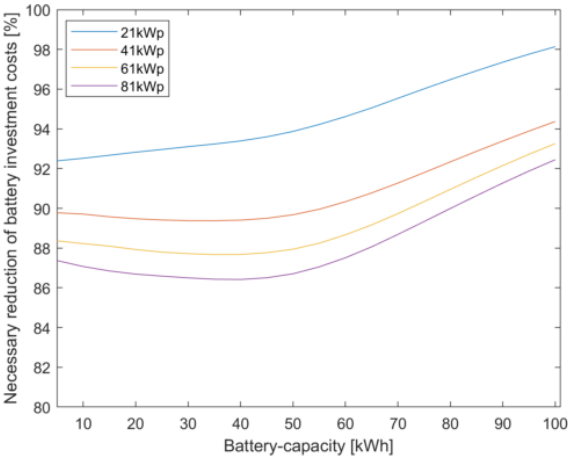


Figure 4.23: Necessary cost reduction compared to investment costs in 2022, cross-building utilisation [%]

As Figure 4.23 points out, the necessary cost reduction ranges from about 86% for a 81 kWp PV-system and a 40 kWh battery storage to about 98% for a 21 kWp PV-system and a 100 kWh battery storage system. The previous comparison of a 41 kWp PV system between multi-apartment building and cross-building utilisation is now also illustrated with numbers. If one compares a 41 kWp PV system and a battery storage capacity of 40 kWh, the cross-building use-case must be about four percentage points cheaper, which can be explained by the higher self-consumption without storage.

In absolute terms, this means about 82 €$/kWh_{batt}$ as opposed to about 89 €$/kWh_{batt}$, a necessary reduction of about 8%.

4.5.2.2 Sensitivity analysis

Similar results as for single-family buildings as well as for multi-apartment buildings can also be expected for the sensitivity analysis of the cross-building use of the battery storage. The initial parameters are shown in Table 4.9.

Table 4.9: Parameter sensitivity analysis cross-building utilisation

Parameter	**Value**
PV-capacity	40 kWp
Battery capacity	60 kWh
Electricity price	15 c/kWh
Feed-in remuneration	6 c/kWh
IRR	5%
Battery lifetime	13a
Variation of Parameters	-50% to +50%

Due to the fact that the PV system is considerably larger in relation to the annual consumption compared to multi-apartment buildings, the initial value is also higher at around 77 €$/kWh_{batt}$, see Figure 4.24. An increase in the electricity price by 50% leads to additional potential investment costs of about 200 €$/kWh_{batt}$, while a reduction by 50% leads to negative investment costs of just under -50 €$/kWh_{battery}$. Due to the choice of parameters, the sensitivity analysis also shows similar effects for the feed-in remuneration, IRR and battery lifetime as in the other use cases.

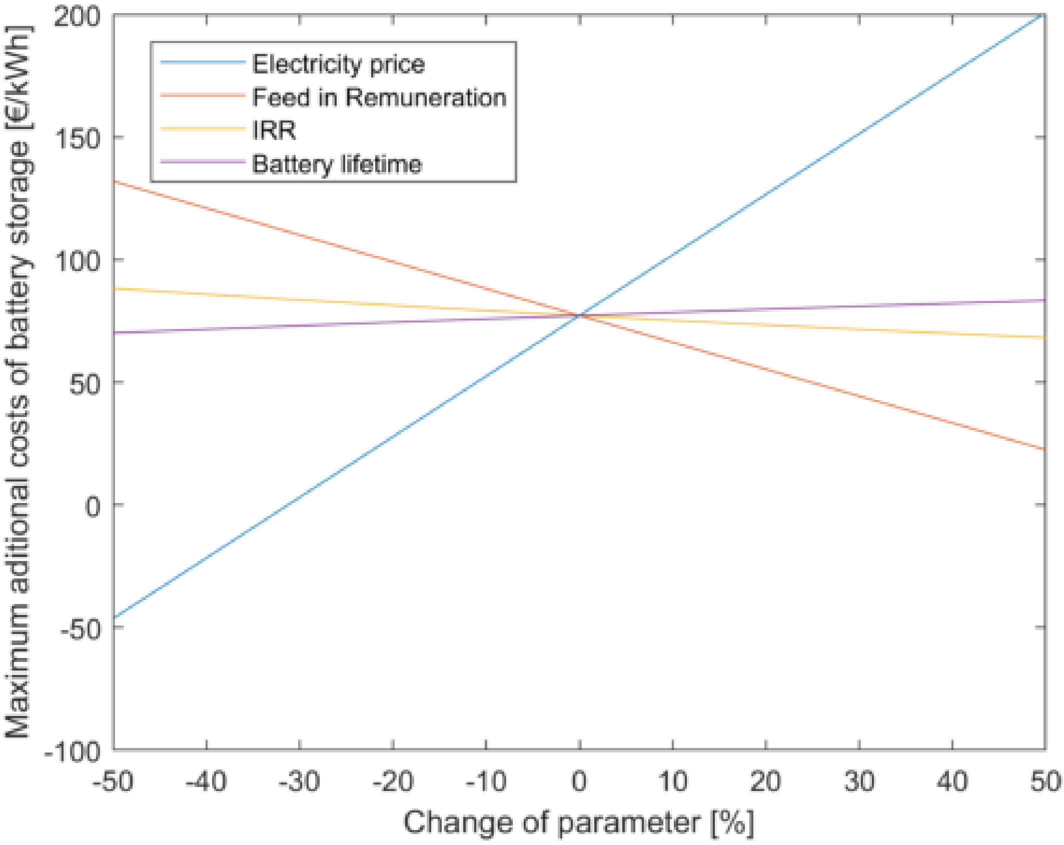


Figure 4.24: Sensitivity analysis for additional storage investment costs in cross-building utilisation [€/$kWh_{battery}$]

For reasons of lucidity, only one combination of PV system and battery storage was shown in the sensitivity analysis in all three use cases. For a detailed comparison, all combinations of PV and battery storage would have to be shown. Depending on the choice of the capacity of the PV system and the battery storage, the same basic characteristics will show up, but can differ in terms of the amount.

5 Economics of electricity storage - electric vehicles

The previous chapters have shown that although the investment costs for storage have fallen significantly, it is still not possible to operate it economically, or only with great effort. Battery-driven electric mobility, along with hydrogen-powered vehicles, currently are the most promising technologies for the decarbonisation of the transport sector, as long as the electricity used is generated from 100% renewable energy sources. However, in the future, it will be necessary to rely not only on a technological change, but also on alternative transport concepts, a different modal split, and public transport to achieve the emission targets, and avoid further congestion on the roads. Electric vehicles can also be used as intermediate storage and are seen as a flexibility option for the energy system. In the following chapters, on the one hand, the detailed modelling of the driving profiles and thus also the demand profiles for different driving purposes are modelled. On the other hand also the optimised charging in single-family buildings is determined on the basis of an average driving profile and possible savings are evaluated.

5.1 Modelling stochastic electricity demand of electric vehicles based on traffic surveys - the case of Austria

To estimate the electricity demand that goes along with the substitution of fossil fuel based private motorised transport with battery-driven electric mobility analysis on both nationwide scale and in individual smaller municipalities, appropriate modelling requires reliable data regarding the driving behaviour. These sections show a method for estimating the actual demand profile of individual traffic at various detail levels. To provide optimal solutions for the interaction of EVs with the electricity grid it is important to design effective charging strategies. Since e-mobility has played a significant role in discussing climate-friendly transport for quite some time (C. C. Chan, 1993; S. Eaves and J. Eaves, 2004), there is a broad selection of literature available dealing with different approaches to model BEV load and charge profiles. Daina, Sivakumar, and Polak (2017) analyse different methodologies to model load and charge profiles of electric mobility. The models are categorized according to the time scale of the electric vehicle (EV) usage patterns and according to significant methodological differences that are applied. The modelling is broken down into travel statistic models, which are based on data from conventional vehicles. Further classifications range from activity-based approaches as daily or multi-day profiles derived from differences in lifestyle and activities to Markov Chain models. A Markov model is a stochastic model used to model changing systems randomly. It assumes that future states only depend on the current state, not on the events that occurred before. Considered states of a vehicle can include driving, parking in a residential area, parking in a commercial area and parking in an industrial area. The authors conclude that there is an urgent need to develop new modelling frameworks to take into account both, long-term strategic decisions of consumers and short-term decisions on EV use, as well as the design of price and non-price incentives for behavioural change. Activity-based modelling offers an attractive starting point to achieve this goal. The paper by Pareschi et al. (2020) deals with the question whether travel surveys provide a good basis for modelling EV driving patterns. The paper shows that existing Household Travel Surveys (HTS) and other travel diaries usually provide sufficiently accurate and abundant empirical information. However, they state that there is more uncertainty regarding the future role of EVs and critical parameters in the analysis like charging losses, charging rates and powertrain design. The paper concludes that conventional HTS are a suitable basis to generate EV insights with some critical parameters to be considered. A further Markov chain tool to estimate EV charging behaviour is presented by Sokorai et al. (2018). This tool enables the modelling of the stochastic nature of a charging stations day-to-day usage if precise data sets of the driving behaviour are available. In addition, a case study to verify the algorithm is conducted. This study concludes that if adequate data sets on travel patterns with appropriate PEV statistics and real probability values are available as a model input, the algorithm can provide valuable stochastic information about electricity consumption at a given location. Other papers based on the methodology of the Markov chain are presented by Schlote et al. (2012) and Fischer et al. (2019). This paper presents a stochastic bottom-up model to evaluate the impact of EVs on load profiles at different parking places and their potential for load management systems. This paper also considers socio-economic, technical and spatial criteria that influence the charging of electric vehicles. The model is used to analyse the effects of uncontrolled charging of EVs on the load profile of households. They find that uncontrolled charging causes a peak load increase up to a factor of 8.5 depending on the charging infrastructure. The work carried out by Hu, Li, and Bu (2019) investigates the challenges that EVs add to the electricity grid at different penetration levels, taking into account the uncertainties caused by the stochastic charging and discharging behaviour. To cope with these uncertainties, a Monte Carlo-based simulation is used to generate EV charging and discharging profiles. The results in this paper show that the specific electricity grid studied can accommodate a high penetration of EVs by limiting charging to off-peak times. Lojowska et al. (2012) also propose a Monte Carlo-based methodology in their paper for estimating the demand for electric vehicles based on a stochastic approach to modelling transport patterns. The focus of this paper is on the scenario of mainly domestic charging availability. The Monte Carlo simulation was performed for 1000 EVs and then scaled to a region with one million EVs. The authors conclude that total demand can increase if there are no incentives to spread the charging demand of EVs. The work of Paevere et al. (2014) presents a methodology to obtain spatial and temporal projections of the retail electricity demand of EVs, their load shift potential and the impact on household peak loads. The paper focuses on the territory of the State of Victoria, Australia and discusses differences in the potential for EV diffusion in different regions. In addition, regional statistics are used for the length of trips and arrival times and on this basis, EV charging and discharging is calculated. They conclude that the form and extent of EV demand profiles are subject to geographical variations. Areas where commuting is dominant generally have higher peak load demand, due to relatively longer trip distances and less diversity in home arrival times. An agent-based approach using the established modelling tool NetLogo is applied in the paper of Chaudhari et al. (2019). The aim is to closely mimic the human aggregate behaviour and its influence on the electricity demand due to EV charging. The model implemented in this paper simulates and defines each EV by its charging characteristics, mobility behaviour and vehicle type. This creates an environment in which decision-making and various circumstances are taken into account to predict the charging behaviour of individuals as well as groups. The simulations in this paper were performed over a period of 24 h and for several days. The individual and total power demand of electric vehicles were determined for different scenarios. In addition, this model should allow for both commercial and private EVs with their different driving purposes. The authors conclude that the results highlight the practical applicability of the ABM-based approach to calculate the charging demand of EVs. Another agent-based approach to estimate EV's charging demand is outlined by Lee, Yazbeck, and Brown (2020). In this paper, an agent-based EV model is evaluated against real data observed during the "My Electric Avenue" project. The main finding is that, within the constraints of the available trial data, the agent model is able to replicate dominant charging pattern features. Forecasting the electricity demand of EV's is performed in the work by Moon et al. (2018), López and Fernández (2020), as well as in Cama-Pinto et al. (2020) and Zhang et al. (2019). The latter was conducted for autonomous vehicles. Forecasting electricity demand using big data technologies is discussed by Arias and Bae (2016). Furthermore, charging EVs in the smart city (Shuai, Maille, and Pelov, 2016) and an empirically validated methodology to simulate electricity demand for electric vehicle charging are outlined in Harris and Webber (2014). A user equilibrium model is discussed in Ferro, Minciardi, and Robba (2020). In this paper, an approach is proposed that extends the User Equilibrium (UE) principle in order to determine, besides the flow over the network links, the service requests from the drivers to the various service stations. In addition, there are several related publications that deal with similar topics. On-road charging of electric vehicles (Stamati and Bauer, 2013) using Contactless Power Train (CTP) where the total power demand for all the passing by vehicles using the system is calculated and the possibility of powering the EVs directly from renewable energy sources is discussed. In Su et al. (2019), the optimal schedule of the charging behaviours of EVs with distinct energy consumption preferences in Smart Communities (SC) is outlined. In this paper, the authors propose a contract-based energy blockchain for secure EV charging in SC. An agent-based approach is proposed in Querini and Benetto (2014) and discussed for EV deployment policies in Luxembourg. Day ahead bidding strategies for electric vehicle aggregators in uncertain electricity markets are outlined in Zheng et al. (2020), while in Schwarz, Auzépy, and Knoeri (2020), the effects of electricity prices on the integration of high shares of photovoltaics are analysed. The paper by Ramsebner, Hiesl, and Haas (2020) directly builds on the methodology in this thesis. The disaggregated demand profiles, as well as driving and parking times, were used as input for a linear optimisation model. This optimisation model aims to charge electric vehicles in a cost-optimal way, taking into account the SoC and considering different charging strategies. As can be seen from the literature described, there are many different ways to model the demand and charging behaviour of electric mobility. Depending on the application and the systemic framework on micro or macro level, the models are able to answer a broad range of research questions. As already concluded in Daina, Sivakumar, and Polak (2017), modelling the driving behaviour of electric mobility on the basis of traffic surveys is agreed to be quite useful and sufficiently accurate. Therefore, the methodology presented in this thesis is appropriate for our objectives and is also applied in the Urcharge project. The main contribution of this analysis lies in the transparent and straightforward modelling of load profiles, the easy calibration for different mobility behaviour, based on traffic surveys and in the high time resolution of the load profiles as a quarter of an hour. The proposed methodology makes it possible to generate demand patterns for individual vehicles, different driving purposes but also for an aggregated average demand pattern including all driving purposes, which are scalable according to the share of EVs in a region or in a whole country, in this thesis, demonstrated by the example of Austria. Furthermore, different regional parameters can be applied to analyse demand patterns in different seasons or to distinguish between urban and rural areas. In addition, various distributions of routes and travel times within the driving purposes, as well as the mix of driving purposes on weekdays and weekends are taken into account. By focusing on individual vehicles and driving purposes, a holistic bottom-up analysis can be carried out on an aggregated level. The methodology presented strictly distinguishes between driving demand profile and charging profiles. The strict separation between the generation of demand profiles and a subsequent generation of charging profiles allows the analysis of the effects of different charging management approaches. For example, uncontrolled charging, cost-minimised charging via a linear optimisation model and corresponding pricing or the evaluation of load shifting potentials on different levels of aggregation.

5.1.1 Data and method

Basically, the model is developed to analyse individual demand profiles on the one hand and aggregated or average load profiles on the other hand to estimate the electricity demand by EVs. The fundamental procedure for creating an average load profile that can be scaled up to a municipal and countrywide level is described in Figure 5.1. First of all, the start times of the outward and return journey are calculated on a daily basis for different driving purposes, see Table 5.1, whereby a minimum difference between these two times is specified, in order to guarantee a certain parking time. These start times are then assigned to different routes associated with route times and assumed grid-to-wheel consumption based on the calculated distance per route. The daily starting times and the resulting consumption are compiled into an annual driving profile. The calculation of the annual profiles is carried out in quarter-hourly resolution. This results in a vector of the size: 35,040 (24 h/day × 4 quarter hours/hour × 365 days) × number of calculated vehicles × number driving purposes (eight for the case of Austria) (see Figure 5.2).

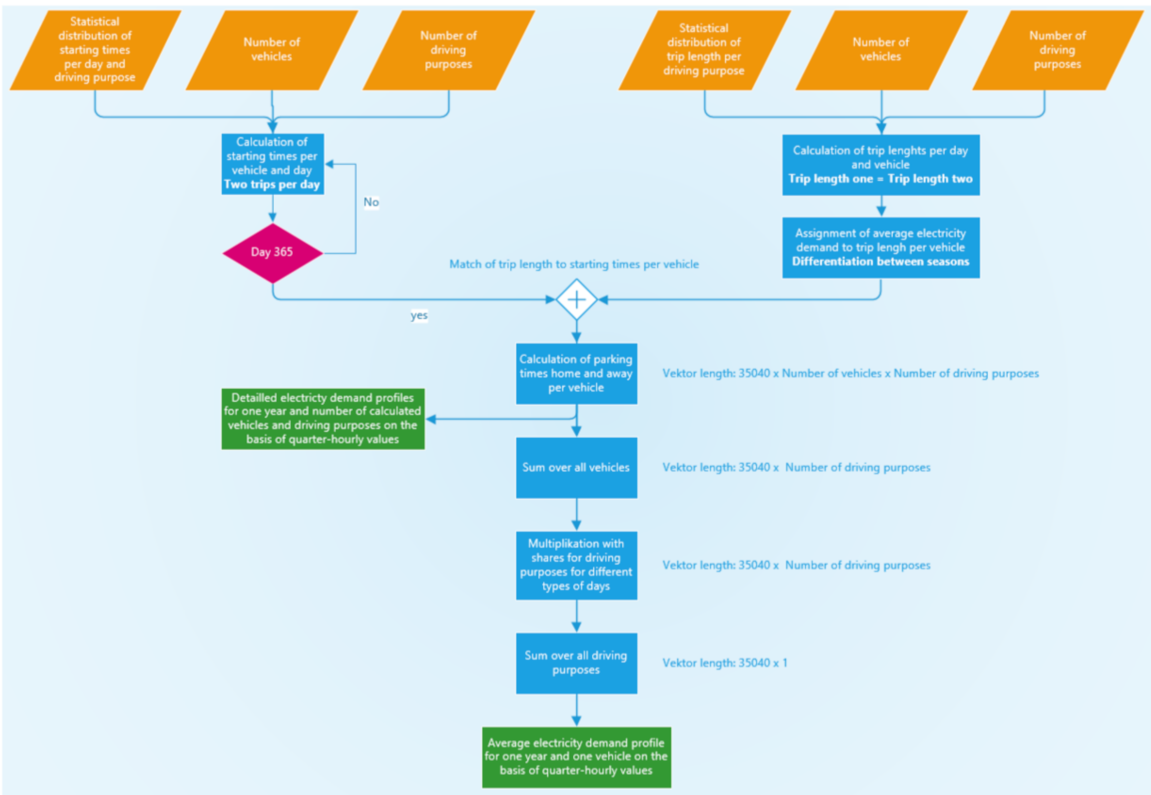


Figure 5.1: Fundamental methodology for creating detailed, as well as an average electricity demand profile for EVs

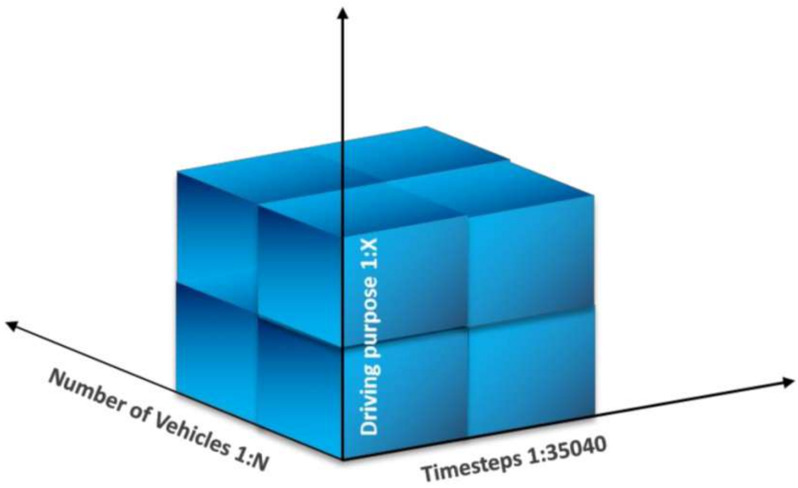


Figure 5.2: The resulting demand matrix considering a time resolution of a quarter of an hour, X driving purposes and N vehicles

This vector could then serve as input for a subsequent linear optimisation model, which aims at charging the vehicles at minimal cost. The electricity demand at each time step is combined to an average total load profile based on the shares of the individual driving purposes, resulting in a vector of 35,040 time steps and x number of EVs. Finally, an average load profile is calculated across the number of vehicles, which can then easily be scaled with the EV penetration rate assumed. If the consumption of individual driving purposes is to be analysed, this can be done before averaging and by restricting the consumption vector.

5.1.1.1 Differentiation between driving purpose and type of day

In order to generate load profiles for Austria, the latest traffic survey from 2014 (Tomschy et al., 2016) is used. This traffic survey examined and recorded the entire mobility behaviour for Austria divided into urban and rural regions. In addition, a distinction was made between working days, Saturdays and Sundays and seasonal differences. The study shows that in Austria about 104 billion kilometres are driven per year, with motorised private transport accounting for about 76 billion kilometres. Public transport represents approximately 21 billion kilometres, with 11 kilometres covered by railway. Pedestrian and bicycle traffic sum up to about 4 billion kilometres. For the calculation of demand profiles for Austria, it is assumed that the essential parameters such as starting times, distance travelled and the parking times for e-mobility do not change significantly and use the following data and estimations for motorised individual transport to model the demand profiles. According to the study (Tomschy et al., 2016), the following driving purposes are used for modelling, see Table 5.1:

Table 5.1: Driving purpose and type of the day used for modelling e-mobility demand pattern.

Weekday / Saturday / Sunday
To the workplace / Commuter
Drop-off and pick-up routes
Leisure
Business
Shopping
Visit
School Education
Errand

As outlined in Table 5.1, eight driving purposes have been identified for Austria in general. The composition of the total trips from these eight driving purposes is different for weekdays, Saturdays, Sundays and public holidays, as shown in Section 5.1.1.3.

5.1.1.2 Stochastic distribution of starting times

The different driving purposes also show different distributions of the start times, which have to be considered in the modelling. Figure 5.3 shows the start time distribution of the respective trip purposes for the outward and return journey, which are modelled as Gauss curves in a next step.

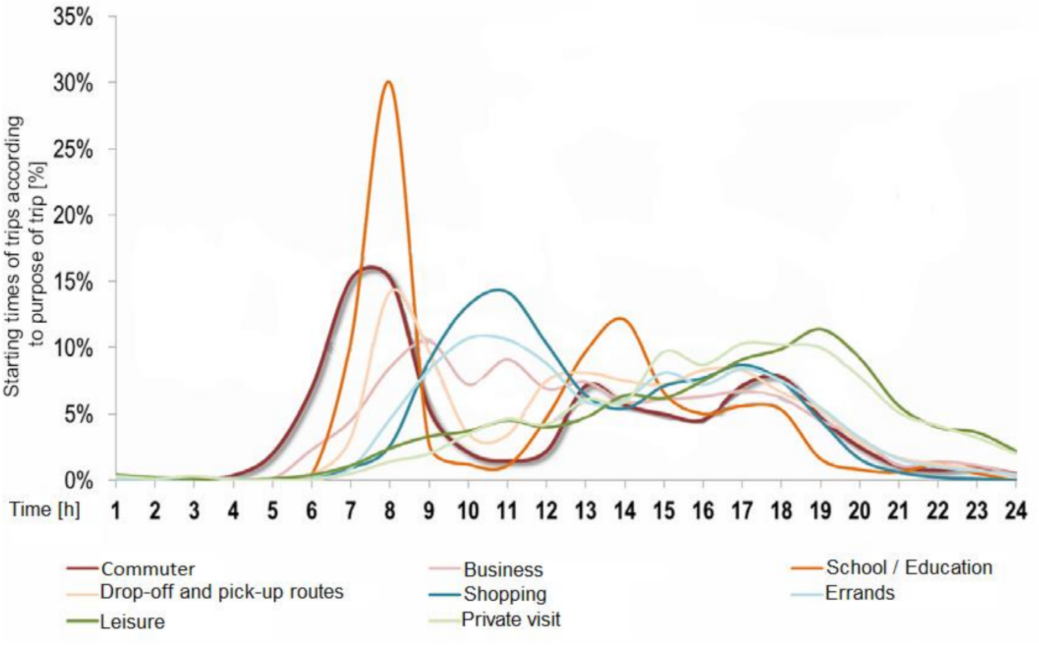


Figure 5.3: Distribution of starting times for outward and return journey and for different driving purposes. Reproduced from Tomschy et al. (2016)

The Gauss distribution for a simple reproduction of the start time distribution for both the outward and return paths is used. For an even more precise reproduction of the curves, a superposition of several Gauss curves can be used. The Gauss distribution is defined in Equation 5.24,

$$f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{5.24}$$

with

$$\begin{aligned} \mu &= \text{Average value} \\ \sigma^2 &= \text{Variance} \\ x &= \text{Random value} \end{aligned}$$

As illustrated in Figure 5.4 for commuters, the actual distribution of starting times depends strongly on the number of vehicles calculated. The more vehicles are calculated, the more the starting times actually match the applied distribution. For a realistic representation of the distribution in an overall load profile, a relatively large number of vehicles must therefore be calculated per trip purpose. With a time resolution of a quarter of an hour and a calculation of 1,000 vehicles (representing 1000 battery storage systems with different State of Charge (SoC)) per driving purpose, this results in 35,040 (time steps per year) × 1000 (vehicles) × 8 (driving purposes) — over 280 million calculation points. Just as for commuters, for all other driving purposes, mean value and variance or standard deviation are defined to determine Gauss distributions for the start times of the outward and return journey. The derived parameters are listed in Table 5.2. The mean start time is given as a time of the day, in the model this time as well as the variance is converted into quarter-hourly values. For example, 6 a.m. is converted to the 24th quarter-hour value of the day (6 h × 4) and a standard deviation of 2.4 h is rounded to 10 quarter-hours.

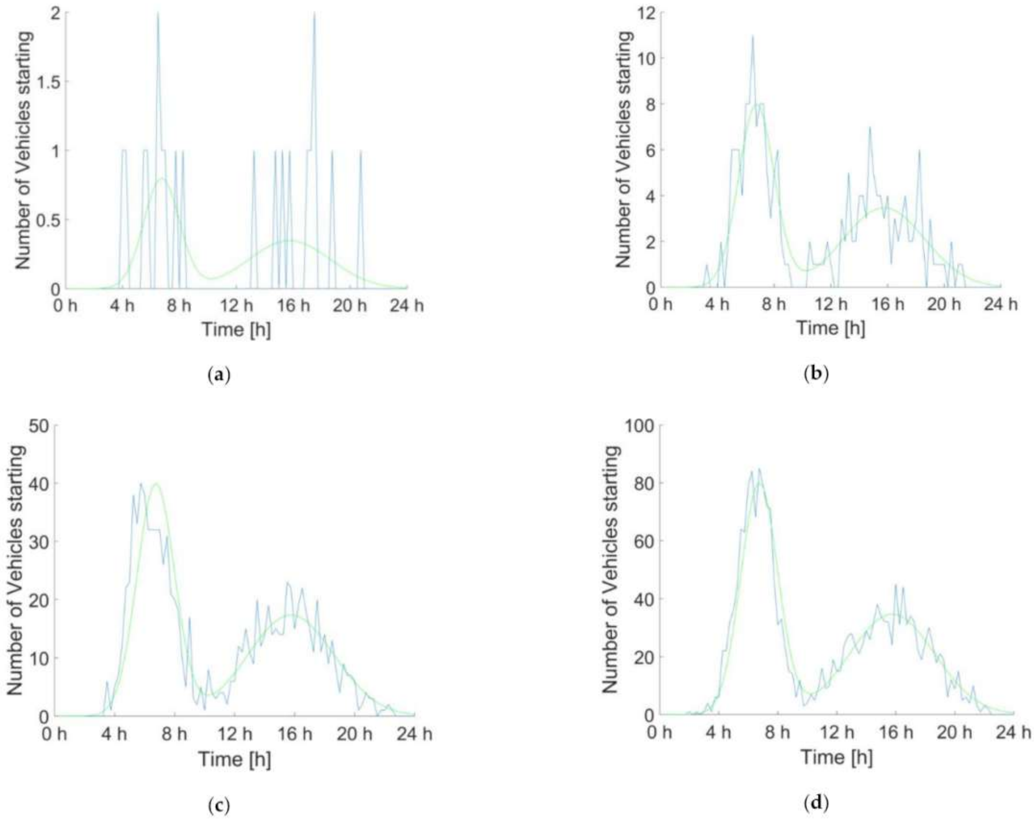


Figure 5.4: Modelling of starting times using Gaussian distributions for different numbers of vehicles. Comparison of perfect Gaussian curve (green line) and reproduction with different number of vehicles (blue) from top left to bottom right (a-d): 10 vehicles, 100 vehicles, 500 vehicles, 1000 vehicles.

Table 5.2: Expected value and variance of the norm distributions of the start times of the individual routes per driving purpose.

Driving Purpose	Route One	Route Two
To the workplace/Commuter	$\mu = 7:30$ am $\sigma = 1$ h	$\mu = 4:00$ pm $\sigma = 2.88$ h
Drop-off and pick-up routes	$\mu = 8:00$ am $\sigma = 0.75$ h	$\mu = 3:30$ pm $\sigma = 2.88$ h
Leisure	$\mu = 10:00$ am $\sigma = 2.5$ h	$\mu = 7:00$ pm $\sigma = 1.5$ h
Business	$\mu = 10:00$ am $\sigma = 1.5$ h	$\mu = 3:00$ pm $\sigma = 3.13$ h
Shopping	$\mu = 10:30$ am $\sigma = 1.5$ h	$\mu = 5:00$ pm $\sigma = 2.5$ h
Visit	$\mu = 11:00$ am $\sigma = 2$ h	$\mu = 5:30$ pm $\sigma = 4.25$ h
School/Education	$\mu = 8:00$ am $\sigma = 1.5$ h	$\mu = 3:30$ pm $\sigma = 4.25$ h
Errands	$\mu = 10:30$ am $\sigma = 1.5$ h	$\mu = 4:00$ pm $\sigma = 2.5$ h

In order to consider the fact that not all trips are of the same length, a statistical distribution of the distances travelled depending on the purpose of the trip, based on the original data, is introduced. The analysis of the empirical data results in different distributions of the distances travelled depending on the purpose of the trip and the day of the week. For the sake of simplicity, all trips per purpose of the trip were summarised and analysed according to their distribution, regardless of the type of the day. To reproduce the distribution as precisely as possible, the distances were divided into 200 classes of 1 km each, see Figure 5.5 as an example for the distribution of trip lengths for commuter traffic.

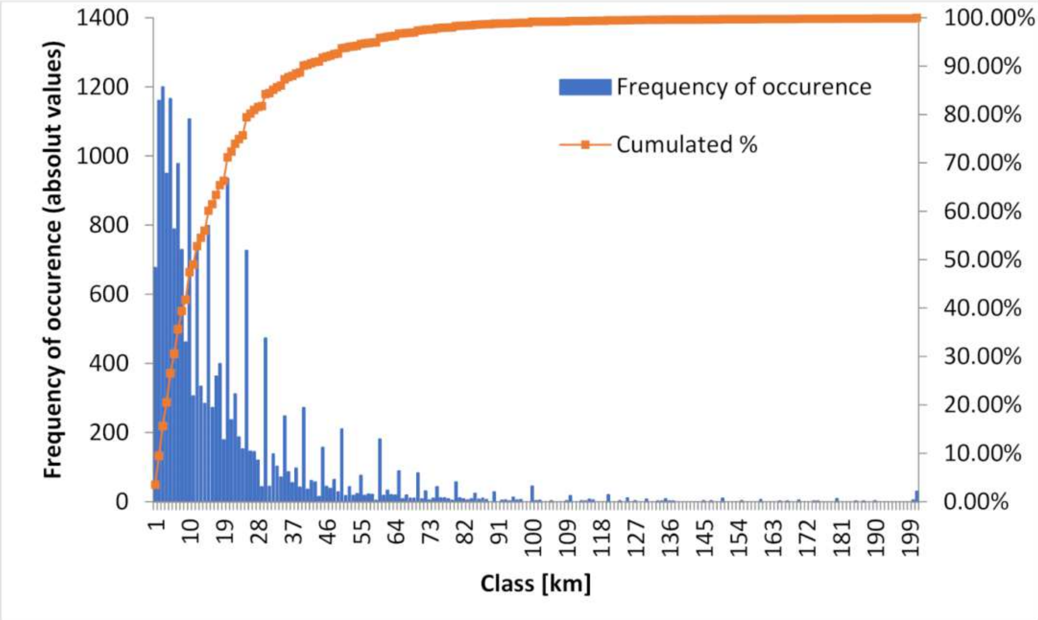


Figure 5.5: Probability function and distribution function for the purpose "to the workplace/commuter" Reproduced from Tomschy et al. (2016)

The actual length of each route per driving purpose was then based on the class average. For the class between zero and one kilometre for example the actual length is 0.5 km. The maximum driving length was limited to 200 km because the analysis of the data showed that only few trips (e.g., 0.16% in the case of commuters) exceeded 200 km. Since the discrete distribution of the trip lengths was determined, the multinomial distribution was chosen as a function to model the statistical allocation of the trip lengths to the individual daily trips. The multinomial distribution is a generalisation of the binomial distribution. If mutually exclusive results are possible for a random process m and the random process is repeated n times independently, the probabilities can be calculated using the multinomial distribution. $\mathrm{x_1}, \ldots, \mathrm{x_k}$ has a probability of occurrence of $\mathrm{p_1}, \ldots, \mathrm{p_k}$. The probability of the occurrence of a certain distance is known. The n-repeats are recalculated for each day according to the number of cars. In this way, each trip gets assigned to a random length according to the distribution. The multinomial probability distribution is defined as follows, see Equation 5.25,

$$f(n_1, \ldots, n_k | N; p_1, \ldots, p_k) = \frac{n!}{(n_1! \ldots n_k!)} \prod_{i=1}^{k} {p_i}^{n_i}, \sum_{i=1}^{k} n_i = n, \sum_{i=1}^{k} p_i = 1 \tag{5.25}$$

with

n = Number of vehicles

k = Number of path length

p = Probability of path length

According to the study, the average annual distance travelled by car is 13,300 km/a. With an average distance of 16 km for individual motorised traffic per trip, this means that an average of 2.28 trips are made per day. Since only 2 trips per day are assumed in the modelling, the return path is assigned the same distance as the outward path. This results in an average length of 16 km across all driving purposes. In order to be able to represent the average driving performance of 13,300 km per year, the average annual route length and thus all route lengths need to be scaled up by a factor of 1.14.

5.1.1.3 Share of driving purposes on overall trips

Although the driving purposes and start times remain the same for working days, Saturdays, Sundays and holidays, the respective shares vary considerably. For example, the share of commuter traffic on the overall trips on a working day is much higher than on a Saturday or even a Sunday or public holiday. This shift in the shares of driving purposes results in different demand profiles for weekdays, Saturdays, Sundays and holidays. In order to calculate the respective shares of the driving purposes, one must first consider the total routes for all transport modes and then break them down to motorised individual traffic, which, however, is not outlined directly in the statistics. Based on the number of trips per driving purpose from Table 5.3, the average trip length of 16 km for motorised private transport is used to calculate the kilometres travelled per day. However, since the trips are only partially covered by private motorised transport, the total distance covered per day must be aligned with the respective shares, see Table 5.4, in order to be able to derive the kilometres driven per day, see Equation 5.26 As the traffic-survey does not show whether the distribution differs between Saturdays, Sundays and holidays, the same distribution as on working days is used for the calculation of kilometres travelled.

$$D = N * s * l \tag{5.26}$$

with

$$
\begin{aligned}
D &= \text{Distance travelled by vehicle and day [km]} \\
N &= \text{Total number of trips completed per day [1]} \\
s &= \text{Share of motorised individual traffic in total number of trips travelled [1]} \\
l &= \text{Average distance travelled per trip by motorised individual traffic [km]}
\end{aligned}
$$

Table 5.3: Number of total routes and share of driving purposes in total route.

Trip Purpose	Working Day	Working Day	Saturday	Saturday	Sunday	Sunday
	Share of total trips [%]	Number of trips	Share of total trips [%]	Number of trips	Share of total trips	Number of trips
Total trips/day	100	22,090,000	100	19,851,000	100	14,885,000
of which						
To the workplace/Commuter	26	5,743,400	7	1,389,570	5	744,250
Drop-off and pick-up routes	7	1,546,300	5	992,550	5	744,250
Leisure	15	3,313,500	29	5,756,790	47	6,995,950
Business	5	1,104,500	2	397,020	2	297,700
Shopping	16	3,534,400	29	5,756,790	3	446,550
Visit	8	1,767,200	15	2,977,650	26	3,870,100
School/Education	8	1,767,200	0.5	99,255	0.5	74,425
Errands	13	2,871,700	12	2,382,120	11	1,637,350

Table 5.4: Kilometres per day and respective share of motorized individual traffic on total trips.

Trip Purpose	Working Day	Working Day	Saturday	Saturday	Sunday	Sunday
	Share of motorised individual transport in total trips [%]	Distance [km]	Share of motorised individual transport in total trips [%]	Distance [km]	Share of motorised individual transport in total trips [%]	Distance [km]
Kilometres/day individual transport		162,299,648		137,003,662		95,537,884
of which						
To the workplace/Commuter	60	55,136,640	60	13,339,872	60	7,144,800
Drop-off and pick-up routes	67	16,576,336	67	10,640,136	67	7,978,360
Leisure	30	15,904,800	30	27,632,592	30	33,580,560
Business	70	12,370,400	70	4,446,624	70	3,334,240
Shopping	45	25,447,680	45	41,448,888	45	3,215,160
Visit	45	12,723,840	45	21,439,080	45	27,864,720
School/Education	9	2,544,768	9	142,927	9	107,172
Errands	47	21,595,184	47	17,913,542	47	12,312,872

Table 5.5: Share of driving purposes in the total routes of motorised individual traffic in %.

Trip Purpose	Working Day	Saturday	Sunday
Share of individual transport per day	100.0	100.0	100.0
of which			
To the workplace/Commuter	34.0	9.7	7.5
Drop-off and pick-up routes	10.2	7.8	8.4
Leisure	9.8	20.2	35.1
Business	7.6	3.2	3.5
Shopping	15.7	30.3	3.4
Visit	7.8	15.6	29.2
School/Education	1.6	0.1	0.1
Errands	13.3	13.1	12.9

As can be seen from Table 5.5, commuter traffic dominates on working days, followed by shopping and private errands. On Saturdays, shopping dominates with over a third of the trips made, followed by leisure trips and private visits. On Sundays, on the other hand, leisure trips are at the top of the list almost the same as visiting trips. See also the graphical visualization in Figure 5.6.

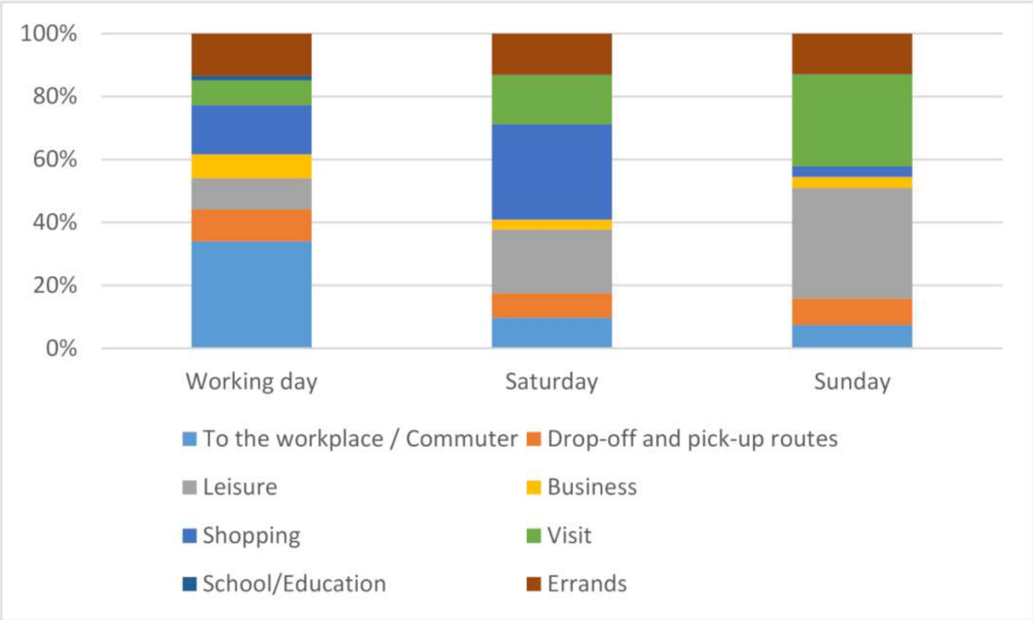


Figure 5.6: Share of driving purposes in the total routes of motorised individual traffic, graphical visualisation.

5.1.1.4 Electric vehicle consumption

The grid-to-wheel consumption of the vehicles is assumed to be the same for all driving purposes and vehicles. Even if there certainly are differences in the consumption of individual vehicles, as well as different routes, it seems justifiable for the present modelling to assume these as average consumption, as this would also be averaged in the large number of vehicles calculated. However, it is not the aim of this study to analyse the consumption of different vehicle models. Nevertheless, we consider the fact that consumption tends to be higher in winter than in summer as also outlined in the study of Association (2021) and Iora and Tribioli (2019). These studies do not focus specifically on Austria, but on the differences in the electricity demand of electric vehicles in summer and winter. Since, to the best knowledge of the authors, there is no representative study for Austria, an average pattern was assumed, which is believed to represent the climatic conditions and circumstances in the western federal provinces with their alpine character, as well as in the eastern regions with a rather mild climate and the different types of vehicles. For this reason, consumption throughout the year is interpolated between a maximum of 17 kWh/100 km in winter and a minimum of 15 kWh/100 km in summer, see Figure 5.7.

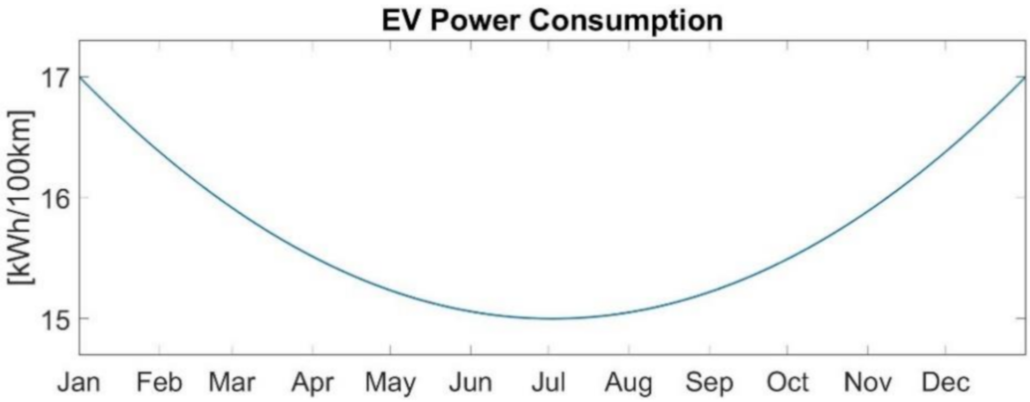


Figure 5.7: Development of EV grid-to-wheel consumption throughout the year. NOTE: For reasons of visualisation, the y-axis was limited between 14.5 kWh/km and 17.5 kWh/km.

5.1.2 Modelling results

As already discussed in the previous chapters, this methodology provides an excellent starting point to answer many different research questions, especially regarding optimal load management. On the one hand, it is possible to analyse single trip purposes, single vehicles, and groups of vehicles regarding their quarter of an hour, daily or yearly electricity demand, driving distances, starting times, or even parking times at home or away from home. On the other hand, it is possible to analyse average load profiles for specific trip purposes, mixed trip purposes, and an average overall load profile that can easily be scaled up for a whole region or country, in this case Austria. In the following chapter, the modelling results are presented by means of individual and average load profiles. For this purpose, 1000 individual vehicle demand profiles were created for each trip purpose.

5.1.2.1 Individual demand profiles versus average demand profiles

From the methodology chapters, it is quite clear that the individual driving profiles change in length per trip and the starting times, depending on the driving purpose. How this affects load profile modelling is analysed in more detail in the following sections. Annual aggregated and averaged model results based on the input data already discussed show that the distances travelled and the annual consumption per trip purpose vary enormously (see Table 5.6). The shortest distance of a single-vehicle is observed for drop-off and pick-up routes with 5476 km/a, whereas the longest distance is observed for business routes (23,674 km/a). The modelled average distance per trip of 16 km is precisely in line with the study results (Tomschy et al., 2016). The large number of vehicles calculated (1000) results in a relatively good statistical distribution of both the start times and the trip lengths. The annual consumption of individual vehicles varies between 690 kWh/a and 3711 kWh/a, and the variation of annual consumption depends not only on the route length but also on the different grid-to-wheel consumption in summer and winter. The average consumption per trip is 3 kWh across all driving purposes.

Table 5.6: Model results for eight driving purposes considering the underlying 1000 randomly generated profiles.

Trip Purpose	Min. Distance of Vehicles [km/a]	Max. Distance of Vehicles [km/a]	Average Distance of Vehicles [km/a]	Average Distance per Trip [km]	Min. Demand of Vehicles [kWh/a]	Max. Demand of Vehicles [kWh/a]	Average Demand of Vehicles [kWh/a]	Average demand per trip [kWh]
to the workplace/commuter	10,430	16,080	12,973	17.8	1627	2509	2032	2.79
drop-off and pick-up routes	5476	9426	7246	10	854	1477	1135	1.56
Leisure	8422	14,750	11,338	15.6	1320	2315	1776	2.44
Business	13,600	23,674	18,228	25	2135	3711	2855	3.92
Shopping	4442	7234	5581	7.7	690	1134	874	1.2
Visit	9526	17,332	12,806	17.6	1497	2744	2006	2.76
School/Education	13,508	21,420	16,993	23.3	2113	3362	2662	3.66
Errands	6006	11,006	8152	11.2	942	1714	1277	1.75

Depending on the analysis and the kilometres driven, these results must be adjusted or scaled to the respective regional conditions. In our case, as we will see later, we will adapt these results specifically to Austria, also considering the type of the day as an input parameter. Since we have simulated only 2 instead of 2.28 routes per day for simplicity, there is a deviation in the average annual kilometres driven (11,665 km calculated vs. 13,300 km (Tomschy et al., 2016)), and thus, also in the annual average consumption. If individual vehicles are to be analysed, it is possible, on the one hand, to select the vehicle (from the 1000 calculated) that comes closest in terms of distance, or on the other hand, to scale it with the number of kilometres required. If driving purposes are to be analysed more precisely, the average demand profile must be scaled with the actual distance driven or the actual consumption. In the following, the results at vehicle level are compared to the mean value of the total calculated vehicles per trip purpose. For reasons of clarity, only the "shopping routes" and "business routes" are compared. In Figures 5.8 and 5.9, the green and blue lines represent a vehicle's consumption per day and year respectively. The orange line represents the average value per 1000 vehicles per trip purpose. The y-axes on the left side represent the demand of the individual vehicles while the y-axes on the right side of the graph represent the average vehicle's demand. The two individual vehicles were selected out of 1000 in such a way that the vehicle with the overall lowest annual consumption (green line) and the vehicle with the overall highest annual consumption (blue line) are evaluated in order to get a feeling for the differences in the respective peaks and in the frequency of the peaks that occur. The electricity demand during the trip is only assigned to one quarter of an hour in the model. However, the previously calculated distance and the average speed of 60 km/h result in corresponding trip times of one minute per km. Together with the electricity demand, the length of the journeys and the times when the vehicle is on the road, the parking times at home and away from home are calculated and assigned to the individual vehicles.

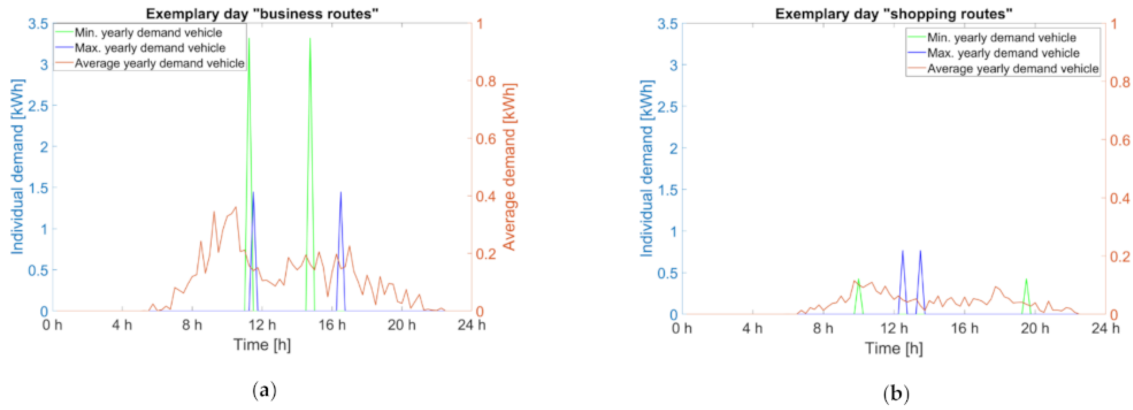


Figure 5.8: Electricity demand of two individual vehicles (green, blue) compared to the average demand of the respective trip purpose (orange) for an exemplary day. (a) business routes; (b) shopping routes.

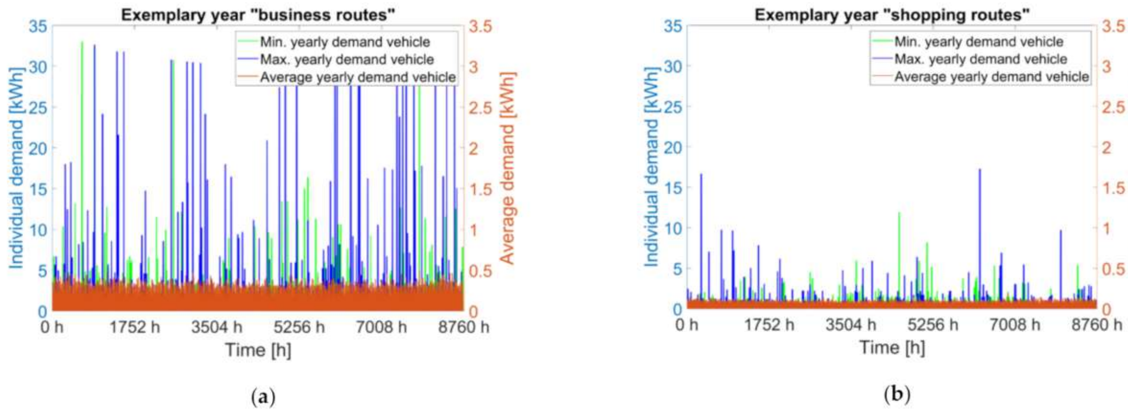
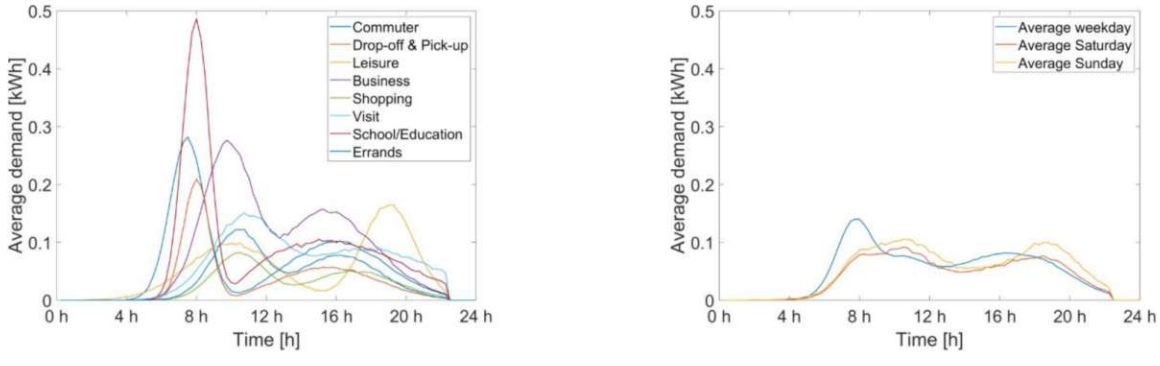


Figure 5.9: Electricity demand of two individual vehicles (green, blue on left axes) compared to the average demand of the respective trip purpose (orange on right axes) for an exemplary year. (a) business routes; (b) shopping routes.

Figures 5.8 and 5.9 show how individual demand profiles and averaged demand profiles behave within a day and over a year. The daily perspective shows that due to the distribution of the start times and the distribution of the path lengths, the averaged load profile for a trip purpose has a significantly different characteristic than the individual vehicle. It becomes clear that the peak load of a vehicle can be significantly higher than the peak load of an average load profile. The average load profile tends to follow a continuous load curve, whereas an individual vehicle's profile is limited to a few points in time during the day. The peaks of individual vehicles at individual points in time are no longer as significant in an average load profile. In addition, it can be seen that a vehicle with a low annual consumption also has higher peak loads on some days than a vehicle with a generally higher annual load profile due to the distribution of the path lengths, as compared with Figure 5.8a. Figure 5.8 also shows that the heights of the peaks, as well as their occurrences, can vary greatly. In the comparison between business trips and shopping trips, it becomes clear that peaks are significantly higher in the business profile and also occur significantly more frequently. This is also reflected in the average profile, which is significantly higher. It is important to note that the current analysis does not consider differences in weekdays and weekends. These differences will be identified in the next section. The advantage of disaggregated modelling of demand profiles lies precisely in the fact that it is possible to extract any information about a vehicle at any time, e.g., current consumption, driving, parked at home and parked away. No information about demand peaks is lost. For subsequent precise analysis of the charging behaviour, a disaggregated demand profile is necessary to be able to calculate the individual charging power at vehicle level depending on the SoC of the battery and afterwards aggregate the total charging power of a vehicle pool. This is difficult to do with an aggregated calculation because the detail of the information is already missing and an average load profile only offers an aggregated representation. However, it is not always necessary to provide all information at a disaggregated level. It is not possible to include several 1000 individual EV demand profiles per country in large energy system models. In such cases, it definitely makes sense to use an aggregated profile.

5.1.2.2 Yearly average demand profile for Austria considering different types of days

In Section 5.1.2.1, the different load profiles were presented based on the trip purpose and on individual and average load profiles. For the analysis of the electricity demand of many vehicles in urban blocks, cities or rural areas and on country level, it makes sense to create an average annual load profile, which consists of all trip purposes. Since the shares of driving purposes differ for weekdays, Saturdays and Sundays (see Section 5.1.1.3, the total demand profile also differs on these types of days. Figure 5.10 shows the consumption of an average day for the different trip purposes on the left side individually and not specifically for weekday, Saturday and Sunday. In the morning, school and commuter trip drop-off and pick-up routes dominate, which of course, correlates with the selected start distribution and the path length distribution modelled according to Figure 5.3. The individual distributions of the individual trip purposes' load profiles, taking into account the shares from Table 5.5 are now combined and different averaged load profiles for weekdays, Saturdays, and Sundays are obtained, see Figure 5.10. Due to commuter dominance with about 34% in the morning, there is an apparent increase on weekdays compared to Saturdays or Sundays. As mentioned previously, the parking times at and away from home are calculated at vehicle level based on the start times and route lengths. This information is required to know when and for how long the vehicle is available for subsequent analyses regarding the charging management of individual vehicle groups.



(a)

(b)

Figure 5.10: Average day for an average vehicle for all driving purposes; and (a) average profile over all driving purposes for weekday, Saturday and Sunday considering the respective share on overall daily trips (b).

For the visualisation in Figure 5.11, however, an aggregated form of the parking times was chosen to clarify how the entirety of the vehicles behaves concerning typical parking times. As can be seen in Figure 5.11, there are slight differences in the availability of vehicles while parked at or away from home. On weekdays, there is a peak around lunchtime in the simultaneity of vehicles parked away from home. The gradient is also slightly higher than on Saturdays, Sundays and public holidays due to commuting. Especially in the evening and at night, almost all vehicles are parked at home. As can be seen in Figure 5.11, by summing up the curves at and away from home, the vehicles are parked mostly either at home or away from home, e.g., at the workplace. Only very few times a day, the vehicles are actually in motion.

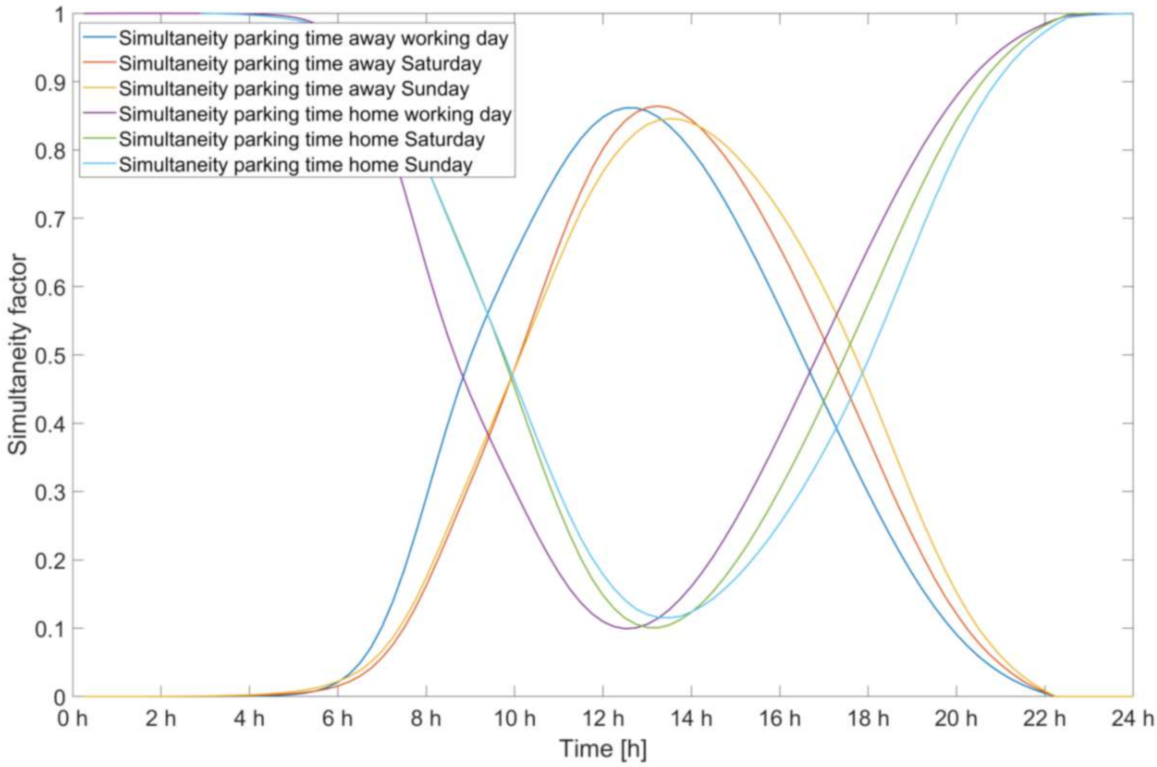


Figure 5.11: Simultaneity of parking times of the calculated vehicles for weekdays, Saturdays and Sundays.

The individual days composition into a continuous annual load profile leads to an annual mileage of approx. 10,570 km/a, which is significantly lower than the mileage of an average vehicle in Austria. Furthermore, it is also less than the average distance of the combined consideration of the different path purposes in Table 5.6. This can be explained by the fact that the length distribution and the different shares of the path purposes in the total profile compose different shares. Therefore, the length also deviates from the previously calculated length where only an average of all path purposes was calculated. To create an Austria-wide aggregated load profile and scale the load profile for different EV penetration rates, this average load profile must first be calibrated to a travelled distance of 13,300 km. Therefore the load profile is calibrated with the factor 1.26 (13,300 km/10,570 km), resulting in the load profile in Figure 5.12.

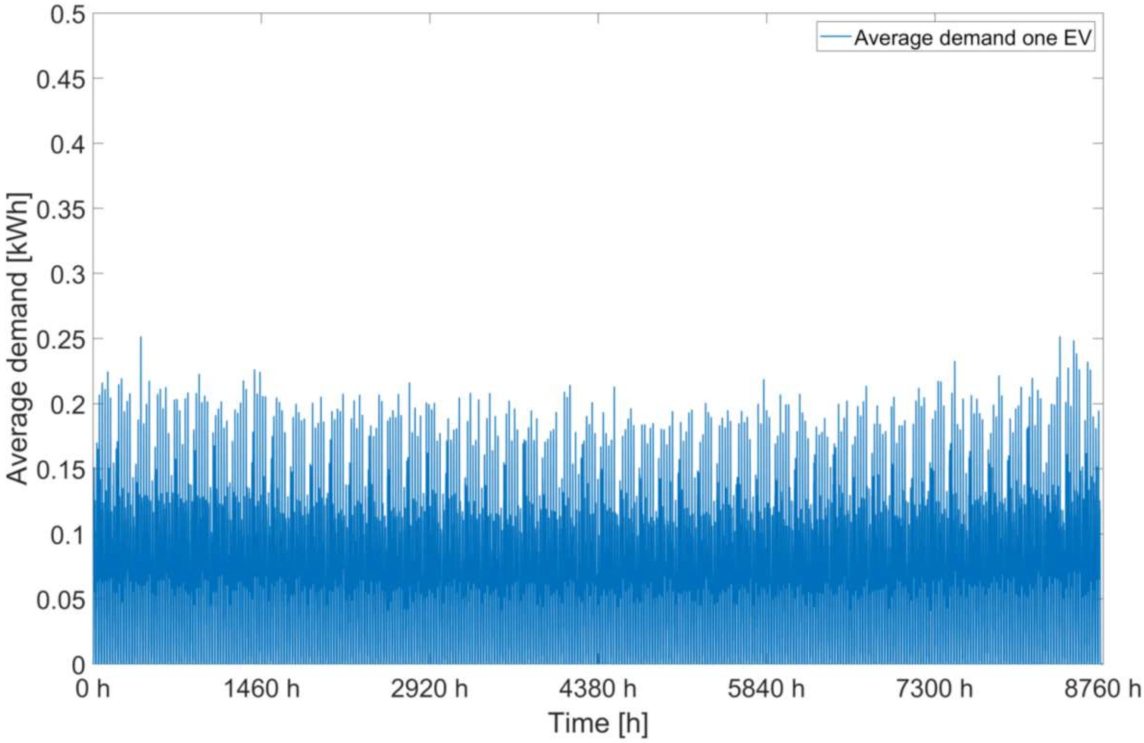


Figure 5.12: Average load profile of an EV considering different driving purposes, weekdays and calibrated to a distance of 13,300 km/a.

Based on this load profile, different scales can now be applied to answer different (research) questions for different regions. From the authors' point of view, the aggregated model results serve mainly as input for system modelling where no detailed individual or disaggregated analysis of demand or driving behaviour is required. As already outlined, for detailed modelling of individual vehicles or vehicle networks' charging behaviour, the disaggregated output of the model should serve as input for further analyses. Such an analysis was implemented, for example, by Ramsebner, Hiesl, and Haas (2020) where the disaggregated demand profiles, as well as driving and parking times, were used as input for a linear optimisation model. This optimisation model aims to charge electric vehicles in a cost-optimal way, taking into account the SoC and considering different charging strategies. To calculate this cost-optimal charging, a disaggregated, high-resolution demand profile is needed as input, which was created by the methodology presented in this thesis.

5.1.2.3 Strength and weakness of the proposed method

The methodology presented aimed at modelling and calibrating high-resolution EV demand profiles based on traffic surveys and at making these profiles versatile in application. These demand profiles should then be available as input parameters for energy system models. The results presented show, that EV demand profiles can be created and evaluated in high temporal resolution per vehicle and trip purpose or on aggregated level as an average load profile. The advantage of the high resolution, disaggregated use of the load profiles is primarily that the information about individual load peaks is maintained and that start, travel and arrival, and parking times can be mapped with quarter-hour accuracy. In addition, the

bottom-up approach has the advantage that a wide variety of aggregated load profiles can be created, which is de facto not possible in the other direction.
In addition, the calibration and creation of these load profiles can be conducted with other country- or regional data. As discussed, the decisive parameters are, on the one hand, the starting times, the distribution of the trip lengths, and, on the other hand, the shares of the different trip purposes among the trips per day. The more precise these data are available, the better the reality can be reproduced in the load profiles.
In order to reproduce this methodology for other countries or regions, the following data is required:

- A breakdown on the driving purpose as precise as possible
- Data on the starting times of the individual routes as accurate as possible
- Data on the distribution of trip lengths as accurate as possible
- Shares of trip purposes on different days

Alternatively, this data could be generated beforehand, or assumptions on average trip lengths must be made. If the data on starting times cannot be modelled using Gaussian distributions, for example, a different, e.g., discrete, distribution can be used to model the trip lengths. The division of the path lengths into path classes and their distribution must also be adapted to the respective data situation. Often, only rugged ranges of the trip length distribution are given in evaluations. In this case, the path class width, as well as the path class centre must be adjusted accordingly and the trip length calculated accepting higher inaccuracy.
In any case, it is important to analyse the data in advance in order to choose the right type of distribution and to assess possible limitations of accuracy due to assumptions and data inaccuracies. The computing time and computing capacity must be taken into account. This means that it is not always possible and reasonable to calculate 1000 vehicles per trip purpose to resolve 35,040 time steps. The high time resolution as well as the amount of vehicles results in more than 280 million data points that have to be calculated. This may be necessary and feasible for the calculation of an average load profile. On a disaggregated level, for example in a subsequent linear optimisation model, the calculation of so many data points, however, reaches the limit of the computational capacity. When simultaneously calculating the cost-optimal charging of 8000 storage units with different SoC's and a resolution of 35,040 time steps, taking into account additional constraints, the calculation time can be exorbitantly high or no solution to the problem can be found. In particular, two things have to be considered before selecting the appropriate method. What purpose do the created demand profiles serve and what data is available. Furthermore, the quality of the input data plays an important role. Depending on the type and accuracy of the available data, the methodology presented here can directly be used. The probability that not all data are available on this level of detail for every analysis is high, and thus, in the case of any data gaps, corresponding assumptions or simplifications must be made, for example concerning the start times or the path length distribution.
Finally, it can be concluded that in order to develop effective charging strategies to reduce the pressure on the electricity grid and to effectively use renewable generation, electrical load profiles for EVs are needed. The methodology presented provides an excellent opportunity to establish such demand profiles on different levels of detail. We find a need for future research

in the consideration of plug-in hybrid vehicles, different charging strategies, as well as Vehicle to Building (V2B) and Vehicle to Grid (V2G) applications, to achieve an optimal integration of electro mobility into the energy system and use the available flexibility options efficiently. External effects that would also change user behaviour were not taken into account. However, it is evident that the COVID-19 pandemic and the associated lockdowns, for example, have changed mobility patterns. This is perhaps less true for the distribution of starting times than for the average distances and lengths of trips. Due to lockdown restrictions, many people switched to home office, and commuters drive to work less frequently. Private visits and shopping trips are also limited. If one also assumes that the modal split will change in the future and public transport will be increasingly expanded and incentivised, the average distances travelled by car will tend to shorten. This will lead to a general reduction in peak loads for EV electricity demand, fewer kilometres driven, and a subsequent reduction in annual electricity demand.

5.2 Techno-economic analysis of electric vehicles in single-family buildings

Since a stationary battery storage system in a household or a multi-apartment building is not economically feasible, the electric vehicle could at least partially store the surplus from the photovoltaic system and thus contribute to the overall economic efficiency. Generally speaking, an electric vehicle, in contrast to a stationary battery storage system, also causes additional electricity consumption but since the battery storage is assigned to mobility, it does not cause any additional costs.

The presented methodology for the generation and analysis of electric mobility load profiles was also used, for instance, in Ramsebner, Hiesl, and Haas (2020) to develop optimal charging strategies in multi-apartment buildings. It was demonstrated that optimised charging of several vehicles significantly reduces the total charging power compared to uncontrolled charging. This has positive effects on the dimensioning of the supply lines as well as the transformer station and can relieve the electricity grids. In addition, it was shown that, depending on the restrictions, CO2-free charging is also possible if the necessary information about, for example, wholesale electricity prices is available to the charging stations. In this thesis, the methodology outlined in Section 5.1 is used to analyse how decentralised PV surplus can be used in an electric vehicle. The focus lies on single-family buildings and different scenarios for the use of the excess are discussed. The optimisation model described in Section 3.4 is applied in this context. The stationary battery storage is replaced by a storage unit in the electric vehicle. The average load profile of the electric vehicle is an additional load profile that can be covered exclusively by the storage unit. Figure 5.13 shows the schematic integration of the electric vehicle into the building and also the external charging option. The scenarios that are investigated are:

- PV Charging at the place of residence: The electric vehicle can only be charged with PV electricity at home. Charging via electricity grid is possible at home as well as external.
- PV Charging at the place of residence and external: It is assumed that PV electricity can be used at home as well as away to charge the electric vehicle. However, grid fees apply. Charging via electricity grid is possible at home as well as at external charging stations.

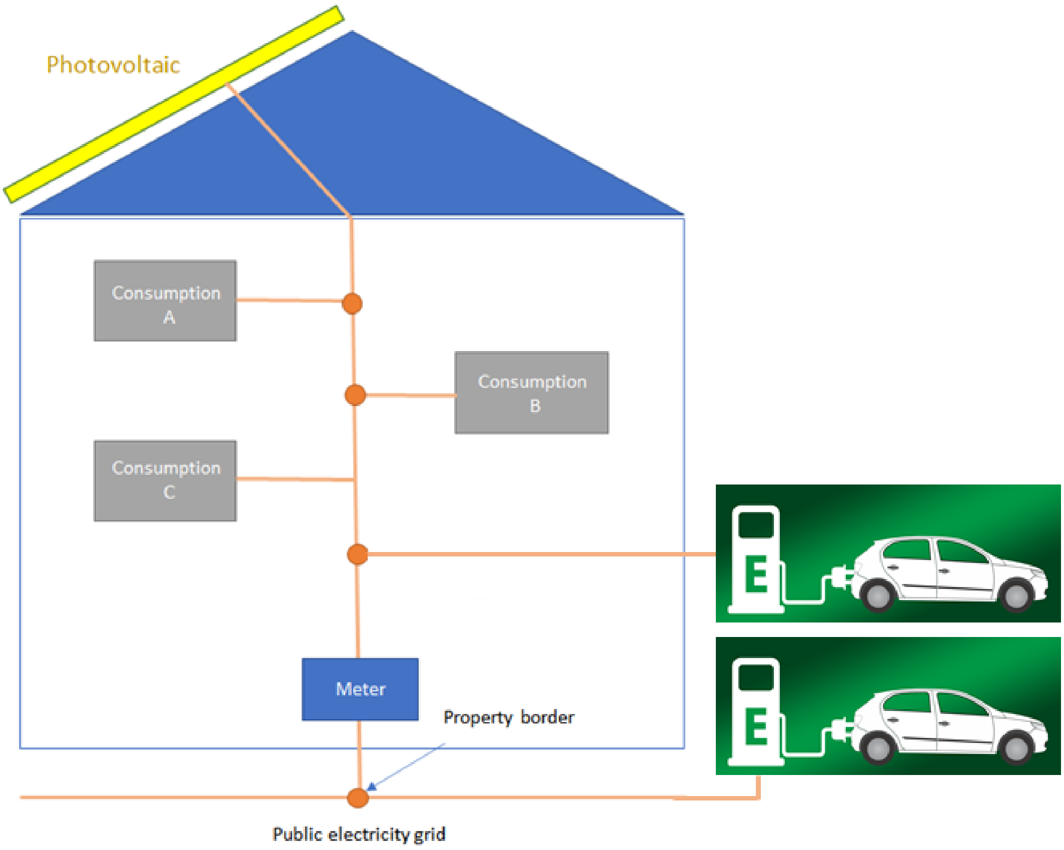


Figure 5.13: Schematic integration of the electric vehicle and charging possibilities in a single-family building and externally

The parameters for the energetic and economic calculation are presented in Table 5.7.

Table 5.7: Parameters for the energetic calculation of PV & electric vehicle

Parameter	Value
PV-orientation	south
PV-capacity	1 - 12 kWp
Battery capacity electric vehicle	40 kWh
Charging power home	3.5 kW
Charging power away	11 kW
Electricity consumption single-family building	1000 - 20.000 kWh/a
Load profile single-family building	H0
Electricity consumption electric vehicle	2080 kWh/a

It is assumed that the electric vehicle can be charged at home single-phase with a maximum possible power of 3.5 kW and away three-phase at a maximum power of 11 kW. The evaluation is carried out for different combinations of annual electricity consumption of the building and PV sizes. The total consumption of the electric vehicle results as an average over all driving purposes and with an average consumption that is slightly higher in winter than in summer, compare Section 5.1.1.4. The distance travelled by this electric vehicle is assumed to be 13,300 km/a according to an average vehicle in Austria (Tomschy et al., 2016).

5.2.1 Energetic calculation

In terms of energetic assessment, the focus lies on self-consumption as well as on the self-sufficiency by the vehicle and the overall self-consumption and self-sufficiency by the building and the electric vehicle. The starting point of the analysis is the rate of self-consumption as well as rate of self-sufficiency of the building alone. Based on these results, the increase in self-consumption as well as the increase of the self-sufficiency by the electric vehicle are evaluated and then also economically assessed.

Self-consumption as well as self-sufficiency for a single-family building are shown in Figure 5.14 and Figure 5.15.

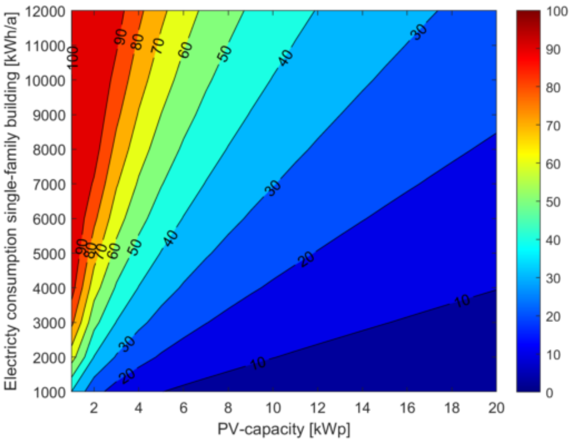


Figure 5.14: Rate of self-consumption for different combinations of PV and yearly electricity consumption - single family building [%]

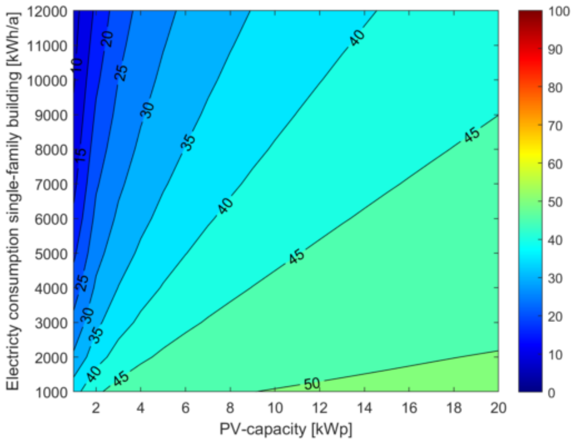


Figure 5.15: Rate of self-sufficiency for different combinations of PV and yearly electricity consumption - single family building [%]

With constant electricity consumption, the rate of self-consumption decreases with increasing capacity of the PV system, whereas the rate of self-sufficiency increases. For a typical household with a consumption of 4000 kWh/a and a 5 kWp PV system, this results in a rate of self-consumption of 34% and a rate of self-sufficiency of 40%.

5.2.1.1 Electric vehicle - PV charging at the place of residence

In this scenario, it is assumed that an electric vehicle can be charged from the PV system at the place of residence. The remaining consumption of the electric vehicle can then be covered either at home or at any external charging station from the electricity grid.

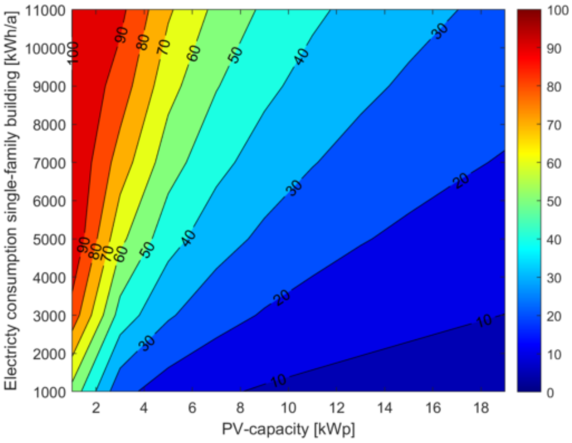


Figure 5.16: Rate of self-consumption for different combinations of PV and yearly electricity consumption - single family building plus electric vehicle [%]

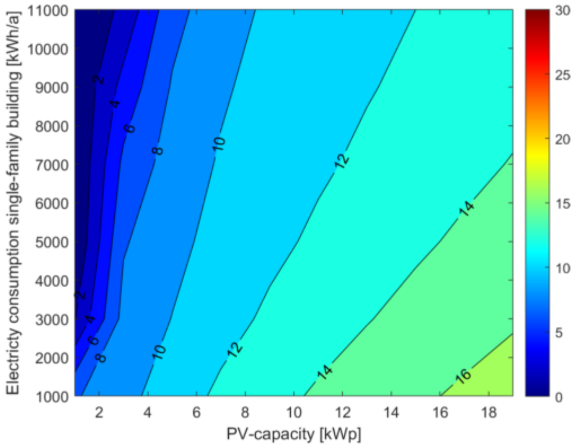


Figure 5.17: Rate of self-sufficiency for different combinations of PV and yearly electricity consumption of the building - electric vehicle [%]

Since the rate of self-sufficiency of the building remains the same as before, Figure 5.16 and Figure 5.17 show the overall self-consumption of the building including the electric vehicle as well as the self-sufficiency of the electric vehicle. As expected, the share of self-consumption increases slightly due to the electric vehicle. In the previously mentioned combination, the self-consumption increases from 34% to about 39%. The self-sufficiency of the electric vehicle lies just under 10%. 90% of the electric vehicle's electricity consumption must therefore be covered by the electricity grid.

This is mainly due to the fact that the parking times of electric vehicles at the place of residence correlate only to a limited extent with PV generation. A much better correlation would be achieved if charging could also take place at the workplace or at the shopping centre, for example. Since an average load profile for all travel purposes is used in this calculation, there can also be significant deviations for individual travel purposes such as commuters, since the parking times of the individual travel purposes vary significantly.

5.2.1.2 Electric vehicle - PV charging at the place of residence & external

Since only a small share of the PV surplus can be used in the electric vehicle in the first scenario, this scenario is expanded to enable the PV electricity generated to be used at other charging stations. The requirement for making this possible is, that both the grid operator and the energy supplier offer this option. The advantage of such a scenario is that a larger share of the generated PV electricity can be used directly by the PV-owner, but it also means more complicated billing and grid fees still have to be paid. Nevertheless, implementing such a scenario can make perfect sense. Firstly, it can increase the acceptance of renewable energies if a PV owner can also use "his own" electricity on the move. In addition, it also ensures that the electric vehicle is preferably charged while away from home when excess PV electricity is available and only in the second instance when it is independently covered by the grid. In other words, it is ensured that the highest possible share of consumption is actually covered by renewable energy. If the charging system is then expanded to include price signals that also reflect the renewable share in the electricity system, maximum charging with renewable electricity could take place. As also explained in Ramsebner, Hiesl, and Haas (2020), this would of course require a certain amount of information to be made available like parking time, length of next trip and state of charge of the battery. In addition, optimal charging also requires that the electric vehicle is plugged into a charging station every time it is parked, so that this optimal charging can take place.

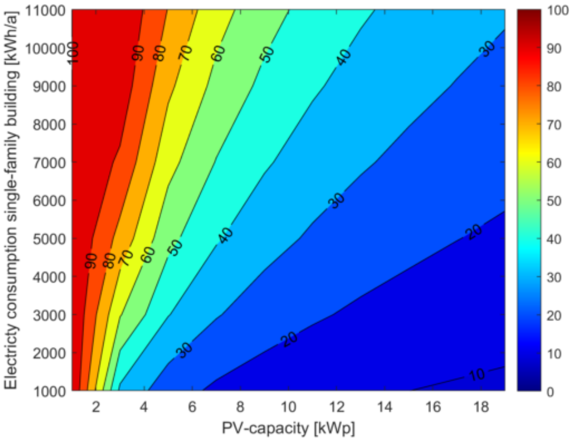


Figure 5.18: Rate of self-consumption for different combinations of PV and yearly electricity consumption - single family building plus electric vehicle [%]

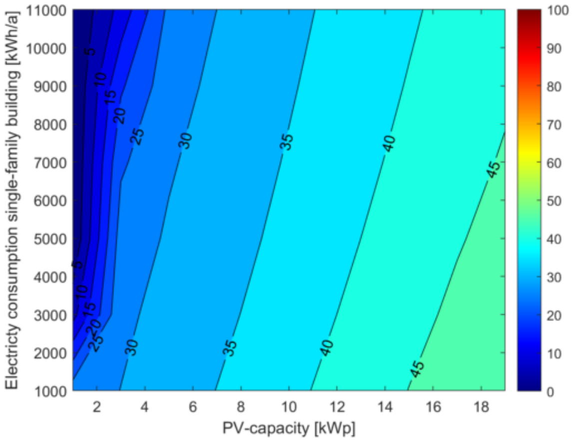


Figure 5.19: Rate of self-sufficiency for different combinations of PV and yearly electricity consumption of the building - electric vehicle [%]

As Figure 5.18 and Figure 5.19 point out, the total rate of self-consumption of the building and electric vehicle increases significantly compared to the first scenario. The rate of self-sufficiency of the electric vehicle has also increased significantly as a result. Depending on annual consumption and PV size, almost 50% of the electric vehicle's consumption could thus be covered by the surplus from the PV system.

5.2.2 Economic calculation

The economic evaluation is carried out in such a way that the additional savings from the increased self-consumption of the PV system are calculated. Since the battery storage does not cause any investment costs by itself, only the additional savings remain to be evaluated.

The savings are monetised as follows:

- Self-consumption at place of residence: 15 c/kWh
- Self-consumption at any other charging station: 8 c/kWh

The savings at any charging station other than at home are modest, because at least the grid fees are still applicable.

5.2.2.1 Electric vehicle - charging at the place of residence

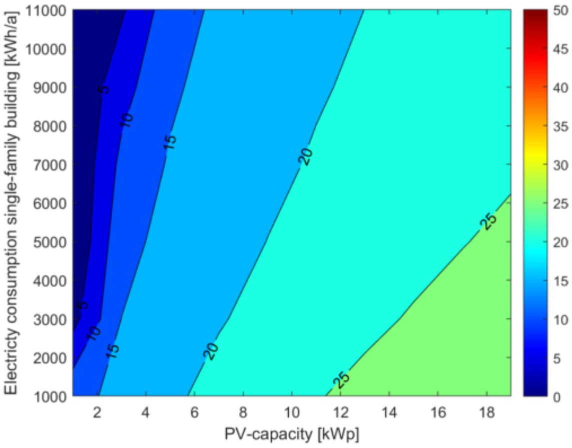


Figure 5.20: Self-consumption savings by supplying the additional load profile of the electric vehicle in different size combinations of PV and load profile [€/a].

As Figure 5.20 illustrates, the savings can be up to 30 €/a. As already stated, the low savings are mainly due to the fact that the vehicle is mainly available for charging at home in the mornings and evenings. Therefore, in this scenario it is not possible to store the full PV surplus directly in the vehicle. Furthermore, the average distance travelled of 16 km per trip is not far enough to actually cause a high consumption and to discharge the battery to such an extent that the surplus could actually be stored. Especially with small PV systems and high electricity consumption in the building, there is also no surplus that could be used in the electric vehicle and thus the savings are not available there either.

A remedy for this can be that the vehicle can be charged even when away from home, e.g. at the workplace or in the supermarket, using the excess PV power generated, thus saving at least the energy price at the external charging station, as shown in the next scenario. Increased self-consumption by the electric vehicle also means that this part is not fed into the grid. This means that the additional self-consumption savings can be calculated at 15 c/kWh, but this also results in "lost" income due to the feed-in remuneration of 6 c/kWh. Thus, if the difference between the self-consumption savings and the possible feed-in remuneration is considered, a margin of 9 c/kWh remains.

5.2.2.2 Electric vehicle - PV charging at the place of residence & external

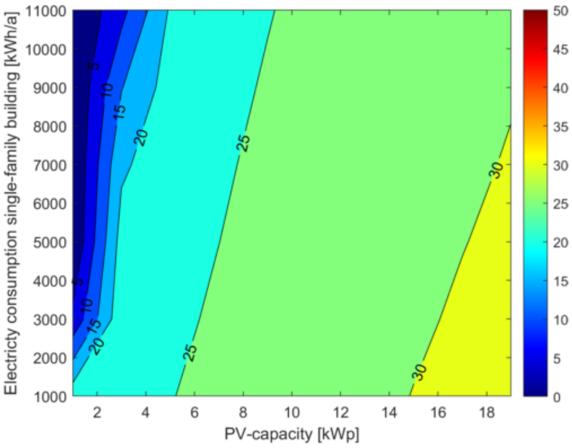


Figure 5.21: Self-consumption savings by supplying the additional load profile of the electric vehicle in different size combinations of PV and load profile [€/a].

Even if the share of the PV surplus that can be used in an electric vehicle increases, the monetary savings that result do not increase equally. If it is assumed that at least the grid fees have to be paid at an external charging station, the full electricity tariff may not be saved. Basically, the situation is the same here as it is for the economic viability of stationary battery storage. The larger the spread between feed-in remuneration and electricity prices or self-consumption savings, the greater the economic benefit. This is also reflected in this case. The savings from PV electricity used at an external charging station are assumed to be 8 c/kWh, whereas the feed-in remuneration is 6 c/kWh.

To make external PV charging also economically interesting, the savings compared to conventional charging from the grid must be greater than the feed-in remuneration. Otherwise, it is economically preferable to simply feed the surplus into the grid. The resulting margin compared to the case without an electric vehicle is therefore only 2 c/kWh in this case.

6 Summary & Conclusion

It has to be stated clearly that the economic prospects of storage are not very bright. The major reason is, that most studies calling for additional storage capacities focus on the technical point of view and neglect the economic performance.
In light of research question 1, On the one hand, for the economics of market-based storage the price spread is an important incentive for arbitrage and the corresponding FLH. A conclusion is that higher CO_2 prices increasing the electricity market prices at times electricity is scarce could contribute to better economic prospects. In addition, there is the issue of grid fee for storage. While there are arguments that storage is a system component and not a consumer, even in wholesale markets it has to be considered that there are also other flexibility measures than just storage that are possible and exemption of storage from grid fees would lead to biases for other options and, distort this market. In this context Sioshansi et al. (2009) stresses the importance of the proper design of market mechanisms that could also improve storage use incentives.
On the other hand, the economics of battery storage highly depends on the corresponding end user electricity prices (including taxes). They benefit from the fact that they do not have to compete with the low price margins on the wholesale markets, but with the significantly higher retail prices for electricity (between 0.20 and 0.30 €/kWh in Western Europe). Of course, in countries like Germany with significantly higher household electricity prices than the European average, the prospects for decentralised storage might be better than in others. However, as battery storage is currently mainly used for complementing PV systems (Haas, Lettner, et al., 2013) and the investment costs are clearly too high despite the higher retail price and battery storage systems cannot be operated economically under these framework conditions. This will be discussed in more detail below.
Although economic viability is currently difficult to realise, technological learning is expected to significantly reduce investment costs by 2040. However, the analyses in this thesis show that even technological learning has only a limited impact on economic viability for the following reasons:

i The investment costs of pumped hydro storage power plants will not decrease significantly in the future, as no remarkable further learning effects are expected and the most favourable site options are already being used.

ii Stationary battery storage systems have the major disadvantage that, despite falling investment costs in recent years, still show a modest economic performance. The overall development of battery investment costs remains uncertain, for the future it is clear that they will continue to fall, but it is not known to which level. Whether the required level calculated in this thesis will actually be reached is difficult to assess from today's perspective

iii For PtG technologies such as hydrogen and methane, it will also be very difficult to compete on the electricity markets despite a high TL potential. The main reason is the low efficiency and the resulting high electricity generation costs after re-electrification of the gases from this process. For hydrogen and methane, however, the economic prospects in the transport sector might be better, due to both higher energy price levels and the general lack of low-carbon fuel alternatives (Ajanovic and Haas, 2015; Ajanovic, Jungmeier, et al., 2013; Ajanovic, 2013).

Finally, it has to be stated that storage is not the only flexibility option. It is in competition with grid extension, load management, and other options (Ajanovic, Hiesl, and Haas, 2020; Ajanovic and Haas, 2015; Haas, Mez, and Ajanovic, 2019; Haas, Lettner, et al., 2013; P. D. Lund et al., 2015). In addition, natural gas as storage and natural gas fired turbines for short-term generation are a flexibility alternative, however, not a fully carbon-free one. Hence, from an economic assessments point of view of electricity storage, the possible competing options have to be considered simultaneously. However, in any case new storages should be constructed only in a coordinated way (EASE/EERA, 2013) and if there is a clear sign for new excess production, in this case from variable RES.

The expansion of photovoltaics in most European countries, but especially in Austria, will have to take place on ground-mounted sites as well as on buildings and integrated into buildings. The potential for installations on buildings is relatively high, even if it is difficult to access in some cases, since e.g. in apartment buildings there must be unanimity among the owners, and must therefore be seen as theoretical potential. In principle, however, the decentralised storage potential is very high at 21.59 TWh with a full expansion of 30 GWp photovoltaics and a corresponding annual generation of about 30 TWh, compare research question 2. This is basically a decentralised storage potential that could be utilised in Austria, should it be necessary. In order to be able to use this potential in a holistic and system-oriented way, aggregators and monetary incentives for storage operators are needed.

In addition to a comparison of long-term storage and battery storage, three different use cases of battery storage were analysed in depth in this thesis, see research question 3. Single-family buildings, multi-apartment buildings and cross-building solutions were considered. Furthermore, sensitivity analyses were carried out to show the influence of the level of the electricity price, the feed-in remuneration as well as the expected return and the battery life-time.

From today's perspective and under the assumed framework conditions, it can be clearly concluded that the current investment costs do not allow the operation of a battery storage system from an economic point of view. This is also in line with the scientific community's position and the findings pointed out before.

Even though the costs for battery storage have generally decreased in recent years, see also Hiesl, Ajanovic, and Haas (2020), and currently average about 1350 $€/kWh_{batt}$ for a gross capacity of 1 kWh and about 1000 $€/kWh_{batt}$ for a gross capacity of 10 kWh, see Figure 4.2, these investment costs are still too high for storage to be operated economically. In all the use cases analysed, the specific investment costs of battery storage would have to drop by at least 85%. For given load profiles and corresponding annual consumption, the cost reduction depends in particular on the capacity combination of photovoltaics and storage. In the baseline scenario, with relatively small photovoltaic systems for the given load profile, self-consumption already accounts for over 80% to 90% and battery storage only has a very small benefit. The O&M costs already exceed the benefit and the investment costs of the battery storage would have to be negative here to be economically viable. Furthermore, it can be seen in all the use cases that the specific investment costs fall more steeply above a capacity of about 1.5 to 2 kWh/MWh, because the increase in battery capacity only brings a smaller increase in self-consumption as well as in self-sufficiency.

As the sensitivity analysis points out, the greatest influence on the investment costs of battery storage systems has the electricity price and the spread between the electricity price and the feed-in remuneration. The higher the assumed electricity price, the higher the self-consumption savings and thus the additional benefit of battery storage. For the economic evaluation of the increase in self-consumption, in countries such as Austria only the variable

components of the household electricity prices can be used. Fixed components such as metering fees or renewable electricity flat rates have to be paid independently. In this thesis, the level of the electricity price was assumed to only include components that may be taken into account in the evaluation. However, the design and composition of household electricity prices varies from country to country and must be analysed separately. The pure level of the household electricity price is no indication of how self-consumption or the increase in self-consumption can be evaluated. Should grid tariffs change in the next few years from a largely energy-driven tariff to a power tariff, this could be an opportunity for battery storage. Although photovoltaic systems would suffer from such a development, as the share of the electricity price for self-consumption evaluation would decrease, (monetary) incentives could achieve that battery storage systems are used in such a way that power peaks in the load profile are covered and thus less grid capacity is needed. This would have a relieving effect on the electricity grid and a positive effect on the economic efficiency and thus on the possible investment costs of battery storage systems.
However, the calculated specific investment costs also depend strongly on the ratio between the feed-in remuneration and the self-consumption savings. If the feed-in remuneration is relatively high, the benefit of the storage system decreases. Since the difference between self-consumption and feed-in is smaller it becomes more and more attractive to feed the electricity into the public grid instead of storing it. The fact that the battery lifetime has a relatively small influence on the result is based on two aspects. Firstly, it is assumed that the battery storage system will only cost 70% of the actual investment costs when it is newly purchased in x years. On the other hand, due to the methodology the total cash flow remains the same and only the time of replacement varies and is thus divided differently between current and future costs through discounting. Resulting from a relatively small difference in the cash flows without battery storage and with battery storage and the reference to specific costs, the interest rate also has a relatively small influence on the possible investment costs.
In general, the space available for photovoltaics is also somewhat limited. In urban areas, where distribution of photovoltaic electricity in multi-apartment buildings is possible, as is the case in Austria, and specially where different load profiles (e.g. household & commercial) prevail, self-consumption is usually relatively high. In such a scenario, an additional battery storage system is even less economical to operate than in single-family buildings. If the photovoltaic electricity is further distributed beyond the property boundaries, the match between PV-generation and aggregate load profiles with different consumption structures (e.g. high daily consumption, shops, general consumption in multi-apartment buildings, e-mobility) is even higher and thus also the self-consumption share. In addition, there are grid fees for storing electricity that have to be paid. Even if these grid fees vary regionally and only amount to a third of the full grid fees in the near vicinity, they still significantly reduce the maximum arguable investment costs.
Another important conclusion is, that the use of decentralised battery storage to increase self-consumption is questionable. If decentralised battery storage systems are already being used in single-family buildings or multi-apartment buildings and across-buildings, they should at least be operated in such a way that they actually have a benefit for the overall electricity system and can thus also generate additional income. However, battery storage competes with other flexibility options such as load shifting, where smart households can adapt their load to generation and increase their self-consumption. Additionally trading platforms (e.g. e-Friends) where surplus electricity is sold or traded directly to other consumers and prosumers in a peer to peer trading algorithm represent a flexibility option to minimise storage

requirements. Electric vehicles as intermediate storage to increase self-consumption and to store the decentralised PV surplus are only economically feasible to a limited extent in single-family buildings, compare research question 4. Even if the battery storage in the electric vehicle does not cause any additional costs in contrast to a stationary storage, the savings through increased self-consumption are very low and are around 30 €per year. Since there is only a slight correlation between PV generation and parking times at home, it is hardly possible to store the surplus in the electric vehicle if it can only be used on site. A potential remedy could be to create monetary incentives to use the surplus directly at external charging stations. This could also increase the acceptance of electromobility and renewable energies in general. In principle, the administrative effort involved must also be taken into account, because it is clear that, from an accounting point of view, the simplest and already functioning solution is to feed in the surplus.

The models and methods presented in this thesis, as well as the results and conclusions, in Sections 3, 4, 5 refer specifically to the situation in Austria, but in principle the methodology presented can also be applied well to other countries.

The basic characteristics of the calculation for photovoltaics on buildings, see Section 3, do not differ in Central Europe. The evaluation of the potential of photovoltaics on buildings can therefore be applied relatively easily to other countries if the available ground space per inhabitant and the number of inhabitants are known. Only the estimation of self-consumption and the resulting storage potential can differ significantly depending on the climatic conditions in the respective country and the load profile to be applied. The analysis of potential battery storage investment costs in Section 4 can also be applied relatively easily to other countries. Only the calculation of PV generation must be adjusted. The further north, the higher the installation angle must be; the further south, the lower the installation angle must be in order to be able to operate the PV system energetically optimal. Furthermore, the specific regulatory and legal framework for the treatment of self-consumption as well as the distribution within a multi-apartment building and for operation across buildings must be replaced, as the implementation is handled differently in each country. The electricity tariff structure and the feed-in remuneration must also be adapted to the extent that only those shares are used for the evaluation of the additional self-consumption by the battery storage system that are also relevant. All these parameters can of course also influence the results, as was partly shown in the sensitivity analysis. However, it can be expected that the general statement about the economic viability of the battery storage system will remain unchanged.

For the modelling of the load profiles of electric vehicles, especially the starting times and the typical trip lengths and their statistical distribution as well as the composition of the trip purposes per day must be taken into account when transferring them to other countries, see Section 5.1.2.3. The more precise the data, the more accurately they can be modelled. In any case, the data should be analysed beforehand so that the correct distributions are chosen and possible limitations can be addressed. If this adaptation for other countries has taken place, these load profiles can in principle also be integrated into the aforementioned optimisation model without restriction and the analyses of possible savings can be made. In principle, however, the same applies here as described above. Attention must be paid to the structure of the end customer electricity price and the level must be adjusted to assess the self-consumption savings.

Abbreviations

a = Annum
AC = Alternating current
BEV = Battery electric vehicle
BIPV = Building integrated photovoltaics
CTP = Contactless power train
DC = Direct current
EAG = Renewable Energy Expension Act
EV = Electric vehicle
FLH = Full-load hours
CH_4 = Methane
DoD = Depth of discharge
H_2 = Hydrogen
EU = European Union
EU-27 = 27 European member states
H0 = Standardised household electricity load profile
IEA = International Energy Agency
IRR = Internal rate of return
kW = kilowatt
kWh = kilowatthour
NPV = Net present value
PHEV = Plug-in hybrid electric vehicle
PHS = Pumped hydro storage
PtG = Power to Gas
PV = Photovoltaics
RES = Renewable energy sources
SC = Smart Communities
SOC = State of charge
TL = Technological Learning
UE = User equilibrium
UPS = Uninterruptible power supply

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