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Optimizing Battery Storage for Germany's 2030 Energy Transition: Scope, Costs, and Carbon Impacts

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Abstract: As Germany advances toward its 2030 energy transition targets, large-scale battery systems are widely promoted as a key instrument to manage the volatility of wind and solar power. This paper develops a data-driven simulation framework to quantify how much grid-scale batteries can realistically contribute to Germany's power system in 2024 and in a 2030 expansion scenario, in terms of backup energy reduction, system costs, and carbon footprint. The analysis uses 15-minute data for generation and load from 2022–2025 and constructs future scenarios by upscaling photovoltaics, onshore wind, offshore wind, and demand in line with "Climate-neutral Germany 2045". Volatility is decomposed into a slowly varying component, covered by backup plants, and a normalized residual load that feeds the batteries; for each battery capacity, an optimal moving-average window is determined to maximize annual battery output and minimize backup energy. Model validation against 2024 pumped-storage operation shows that the framework reproduces observed annual storage output well. Across both 2024 and 2030, battery benefits scale approximately with the logarithm of installed capacity, while costs and battery-related emissions increase linearly. Under optimistic assumptions, about 300 GWh of batteries can supply only 4–6% of annual demand and cannot replace firm backup capacity, implying that batteries are valuable for short-term balancing but have limited potential for seasonal adequacy.

Keywords: German energy transition; volatility; battery storage; feasibility; energy policy; storage economics; carbon footprint

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1. Introduction – the Challenge of Renewable Energy

When policy makers push for a renewable energy (RE) strategy, they usually acknowledge that steady forms of RE technologies, such as hydropower, biomass, and geothermal energy, cannot be built out significantly. Only weather-dependent, variable renewable energy (VRE) is scaleable, even to a very large degree. The issue is that due to their weather-dependency, VRE integration into power grids require transmission grids, storage, and backup-power. The shift towards increasing market shares of VRE in power grids creates thus further challenges, which are ill-studied. This paper develops a data-driven simulation framework to quantify how much grid-scale batteries can realistically contribute to Germany's 2030 power system, both in terms of backup energy reduction and carbon footprint, under deliberately maximally optimistic techno-economic assumptions for renewables and storage.

This investigation is focused on Germany and was inspired by a similar study for the Swiss energy market. Züttel et al. showed that a CO_2-neutral Swiss energy system based on complete electrification and renewable supply is technically feasible but hinges on solving the seasonal storage problem. Doubling hydropower storage capacity, maximising rooftop PV, and deploying a limited number of power plant units that integrate conversion and storage, can provide electricity on demand at overall system costs only about 20% higher than today, with roughly three quarters of demand covered at similar or lower costs. However, the last quarter—winter band energy and aviation fuels—remains technically and economically demanding: domestic renewable hydrogen chains are capital-intensive, and importing hydrogen or synthetic fuels is even more costly. Under these conditions, hydropower and PV without seasonal storage remain the cheapest electricity sources, while advanced nuclear fission and imported bio-oil-based synthetic kerosene emerge as promising low-carbon options for continuous power and aviation and reserve fuels, respectively [1].

Germany, in contrast to Switzerland, doesn't have significant amounts of hydropower storage. That is why policy makers demand the development of battery storage at scale.

In a country so far north (from 47° to 55° N), there is not only the day/night cycle that affects photovoltaics, but also a strong seasonal variability of both solar and wind power production. Photovoltaics on average thus delivers typically 850–950 full-load hours per year, onshore wind power between 1800 and 2,000 full-load hours, and offshore wind power around 3,300-3,500 full-load hours. Therefore, the so-called nominal power output has to be multiplied by 6 or 7 to supply at least the average of the required energy. When storage losses occur, additional primary energy has to be provided either from wind and solar or from backup power plants to compensate for them. In practice, we can expect only 1,500 full load hours per year from VRE in Germany [2].

With the expansion of wind turbines and photovoltaics, there will be periods of energy deficit and periods of surplus. These periods can be short, mainly dominated by daily cycles, but also fairly long due to seasonal effects. Markus Löffler analyzed thoroughly the contributions of wind and solar energy to the German power system during the six years from 2016 to 2021 [3]. He found that during this period, more than 100 times there was hardly any VRE supply for more than 28 hours. The longest so called "Dunkelflaute" (dark lull) lasted for 268 hours in the investigated period. This poses immense challenges to plans of reaching independence from traditional power plants. In particular it makes clear beyond any doubt that battery storage can never replace backup power capacity in Germany. Therefore the focus of this investigation is on the reduction of backup energy utilization, which is directly related to decarbonization, and thus the most important goal of the German energy transition.

A central part of the energy transition is the rapid expansion of photovoltaics and wind power, expected that it covers the majority of electrical energy requirements by 2030. According to the study 'Climate-neutral Germany 2045', which forms the basis for the energy transition [4], this is to be achieved through the expansion of photovoltaics and wind power as follows:

Installed photovoltaic capacity 198 GW (2023: 76 GW): installed onshore wind capacity 93 GW (2023: 59 GW); and installed offshore wind capacity: 27 GW (2023: 8 GW).

The total planned installed renewable energy production capacity is therefore 318 GW. It is also assumed that the total annual load will increase from 458 TWh in 2023 to 656 TWh in 2030, in line with the expectation of further electrification of the mobility and heating sectors. This increase in load is used as a reference for power demand.

There are two purposes for introducing batteries in the context of volatile energy production. The primary purpose is to stabilize the grid when the volatile production exceeds the regulating potential of conventional power plants [5]. Current implementations of grid scale batteries mostly serve this purpose. On a European level, there are plans of storage expanson for 2030 and also 2050 [6].

The secondary function of battery storage is to utilize surplus energy production to compensate for periods of supply deficit. This study investigates strategies for the optimal deployment of batteries to fulfill these objectives and delineates the fundamental, economic, and environmental (carbon footprint–related) constraints that limit their practical implementation.

1.1. Scenarios of the Energy Transition

The three primary goals of any energy policy are environmental sustainability, security of supply, and economic affordability. Environmental Sustainability today mostly focuses on decarbonization: transitioning to low-carbon, renewable energy sources (wind, solar, hydro) to reduce CO_2 emissions. Security of Supply means ensuring the energy system remains reliable, resilient, and independent of volatile foreign imports. Affordability in particular means economic feasibility: Maintaining competitive energy prices for consumers and industries, ensuring a "just transition" that does not

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disproportionately burden vulnerable populations. Apart from these, there is the simple criterion of technical and practical feasibility.

When investigating scenarios of energy transitions, it is important to measure the effects of policy decisions with these goals in mind, in particular technical feasibility. This leads to the following guiding questions of the investigation:

- How much energy is saved with the expansion of battery installations?
- How much backup energy can be saved with the expansion of battery installations?
- How does the overall costs scale with expansion of volatile energy installations and with the expansion of battery installations?
- What are the implications on cost of electrical energy by expanding wind and solar, and consequently by expanding storage with batteries?
- What is the carbon balance with growing contributions from wind and solar, and with growing amount of batteries, and with the implied grid expansion?
- What implications would a change from fossil fuel backup to nuclear backup have regarding these questions?

1.2. Challenges and Limits of Battery Deployment

There is an inherent problem when storing volatile energy that battery utilization necessarily decreases when battery capacity is increased. This phenomenon is often attributed to diminishing marginal returns and "self-cannibalization", where additional storage capacity competes for limited surplus energy, leading to lower utilization per unit. Various publications highlight this as a key economic and operational challenge, particularly in high-variable renewable energy (VRE) scenarios [7–10]. Up to now there is, however, no precise functional description. It is described as declining non-linearly (e.g., steeply at first, then tapering) as capacity scales up, with economic viability requiring at least 100 full load cycles per year—thresholds often unmet in larger deployments. This publication presents a simple functional relation between battery capacity and the upper limit of return in the form of full load cycles, delivered energy, or saved backup energy. The implications are important for investors who contemplate battery park investment, and policy makers.

2. Materials and Methods

The key question of this investigation is how to make optimal use of batteries for adapting volatile energy supply to a given demand. Therefore it is essential to start with real measured data and not with models. Volatile power sources such as wind and photovoltaics contribute considerably to German electric energy. The market share of volatile energy sources is already larger than 50% in Germany. Therefore the existing measured energy production and consumption data provide an excellent, representative source of information about the nature of the energy input and output to any storage system.

2.1. Applied Data Sets

The detailed energy supply and demand information is collected and made publicly available by the Fraunhofer Institute for Solar Energy Systems ISE [11] at a time resolution of 15-minute intervals. It provides all types of electricity supply to the German grid, also the total demand, and electricity imports as well as electricity exports.

We use the energy supply and demand data from the years 2023 to 2025 as representative datasets for future scenarios. They are used to extrapolate to future projected variable renewable energy (VRE) market shares by expanding the production from renewables as well as the pay load. Fossil fuel energy sources are used only as backup in our future scenarios. Data of the year 2022 is only used for determining well-defined initial values of the simulated processes. Since renewable energy has the highest feed-in priority in the German electricity grid, we are fairly safe in the assumption that the provided data are representative of future conditions. Only during times of extreme overproduction has there been a slight deviation from the true supply data, due to rules for switching off PV or wind power plants in times of grid instability, and network bottlenecks. Indicators of this are an increasing number of hours with negative prices at the electricty spot market. From this point of view, older data sets would be preferable, but on the other hand, a higher contribution of renewables gives a more realistic impression of the near future of 2030.

The supplied data are based on 15 minute intervals, therefore each day is represented by 96 representative power demand and supply values.

2.2. Preparation of the Data – the Normalized Residual Load

The key input data is VRE, which consists of the projected PV power during time unit i, P_i^{PV}, onshore wind power P_i^{Onshore}, and offshore wind power P_i^{Offshore}. For our 2030 scenario, we assume a possible change of the VRE mixture relative to the reference year 2024. To do so, PV power is scaled with factor a, wind onshore power is scaled with b, and wind offshore power is scaled with c. The number of processed data points is n, in the case of the chosen data set and yearly calculations, n is 4 times the number of hours of a year.

There are also three other renewable sources, hydropower and bio-fuels, which cannot be built out significantly but need to be extrapolated differently to the future. The potential of hydro power P^{Hydro} in Germany is more or less fully tapped, and will not change significantly. It cannot be scaled nor controlled. We therefore take it as a fixed contribution distributed as in the reference year with the current averaged value of approximately 1.9 GW. The contributions from biomass P^{Bio} of approximately 5.4 GW, the currently small contribution of geothermics P^{Geo} and waste P^{Waste} are only theoretically dispatchable renewable energy (DRE), but are built to run steadily. To optimize the power grid in favour of VRE, we treat them in the scenario 2030 fully as dispatchable energy, although it is highly unlikely that all such powerplants can be refitted to a non-steady production paradigm.

The total delivered renewable energy P_i^{RE} is therefore

$$P_i^{\text{RE}} = P^{\text{Hydro}} + P^{\text{Bio}} + P^{\text{Geo}} + P^{\text{Waste}} + a \cdot P_i^{\text{PV}} + b \cdot P_i^{\text{Onshore}} + c \cdot P_i^{\text{Offshore}} \tag{1}$$

The production side of an energy scenario is thus based on the reference year 2024 and on the three scaling constants a, b, c, upscaling historical records. On the consumption side, there is the load at each time interval P_i^{Load}, scaled with the constant d. At any one moment the requirement of having a stable net is to make sure that supply and demand are balanced. Therefore the decisive indicator of the energy system is the residual load P_i^{Residual}, which measures the degree of imbalance or volatility:

$$P_i^{\text{Residual}} = d \cdot P_i^{\text{Load}} - P_i^{\text{RE}} \tag{2}$$

There are two tools to resolve the imbalance: backup power and storage devices, in particular grid-scale batteries. [1] During the time of the energy transition, there must be backup power P_i^{Backup} in addition to energy storage facilities. Backup power is provided from either fossil power plants with coal, oil, gas, or nuclear power plants. The key concept of this publication is to split backup power into a slow changing contribution $P_i^{\text{Backup-slow}}$ to take care of the seasonal and other slow changes and a fast changing contribution $P_i^{\text{Backup-fast}}$ to respond to the remaining short term changes.

$$P_i^{\text{Backup}} = P_i^{\text{Backup-slow}} + P_i^{\text{Backup-fast}} \tag{3}$$

The motivation for this concept is illustrated with Figure 1. Using the data set from the reference year 2024, all constants $a, b, c,$ and d are set to 1. In order to charge batteries from the volatile surplus, the residual load must be negative. The initial residual load (blue graph) in this month is above 0 until

[1] Cross-border electricity imports and exports are not assumed to provide a material contribution in this analysis. In many scenario studies they are treated as a residual balancing option without explicitly assessing the availability of corresponding capacity in neighbouring countries, effectively shifting domestic adequacy problems abroad.

the 25th. Therefore without additional backup power for the most part of the month, the batteries would not be charged. In order to make use of the existing volatility, an offset has to be provided from backup power. Using a constant backup power is not optimal, because the supply from wind and photovoltaics has seasonal variability. Therefore a moving average is choosen with a window size m ranging from a few hours to several days to define an adaptive slow backup (orange graph) power level. m is the number of data elements of the time series window. With 4 data points per hour, m would be 96 for 24 hours. Obviously the averaging must be done with the preceeding data elements of the time series, the current time interval being the last element of the time window.

$$P_i^{\text{Backup-slow}} = \frac{1}{m} \cdot \sum_{j=1}^{m} P_{i-j+1}^{\text{Residual}} \tag{4}$$

Subtracting the slow backup time series from the residual load results in what we define as the normalized residual load P_i^{NR}, visualized as the green graph in Figure 1:

$$P_i^{\text{NR}} = P_i^{\text{Residual}} - P_i^{\text{Backp-slow}} \tag{5}$$

This has the effect that most volatility of the normalized residual load is around zero, so that volatile surplus and deficit are approximately equal, and the number of sign changes is maximal. This enables a maximum number of charges and discharges ("cycles") of the batteries. There is an important aspect that needs to be mentioned. Although the mathematical proceedure to produce the normalized residual load is energy-neutral, not creating extra energy requirements directly, a part of the backup energy is transferred to the surplus of the normalized residual load. By creating extra surplus energy used as battery input, not only have the battery losses to be paid by extra backup energy supply, but in the case of larger surplus than the batteries can handle, this is useless energy. In practice such surplus has to be removed by curtailing wind or solar plants. Therefore the filtering window (size m) should not be made larger than necessary for optimizing battery outflow. Therefore the filtering window will be determined by exactly the criterion to maximize battery outflow.

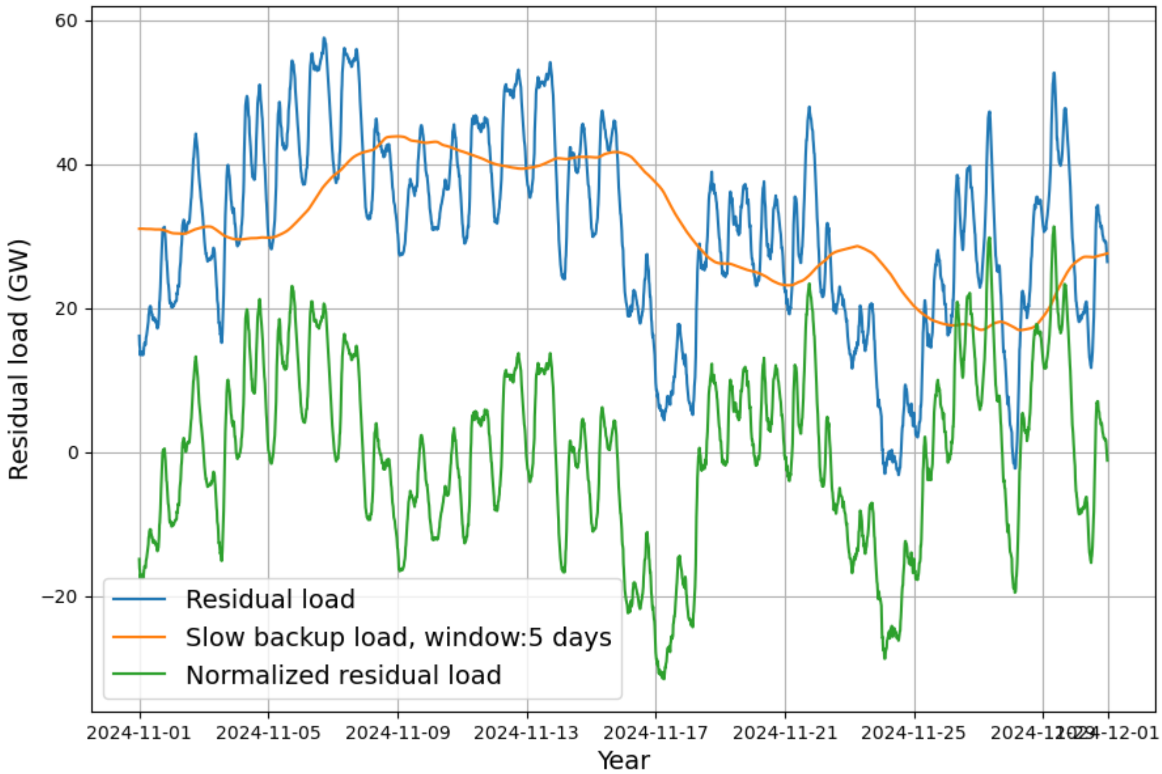

Figure 1. Residual load in November 2024 (blue), slow backup (orange), and normalized residual load.

Fossil or nuclear backup power plants can be scaled down to 30% of their nominal power [12] at a rate of 3-5%/minute of their nominal power. They may also get switched off completely. But starting and stopping are rather slow processes, in particular for coal and nuclear power plants [13]. When the rate of change of demand is slow enough, this can be accomodated by the filtered demand $P_i^{\text{Backup-slow}}$. Therefore the slow backup may include switching off plants completely. The side effect of this may be a lack of inertia. Lack of inertia [14] is not considered in this investigation; adequate treatment would exceed the scope of the paper.

We restrict backup power to slow backup at this stage, separating the domains. The simulation aims at maximizing battery economics, therefore back-up power does not interfere in the normalized residual power. Doing this opens the possibility to compare countries with different conditions. While all seasonal effects are mapped to the slow backup power, the normalized residual load and therefore the consequences for battery operation should be comparable in all countries. For the basic operations we will compare the ideal case without storage losses with the results from real batteries based on our assumptions, thus avoiding the argument that unexpected outcomes may have resulted in too pessimistic assumptions.

2.3. Scope of the Problem

In order to evaluate the possibilities of batteries in conjunction with volatile energy on a national level, the energy system is analysed qualitatively. There are two causes of volatility. Primarily there is volatility of production – photovoltaic energy is restricted on a limited and seasonally varying number of hours every day. Wind power is even more turbulent, sometimes there are several days without significant wind, but also several stormy days in a row.

The second cause of volatility in the energy system is the daily and seasonal demand patterns, typically a reduction of demand during the night, with demand peaks at noon and in the early evening. Additionally, there are seasonal patterns with a significant load increase during winter time, interrupted during by Christmas and New Year holidays. With an approximately 50 GW average demand, the currently planned grid size battery storage until 2030 of approximately 100–300 GWh [4,15] can roughly bridge the total demand for 2–6 hours. Even with a hypothetical expansion of battery storage to 1 TWh, the maximum duration of a full supply by batteries is less than a day. The main use of batteries is for storing surplus volatile energy. In this case the potential value of batteries is to regain surplus volatile energy that would otherwise have to be curtailed, and also bridge gaps of volatile deficit. But even during times of no or little supply from wind and solar, batteries can be used to store energy from backup power, e.g. during the night, and return it to the grid during hours of peak demand, with the intention to reduce peak demand and rate of power changes of the backup power systems.

2.4. Battery Processing

The battery process is characterized by the battery being charged when there is surplus power P_i^+, scaled with an effciency factor η, and discharged when there is deficit power P_i^-. The charging rate is limited by the maximum inflow rate P^{in}; the discharging rate is limited by the maximum outflow rate P^{out}. The battery charge level at time i ("stored energy") E_i^s is limited by the battery capacity $E_{\max}^s$, and cannot be discharged below zero.

Following the concept described above, the source for the battery process P_i is the negative normalized residual load

$$P_i = -P_i^{\text{NR}}$$

The battery charge E_i^s is then recursively defined as in our previous publication [8], where $P_i^+ = Max(0, P_i)$ and $P_i^- = Min(0, P_i)$:

$$E_{i+1}^s = Max(0, Min(E_{\max}^s, (E_i^s + 0.25 \cdot (\eta \cdot Min(P^{\text{in}}, P_i^+) + Max(-P^{\text{out}}, P_i^-))) \tag{6}$$

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This seemingly complex equation is simplified enormously when assumung an ideal battery without losses and infinite capacity, and a sufficiently large initial charge E_0^s, so that the battery charge cannot drop below 0, when the total average of the P_i is larger than 0:

$$E_{i+1}^s = E_i^s + 0.25 \cdot P_i \tag{7}$$

This is the negative cumulative sum of the residual load time series, converted to stored energy. It shows – without necessity to discuss any otherwise limiting parameters – the minimum storage capacity required to store a given volatility series for a year or longer. The amount of energy that is used from batteries depends for a given set of energy data on the battery capacity $E_{\max}^s$ and the filter mask size m as a consequence of Equations (4) and (6). It is derived from the battery charge time series by adding all neighboring negative charge differences, i.e. discharges:

$$E^{\text{used}}(E_{\max}^s, m, P^{\text{in}}, P^{\text{out}}) = -\sum_{i=1}^{n} Min(0, E_i^s - E_{i-1}^s) \tag{8}$$

It will have to be validated that the maximum charging rate P^{in} and maximum discharding rate P^{out} are large enough not to be a significant bottleneck. While batteries have high charge and discharge rates, typically two hours to fully charge or discharge [16], the grid capacity may turn out to be a limiting factor.

2.5. Optimization of filter mask for a given battery capacity

For a given residual load P_i^{Residual} there is deficit energy that has to be provided. Following the concept described above, the normalized residual load is used:

$$E^{\text{deficit}} = 0.25 \cdot \sum_{i=1}^{n} Max(0, P_i^{\text{NR}}) \tag{9}$$

If there is no battery storage, then the backup power plants must deliver exactly this deficit energy. The source for battery storage is the surplus energy, which is the negative part of the residual load:

$$E^{\text{surplus}} = -0.25 \cdot \sum_{i=1}^{n} Min(0, P_i^{\text{NR}}) \tag{10}$$

The surplus of the initial residual load is very small in the example of Figure 1. By means of changing the size of the filter mask the available surplus energy is varied. This is illustrated in Figure 2. Obviously with no or little initial surplus energy, battery input must be provided by backup power plants. Therefore the energy stored and provided by batteries that are fed by the normalized residual load, may well come partly or totally from backup power plants. Thus for minimizing emissions, minimizing remaining backup energy is a better goal than only maximizing battery output. Nevertheless, smoothing energy supply in times of total backup supply is valuable for stabilizing the grid and reduzing inefficiencies due to fast power reduction and increase of backup power stations [17,18]. The graph of Figure 2 has a log-scaled x-axis. It exhibits a surprizingly linear relation between the log of the window size, which is proportional to time, and the resulting surplus resp. deficit energy. This observation is a key to understanding the behaviour of storage devices for volatile energy.

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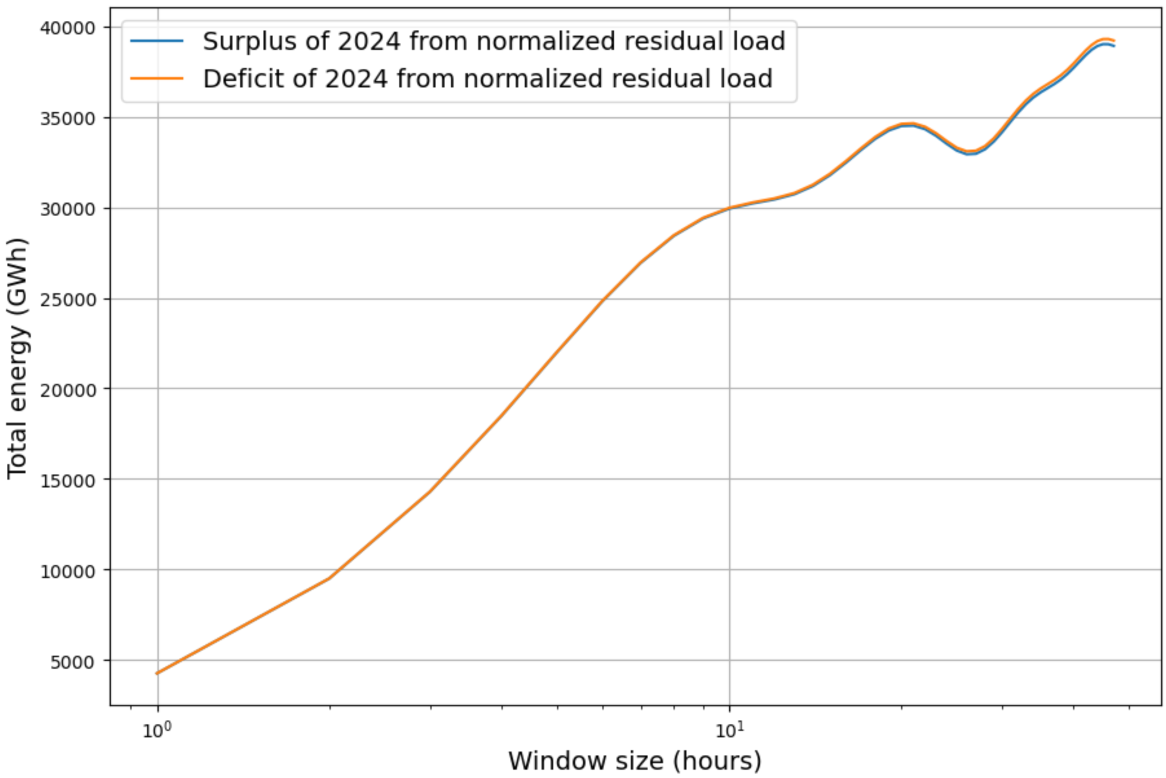

Figure 2. Potential surplus and deficit energy of normalized residual load in 2024 depending on filter window size.

The considerations in subsection 2.3 give reasons to assume that for a given battery size, there is an optimal filter mask size m that optimizes the achievable amount of energy flow from the battery. Figure 2 indicates that the surplus energy might exceed the required energy to load the batteries. This should be avoided, because unusable surplus energy has to be curtailed or exported, increasingly at negative prices [19].

From the Equations (4),(6), and (8), we conclude that the achievable energyflow from the batteries E^{used} is primarily a function of the filter mask size m for a battery with a given capacity. Therefore we optimize m for achieving maximal battery outflow:

$$\max_m \left(E^{\text{used}}(E^s_{\max}, m) \right)$$

While the optimization of the battery outflow is a useful goal, the ultimate goal is to minimize both backup energy as well as backup power requirements. Both battery outflow and backup energy are related, but the maximum of battery output not always coincides with minimum backup energy. In order to simplify the introduction of this new concept, for now the criterion for the optimal filter window size is the optimization of battery output.

There is, however, a fundamental problem. A scenario requires at the very least the backup energy corresponding to the difference between the deficit and the surplus. When the deficit is as dominant as in 2024 (202 TWh) compared to the surplus (approximately 1 TWh), battery storage from the surplus energy can at best reduce the deficit by 1 TWh under the 100% lossless assumption. Realistically with 15-20% expected losses the usage of batteries can only increase the required backup energy instead of reducing it. The economic potential for batteries is restricted by the surplus of the initial residual load. Due to limited capacity, there is also no point in using batteries in situations with dominant seasonal variability but hardly total surplus. This explains why batteries have hardly been used on a grid level in Germany before 2025. We can also conclude that in the past and currently the pumped hydro plants are not used for saving backup energy but only to stabilize the grid and equalize demand variability. With growing contributions of volatile production, this field of application should not be

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underestimated. Therefore measuring the minimum backup energy is essential for the assessment of a scenario.

3. Cost Considerations

The general strategy adopted in this paper centres on leveraging sources and data from institutions recognised for their renewable energy (RE) expertise. In all cost-related analyses, the approach prioritises the adoption of the lowest cost and highest benefit assumptions that are justified by reputable, RE-friendly organisations. This methodological framework ensures that the evaluation of energy system components, including battery storage and backup options, reflects optimistic yet credible projections, thereby supporting robust and forward-looking scenario assessments.

The assumptions for solar and wind energy are as follows: The annual costs for backup energy technologies—biomass, nuclear, and fossil power plants—are divided into fixed and marginal components. Fixed costs (expressed in €/MW per year) encompass annualized installation, capital expenditures, and ongoing maintenance and operational expenses. Marginal costs (expressed in €/MWh) represent the variable costs incurred per unit of energy generated.

The values chosen reflect typical cost estimates for each technology, serving as the basis for scenario modeling and comparative analysis within the study. These assumptions are grounded in current literature and industry benchmarks to ensure scientific robustness and transparency in the cost assessment framework. An arbitrary, but rather low Weighted Average Cost of Capital (WACC) of seven percent was used, i.e., well in the range of utility investments.

We use mostly an LCOE study by Fraunhofer ISE [20]. LCOE stands for Levelized Cost of Energy and means the full cost of energy provision at producer level, hence excludes system cost. To include the latter, we make explicit assumptions on the cost of grids, battery storage, and backup-power.

The Fraunhofer study computes technology-specific levelized costs of electricity (LCOE) using a discounted cash-flow (net present value) framework with real 2024 prices and technology-specific weighted average costs of capital, applied consistently across all technologies and years. For each assessed technology (PV, wind, biomass, biogas, fossil plants, hydrogen plants, fuel cells, nuclear), it defines upper and lower parameter ranges for CAPEX, lifetimes, fixed and variable OPEX, fuel and CO_2 prices, full-load hours and financing conditions based on market data, literature and estimates by Fraunhofer, then derives LCOE bands by combining these extremes with representative site conditions (irradiation, wind yield, full-load hours). Future LCOE trajectories to 2045 are generated by applying technology-specific learning curves (progress ratios) to CAPEX, coupled with exogenous scenarios for global capacity deployment, fuel and CO_2 price paths, and evolving full-load hours in a decarbonising German power system.

3.1. Cost Assumptions of Generation from Wind and Solar

Fraunhofer does not give a single point for 2030, but its learning-curve projections allow interpolation between 2024 and 2045; the report provides explicit ranges for 2045. For onshore wind, LCOE in Germany are expected to fall from 4.3–9.2 ct/kWh in 2024 to about 3.9–8.3 ct/kWh long-term, with 2045 values in this band driven mainly by higher full-load hours at new sites.

For offshore wind power, LCOE is expected to decline from 5.5–10.3 ct/kWh in 2024 to roughly 5.1–9.4 ct/kWh by 2045, reflecting moderate CAPEX reductions and high full-load hours.

For PV, ground-mounted utility-scale plants are projected to reach around 3.0–5.0 ct/kWh by 2045, down from 4.1–6.9 ct/kWh in 2024, assuming CAPEX falls to about 460 €/kW. Small rooftop PV systems are projected at 4.9–10.4 ct/kWh by 2045, compared to 6.3–14.4 ct/kWh in 2024. Under the study's learning-rate and market-growth assumptions, 2030 values lie between today's and 2045's ranges, implying roughly mid-single-digit to low-teens ct/kWh for PV and mid-single-digit ct/kWh for good onshore wind sites by 2030.

Throughout the study, we thus use the following parameters, in line with our optimistic view on RE price points.

- The annualized total cost of utility-scale photovoltaic capacity is assumed to be 47,500 €/MW_p·year, based on an investment cost of 500,000€/MW_p, an operation-and-maintenance factor of 2% per year and a technical lifetime of 25 years, in line with industry reports.
- The annualized total cost of onshore wind capacity is assumed to be 115,000 €/MWp·year, derived from an investment cost of 1,000,000 €/MWp, an operation-and-maintenance factor of 3% per year, and a technical lifetime of 20 years.
- The annualized total cost of offshore wind capacity is assumed to be 405,000 €/MWp·year, derived from an investment cost of 3,000,000 €/MWp, an operation-and-maintenance factor of 5% per year, and a technical lifetime of 20 years.

3.2. Cost Assumptions of Battery Storage

Fraunhofer specifies CAPEX paths and derives LCOE for PV–battery systems for 2035 and 2045 (but not 2030 explicitely). For CAPEX of battery storage (usable capacity, including installation), the study assumes the following reductions: for small residential PV-battery systems, from 500–1,000 €/kWh in 2024 to 288–840 €/kWh in 2035 and 180–700 €/kWh in 2045; for commercial rooftop systems, from 450–800 €/kWh in 2024 to 270–675 €/kWh in 2035 and 150–580 €/kWh in 2045; for utility-scale PV-plus-storage, from 400–600 €/kWh in 2024 to 225–473 €/kWh in 2035 and 130–400 €/kWh in 2045. In terms of resulting LCOE for PV-battery systems, Fraunhofer projects that by 2045 small residential PV-battery systems reach about 5.9–16.1 ct/kWh, commercial rooftop systems 4.9–11.6 ct/kWh, and utility-scale PV-battery systems 3.7–7.6 ct/kWh, all assuming fixed PV-to-battery ratios and the CAPEX trajectories above; 2030 values will be higher, between today's (6–22 ct/kWh depending on segment) and these 2045 ranges.

In line with our optimistic views on technical progress in the sector, we choose as annualized cost of battery storage energy capacity 11,750 €/MWh·year, based on an investment cost of only 100,000 €/MWh of installed storage capacity (thus well below the lower bound of Fraunhofer). For the operation-and-maintenance factor, we choose 2% per year, and a technical lifetime of 16 years (Fraunhofer: 15 years). The cost basis explicitly refers to the installed energy capacity of the battery system.

3.3. Cost of Backup Energy

The cost of backup is split into three components: biomass, nuclear, and fossil power plants. Again, we use Fraunhofer ISE's LCOE study to do a compact, literature-consistent characterisation of annual fixed and variable costs for dispatchable plants based on biomass, hydropower, natural gas, and hydrogen.
Their yearly cost is composed of two components,

- fixed annual costs, i.e., amortization costs from the annualized installation, capital costs including a reasonable profit margin, and yearly maintenance and operations cost,
- variable or marginal costs, i.e., the cost of producing an additional kWh of energy, thus, mostly fuel cost.

In the expectation of a completed coal phase-out, we assume that by 2030 there will only be gas powered backup power plants. This isobviously unrealistic but favourable for the carbon imprint of the residual load, which is lower if not coal but gas-fired powerplants supply the backup power.

3.3.1. Biomass

For its LCOE analysis of biomass-generated electricity, Fraunhofer no longer assumes pure baseload, with >7,000 full-load hours per year, but a range of 4,000–6,300 full-load hours for biogas and solid biomass, explicitly motivated by the system need to use these plants "to balance the supply-dependence of electricity generation from solar and wind." Overnight investment costs of roughly 3,000–4,500 €/kW, technical lifetimes of 20–25 years and real discount rates of 6–8% imply annualised fixed costs on the order of 150–250 €/kW·year, including fixed O&M. Variable costs are

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dominated by fuel: feedstock plus logistics commonly amount to 60–100 €/MWh of its fuel, which at electrical efficiencies of 25–35% translates into 170–300 €/MWh of electricity, to which 5–10 €/MWh variable O&M must be added.

For our analysis, we use annual fix costs of 150 €/kW·a and variable costs of 175 €/MWh.

3.3.2. Natural Gas

Fraunhofer models electricity from natural gas with technology-specific assumptions for CCGT and simple gas turbines, covering CAPEX, lifetime, WACC, efficiencies, fuel prices, CO_2 prices and declining full-load hours in a high-RES system.

For combined-cycle gas turbines (CCGT) it assumes: overnight investment costs of 900–1,300 €/kW in 2024, a technical lifetime of 30 years, and a financing structure of 60% debt and 40% equity with a 7% nominal interest rate on debt and 10% return on equity, yielding a nominal WACC of about 8.2% (≈6.4% real at 1.8% inflation). Fixed O&M is set at 20 €/kW·a, and variable non-fuel O&M at 5 €/MWh. Net electrical efficiency is assumed to be 60% in 2024, increasing to 61% in 2035 and 62% in 2045.

For open-cycle gas turbines (GT) Fraunhofer uses specific investments of 450–700 €/kW, the same 30-year lifetime, the same debt-equity split and WACC as CCGT, fixed O&M of 23 €/kW·a, and variable non-fuel O&M of 4 €/MWh. Electrical efficiency is assumed to be 40% and constant over time.

Fuel and CO_2 inputs are exogenous: natural gas prices of 38 €/MWh in 2024, falling to 27 €/MWh from 2030 onward, and CO_2 certificate prices rising in real terms from 75–90 €/t in 2024 to 175–375 €/t in 2045. Fraunhofer assumes that full-load hours for gas plants decline as renewables expand: for CCGT, from 3,000–6,300h in 2024 via 1,000–4,500h in 2035 to 500–2,500h in 2045; for GT, from 500–3,000h in 2024 to 500–2,000h in 2045. Together, these assumptions produce LCOE ranges for new CCGT plants of 10.9–18.1 ct/kWh in 2024, rising to 14.1–40.5 ct/kWh by 2045, and for gas turbines of 15.4–32.6 ct/kWh in 2024, increasing to 18.6–40.5 ct/kWh by 2045, with the upward trend driven mainly by CO_2 prices and reduced utilisation.

Throughout this study, we use fixed costs of 150 €/kW·a and variable costs of 175 €/MWh.

3.3.3. Coal

Fraunhofer models lignite and hard-coal power with technology-specific assumptions for CAPEX, lifetime, WACC, efficiencies, fuel prices, CO_2 prices and declining full-load hours.

For lignite plants (≈1,000 MW reference size), it assumes specific investments of 1,850–2,550 €/kW in 2024, a technical lifetime of 40 years, fixed O&M of 42 €/kW·a and variable non-fuel O&M of 0.005 €/kWh. Financing is set at 60% debt and 40% equity, with a 7% nominal interest rate on debt and 11% return on equity, implying a nominal WACC of 8.6% (≈6.8% real). Net electrical efficiency is assumed to rise slightly from 38% (2024) to 40% (2045). Fuel prices for lignite are kept constant at 2.3 €/MWh over 2024–2045.

For hard-coal plants (≈800 MW reference size) specific investments are 1,700–2,300 €/kW in 2024, with 30-year lifetime, the same 60/40 debt-equity split, 7% debt interest and 11% equity return, yielding the same WACC as lignite (8.6% nominal, 6.8% real). Fixed O&M is 37 €/kW·a, variable non-fuel O&M 0.005 €/kWh, and net electrical efficiency increases from 39% (2024) to 41% (2045). Hard-coal fuel prices are held at 11.6 €/MWh throughout.

Full-load hour for both coal types are modelled as falling in a decarbonising system: lignite from 3000–6,300h (2024) via 1,150–3,650h (2035) to 500–1,000h (2045); hard coal from 3,000–5,200h (2024) to 1,150–2,650h (2035) and 500–1,000h (2045). CO_2 certificate prices rise in real terms from 75–90 €/t in 2024 to 175–375 €/t in 2045, making CO_2 costs a dominant variable component for coal. Under these assumptions Fraunhofer finds 2024 LCOE for new lignite plants of 15.1–25.7 ct/kWh and for new hard-coal plants of 17.3–29.3 ct/kWh, with costs increasing further towards 2045 due to higher CO_2 prices and lower utilisation, even before including any decommissioning or external waste-disposal costs.

Throughout this study, we use 150 €/MW·a and variable costs of 175 €/MWh.

 doi:10.20944/preprints202602.1492.v1

3.3.4. Nuclear Energy

While we follow Fraunhofer ISE parameters to assess the LCOE of various energy technologies, we make an exception on nuclear energy, where the ISE clearly lacks the relevant expertise, which has been widely critized by various authors, including the authors of this paper. A statement of the German nuclear industry association KernD summarizes the points of critique well [21].

Before new-build projects have to be considered, it is important to note that Germany still has the option to re-use its 17 sites where nuclear powerplants (NPP) still exist. They are currently being demolished but this process is slow and takes decades to conclude. The restart of up to eleven NPPs is still possible at much lower investment cost of €2-3 billion per unit, compared to new-build projects. At other former NPP locations, any new-build project will profit from the site licensing and the relevant infrastructure that exists [22].[2]

If Germany started pursuing a new-build strategy despite perceived high costs, it could benefit from its experience with the ’Konvoi’ reactors that were built in the 1980s. At the time, the leading engineers of all O&M and their supplier convened quarterly to discuss progress, issues, and improvement potential of new-build projects. In consequence, each NPP was built cheaper, faster and more reliably than its predecessor.[3] Nuclear energy thus undertakes a steep learning curve with a serial construction of even large-scale reactors

In consequence, we use the following parameters for nuclear energy: Construction cost of 4,000,000 €/MW and annual operating costs of 200,000 €/MW.

3.4. Costs Due to Grid Expansion and Losses

The assessment of specific grid expansion costs proceeds by relating projected cumulative electricity grid investment in Germany up to 2045 to the planned expansion of weather-dependent generation capacity. This yields an approximate cost metric in euro per gigawatt of additional variable renewable energy (VRE) capacity. The underlying methodological assumption is that, in a climate-neutral pathway, the bulk of long-run grid reinforcement and extension is induced by the spatial relocation and magnitude of generation associated with large-scale deployment of wind and solar power, even though other drivers (electrification of demand, electrolysers, spatial shifts in load) also contribute [23].

For the cost side, the analysis draws primarily on the official German transmission grid development plan (Netzentwicklungsplan Strom 2023–2037/2045) as validated by the Federal Network Agency (Bundesnetzagentur), which reports an investment volume on the order of 330–360 billion € for the transmission network up to 2045. To capture the full system perspective, it is advisable to also use an IMK/Hans-Böckler-Foundation study that aggregates both transmission and distribution grid investments and estimates around 650 billion € of electricity grid expenditure (approximately 328 billion € for transmission and 323 billion € for distribution networks) by 2045 in a climate-neutral scenario. On the capacity side, the calculation employs expansion targets from scenario studies by Agora Energiewende, such as “Towards a Climate-Neutral Germany by 2045” and “Climate-neutral power system 2035,” which project a total installed renewable capacity of roughly 700 GW by 2045, with the majority of this being incremental wind and solar additions relative to today [24].

Combining these figures yields a simple ratio of cumulative grid investments to cumulative VRE capacity expansion. Using the total grid cost estimate, 650 billion € divided by approximately 700

[2] NOTE to the reviewer: A revised report, where drafts are available to us, is going to be published by end of February 2026 and we will include it before publication.

[3] The often-cited Fraunhofer ISE nuclear cost figures represent one specific, highly conservative scenario rather than a universally accepted benchmark. They assume high overnight capital costs, long construction times, relatively high risk premia (WACC) and conservative lifetimes, which mechanically drive levelised costs upward. By contrast, international evidence (e.g. OECD-NEA/IEA and national regulators) shows that standardised designs, experienced supply chains and state-backed low-risk financing can yield substantially lower LCOE, often in the range of roughly 40–80 €/MWh for new-build, with even lower costs for existing plants under life time extension. The core controversy is therefore not "what nuclear costs", but which assumptions about CAPEX, construction duration, lifetime, capacity factor and financing are appropriate for the context considered. Scientifically robust comparisons should report nuclear as a cost range defined by transparent scenario assumptions and test sensitivities, rather than relying on a single, highly pessimistic parameter set.

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GW of renewable capacity implies grid-related costs of about 0.93 billion €/GW, that is, roughly 930 €/kW of additional VRE capacity. Restricting the numerator to transmission grid investments alone (roughly 330–360 billion €) and keeping the same 700 GW denominator results in a range of about 0.47–0.51 billion €/GW. These values can be interpreted as indicative "grid adders" per unit of variable renewable capacity in long-term system planning and levelized cost comparisons [25].

It is important to emphasise that this allocation is an analytical convention rather than a structural law: grid costs are not exclusively caused by renewables but by the joint evolution of generation, demand, and spatial patterns of both. Nevertheless, given that all major decarbonisation scenarios for Germany foresee a strong dominance of wind and solar in the generation mix, the bulk of incremental grid reinforcement can be reasonably attributed to accommodating variable renewables. In that sense, the derived range of roughly 0.5–1.0 billion €/GW provides a scientifically grounded order-of-magnitude estimate of grid expansion costs per unit of additional weather-dependent generation capacity under current official planning and established scenario studies [4].

In line with our approach to represent VRE integration cost under optimal conditions, we parametrize grid expansion and related infrastructure cost as 500,000 €/MWp·year per unit of newly installed VRE power capacity.

Another important factor for modelling is grid losses. In its series of 'Electricity Information' handbooks, IEA reports historically a range of 4-6% in losses compared to electricity consumption. Nevertheless, in line with our desire to represent costs in an idealized way, we ignore grid loss costs.

3.5. Costs from Subsidies

The current average fixed prices for new wind and solar plants are 82 EUR/MWh. This legacy creates additional costs in the energy system, because the prices achieved at the exchange are usually considerably lower, in particular during times of surplus.

4. Carbon Footprint Considerations

Similarly as with costs, the carbon footprint consists of the contributions of all components. Due to the difficulties of correct attribution, the carbon footprint of the electrical grid is left out in this investigation although VRE require massive grid investments.

The key components to consider in a renewable energy scenario are the carbon footprints of production, namely from photovoltaics and wind power, the carbon footprint of batteries, and that of backup power plants.

The carbon footprint of batteries is mainly generated during production. Currently they are published to be 96 kg CO_2/kWh for NCM batteries and 77 kg CO_2/kWh for LFP batteries [26]. Other publications estimate 150–200 kg CO_2/kWh [27], the lower bound for LFP batteries. We assume the larger number to be true, because it adequately takes into account mining of raw materials. We therefore assume LFP batteries with a carbon footprint of 150 kg CO_2/kWh battery capacity. Furthermore, we assume a lifetime of 2,000-4,000, on average 3,000, full load cycles an a maximum life span of 20 years, independent of the number of load cycles. Therefore for less than 150 full load cycles per year, the maximal life span ist the limiting factor, assuming that there are no other limiting factors such as adverse weather extremes during operations. As our calculations show, batteries can profit from hardly more than 150 full cycles per year. We can therefore assume a yearly carbon footprint of 7.5 kg CO_2/kWh = 7500 t CO_2/GWh. The yearly carbon footprint for the delivered Energy E^{used} from a battery of the capacity $E^s_{\max}$ is thus, when both are measured in GWh:

$$CF^{\text{Battery}} = 7500 \cdot \frac{E^s_{\max}}{E^{\text{used}}} (\text{g CO}_2/\text{kWh}) \tag{11}$$

In order to simplify calculations, the carbon footprint of energy from batteries does not consider the CF of their input energy, which is a mixture of renewable and backup energy, and the CF of the suppliers must thus be accounted for by their other uses.

 doi:10.20944/preprints202602.1492.v1

Regarding the VRE carbon footprint, the CF of PV modules from China has been estimated to be 3060 t per installed MW_p [28]. With a realistic expected lifetime of 25 years this results in 122 t/MW_p per year.

On the basis of a study from 2014, the carbon footprint for wind power plants amounts to 56 t CO_2 per installed $MW_p \cdot a$ according to [29], with an assumed lifetime of 20 years. We do not differenciate between onshore and offshore installations. The contribution of VRE to the carbon footprint therefore is for installed power $P^{\text{PV}}_{\text{installed}}$, $P^{\text{onshore}}_{\text{installed}}$, and $P^{\text{offshore}}_{\text{installed}}$:

$$CF^{VRE} = \frac{122,000\text{t}/\text{GW}_p \cdot P^{\text{PV}}_{\text{installed}} + 56,000\text{t}/\text{GW}_p \cdot (P^{\text{onshore}}_{\text{installed}} + P^{\text{offshore}}_{\text{installed}})}{E^{\text{VRE}}_{\text{direct}}} \tag{12}$$

The installed VRE power of 2024 is known to be $P^{\text{PV}}_{\text{installed}} = 93\ \text{GW}_p$, $P^{\text{onshore}}_{\text{installed}} = 62\ \text{GW}_p$, and $P^{\text{offshore}}_{\text{installed}} = 9\ \text{GW}_p$. Therefore with $E^{\text{VRE}}_{\text{direct}} = 195,824$ GWh in 2024 the specific VRE CF is

$$CF^{VRE}_{2024} = \frac{15,322,000\text{t}}{E^{\text{VRE}}_{\text{direct}}} \approx 78\text{g}/\text{kWh}$$

and with $E^{\text{VRE}}_{\text{direct}} = 386,022$ GWh in 2030 the specific VRE CF is

$$CF^{VRE}_{2030} = \frac{36,553,920\text{t}}{E^{\text{VRE}}_{\text{direct}}} \approx 95\text{g}/\text{kWh}$$

This corresponds to the expected lower utilization rate of VRE with increasing installations. Batteries help to mitigate this effect, ideally reducing the surplus energy to significantly smaller values. By assuming that the input energy to the batteries is considered to be "free", the increased VRE CF ist adequately taken into account. Neither the exported VRE nor the curtailed VRE is included in the calculation, in line with carbon regulation.

The carbon footprint of natural gas (500 g/kWh), coal (800 g/kWh), and lignite (1000 g/kWh) backup ower plants [30] is averaged according to their expected utilization in 2030.

4.1. Limits of Battery Deployment

If the goal of combining renewable energy sources with batteries is to eliminate or at least drastically reduce carbon emissions, it is essential to ensure that this objective is not undermined.

We show in the Results that key outputs – annual battery outflow, full load cycles, and reduction in backup energy – scale approximately linearly with the logarithm of battery capacity, within a well-defined but limited range of scenarios and capacities.

Taking the key target parameter, the minimum backup energy, $E^{\text{backup}}_{\text{min}}$ and the battery capacity C is to be approximated with ($ln()$ is the natural logarithm function)

$$E^{\text{backup}}_{\text{min}} = f \cdot ln(C) + g \tag{13}$$

Both $E^{\text{backup}}_{\text{min}}$ and C are measured in GWh. The logarithmic decline in storage effectiveness can be viewed as adding many smaller batteries in sequence: the first cuts volatility by a given fraction, the next acts only on the already-reduced volatility, and so on, so each equal gain requires ever more capacity. Such a sequence can be approximated by parts of the function $y = 1/x$. Summing up all of these small batteries corresponds to integration. The integral of $y = 1/x$ is $Y = ln(x)$, the logarithmic function. Practically this means that more and more batteries are required to achieve the same amount of volatility reduction.

Obviously, this is only a plausibility argument, eventually the data will speak for itself.

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4.1.1. Carbon Footprint as a Limiting Factor of Battery Expansion

In order to be able to make a judgement about carbon footprint at any stage of the battery rollout, it is important to know the marginal gain: How much backup energy is saved by expanding battery installations by e.g. 1 GWh. This is achieved by taking the derivative of Equation (13):

$$\frac{dE_{\text{min}}^{\text{backup}}}{dC} = \frac{f}{C} \tag{14}$$

Assuming the carbon footprint of gas powered backup plants to be 500 g/kWh = 500 t/GWh [31], the carbon footprint of an additional battery that reduces the required backup production by 1 GWh must be less than 500 t/GWh. From Equation (11) follows that

$$500 > 7500 \cdot \frac{\Delta C}{-\Delta E_{\text{min}}^{\text{backup}}} \tag{15}$$

Approximating the differentials by finite differences in Equation (14) and combining it with Equation (15) leads to the maximum battery capacity C where the carbon footprint with additional battery storage is smaller than with gas power plants:

$$C < -f \cdot \frac{500}{7500}\text{GWh} \tag{16}$$

4.2. 'Hindcasting' Scenario: Energy Production and Storage in 2024 for Model Calibration

We first analyse 2024 data to validate the simulation against observations. The 38 GWh of pumped-storage capacity is represented in the battery model with adapted parameters, allowing us to compute the optimal operating conditions and the maximum theoretically extractable energy, which is then compared to the measured output of all German pumped-storage plants.

Subsequently, we assess optimized battery expansion not only in terms of additional battery-delivered energy but, more importantly, in terms of the resulting reduction in required backup energy—the key metric for a renewable-based energy transition.

From the given data [11], the relevant energy budget parameters of 2024 are given in Table 1.

Table 1. Energy balance of 2024 in Germany.

	GWh	%
Total load	465503	100.0
Hydro	22276	4.8
DRE	46348	10.0
VRE	196031	42.1
Residual load	200848	43.1
Initial Deficit	202211	43.4
Initial Surplus	1363	0.3
Directly used VRE	194668	41.8

Therefore 56.6% of the total load were covered by renewables, where both DRE and VRE are included, and the deficit of 43.4% had to be covered by backup and batteries. While it is obvious that in this scenario also the battery input has to come from backup power plants, it is instructive, however, to assess how much of the volatility can be converted by means of batteries.

4.3. Planned Expansion of Energy Production for 2030

The next milestone date of the German energy transition is in 2030. This has to do with the goals of CO_2 reduction set by the German constitutional court [32]. Therefore it is of urgent importance to find out what can be realistically reached with the tools that are planned for sustainable energy production until then [4]:

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- Increase the production of wind an solar energy to a total of 339 GW of installed power by expanding wind and solar energy production of 2024 with three expansion factors for photovoltaics, wind offshore, and wind onshore, respectively.
- As a consequence of the expected transition to electric cars and heat pumps for domestic heating, the total load is expected to rise to 667 TWh per year, by expanding the 2024 measured load values by 1.45.
- In order to reduce the expected volatile surplus and fill the gaps of the deficit it is planned to install 300 GWh of battery storage.
- as an option, it is considered to change the supply from biofuels from fixed to variable.

With these adaptations the energy balance of the scenario 2030 is displayed in Table 2.

Table 2. Energy balance of 2030 in Germany.

	GWh	%
Total load	674979	100.0
Hydro	22276	3.3
DRE	46348	6.9
VRE	411306	60.9
Residual load	241397	35.8
Initial Deficit	266681	39.5
Initial Surplus	25284	3.7
Directly used VRE	386022	57.2

This scenario has not only a significant surplus of 25 TWh available as potential input for battery storage independent of backup supply, but also the DRE is not included in the residual load, but assumed to be available as dispatchable backup energy of 46 TWh. The total deficit to be covered, however, is 267 TWh.

Again, it should be stressed that we ignore the impact of electricity import and export. These can alleviate some of the issues at the expense of German's neighbouring countries, but the target of most European countries are self-sufficiency in power supply.

5. Results and Discussion

5.1. The Effect of the Normalized Residual Load on the Total Storage Requirements

By means of Equation (7), an assumed infinite capacity with no losses is charged from the initial residual load of 2024. The result is displayed in Figure 3.

Under ideal conditions, the volatile part of the produced energy in 2024 requires a lossless battery storage of approximately 12 TWh to fully balance VRE with load.

Now the filtered residual load is created according to Equation (4) with an arbitrary selected filter window size of 24 hours, i.e. 96 data points. This is shown in Figure 4. The normalized residual load according to Equation (5) is used as input to Equation (7) resulting in the charge of a lossles,s unconstrained battery. This is displayed in Figure 5. Due to the fact that now part of the slower volatility has been absorbed by the filtered residual load, the normalized residual load can be controlled nicely for subsequent processes by means of the filter size. The resulting idealized storage load is displayed in Figure 5. Now the remaining fast volatility can be dealt with a 800 GWh storage device. This is less than 10% of the requirement for the initial residual load.

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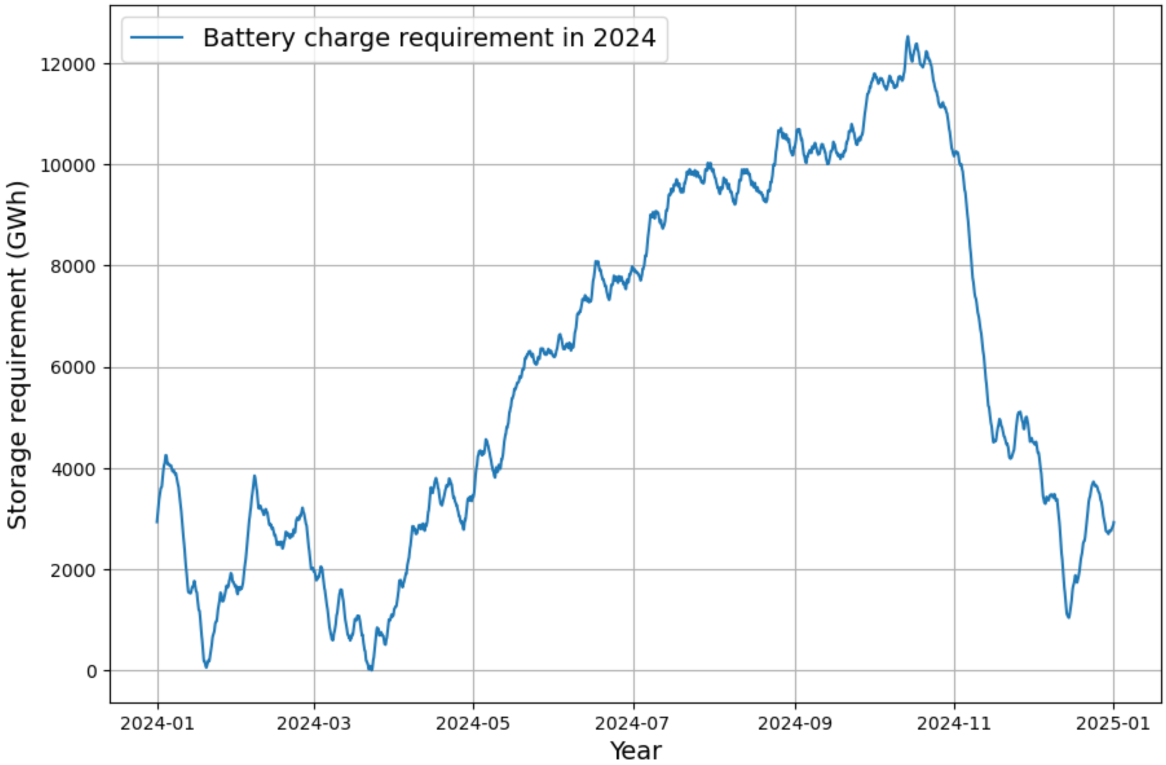

Figure 3. Storage load for a lossless battery of unlimited capacity from the residual load in 2024.

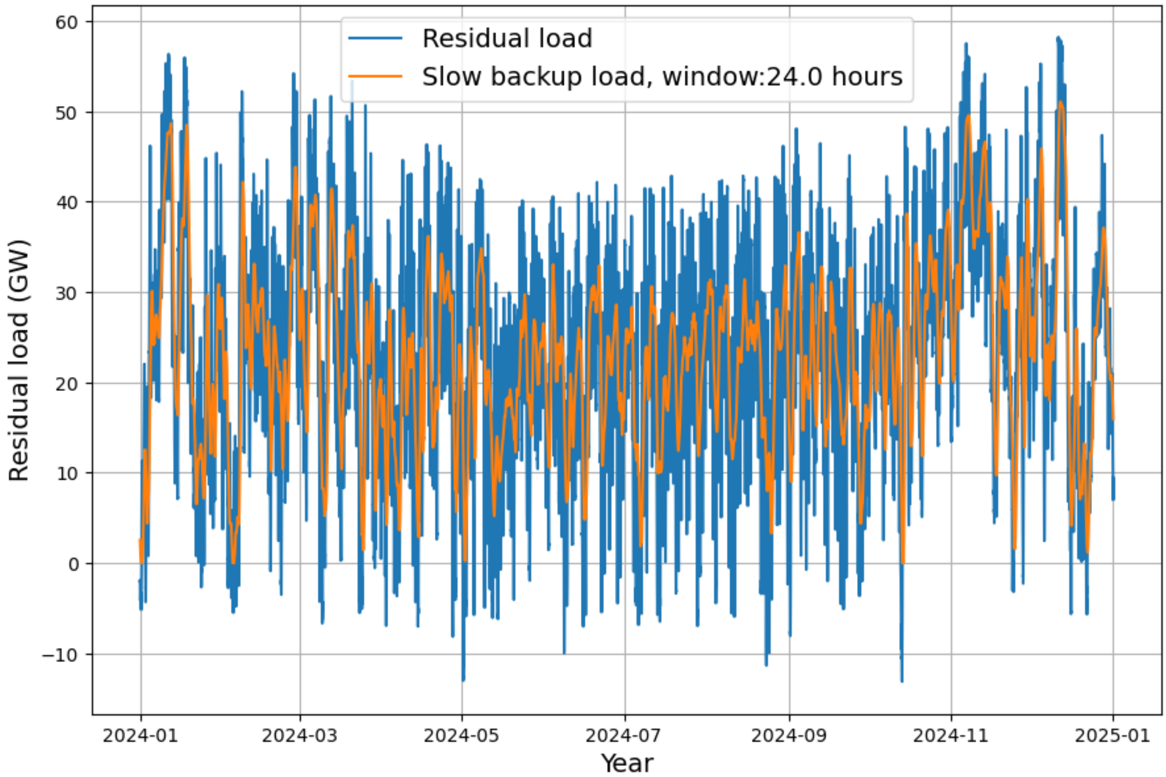

Figure 4. Initial residual load of 2024 (blue) and filterend residual load with filter window size of 24 hours (orange).

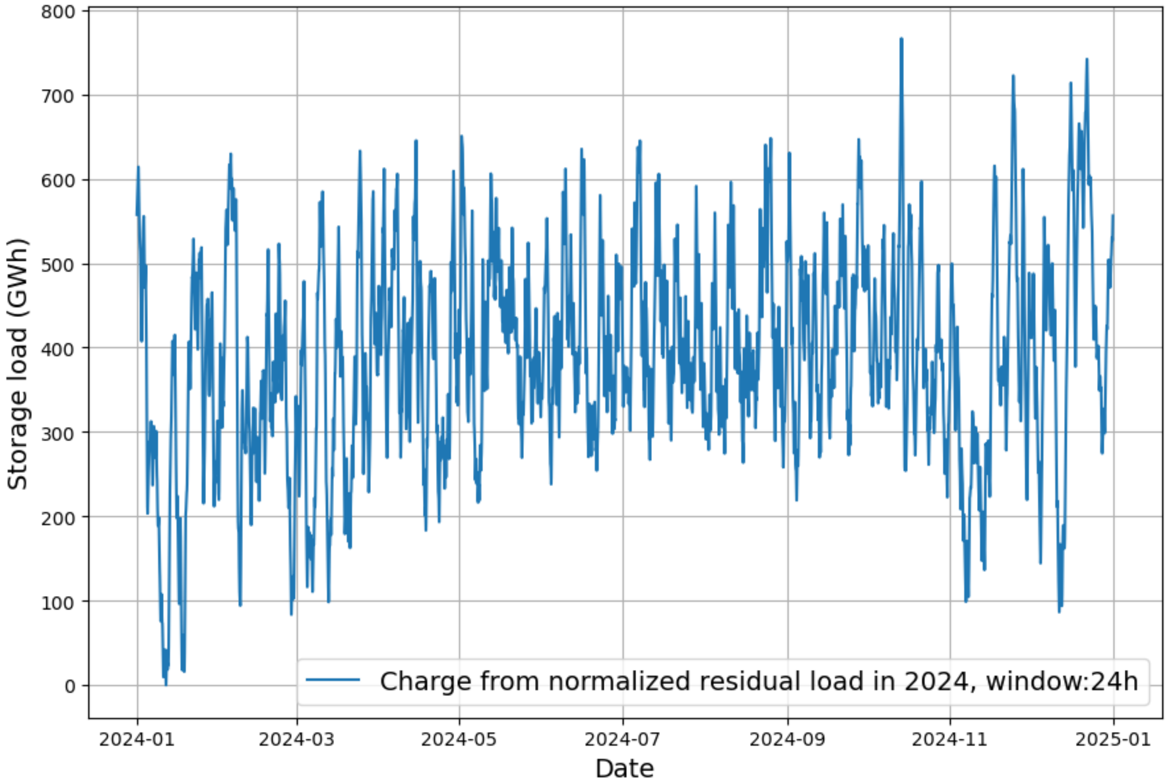

Figure 5. Storage load for a lossless battery of unlimited capacity from the normalized residual load with a filter window size of 24 hours in 2024.

5.2. Simulation of the German Pumped Storage in 2024

By testing all m from 1 to 96 (this corresponds from 15 minutes to 24 hours), the outflow of a battery is determined, which corresponds to the total capacity of all German pumped hydro plants (capacity 38 GWh, efficiency 80%, max. inflow 7 GW, max. outflow 7 GW) [33]. The energy outflow as a function of filter window size is shown in Figure 6

The maximum outflow at window size 8 hours is approximately 15 TWh in 2024. The reported outflow from the data set is 10.3 TWh [11]. Considering the fact that our simulation optimistically assumes unrestricted grid capacity (copperplate assumption), this not only shows that our model is compatible with reality, but also that the pumped hydro plants are operated very efficiently, close to their theoretical limit. Furthermore it is known that energy production in Germany is planned 24 hours in advance. If this is taken into account and a filtering window of size $m = 96$ (24 hours) is used, the theoretical outflow in 2024 from the simulated pumped storage plants is 10.5 TWh, a near to perfect match to current reality.

With this filtering, the flexibility requirements for the slow backup plants are reduced from more than 20%/hour to approximately 10%/hour of their maximum capacity, as shown in Figure 7.

Figure 8 displays the maximum achievable number of full load battery cycles per year in 2024. Although these numbers are quite impressive with more than one full battery cycle per day for small battery capacities, according to the feasibility criterion of at least 2,000 full load hours per year [7] this would limit the deployment of batteries to 100 GWh, even if 8-hour batteries are installed. Current battery projects are dominantly 4-hour batteries [34], with one exception of a planned 19-hour battery in the UAE (19 GWh capacity, 1 GW power).

Figure 9 displays the required backup energy as a function of filter window size. Clearly the minimal backup energy requirement is when there is no battery or pumped storage storage at all. The graphs indicate that all possible battery output is generated by backup power and not by volatile surplus. Therefore for a lossless battery, input and output are equal independently of window size. Therefore backup is constant over all filter window sizes. With real batteries the backup energy follows

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directly the outflow from the battery, which means, that the backup plants have essentially to "pay" for the battery losses. This means that in terms of backup, in 2024 nothing is gained from storage. Obviously the existing pumped storage plants were not built to save backup energy, but to keep the grid stable.

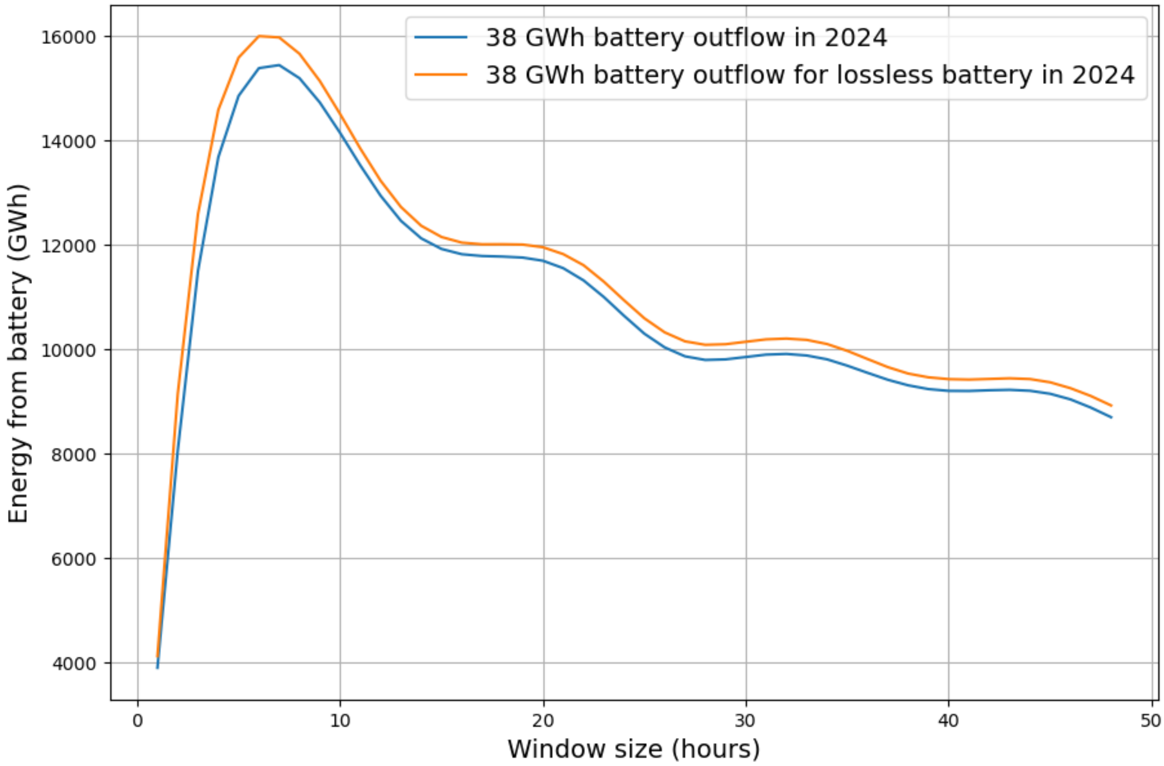

Figure 6. Battery outflow as a function of filter window size, emulating the German pumped hydro plants in 2024 with 38 GWh capacity and an equivalent C-rate of 0.18C [16].

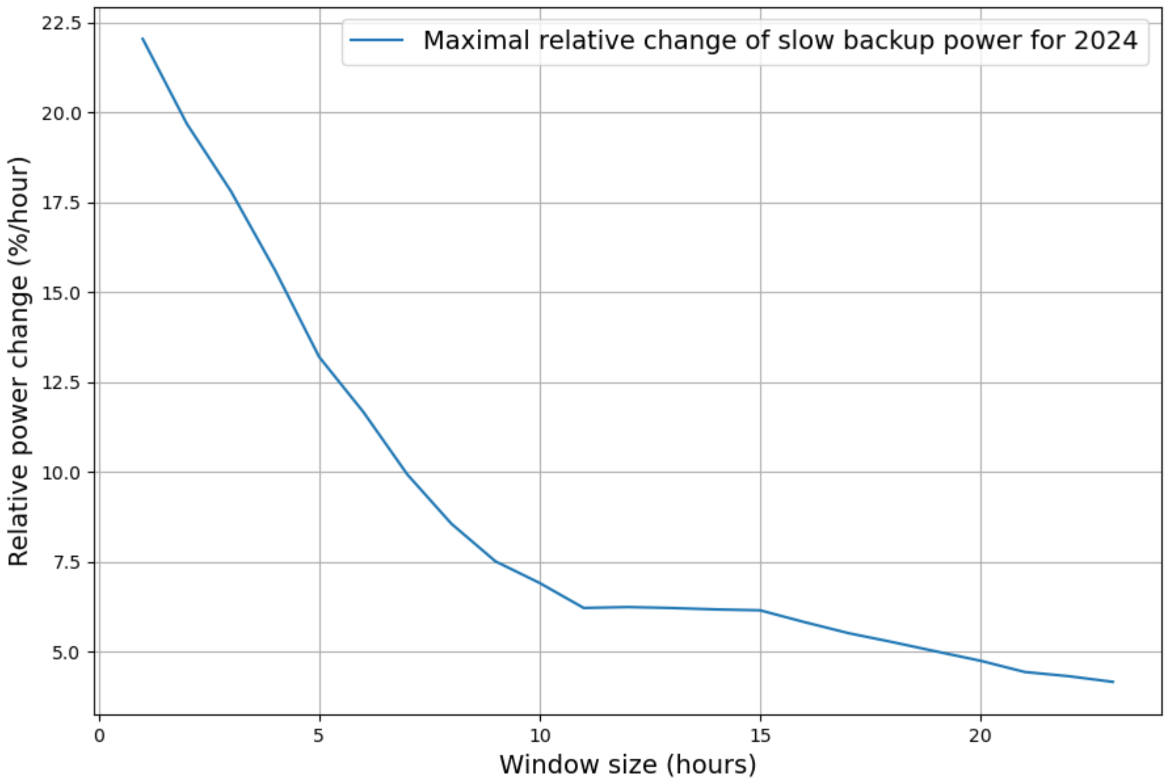

Figure 7. Flexibility requirements for backup power stations as a function of filter window size in 2024.

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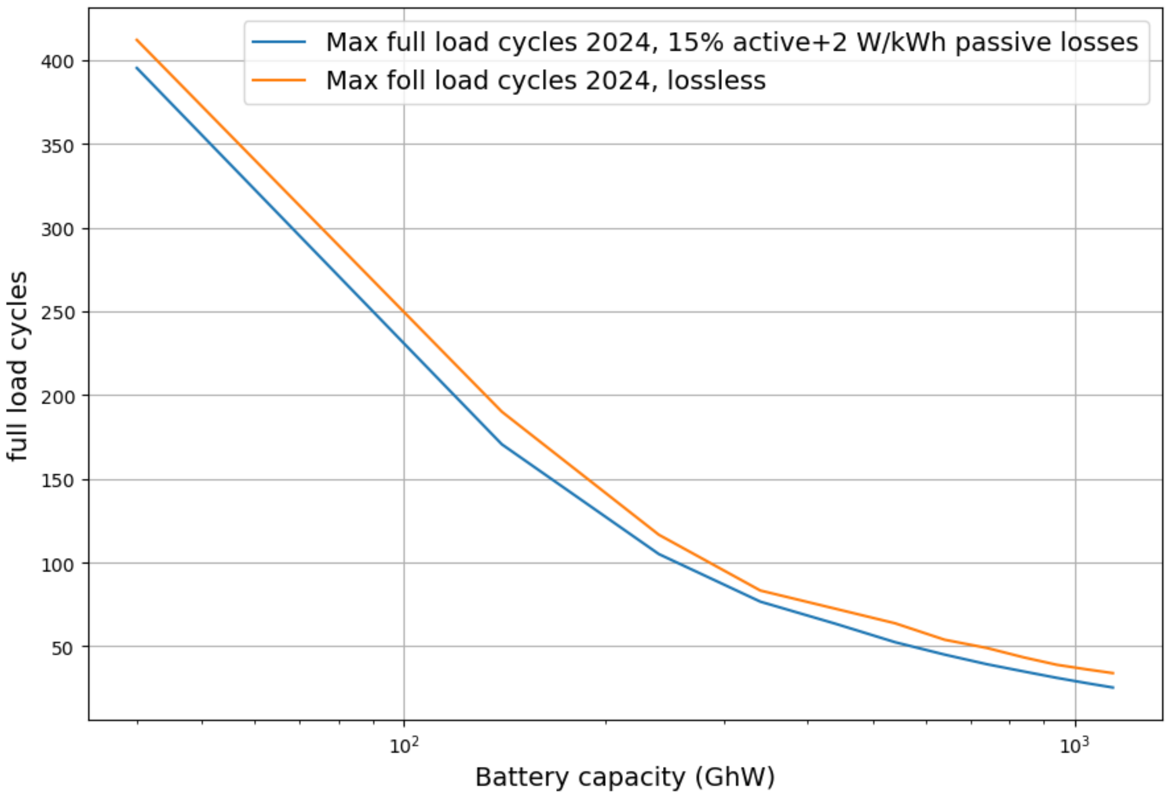

Figure 8. Maximized full load cycles as a function of battery capacity in 2024.

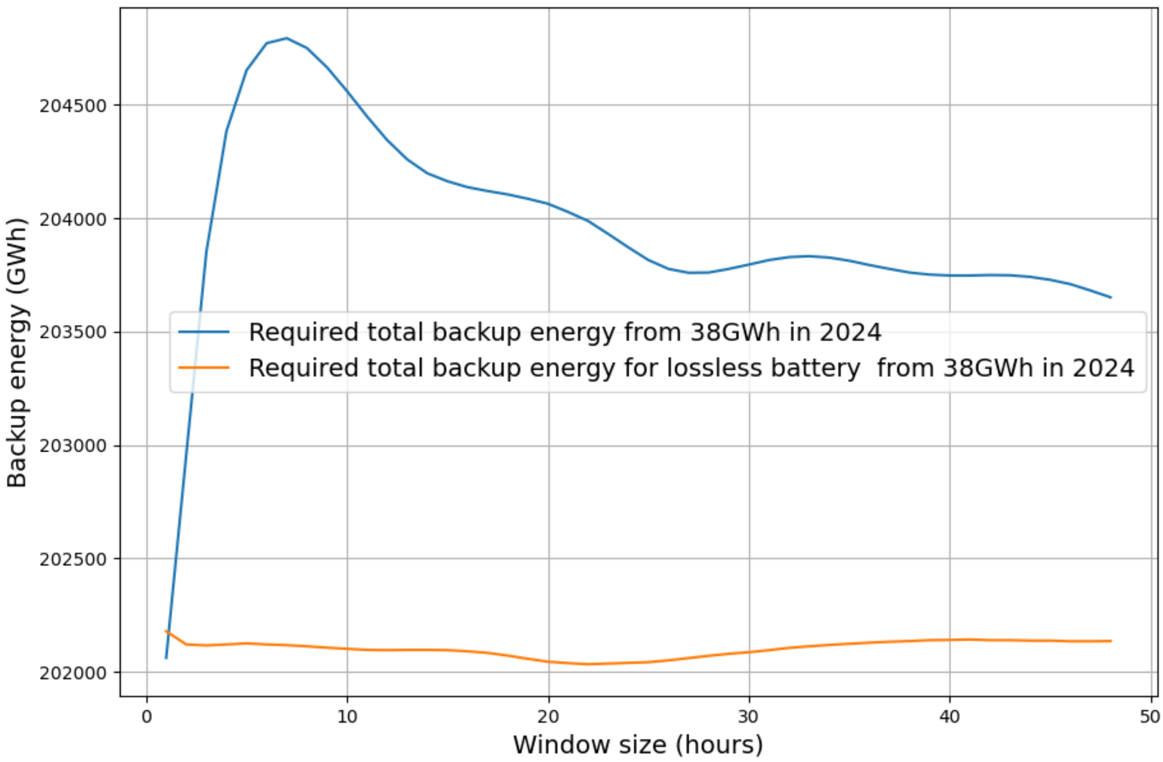

Figure 9. Total backup energy for 2024 with simulated 38 GWh pumped storage plants as a function of filter window size.

The final result in Figure 10 shows what 38 GWh of storage can achieve. The battery relevant signal is the green graph of the normalized residual load, the negative part of which (the surplus) is the input to the battery. The red graph represents deficit and surplus after battery processing. Hardly

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any surplus is left, which means that the battery has performed quite well, despite the fact that it was not sufficient to fill all deficits of the normalized residual load. These will have to be dealt with by (fast) backup power plants.

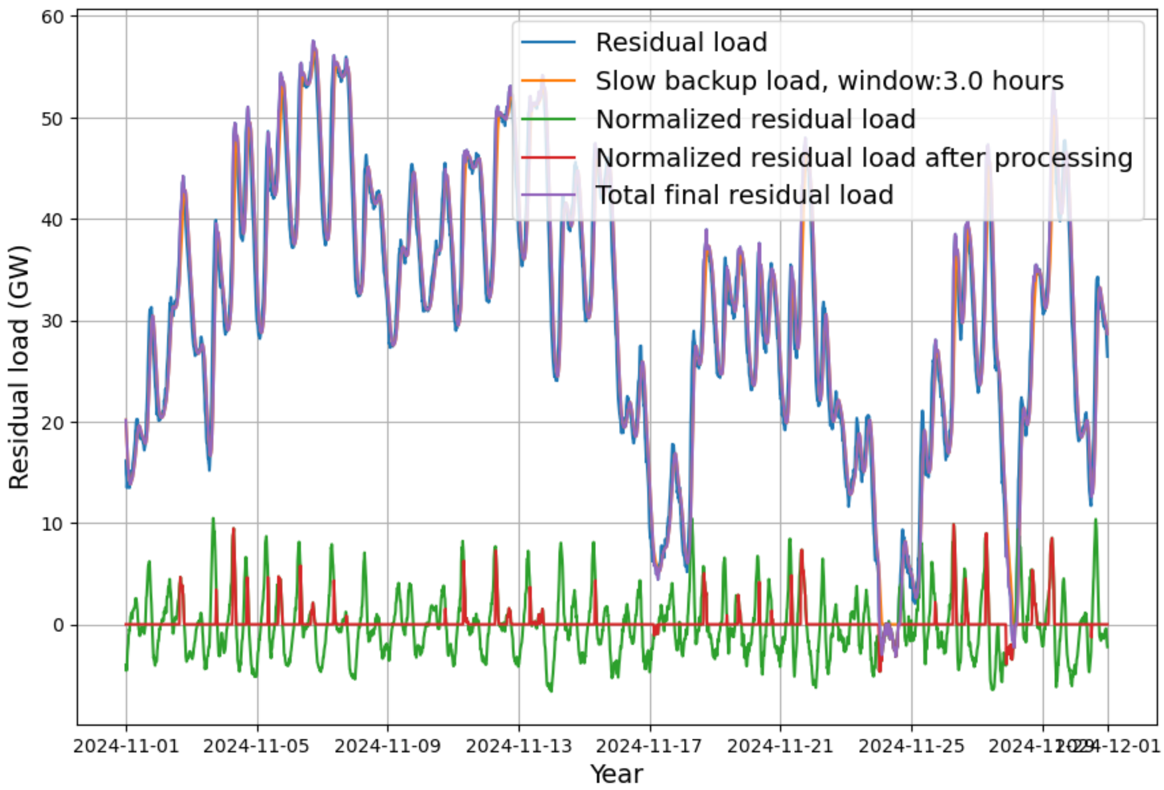

Figure 10. Simulation of pumped storage in November 2024, effect of 40 GWh storage from green to red graph. Positive values are energy deficits, negativ values are surplus.

5.2.1. Main Goal of the Investigation, Maximum Battery Output and Minimum Backup

After these preparations, the final scenario goals are discussed, the maximum battery output flow as a function of battery capacity, and the minimum total backup requirements as a function of battery capacity. This means that at each data point, the optimum filtering window size m is determined for each battery capacity. It may well be that maximizing battery output energy requires a different window size as minimizing backup energy.

Above, storage scenarios have often been calculated with lossless batteries, which is an unrealistic assumption. From now on, the results presented show both the lossless case and the case of realistic losses. Over the whole lifetime, 15% loss for each stored kWh seems rather optimistic. Althogh in the beginning, Li ion batteries may exhibit smaller losses of 10%, there is considerable performance degradation of the assumed lifespan over 20 years. Furthermore, passive battery losses must be taken into account. These are cooling energy, inverters, transformers, control and other infrastructure to keep the batteries running smoothly. A cautious estimate are constant 2 kW per MWh installed battery capacity. With more optimistic assumptions, the result will be somewhere between these two values. Figure 11 shows the maximum battery output for varying battery capacity values.

It needs to be pointed out that the x-axis is scaled logarithmically. The nearly linear graph means that in order to get the same additional outflow that was gained by increasing storage from 50 to 100 GWh, the 100 GWh must be increased to 200 GWh, and then again from 200 to 400 GWh, etc. The capacity investment doubles each time for achieving a similar effect. With other words, the battery expansion costs scale exponentially with the storage demand, or the effect is a function of the logarithm of capacity storage, up to a saturation threshold at about 800 GWh. Increase in storage capacity above this threshold doesn't increase battery ouput.

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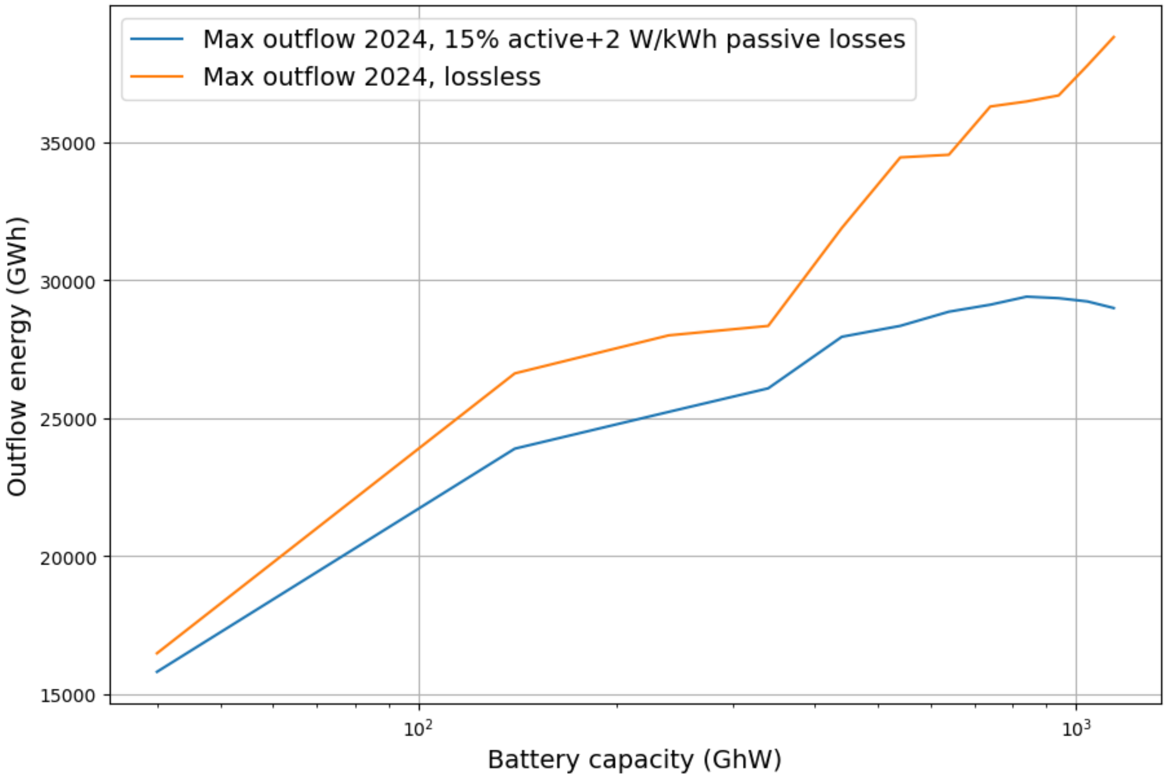

Figure 11. Maximized battery outflow as a function of battery capacity in 2024.

The key criterion for economic profitability is, besides the price spread between buying and selling power, the full load cycles of a battery. Figure 8 indicates that for small total capacities (i.e., 40 GWh), close to 400 full load cycles are possible, slightly more than one full cycle per day. This is made possible by the introductrion of the normalized residual load, utilizing all fast variabilities. Again the number of full load cylces decreases with a negative log function of capacity, reaching the critical value of 100 cycles per year with a capacity of 300 GWh. With a 4 hour battery this would result in 400 full load hours per year.

Figure 12 shows the minimum annual backup energy requirement. In the idealized, lossless case, this requirement decreases with increasing battery capacity, whereas with realistic batteries it actually increases with capacity. This indicates that, given the limited volatile renewable contribution in 2024, adding battery storage leads to higher fossil backup use. Nevertheless, batteries remain valuable for grid stabilization and short-term load shifting, helping to reduce intra-day mismatches between supply and demand. Figure 7 illustrates how the required rate of change of slow backup power declines as the filter window size increases.

The interesting question is what can be achieved with the optimized battery system at the next milestone of the energy transition in 2030?

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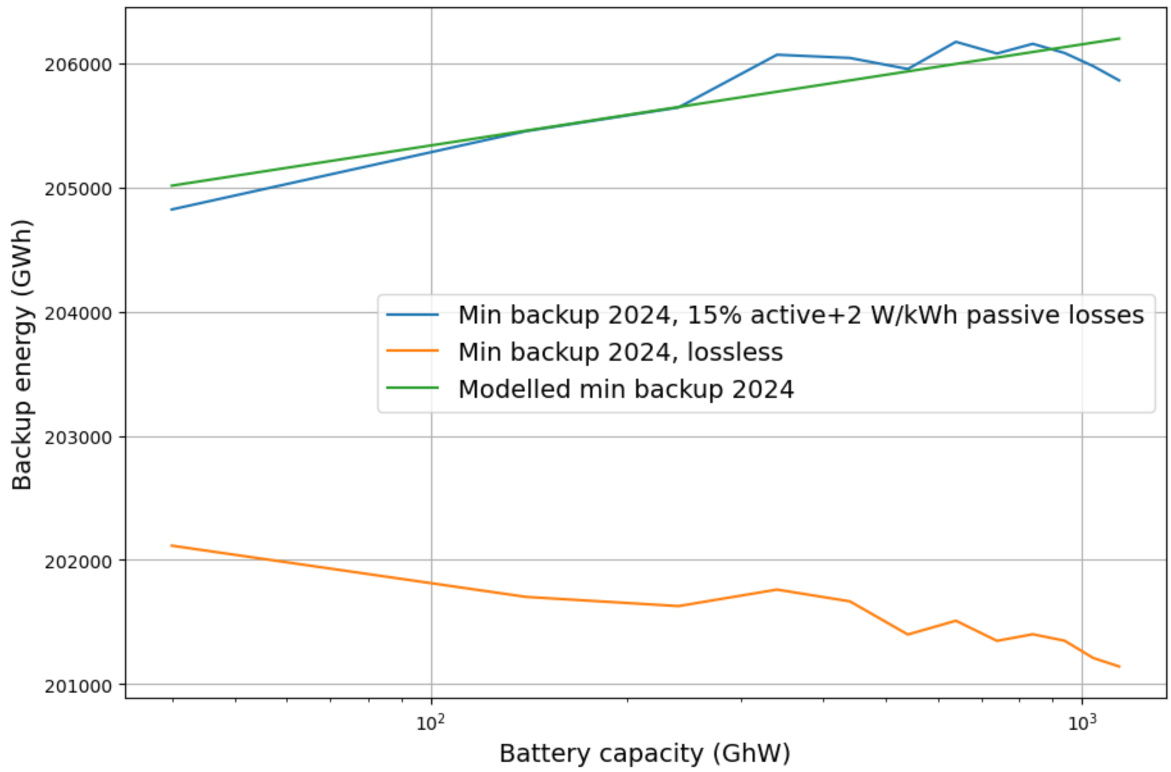

Figure 12. Minimized backup energy for 2024 as a function of battery capacity.

5.3. Scenario 2030 – Increased Variable Renewable Energy and Increased Load

Figure 13 shows the optimal full load cycles dependent on the battery capacity. It looks similar to the graph of 2024, but the inital value is considerably larger, nearly 500 full cycles per year, and the 100 cycle limit is at about 500 GWh. This means that with more available volatility battery usage becomes more efficient. The full load cycles are also following the pattern of declining utilization linear to the log of battery capacity.

Figure 14 displays the maximally achievable battery outflow over the year, for both cases of lossless batteries and with realistic batteries (15% active losses, 2 W/kWh passive losses). It is interesting to see that with real batteries, the maximum possible battery output is capped at about 65 TWh/year for battery capacities over 500 GWh. Again the x-axis is scaled logarithmically, with the implication that for the same relative additional effect battery capacity has to grow exponentially.

Regaring backup power capacity, the result is as expected. For all battery capacities up to 1000 GWh the required backup power remains constant at 93.5 GW. The periods of hardly any VRE supply are simply too long to be bridged by batteries.

The decline of the optimum, i.e. minimum required backup energy from growing battery capacities develops correspondingly. In the diagram Figure 15 with a logarithmically scaled x-axis the backup energy declines approximately linearly. With real batteries, the decline stops at a battery capacity of about 600 GWh. Nothing can be gained by increasing battery capacity beyond this threshold.

The decline before the threshold is reasonably linear, so that up to 500 GWh the Relation between the minimal backup energy $E_{\text{min}}^{\text{backup}}$ and the battery capacity C can be approximated with Equation (13)

Both $E_{\text{min}}^{\text{backup}}$ and C are measured in GWh. With the data of the blue graph of Figure 15, the estimated values of f and g are $f = -5,163$ GWh, $g = 289,000$ GWh with $R^2 = 0.89$. From Equation (16) follows that $C < 345$ GWh.

This means that with battery storage installation of 330 GWh or more in the described constallation of the 2030 Scenario, deploying more batteries has a larger carbon footprint than using gas power plants.

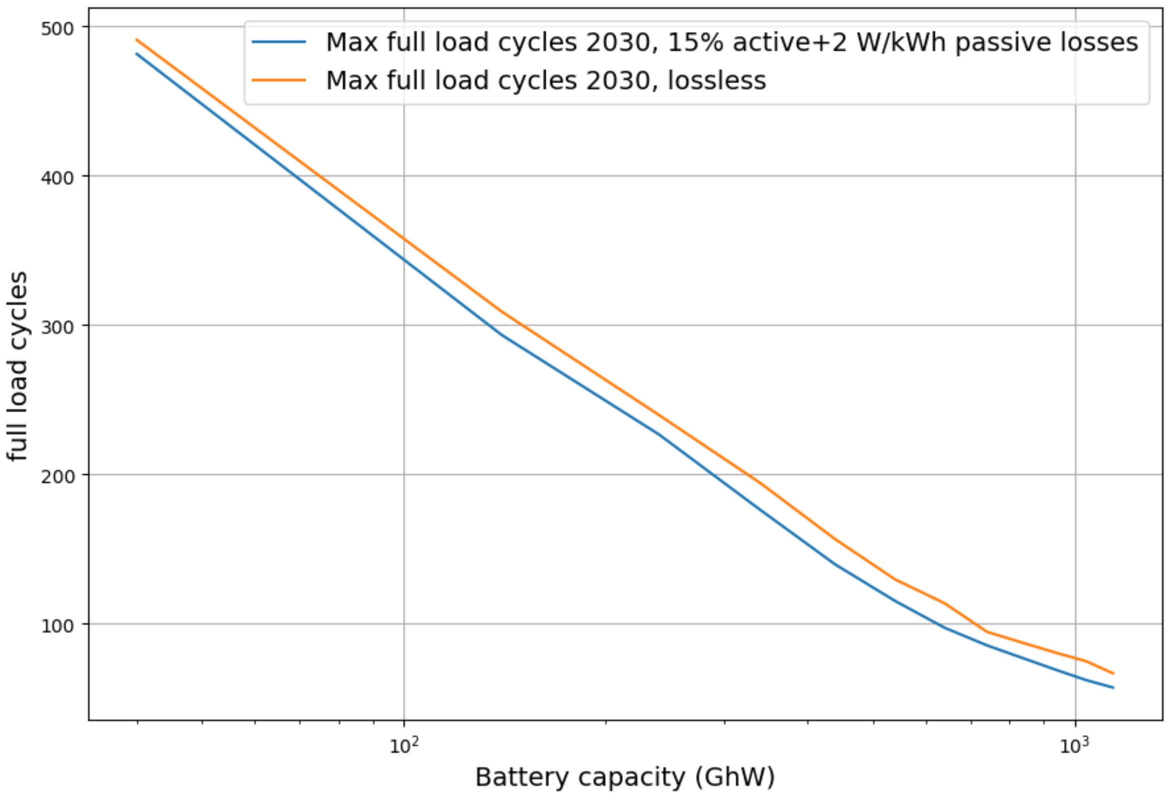

Figure 13. Maximized full load cycles as a function of battery capacity in 2030.

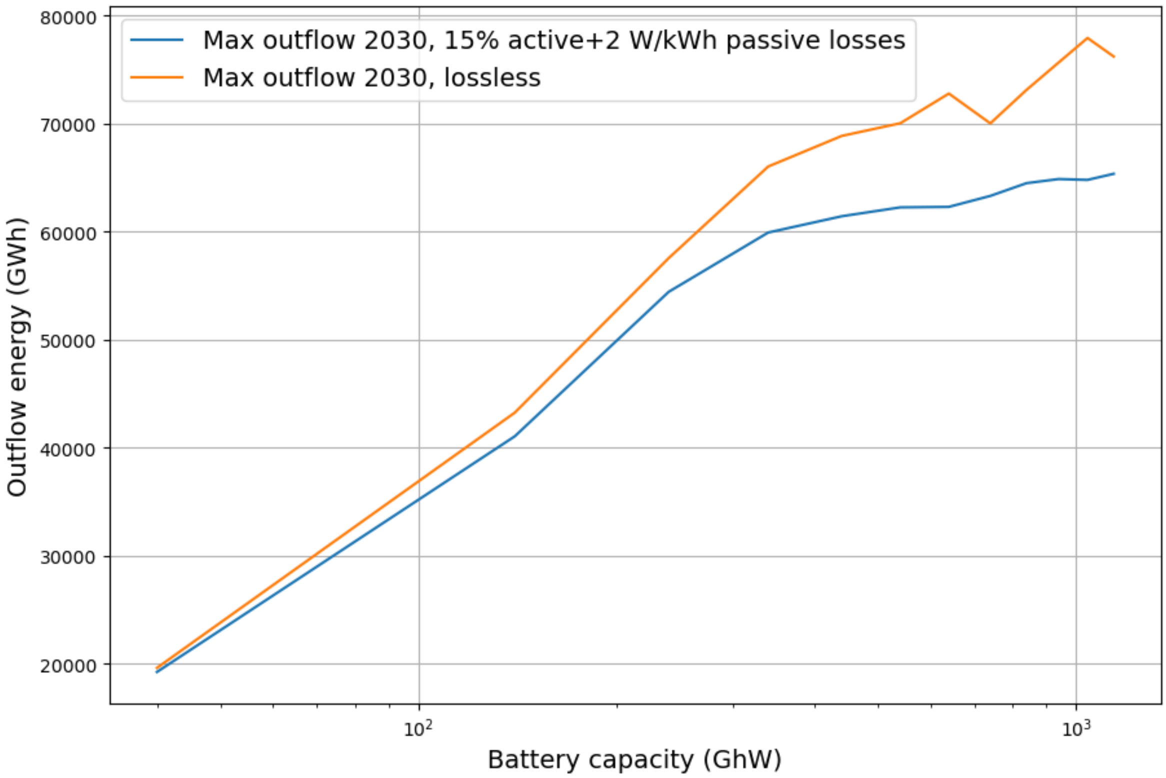

Figure 14. Maximized battery outflow for 2030 as a function of battery capacity.

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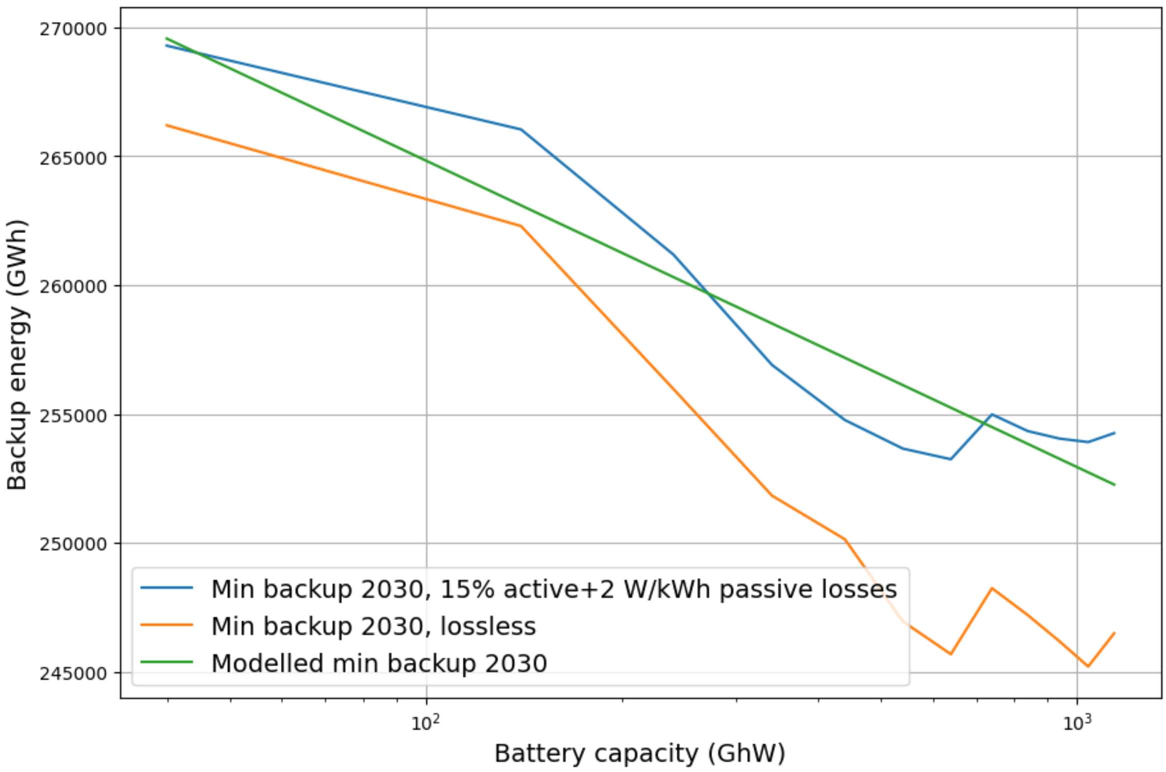

Figure 15. Minimized backup energy for 2030 a function of battery capacity.

5.4. Cost of Battery Expansion

Related to this are the actual costs for battery delivered energy, i.e. output flow. This is based on the assumption of annual costs of 11,750 € for each MWh of battery installed as discussed in section 3.2. The result is displayed in Figure 16, blue graph

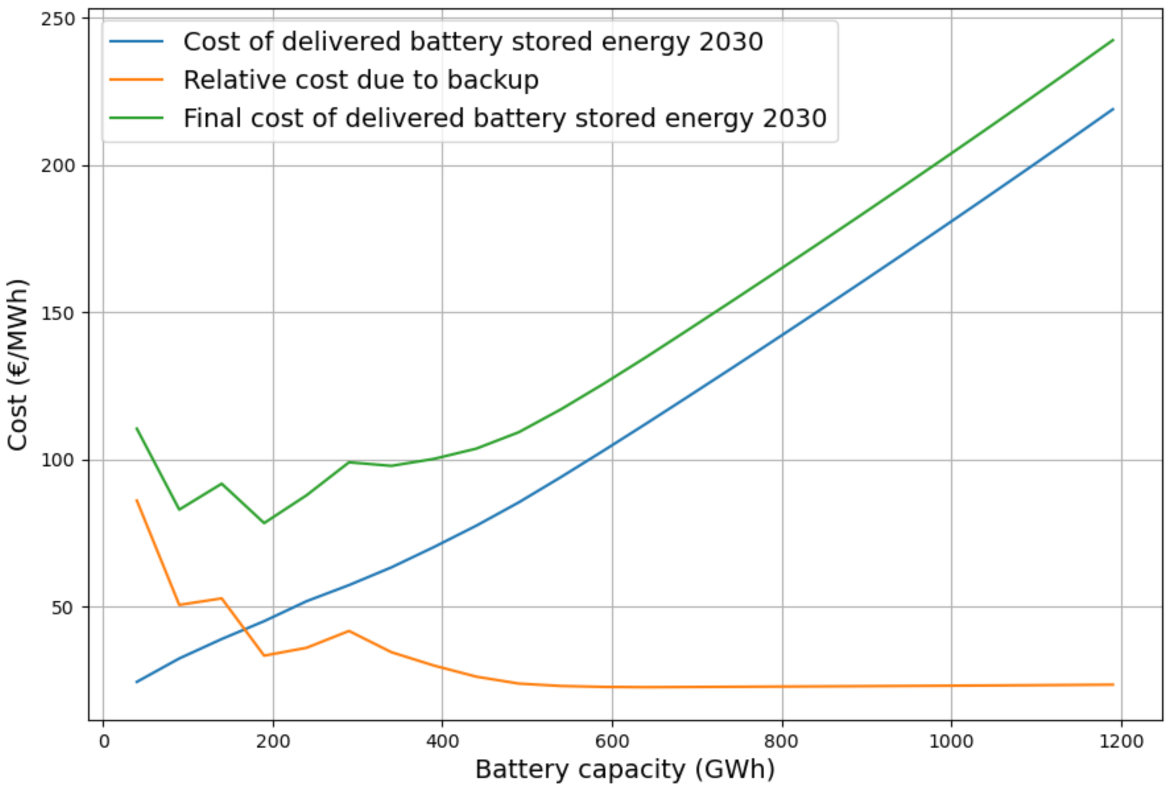

Figure 16. Averaged cost of battery delivered energy for 2030.

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Obviously battery costs scale linearly with capacity. However, the reduction in the form of avoided backup energy (Figure 16, orange graph) is limited in several ways. Not only comes the enhancement of volatility by the proposed filtering method at the cost of increased backup energy demand, but the backup reduction scales only linear in the logarithm of the capacity, and the constant minimum are the costs for battery losses. The combined optimum regarding cost is already reached at a capacity of about 200 GWh. Due to the small effect and large fluctuations it is fair to say that there is no real cost reduction by the introduction of batteries. And with further expansion of battery installations, the costs per kWh rise at the rate of battery investments.

5.5. Carbon Footprint of Battery Expansion

The relevant carbon footprint for the 2030 scenario, illustrated in Figure 17, consists of two main components: (1) the increase associated with the number of batteries, which follows a linear dependence on total battery capacity as described by Equation (11), and (2) the reduction in backup energy requirements due to the storage of surplus energy, as approximated by Equation (13).

The reference level of carbon footprint is determined by the production mix of backup energy. We have assumed biomass etc. to be DRE, their contribution of 46 TWh reduced the backup carbon footprint to about 420 g/kWh. For small battery capacities, the carbon footprint reduction resulting from decreased backup energy flows outweighs the additional footprint caused by the batteries themselves. However, while the benefit—i.e., the reduction in required backup energy—grows only logarithmically with battery capacity, the corresponding carbon footprint of the batteries increases linearly with capacity. The maximum CF reduction of about 15 g/kWh is reached with a battery capacity of 500 GWh.

Figure 17 thus illustrates the principal finding of this analysis: In systems dominated by volatile energy sources, the benefit of battery storage scales logarithmically with its size, whereas its associated cost, represented by the carbon footprint, scales linearly. In other words, the reduction of backup energy constitutes the benefit, while the carbon footprint represents the cost.

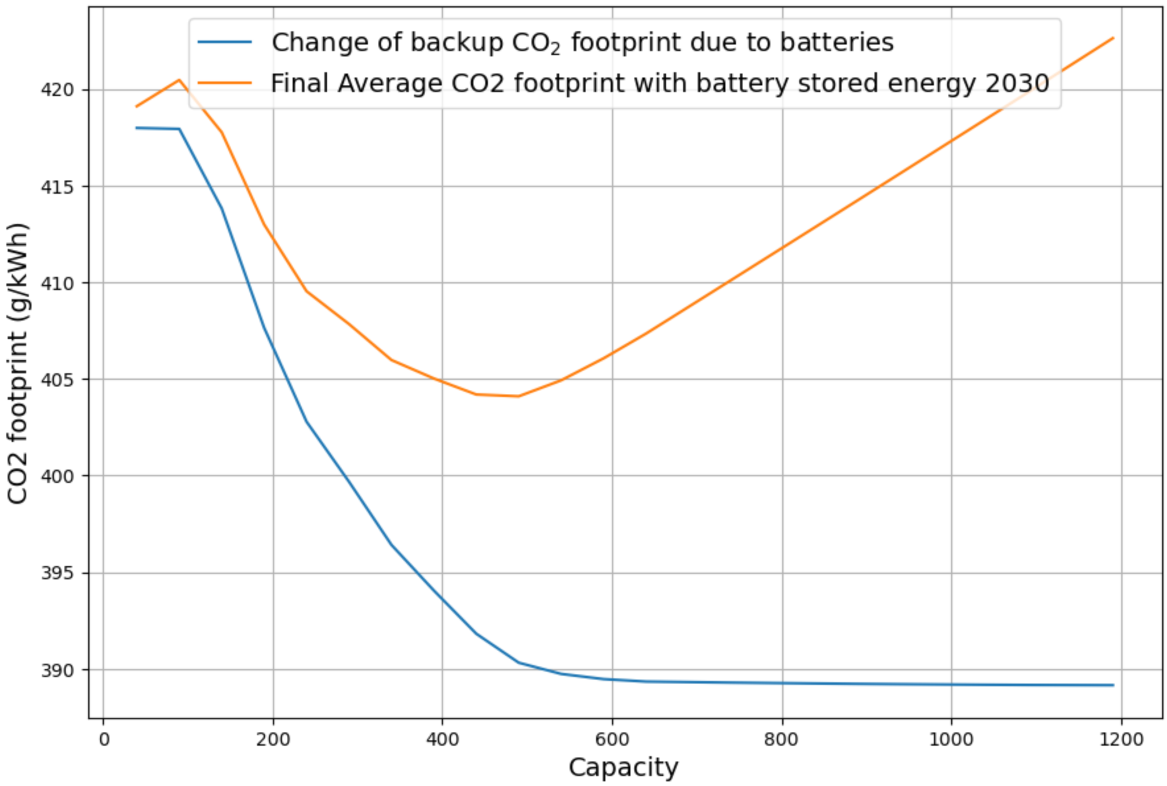

Figure 17. Carbon Footprint for backup and batteries as a function of battery capacity in 2030.

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5.6. Nuclear Power Complementing Battery Storage

This leads to the question whether there are alternatives or complementary concepts after the exhaustion of the optimum battery capacity, which is at about 300 GWh for the 2030 scenario? When decarbonization is the goal, then the option of reactivating the decommissioned nuclear power plants is to be considered. According to the study by the Radiant Energy Group [22], 11 of the formerly 17 reactors can be reactivated within the next six years, with a total power of approximately 10 GW[4]. Assuming that this is possible until 2030, even though it is challenging if decisions are made during early 2026, then these NPP could replace part of the backup plants by 2030.

Giving the NPPs the maximum priority of all backup systems and assuming 95% availability, but only overshooting the initial residual load by at most 3 GW (Minimum power avoiding shutdown) they can provide appr. 70 TWh of flexible backup power. The target power of the NPPs is not the residual load, but the slow backup power. This is illustrated in Figure 18.

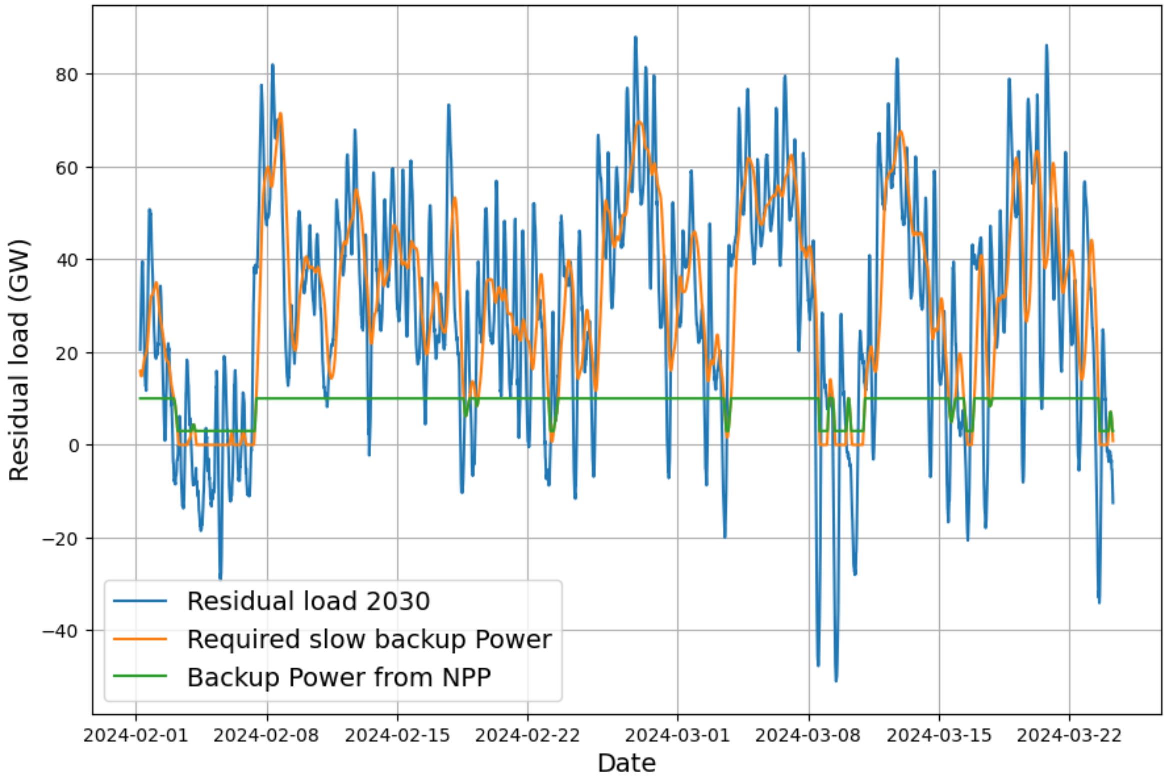

Figure 18. Residual load 2030 time series (blue), required slow backup power (orange), NPP backup power (green).

This has the effect that there are only few occasions when NPP backup power has to be ramped down to their minimum 30% utilization. A considerable number of the small surplus peaks of the residual load, which would have caused the NPPs to ramp down, have been transferred to the normalized residual load in order to provide the input energy for the batteries. As a consequence the theoretic utilization of the NPP rises from 74 TWh to 77 TWh. Nevertheless we assume conservatively only a utilization of 70 TWh due to maintenance-induced down-times, still resulting in more than 6100 full load hours for the NPPs.

Apart from this convenient effect, the slow backup is conceptually fully separated from the battery process which is only operating on the normalized residual load.

[4] NOTE to the reviewers: The updated report is available to us and will be published within the month of February 2026.

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5.6.1. Cost Results When Integrating Nuclear Power

Due to the smaller operational cost of NPPs the average specific cost of backup is assumed to be 140 €/MWh, and therefore the total cost is a bit lower than previously. This is displayed in Figure 19.

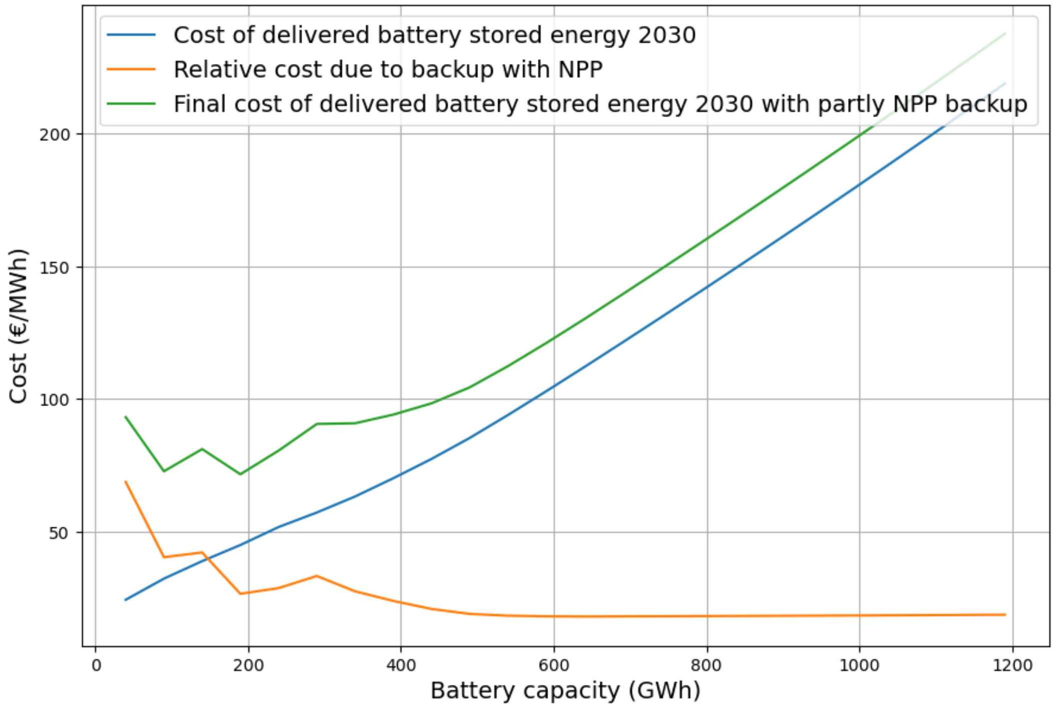

Figure 19. Averaged cost of battery delivered energy for 2030.

5.6.2. Carbon Footprint When Integrating Nuclear Power

The main effect of introducing nuclear power is to reduce the carbon footprint of the backup power mix due to its contribution of appr. 70 TWh. This reduces the average backup carbon footprint to about 285 g/kWh. The additional effect of battery expansion is displayed in Figure 20.

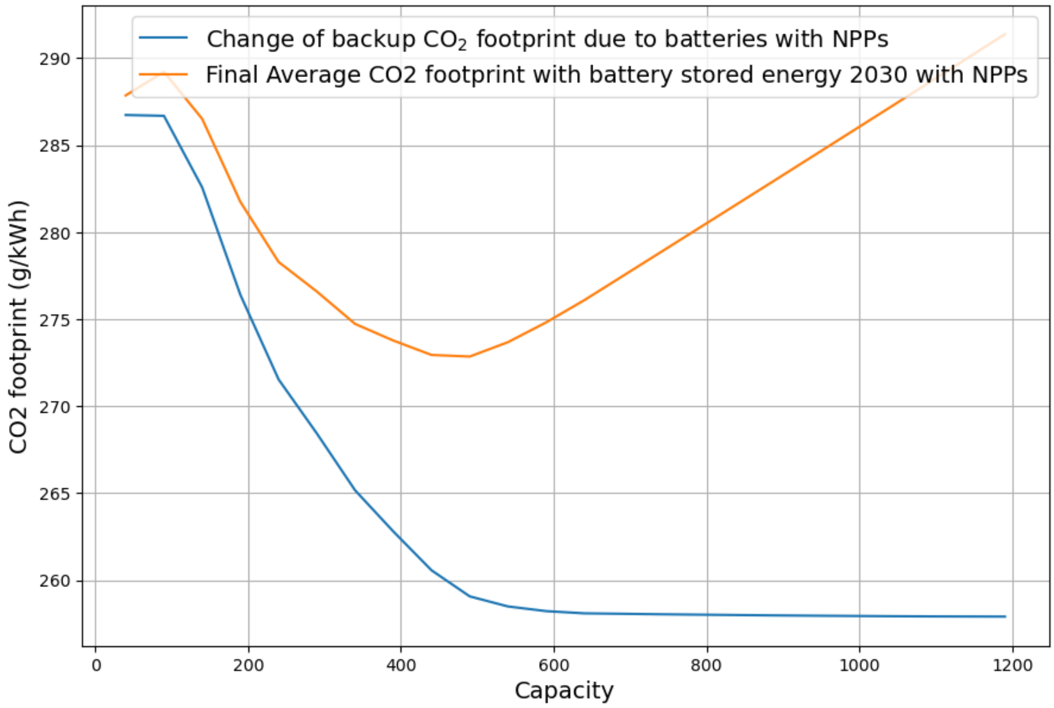

Figure 20. Carbon Footprint for backup and batteries as a function of battery capacity in 2030.

6. Conclusions

This study has examined the technical, economic, and climatic implications of deploying grid-scale batteries in Germany's power system on the way to 2030, using high-resolution empirical data and deliberately optimistic assumptions for wind, solar and storage technologies. By separating slow-varying from fast-varying components of the residual load and exposing batteries only to the normalized residual load, we derived an upper bound on the useful contribution of batteries to balancing volatile renewables in a realistically constrained system.

Our analysis shows that the benefits of battery deployment—in terms of delivered energy, full-cycle utilisation and especially reduction in backup energy—grow approximately linearly with the logarithm of installed storage capacity over a wide range. In contrast, both the financial cost and the lifecycle carbon footprint of batteries scale linearly with capacity. This structural mismatch gives rise to pronounced diminishing returns: each doubling of capacity yields similar incremental benefits, so that very large expansions generate only modest incremental value to the power generation system.

Under 2024 conditions, where surplus VRE is scarce relative to deficits, even idealised batteries cannot reduce annual fossil backup energy, and realistic batteries with active and passive losses actually increase fossil generation requirements. Pumped-hydro plants, when emulated within our framework, are found to operate close to their theoretical optimum and primarily serve grid stability rather than fossil displacement.

In a 2030 scenario based on official expansion targets (≈320–340 GW wind and solar and a load increase to ≈670 TWh), the higher VRE share does improve the utilisation of batteries. Small aggregate capacities can reach 400–500 full cycles per year, and a few hundred GWh of storage can in principle deliver several tens of TWh annually. However, even in this more favourable setting, maximal annual battery output saturates at around 65 TWh once total storage exceeds 500 GWh, and the reduction in required backup energy plateaus at a similar scale.

When lifecycle emissions are taken into account, using a conservative 150 kg CO_2/kWh for LFP battery manufacture and realistic cycle counts, we find that the carbon footprint of incremental battery additions becomes larger than the avoided emissions from modern gas-fired backup at around 330–350 GWh of installed capacity. Beyond this point, additional storage increases total system emissions rather than reducing them. At the same time, even 300 GWh of batteries can supply only about 4–6% of annual German electricity demand and does not allow the retirement of any firm backup capacity, which must continue to cover almost the entire load in times of weather-related low wind and PV utilization.

These findings imply that, in Germany's climatic and demand context, grid-scale batteries are well suited for short-term balancing, ramp-rate reduction and ancillary services, but they cannot by themselves resolve the fundamental seasonal and multi-day variability of wind and solar at acceptable cost and carbon intensity. This has dramatic consequences, as the ultimate target of the German energy transition is to reduce energy from 'backup' systems steadily down to zero. Our analysis suggests that there is no decarbonisation scenario conceivable without a carbon-free backup system and substantially lower carbon footprint in battery production.

An efficient and climate-robust transition therefore requires a portfolio approach in which batteries are deployed up to their economically and ecologically optimal scale, while long-duration adequacy is provided by other means. Among these, firm low-carbon generation—such as the reactivation or new deployment of nuclear power plants, as suggested by recent feasibility studies—appears to offer substantially larger contributions to both security of supply and decarbonisation than further large-scale battery expansion.

Our findings are robust, since we consistently erred on the positive side for renewable energy and battery costs, usage, and carbon footprint. Under real-world conditions, cost and carbon savings from battery usage will be lower than described here. We even excluded coal power, which still has a substantial market share in German's electricity system, and will not be phased out within the next decades, as our study shows, unless other backup capacity using natural gas or nuclear energy, has

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been deployed. The only factor that could weaken our conclusions is the ignorance of Germany's ability to im- and export electricity at high scale of up to ≈20 GW. However, only if neighbouring countries formally agree to provide backup power at all times, Germany can reduce its capacity of dispatchable power sources.

The methodological framework introduced here—based on normalized residual load, filter-window optimisation and explicit treatment of backup and storage losses—can be applied to other countries and climate zones. Because the shape and seasonality of VRE and demand differ substantially across regions, repeating this analysis with local datasets will be essential to determine whether the logarithmic scaling and associated limits of battery deployment observed for Germany also hold elsewhere, or whether other systems can sustain higher storage market shares.

Finally, our study suggests that investors planning to build battery storage in Germany should carefully reflect our findings. The number of cycles a battery can exploit price differentials in a grid is, together with the price spread, the most important parameter that determines the profitability of a battery business case. Our study suggests that even under idealized conditions, battery owners will find it difficult to make a profit. A further caveat is for policy makers: If the VRE & battery strategy is structurally not able to provide a decarbonization of the power supply, then other strategies, such as a re-entry into nuclear energy, need to developed.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CAPEX	Capital expenditures
CCGT	Combined-cycle gas turbine
CF	Carbon footprint
DRE	Dispatchable renewable energy
GT	Open-cycle gas turbine
KND2045	Klimaneutrales Deutschland 2045 (climate neutral Germany 2045)
LCOE	Levelized Cost of Energy
LFP	Lithium iron phosphate (batteries)
NMC	Nickel, manganese, cobalt (type of battery)
NPP	Nuclear power plant
OPEX	Operational Expenditures
PV	Photovoltaics
RE	Renewable energy
VRE	Variable renewable energy
WACC	Weighted average cost of capital

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