

Article

Techno-Economic Optimisation of Wind Curtailment Utilisation with Battery Storage Dispatch to Electricity and EV Charging Markets

Dimitrios Apostolou ^{1,*}  and Emmanouil Gryparis ²

¹ Department of Mechanical Engineering, University of the Peloponnese, 1 Megalou Alexandrou Str., 26334 Patras, Greece

² Department of Electrical and Electronics Engineering, University of West Attica, 250 Thivon Ave., 12244 Athens, Greece; egryparis@uniwa.gr

* Correspondence: d.apostolou@uop.gr

Abstract

This research examined whether battery energy storage could economically utilise event-conditioned curtailed wind energy by optimally allocating stored electricity between wholesale grid export and EV charging. The analysis focused on a 43.2 MW onshore wind farm in Central Greece. Expected non-curtailed generation was estimated from ERA5 100 m wind data and the Vestas V117 power curve, calibrated against measured non-event production, and compared with measured output during IPTO-reported curtailment-event hours. The estimated recoverable curtailed energy was treated as the sole BESS charging source, and three scenarios were evaluated: grid-only discharge, EV-only discharge, and joint grid-plus-EV allocation. The dispatch and sizing problem was formulated as an MILP-based, NPV-oriented optimisation including an explicit no-investment alternative and was assessed over a 20-year FCFE horizon using Monte Carlo simulation and sensitivity analyses. The calibrated model reduced holdout nRMSE from 21.92% to 17.83% and mean bias from −4.309 to 0.117 MWh. Under the base scenario, 1537 event hours yielded positive estimated curtailment, corresponding to 10.26 GWh. The no-investment option was the global NPV-maximising solution in all baseline scenarios. The best non-zero BESS P_{max}/E_{max} was 0.25 MW/0.5 MWh, with expected NPVs of −332.6 k€, −356.3 k€, and −321.0 k€ for grid-only, EV-only, and grid-plus-EV operation, respectively. EV-premium breakeven required 1207.5 €/MWh for EV-only and 1186.4 €/MWh for grid-plus-EV operation. The results show that market diversification improves curtailed-energy utilisation, but curtailed-energy-only BESS investment remains financially unattractive under the observed conditions.

Keywords: curtailment; wind power; electricity market; BESS; EV charging



Academic Editor: Michel Duval

Received: 5 June 2026

Revised: 22 July 2026

Accepted: 27 July 2026

Published: 30 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

In recent years, Europe has been fully focused on the goal of becoming the first energy-neutral continent on the planet [1,2]. Global agreements, such as the Kyoto Protocol [3] and the Paris Agreement [4], as well as the European Union's own initiatives, play an active role in the transition to a low-carbon electricity sector [5].

The energy transition focuses on the gradual shift in the energy mix from fossil fuels to renewable energy sources (RES), radically changing the methods of electricity production, distribution, and consumption [6]. At the same time, it aims to replace the

fleet of conventional vehicles with electric ones, thereby reducing CO₂ emissions in the polluting transportation sector [7]. However, the increased penetration of renewable energy sources and electric vehicles (EVs) creates a need for investments in new, modern electricity transmission and distribution systems. The growing penetration of renewable energy and electric vehicles requires smart grids, capable of managing bidirectional energy flows and integrating battery energy storage systems that improve system flexibility and facilitate the integration of variable renewable energy generation [8,9].

In modern power networks, there is an increasing penetration of electricity generation from RES, with photovoltaic and wind farms being the main technologies. The figure below (Figure 1) illustrates the increased integration of the aforementioned renewable technologies in electricity generation compared to fossil fuels during the period 2015–2025. As can be seen, wind and solar power generation have constituted a significant portion of the energy mix over the past decade; in fact, by 2025, they surpassed energy production from fossil fuels by 1.4%.

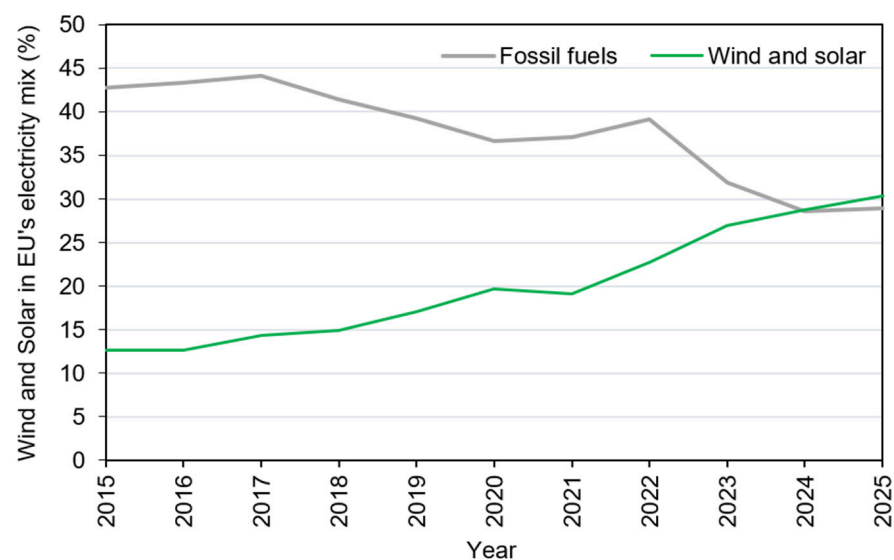


Figure 1. Share of electricity generation from wind and solar in the EU based on [10].

As the deployment of renewable energy systems gains momentum, the phenomenon of curtailment has become increasingly prevalent, especially when production surges and the network's capacity to adapt is constrained. An example of this trend can be seen in Germany, where the monthly output of wind power and the resulting curtailment are meticulously tracked. Between July 2022 and June 2024, the data reveals a notable correlation, with some months witnessing a staggering curtailment of over 1 TWh of wind energy, a testament to the fact that even the most advanced power systems are not immune to this issue, as depicted in Figure 2.

According to the studies [11,12], curtailment is currently a phenomenon that modern electricity grid operators need to tackle, as the energy generated by RES cannot be fully utilised, negatively affecting the unit's capacity factor. In addition, research steps forward on how wind energy curtailment can be reduced through dispatch optimisation, load shifting, and energy storage practices.

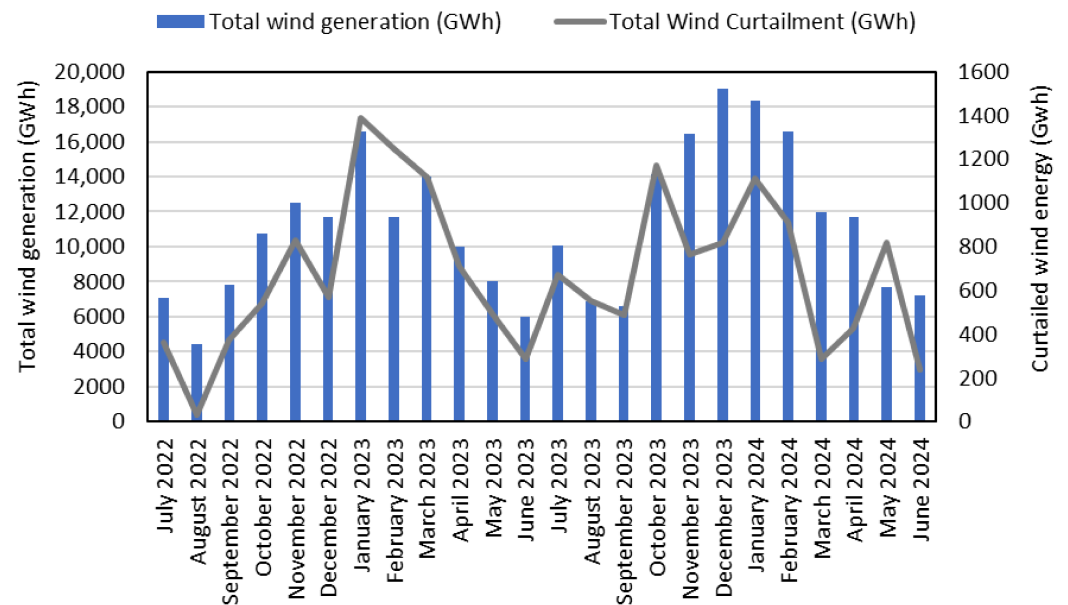


Figure 2. Monthly total wind generation (blue bars, left axis) and curtailed wind energy (grey line, right axis) in Germany from July 2022 to June 2024 based on [13].

The limited utilisation of energy generated from alternative sources is often due not only to the stochastic nature of production, but also to difficulties in its transmission and distribution, as well as to technical and operational constraints of the grid. The paper by Szinai et al. [14] highlights the unique challenge modern power systems face in managing congestion due to the high penetration of renewable sources and emphasises the need for more flexible systems to reduce curtailed energy. A similar study was presented at a conference on the European energy market [15], which showed that the extent of curtailment of renewable energy production is significantly influenced by the existing grid, which is not adequately configured to handle the enormous volume of energy produced, leading to significant bottlenecks in energy transmission. Research findings underscore the significant impact of transmission limitations and network congestion on the curtailment of renewable energy sources, emphasising the crucial role that adaptable solutions like battery energy storage systems and responsive demand management can play in mitigating these effects.

Another study [16] emphasised that flexible demand management and shifting consumer needs to time periods with significantly increased renewable energy production can lead to optimal utilisation of the energy itself and, at the same time, to system balancing. At the same time, the green energy generated by wind farms can be utilised by EVs. In addition to serving as a means of transportation, these vehicles also function as potential energy storage systems. Therefore, they can be used as flexible loads, market-responsive assets—not merely passive ones—capable of absorbing the excess wind energy generated that is otherwise curtailed from the grid, using smart charging techniques [17].

Based on the current literature and the requirements of existing energy grids, investment in battery energy storage systems (BESS) is essential as a key technological factor in the more efficient utilisation of the already increased electricity generation from photovoltaic and wind power plants. In this context, the study [18] focused on the economic efficiency indicators of the energy system, demonstrating that storage systems and the expansion of transmission networks can significantly contribute to reducing the amount of energy injected into the grid. At the same time, the proper siting and operation of BESS in electricity transmission and distribution networks is of research interest, as examined in the paper [19].

To this end, contemporary research is increasingly focusing on techno-economic optimisation frameworks that combine storage dispatch, EV charging coordination, and market participation strategies. According to the following studies [20–22], proper management of the power grid, storage systems, EV charging, and overall load management can significantly reduce the variability of RES and the curtailment of these sources. On the other hand, the complete elimination of curtailment is unlikely to be achieved, as it is not always the most cost-effective solution from an economic standpoint. It is important to strike a balance between infrastructure investments, operating costs, and the demands of the energy market.

Recent studies are shifting the perspective on energy curtailment, viewing it as a valuable energy resource. This is coupled with rapid technological advancements in storage systems and the shift in the vehicle fleet from conventional fuels to electric drivetrains. In this context, the study [23] argued that surplus energy should be considered a new economic factor in the energy market, and its positive environmental impact must also be highlighted. Furthermore, the study [24] complemented the value of EV deployment in the context of surplus energy. As flexible consumers, EVs have the ability to shift electricity demand hours, reduce system operating costs, contribute to the utilisation of curtailed energy, and play a pivotal role in the evolution and improved operation of electrical systems. The aforementioned studies, however, focus primarily on a technical assessment of the recovery and storage of curtailed renewable energy. The proper sizing of BESS is usually omitted, as is the role of curtailed energy in the electricity market and at EV charging stations.

Although researchers are increasingly focusing their attention on the phenomenon of curtailment of renewable energy generation, the increased integration of EVs into modern power grids and storage systems, significant research gaps still exist. For the most part, current research does not consider curtailed energy as a usable energy resource that can be stored in battery systems. At the same time, electric vehicles are considered flexible electrical loads and are not regarded as an alternative market for the exploitation of stored energy. Furthermore, some studies examine storage systems with predetermined sizes, and their analysis is limited to their operation. However, selecting the correct size of a BESS is a fundamental factor for the economic success of the investment, as larger capacities may enhance the utilisation of curtailed energy, but also entail higher initial costs, increased replacement requirements, and greater financial risk. For this reason, the simultaneous examination of the sizing and allocation of stored curtailed wind energy between the wholesale electricity market and electric vehicle charging stations remains under-studied in the international literature.

2. Aims and Objectives

Based on the above, it is apparent that the rapid growth of RES technology investments has increased the frequency and magnitude of RES curtailments in power systems. BESSs have demonstrated their ability to act as the coupling technology between curtailed wind power generation and market opportunities, including electricity and transportation. The electrification of transport is accelerating, and EV charging demand is increasing not only in magnitude, but it can also be time-shifted, potentially creating a higher-value outlet for energy compared with the wholesale market prices.

Therefore, this paper aims to investigate the context of coping with wind power curtailments, causing, on the one hand, financial impacts to investors and, on the other, clean-energy losses that otherwise could be utilised for fossil-fuel independence in the electricity and transportation markets.

The main scope of this research is to address the dispatch decisions on how much curtailed wind-produced energy to store, when to discharge, and how to allocate the discharged energy between providing electricity to the grid and EV charging facilities by maximising the investment profits of a BESS investment. These decisions are constrained by battery operating limits, efficiencies, degradation, grid-export limits, and EV charging capacity and demand. The resulting control problem is formulated here as a Net Present Value (NPV)-oriented dispatch and sizing problem, in which profitability is the primary decision criterion while curtailment utilisation and EV charging supply are evaluated through scenario-based comparisons and sensitivity analysis.

The novelty of the research output is documented through the introduction of an NPV-oriented, curtailment-constrained storage dispatch framework that connects two competing value streams: wholesale electricity sales and EV charging supply. Unlike previous studies that primarily examine congestion management, storage deployment, or single-market BESS operation [14,18–23], the proposed framework explicitly (i) models curtailment-limited charging, making the available energy endogenous to curtailment events; (ii) treats the EV charging outlet as a distinct market channel with its own demand and power constraints, and with a market-linked remuneration signal differentiated from hourly wholesale electricity prices; and (iii) quantifies the techno-economic implications of allocating curtailed wind energy between two competing value streams, namely wholesale electricity export and EV charging supply. Additionally, the proposed framework simultaneously optimises the calculation of energy storage system capacity and the management of their operation, using a calibrated and validated dataset on power curtailment.

Therefore, the present work aims to answer the following three RQs:

- How can a BESS dispatch policy allocate the stored curtailed wind-farm energy between the electricity grid and EV charging facilities by maximising the project NPV over the storage lifetime?
- What are the benefits of the proposed allocation strategy compared to simpler benchmarks such as grid-only, EV charging-only?
- How sensitive is the optimal allocation of stored energy and the NPV-maximising outcome to the BESS size, state of charge (SoC) operating range, EV charging demand, and EV-remuneration premium?

This paper is organised into three main sections: the methodology describing how the examined scenarios are developed, the data analysis presenting the results, and the discussion interpreting the findings to assess how the research questions are addressed and what new insights the study adds to the existing literature.

3. Methodology

The methodology was developed to examine wind-farm curtailments from an economic loss perspective for RES-BESS investors, and a clean-energy resource that could have been utilised to support fossil-fuel independence in the electricity and transportation sectors. In line with the scope of the study, the analysis addressed three operational questions: how much curtailed wind-produced energy was stored in a BESS, when it was discharged, and how the discharged energy was allocated between wholesale electricity export to the grid and supply to EV charging facilities. The assessment was conducted at hourly resolution over the most recent two-year period available for a wind park located in Greece's central region, with the simulation time step set to $\Delta t = 1$ h.

3.1. Wind Farm

The proposed onshore wind farm is an operational wind farm located in the 'Viotia' administrative district in Central Greece. The location of the wind farm is in proximity to

the main national road connecting the two larger Greek cities of Athens and Thessaloniki, which facilitates the coupling of the installations to an EV charging station serving EVs travelling via the national highway.

The wind farm consists of 12 Vestas V117-3.6 MW wind turbines (Vestas Wind Systems A/S, Aarhus, Denmark), totalling a nominal power rate of 43.2 MW ($P_{rated,WF}$).

The hourly wind-farm generation model was developed in two stages. First, ERA5 wind data and the Vestas V117 manufacturer power curve were used to construct a raw wind-to-power index. Second, this raw index was calibrated against hourly measured wind-farm production during non-curtailment-event hours in order to obtain an expected net generation profile representative of normal plant operation. The calibrated expected generation, rather than the unadjusted manufacturer-curve output, was used in the curtailment-estimation procedure.

Hourly reanalysis data were obtained from the Copernicus Climate Change Service ERA5 “hourly data on single levels” dataset [25]. The 100 m eastward and northward wind components were used to derive an ERA5 100 m wind-speed predictor. Because the actual turbine hub height, on-site wind-speed observations, and terrain-resolved flow measurements were unavailable, ERA5 100 m wind speed was not treated as a direct hub-height measurement. Instead, it was treated as a spatially averaged meteorological predictor whose relationship with observed wind-farm generation was empirically calibrated using non-curtailment-event production data provided by the Greek Transmission System Operator (TSO).

The wind-farm centroid was represented by the WGS84 coordinates (lat, lon) = (38.45° N, 23.46° E), and the nearest ERA5 grid point with $0.25^\circ \times 0.25^\circ$ spatial resolution was selected. The use of this coarse-resolution predictor introduces potential uncertainty associated with terrain-induced flow effects, spatial smoothing, wake effects, and other site-specific losses. These effects were not separately measured, and therefore, they were addressed through empirical calibration and out-of-sample validation against observed wind-farm production.

The ERA5 100 m wind-speed predictor, $U_{ERA5}(t)$ in m/s, was calculated from the eastward and northward ERA5 wind components ($u(t)$ and $v(t)$ respectively) using Equation (1).

$$U_{ERA5}(t) = \sqrt{u(t)^2 + v(t)^2} \quad (1)$$

The ERA5 wind-speed predictor was converted to a raw single-turbine power index using the Vestas V117 manufacturer power curve [26]. $P_{turb,raw}(t)$ is the raw manufacturer-curve power output of one wind turbine at hour t , in MW; U_i represents wind-speed points of the Vestas power curve, in m/s; and P_i is the corresponding turbine power output, in MW:

$$P_{turb,raw}(t) = \text{interp}(U_{ERA5}(t); \{U_i\}, \{P_i\}), \quad (2)$$

The output is set to zero outside the turbine operating range, that is, below the cut-in speed and above the cut-out speed, while it is held constant in the rated region according to the plateau of the power curve. The total raw manufacturer-curve wind-farm power output, $P_{WF,raw}(t)$, in MW, is then computed by multiplying the raw single-turbine index by the number of turbines, N_T (=12):

$$P_{WF,raw}(t) = N_T \cdot P_{turb}(t) \quad (3)$$

The corresponding raw hourly energy index of the wind farm ($E_{WF}^{pot}(t)$) in MWh, is given by Equation (4).

$$E_{WF,raw}(t) = P_{WF,raw}(t) \cdot \Delta t \quad (4)$$

Calibration and Validation of Expected Non-Curtailed Generation

The Greek TSO (i.e., IPTO S.A.)-based curtailment-related event dataset [27] was used only to identify the calendar of reported curtailment-event hours, denoted by T_{IPTO} .

For every matched hour t , the IPTO-event indicator was defined as:

$$I_{IPTO}(t) = \begin{cases} 1, & \text{if } t \in T_{IPTO} \\ 0, & \text{otherwise} \end{cases}$$

where I_{IPTO} is the IPTO-event indicator at hour t and is used to separate normal-operation observations from IPTO-event observations.

The normal-operation sample, T_{normal} , consisted of all matched hours for which $I_{IPTO}(t) = 0$ and measured wind-farm energy was available. These observations were ordered chronologically as t_i , where $i = 1, \dots, N_{normal}$. The number of eligible normal-operation observations and the chronological training cutoff were defined as:

$$N_{normal} = |T_{normal}|, k = \lfloor 0.7 N_{normal} \rfloor$$

where N_{normal} is the total number of eligible non-IPTO-event observations and k is the number of observations assigned to the training subset. Thus, the first k chronological observations, t_1 to t_k , formed the training subset, whereas observations $t_{(k+1)}$ to $t_{(N_{normal})}$ formed the independent holdout subset.

A non-decreasing isotonic calibration function $\hat{g}_{train}$ was fitted using only the training subset. The function maps the raw ERA5/manufacturer-curve wind-farm energy index $E_{WF,raw}$ to measured wind-farm energy. The fitted training function was then applied to the holdout subset to calculate mean absolute error (MAE), root mean square error (RMSE), mean bias error (MBE), normalised RMSE, and Pearson correlation coefficient.

Eligible non-IPTO curtailment-event observations were ordered chronologically. The first 70% were used to fit the calibration model, while the remaining 30% were retained as an independent temporal holdout sample. The calibrated expected non-curtailed wind-farm energy was calculated as:

$$\hat{E}_{WF,net}(t) = \min \left\{ P_{WF,rated} \cdot \Delta t, \max \left[0, \hat{g}_{final}(E_{WF,raw}(t)) \right] \right\} \quad (5)$$

where $\hat{E}_{WF,net}$ is the calibrated expected non-curtailed wind-farm energy at hour t , in MWh, $P_{WF,rated}$ is the rated wind-farm power in MW, and $\hat{g}_{final}$ is the non-decreasing calibration function estimated using isotonic regression.

The function $\hat{g}$ was fitted only on the chronological training subset of non-IPTO curtailment-event observations. The lower and upper bounds in Equation (5) ensure that the calibrated expected hourly energy remains between zero and the rated hourly wind-farm energy. This empirical calibration captures the persistent relationship between the ERA5-derived raw energy index and observed plant output. It implicitly addresses systematic effects associated with the unknown hub height, ERA5 spatial smoothing, terrain, average wake losses, electrical losses, and other persistent site-level deviations.

Turbine-level availability, outage, and maintenance records were not available for the present analysis. Accordingly, the calibration does not separately identify temporary availability losses, wake losses, and meteorological-model error. The model was therefore evaluated on the independent holdout sample using MAE, RMSE, MBE, normalised RMSE relative to the 43.2 MW rated power, and the Pearson correlation coefficient.

3.2. Curtailment Estimation

Curtailment was not directly metered in the available datasets. Therefore, the study estimated an event-conditioned curtailed-energy series only for hours identified as IPTO-reported curtailment events. This approach conditions the estimate on the IPTO-event calendar and does not attempt to infer unreported curtailment-like losses outside those intervals.

For every IPTO-event hour, the calibrated expected non-curtailed wind-farm energy from Equation (5) was compared with observed energy from the full measured-energy dataset. A conservative event-hour shortfall allowance was deducted before the residual was classified as estimated curtailed energy:

$$E_{WF,curt}(t) = \max\{0, \hat{E}_{WF,net}(t) - E_{WF,msr}(t) - \varepsilon \cdot P_{WF,rated} \cdot \Delta t\} \quad (6)$$

where $t \in T_{IPTO}$, $E_{WF,curt}$ is the event-conditioned estimated curtailed energy in MWh, $E_{WF,msr}$ is the measured wind-farm energy in MWh, and ε is the event-hour shortfall allowance expressed as a fraction of rated wind-farm power and ranging between 1% and 3% [28].

For all hours outside T_{IPTO} , the estimated curtailed energy was set equal to zero. The revised base case used $\varepsilon = 0.02$, corresponding to a deduction of 0.864 MWh from each event-hour shortfall. Sensitivity cases used $\varepsilon = 0.01$ and $\varepsilon = 0.03$, corresponding to deductions of 0.432 MWh and 1.296 MWh, respectively.

The resulting series should be interpreted as an event-conditioned estimate of recoverable curtailed energy under the reported IPTO-event regime. It is not a directly metered curtailment quantity and cannot capture unreported restrictions or production losses outside IPTO-event hours. Moreover, the 1–3% allowance quantifies the operational threshold used to avoid classifying small estimated shortfalls as curtailment, while it does not represent the full predictive uncertainty of the ERA5-based generation model. That uncertainty is instead reported through the independent holdout validation statistics.

The event-conditioned estimated curtailed-energy series constituted the sole charging source of the BESS. Grid-based charging was excluded, and the battery was modelled as charging only from the estimated curtailed energy available during IPTO-event hours.

Figure 3 depicts the algorithm used for the estimation of the wind farms' curtailed energy.

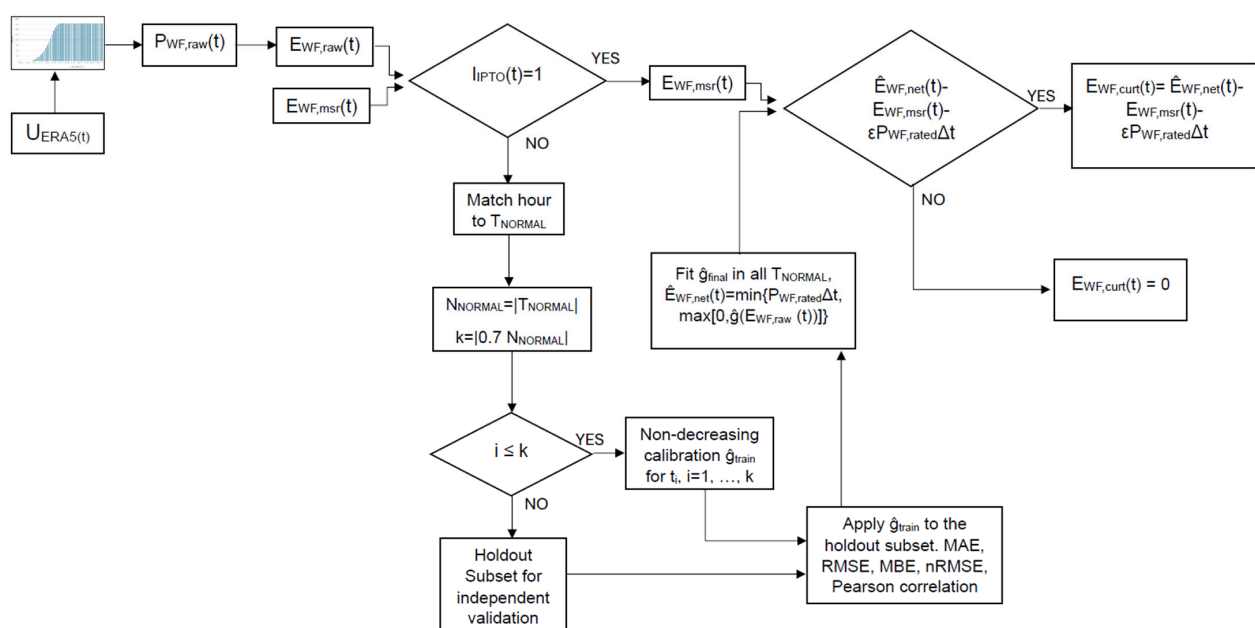


Figure 3. Algorithm used for the calculation of the wind farm's recoverable curtailed-energy series.

The three allowance cases $\varepsilon = 1\%$, 2% , and 3% were propagated through the dispatch, BESS-sizing and financial-evaluation stages. Thus, each allowance case generated its own curtailed-energy input series and its own re-optimised BESS configuration.

3.3. Battery Energy Storage System

A lithium iron phosphate (LiFePO₄–LFP) battery energy storage system was assumed to be co-located with the wind farm and electrically connected so as to absorb only wind energy that would otherwise be curtailed. Therefore, the charging source of the BESS was restricted exclusively to the estimated recoverable curtailed-energy series quantified from IPTO-reported curtailment hours, while grid-based charging was excluded from the analysis. The BESS was modelled at hourly resolution consistently with the temporal resolution adopted for wind generation and curtailment estimation. Each candidate BESS configuration was defined by nominal energy capacity E_{max} (MWh) and symmetric charging and discharging power rating P_{max} (MW). The battery state of charge at hour t is denoted by $S(t)$ (MWh), while $P_{ch}(t)$, $P_{grid}(t)$ and $P_{EV}(t)$ denote charging power from curtailed wind energy, discharge power delivered to the grid, and discharge power delivered to the EV facility, respectively. Positive values of all three variables represent energy flow into their stated destination.

The battery was operated within a bounded SoC range in order to reflect practical operating limitations and reduce excessive degradation. In particular, the allowable SoC range was set between 20% and 80% of the nominal battery capacity [29]. A round-trip battery efficiency of 92% was assumed. To avoid applying the 92% value twice in the state-of-charge balance, symmetric one-way charging and discharging efficiencies were defined as [30]:

$$\eta_{rt} = 0.92, \eta_{ch} = \eta_{dis} = \sqrt{\eta_{rt}} = 0.959$$

where η_{rt} is the round-trip efficiency, η_{ch} is the charging efficiency, and η_{dis} is the discharging efficiency.

Under this formulation, the BESS acted as an energy-shifting asset that stored event-conditioned estimated curtailed wind energy and discharged it at later hours according to the scenario-specific market-allocation constraints. The investment boundary comprised the BESS energy-storage modules, power-conversion equipment and balance-of-plant components. The wind farm and the EV charging facility were treated as pre-existing assets. Accordingly, the capital, operating and replacement costs of the EV charging equipment were excluded from the BESS investment assessment, while its available power capacity remained an exogenous operational constraint in the dispatch model.

Battery ageing was represented through both cycling and calendar mechanisms. Annual equivalent full cycles were calculated using the usable BESS energy capacity rather than nominal capacity. In each simulated project trajectory, battery-module replacement was triggered when either the cumulative cycle-life threshold or the calendar-life threshold was reached, whichever occurred first. In this way, the operational use of the battery affected not only annual revenues, but also long-term reinvestment requirements of the project.

3.4. Dispatch Algorithm

In regard to the scenarios investigated, the dispatch assessment was examined under three defined scenarios (SCs), implemented under identical battery parameters and the same curtailed-energy inputs so that differences in results were attributable to market-allocation rules rather than modelling inconsistencies.

Scenario 1: During the first SC, the BESS stored energy is discharged only to the electricity grid, participating in the day-ahead electricity market.

Scenario 2: In this SC, the BESS was permitted to discharge only to EV charging facilities.

Scenario 3: The wind farm's curtailed stored energy is allocated between the electricity grid and the EV charging facility. The algorithm selected the allocation that maximised economic performance while respecting technical limits and energy demand.

For each SC, candidate BESS configuration ($E_{\max}$, $P_{\max}$) and historical time block, the BESS dispatch was formulated as a deterministic mixed-integer linear programme (MILP). The set of hourly intervals is denoted by T_b . The continuous decision variables are $P_{ch}(t)$, $P_{grid}(t)$, $P_{EV}(t)$ and $S(t)$. A binary operating-mode variable $z(t)$ was introduced to prevent simultaneous charging and discharging within an hourly interval.

The inner dispatch model maximises operating revenue. It does not maximise NPV directly, because capital expenditure, financing, taxation and replacement expenditure are not hourly operational decisions. Those quantities are applied in the subsequent financial evaluation when the candidate BESS configurations are compared.

Equation (7) presents the objective function of the MILP dispatch optimisation.

$$\max \sum \{t \in T_b\} \left[P_{grid}(t) \cdot \lambda_{grid}(t) + P_{EV}(t) \cdot \lambda_{EV}(t) \right] \cdot \Delta t \quad (7)$$

where $\lambda_{grid}(t)$ is the hourly day-ahead electricity price and $\lambda_{EV}(t)$ is the effective remuneration received for energy delivered to the EV outlet in €. The battery state transition is:

$$S(t+1) = S(t) + \eta_{ch} \cdot P_{ch}(t) \cdot \Delta t - \frac{P_{grid}(t) + P_{EV}(t)}{\eta_{dis}} \cdot \Delta t \quad (8)$$

The SoC bounds have been set to:

$$SoC^{min} \cdot E_{max} \leq S(t) \leq SoC^{max} \cdot E_{max}$$

with $S(1) = 0.5 \cdot E_{max}$, and $S(|T| + 1) = S(1)$.

The 50% initial state of charge and terminal equality prevent artificial energy creation at the beginning or end of a historical block. Charging was restricted to the hourly event-conditioned curtailed-energy availability:

$$0 \leq P_{ch}(t) \leq P_{max}, P_{ch}(t) \leq \frac{E_{WF,curt}(t)}{\Delta t}$$

Thus, the BESS can charge only from estimated curtailed wind energy, and only during hours for which the event-conditioned curtailment estimate is positive.

Equation (8), along with the respective constraints concerning the charging process of the BESS, is described by the algorithm presented in Figure 4.

The wind farm and the BESS were assumed to share the same point of connection. P_{POC} denotes the assumed technical active-power limit at the shared point of connection (POC). In the absence of a separate POC metre, measured wind-farm output was used as the available proxy for simultaneous wind-farm export. BESS discharge to the wholesale electricity market was limited by the residual active-power capacity of the shared 150/20 kV substation. The transformer rating is 50 MVA [31] and was represented as active power under a unity power-factor assumption. The non-negative grid-export headroom $H_{grid}(t)$ was pre-computed as:

$$H_{grid}(t) = \max\{0, P_{POC} - P_{WF,msr}(t)\}$$

BESS export to the grid was then constrained by:

$$0 \leq P_{grid}(t) \leq [1 - I_{bIPTO}(t)] \cdot H_{grid}(t)$$

where $lb_{IPTO}(t)$ equals one in an IPTO-reported curtailment-event hour and zero otherwise. Therefore, $P_{grid}(t) = 0$ during every reported event hour. In non-event hours, BESS grid export is limited to the residual point-of-connection headroom after contemporaneous measured wind-farm output.

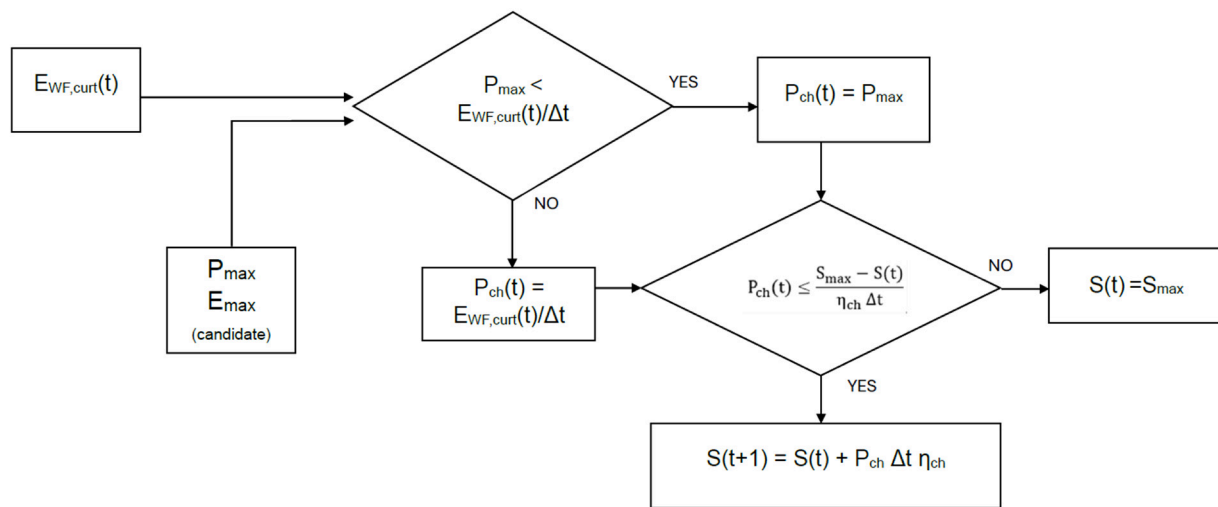


Figure 4. Algorithm followed for the charging process of BESS.

Reported curtailment events may arise from local point-of-connection limitations, upstream transmission congestion, or broader system-level operational constraints. To avoid assuming that the BESS could export to the grid during constrained periods, grid export was prohibited in all IPTO-event hours. For non-event hours, the residual point-of-connection headroom was used as a local export-capability proxy. This formulation does not explicitly model upstream transmission constraints or system-level redispatch restrictions outside reported event hours. Accordingly, the calculated grid-export capability should be interpreted as an upper-bound of the feasible export capability in the absence of time-resolved network-constraint data.

The BESS was not allowed to charge and discharge simultaneously within an hourly interval. This restriction was imposed using the binary operating-mode variable $z(t)$:

$$P_{ch}(t) \leq P_{max} \cdot z(t), P_{grid}(t) + P_{EV}(t) \leq P_{max} \cdot [1 - z(t)], \text{ with } z(t) \in \{0, 1\}$$

When $z(t) = 1$, the BESS may charge but cannot discharge. When $z(t) = 0$, it may discharge but cannot charge. Accordingly, the hourly model does not interpret simultaneous charging and discharging as sequential intra-hour operation. During an IPTO-event hour, the BESS may either charge from curtailed energy or discharge previously stored energy to the local EV outlet, but it cannot export to the grid, and it cannot charge and discharge in the same hour.

In the context of each SC analysis, constraints were applied according to their respective restrictions.

SC1: $P_{EV}(t) = 0$ for all t . During IPTO-event hours, $P_{grid}(t) = 0$.

SC2: $P_{grid}(t) = 0$ for all t . The BESS may charge or discharge to EV's, but not both.

SC3: $P_{EV}(t) \geq 0$, $P_{grid}(t) \geq 0$. The BESS may charge or discharge to EVs and the grid. However, during IPTO-event hours, export to the grid is forbidden.

The charging station was assumed to comprise five 50 kW DC fast chargers and two 150 kW DC high-power chargers. The resulting 0.55 MW charging maximum power ($P_{EV,max}$) also exceeds the 2025 Alternative Fuels Infrastructure Regulation (AFIR) benchmark of 0.4 MW and lies close to the 2027 benchmark of 0.6 MW for light-duty charging

pools on the TEN-T core network, while already including two charging points of at least 150 kW [32].

The EV charging facility was treated as a pre-existing asset. Therefore, the installed charging capacity was modelled as an exogenous operational constraint rather than a BESS investment decision. The base-case EV outlet capacity was $P_{EV,max} = 0.55$ MW. To examine the effect of a larger pre-existing charging facility, additional outlet-capacity cases of 1, 2 and 5 MW were evaluated for the EV-only and combined grid-plus-EV SCs.

The available directional motorway traffic series was used to establish the temporal profile of potential EV demand, but it was not interpreted as energy demand by itself. Following traffic-based motorway charging-demand studies [33,34], the expected number of charging sessions in hour t (N_{EV}) was calculated from the traffic count, the year-specific plug-in electric vehicle share and a charging-stop probability:

$$N_{EV}(t) = V(t) \cdot s_{EV,y}(t) \cdot p_{stop} \quad (9)$$

where $V(t)$ is the one-direction hourly light-vehicle count for the corridor served by the station, $s_{EV,y}(t)$ is the annual share of electric light vehicles in the relevant Greek on-road fleet, and p_{stop} is the probability that a passing electric vehicle uses the charging facility. Because station-specific session data were unavailable, p_{stop} is an explicit scenario parameter rather than a measured quantity. The annual fleet share is obtained from the European Alternative Fuels Observatory (EAFO) historical fleet indicator [35], while new-registration shares are not used as a proxy for the on-road fleet share. Hourly traffic counts ($V(t)$) were based on the Greek National Access Point/‘Hellastron’ toll-station dataset, which provides hourly records by toll plaza and travel direction for light vehicles [36].

The average energy delivered per DC fast-charging session ($e_{session}$) was denoted to estimate the unconstrained hourly charging demand ($D_{EV,raw}$ in MW) and the demand available to the BESS (D_{EV} in MW) as:

$$D_{EV,raw}(t) = \frac{N_{EV}(t) \cdot e_{session}}{\Delta t}, D_{EV}(t) = \min\{P_{EV,max}, D_{EV,raw}(t)\} \quad (10)$$

where $e_{session}$ ranges between 0.008 and 0.06 MWh, consistent with empirical evidence from DC fast-charging sessions [37]. Furthermore, the power delivered by the BESS to the EV outlet was constrained by:

$$0 \leq P_{EV}(t) \leq D_{EV}(t)$$

The low, base and high EV-demand cases are defined in Table 1. These values vary the uncertain traffic-to-demand parameters around the year-specific fleet-share base case.

The financial revenues stemmed from the delivered power to either the grid and/or the EV charging processes. Revenues from electricity-market participation were modelled using hourly energy prices and net energy exported by the BESS. Participation in balancing and ancillary-service markets was not considered, because it would require product-specific reserve/activation data and additional operational constraints to prevent revenue double-counting. Moreover, the present study, as mentioned above, restricted BESS charging to only curtailed wind-farm energy, which limits the feasibility of downward balancing energy provision that typically involves grid-based charging.

Hence, the revenues of the BESS investment for the respective scenarios s could be described as:

$$R_s^{grid}(t) = \lambda_s^{grid}(t) \cdot P_s^{grid}(t) \cdot \Delta t \quad (11)$$

$$R_s^{EV}(t) = \lambda_s^{EV}(t) \cdot P_s^{EV}(t) \cdot \Delta t \quad (12)$$

where R are the revenues in €, and λ represents the electricity price in €/MWh. λ_s^{grid} is the hourly day-ahead electricity price in €/MWh for each SC taken from [38], while λ_s^{EV} is the EV charging price for each SC in €/MWh.

Although an EV charging tariff is available, this retail tariff was not adopted directly as the remuneration parameter of the BESS-dispatched energy. This is because retail EV charging tariffs may include components that are not directly attributable to the BESS-dispatch decision, such as charging-service margins, commercial pricing policies, and site-specific retail mark-ups. Therefore, the EV charging outlet was represented through an effective monthly remuneration parameter defined as the average day-ahead electricity price $\overline{\lambda_m^{grid}}$ plus a fixed EV service premium p_{EV} [39]. This formulation maintained the EV outlet economically linked to prevailing electricity-market conditions, while preserving a distinct value signal relative to hourly wholesale electricity export and avoiding the overstatement of EV revenues that would arise from using the full retail charging tariff directly. Hence, the EV charging price was calculated via Equation (13).

$$\lambda_{EV}(t) = \overline{\lambda_m^{grid}} + p_{EV} \quad (13)$$

with m denoting the calendar month corresponding to hour t in Equation (12).

To assess whether monthly price averaging affected the allocation of stored energy between the grid and EV outlet, an hourly market-linked EV-remuneration case was additionally evaluated using the same EV service premium:

$$\lambda_{EV}^{hourly}(t) = \lambda_{grid}(t) + p_{EV} \quad (14)$$

Each dispatch horizon was solved retrospectively using the complete realised hourly series of estimated curtailed-energy availability, measured wind-farm output, day-ahead electricity prices, and traffic-derived EV charging demand. The resulting dispatch therefore represents a perfect-foresight operational benchmark rather than a real-time control policy.

The dispatch algorithm is presented in Figure 5, where the available stored energy in the BESS is provided to the electricity grid and/or the EV charging facility based on the above-mentioned constraints.

To ensure that profitability reflected financially rational design choices, the BESS was sized separately for each scenario. Battery energy capacity (E_s^{max} in MWh) and rated power (P_s^{max} in MW) were treated as design variables that affected feasible dispatch as well as investment cost.

Table 1 includes the parameters used to determine the curtailed energy, dispatch feasibility, BESS behaviour, market allocation, and the EV-demand profile.

The values shown as low, base and high were not combined into simultaneous pessimistic/base/optimistic packages. They were used in one-at-a-time sensitivity tests. For example, in the EV-demand sensitivities, p_{stop} and $e_{session}$ were varied separately: when p_{stop} was varied, $e_{session}$ was kept at its base value of 0.04 MWh/session, and when $e_{session}$ was varied, p_{stop} was kept at its base value of 0.10.

The BESS energy capacity and rated power were selected through a two-stage discrete search conducted separately for each dispatch scenario and sensitivity case. The candidate set included an explicit no-investment alternative, defined by $(E_{max}, P_{max}) = (0, 0)$, for which the NPV was equal to zero. The first-stage screening grid considered energy capacities of $E_{max} \in \{0.5, 1, 2, 3, 5, 10, 20, 30, 40\}$ MWh, while the rated power was varied over $P_{max} \in \{0.25, 0.5, 0.55, 1, 2, 5, 10\}$ MW. All feasible non-zero energy–power combinations were evaluated, together with the no-investment alternative. For each scenario s (SC1, SC2, SC3), a set of battery energy capacity and rated power configurations was evaluated.

Moreover, for each candidate configuration, the dispatch optimisation was solved with the corresponding bounds of SoC_{max} and P_{max} , delivering feasible values for BESS charging and discharging power, along with SoC at hourly trajectories. If a non-zero BESS candidate yielded the highest expected NPV in the screening stage, a local refinement grid was evaluated around that candidate using 0.5 MWh energy-capacity increments and 0.25 MW power-capacity increments. The final reported BESS configuration was therefore selected from the refined candidate set rather than being restricted to the coarse screening grid.

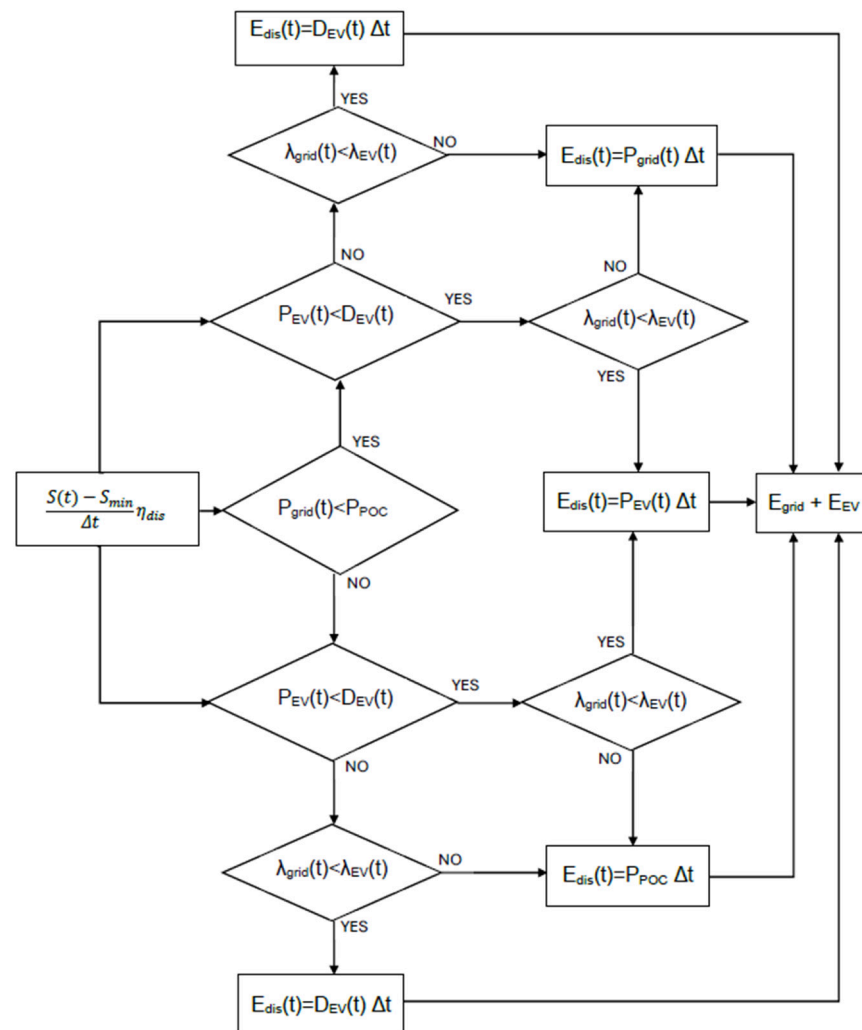


Figure 5. Dispatch algorithm of the BESS stored energy.

To identify the operational constraints that most strongly limit the utilisation of event-conditioned curtailed energy, a one-at-a-time constraint-relaxation diagnostic was applied to the NPV-maximising non-zero BESS configuration of the base case. The selected BESS size was held fixed during this diagnostic in order to isolate operational constraints from investment-sizing effects.

Each constraint was relaxed individually while all other constraints, inputs and scenario rules remained unchanged. The examined constraints were the BESS charging-power limit, BESS discharge-power limit, usable energy capacity, SoC operating range, traffic-derived EV demand, EV outlet capacity and residual grid-export headroom.

Table 1. Base technical and EV parameters used in the dispatch model.

Parameter	Symbol	Value	Units	Source
Wind farm's rated power	$P_{WF, rated}$	43.2	MW	-
Tolerance band	ε	Low: 1% Base: 2% High: 3%	-	[28]
Round-trip efficiency of the battery (base)	η_{rt}	Low: 85% Base: 92% High: 95%	-	[30]
Battery state of charge	SoC	Base: $20\% \leq \text{SoC} \leq 80\%$	-	[29,40]
EV station maximum power (base)	$P_{EV, max}$	Base: 0.55	MW	-
Share of EVs of total passenger fleet (Greece)	$s_{EV, y}$	2024: 0.75% 2025, early 2026: 1.02%	-	[35]
EV charging probability	p_{stop}	Low: 0.05 Base: 0.10 High: 0.20	-	[41]
Energy delivered per charging session	$e_{session}$	Low: 0.02 Base: 0.04 High: 0.06	MWh	[37]
Power export limit	P_{POC}	50	MW	[31]

For each relaxed case c , the incremental effect on an outcome Q was calculated as:

$$\Delta Q_c = Q_c^{relaxed} - Q^{base}$$

where Q denotes BESS charging energy, delivered energy, operating revenue or NPV. The resulting increments are non-additive because each constraint is relaxed separately from the same baseline. They are therefore interpreted as marginal diagnostic effects rather than as a decomposition of total curtailed-energy utilisation.

3.5. Financial Algorithm

The financial assessment converted the annual outcomes of the hourly dispatch model into free cash flow to equity (FCFE) and NPV over a 20-year project horizon. The financial model was intended as a comparative techno-economic assessment rather than a bankable project appraisal. Accordingly, the analysis reports the effect of alternative technical and financial assumptions on the selected BESS investment, while project-specific contractual revenues, taxes, financing terms and support mechanisms would be required for a bankable assessment.

The investment cost (CAPEX) for each SC was represented through a size-dependent function as:

$$IC_s^0 = [(C_E \cdot E_s^{max}) + (C_P \cdot P_s^{max}) + (IC_{BOP} \cdot P_s^{max})] \cdot k_{CAPEX} \quad (15)$$

where IC^0 is the BESS investment cost in €, C_E and C_P are the energy- and power-related cost components in €/MWh of installed capacity and €/MW of installed rated power respectively, while IC_{BOP} represents the balance-of-plant components cost in €/MW. The coefficient k_{CAPEX} was introduced to represent uncertainty in installed BESS capital cost. It scales all size-dependent initial BESS cost components consistently.

The battery degradation was incorporated through an end-of-life replacement approach where the simulated battery usage determined when the storage asset would require replacement and thus triggered additional capital expenditure during the project

lifetime. After solving the hourly dispatch, cumulative cycling intensity was quantified (e.g., via equivalent full cycles derived from discharged energy relative to usable capacity) and annualised to estimate a time-to-replacement based on an assumed cycle-life at end-of-life. Whenever the estimated replacement time fell within the analysis horizon, a replacement CAPEX outflow—typically modelled as a fraction of the initial investment cost reflecting module replacement rather than full system reinvestment—was integrated in the corresponding year and discounted within the NPV calculation.

To calculate the time interval for replacing the main components of the BESS (i.e., battery-module replacement), Equation (16) was used:

$$T_s^{cycle} = \frac{N_{life}}{\bar{N}_s^{cycle}} \quad (16)$$

where T_s^{cycle} is the cycle-limited replacement interval in years, N_{life} is the end-of-life cycles of the battery module, and $\bar{N}_s^{cycle}$ is the annualised BESS cycling rate in cycles per year.

The number of cycles per year (N_s^{cycle}) was derived through Equation (17).

$$N_s^{cycle} = \frac{E_s^{dis}}{(SoC_{max} - SoC_{min}) \cdot E_s^{max}} \quad (17)$$

where E_s^{dis} is the total discharged energy over the simulated period in MWh and was calculated as:

$$E_s^{dis} = \sum_t \left[P_{t,s}^{dis,grid}(t) + P_{t,s}^{dis,EV}(t) \right] \cdot \Delta t \quad (18)$$

Calendar ageing was represented by an independent calendar-life threshold, T_{cal} . The effective replacement interval T_s^{rep} was therefore defined as:

$$T_s^{rep} = \min(T_s^{cycle}, T_{cal}) \quad (19)$$

Therefore, according to the above, the replacement expenditure ($IC_{s,y}^{rep}$) per time interval can be calculated as:

$$IC_{s,y}^{rep} = \alpha \cdot IC_s^0 \cdot I_{s,y}^{rep} \quad (20)$$

with α representing the fraction of initial expenditure of the BESS investment, and $I_{s,y}^{rep}$ equals one when replacement is triggered in year y and zero otherwise. The replacement cost is therefore treated as a simplified installed module-replacement proxy. It does not imply replacement of the power-conversion system, civil works, grid connection equipment or EV charging infrastructure.

The NPV was calculated through a standard annual free cash flow to equity (FCFE) formulation over the project lifetime, set at 20 years [42]. Since the financial parameters used in the present study, such as taxation, loan interest, and discounting assumptions, are indicative rather than project-specific, the economic assessment was formulated as a stochastic comparative analysis rather than a bankable project appraisal. Additional financial inputs consisted of a bank loan with 30% equity and 70% debt, while land lease was not taken into consideration as the BESSs were implemented in the same place as the RES installation.

After timestamp harmonisation, the common hourly dataset was partitioned into two consecutive, non-overlapping 8760 h operational blocks. The blocks began at the first timestamp of the common complete dataset. Any residual incomplete tail was retained for descriptive analysis but was excluded from annual block resampling. Each annual block was solved independently under the same BESS configuration, with the initial state

of charge fixed at $0.5 E_{max}$ and the terminal state of charge constrained to equal the initial state of charge. For each Monte Carlo realisation, 20 annual block labels were sampled with replacement from two consecutive non-overlapping 8760 h operational blocks. All hourly variables within a selected block, including curtailment availability, electricity prices, measured wind-farm output and EV-demand conditions, were sampled jointly in order to preserve their observed within-block dependence. The data used for the calculation of the NPV and the respective defined financial variables are presented in Table 2.

Table 2. Data used for the calculation of the NPV formula.

Parameter	Symbol	Base Value	Low/High Value	Units	Source
Income tax coefficient	Φ	0.22	-	-	[43]
Energy-related cost coefficient	C_E	209,000	Through k_{CAPEX}	€/MWh	[30]
Power-related cost coefficient	C_P	323,000	Through k_{CAPEX}	€/MW	[30]
Battery system BOP	IC_{BOP}	424,000	Through k_{CAPEX}	€/MW	[30]
CAPEX coefficient	k_{CAPEX}	1.0	0.8/1.2	-	-
End-of-life cycles of BESS	N_{life}	8000	6000/10,000	-	[44]
Calendar life of BESS	T_{cal}	15	12/18	y	[30]
Operation and maintenance	OM	2% IC^0	-	€/y	[30]
Replacement cost coefficient	a	0.62	0.50/0.75	-	[30]
EV service premium	p_{EV}	50	50–1200, breakeven diagnostic	€/MWh	[39]
Insurance cost	In	1.0% IC^0	-	€	[42]
Depreciation	Ad_j	10% ($IC^0 - Ad_{j-1}$)	-	€	[45]
Loan repayment period	n_L	10	-	y	-
Loan rate of interest	τ	4.7%	3.5%/6.0%	-	[46]
Cost of equity	r_e	0.08	0.06/0.10	-	[47]

The total annual revenues from electrical grid discharge and from EV charging $R_{tot,s,y}$ were calculated as:

$$R_{tot,s,y} = \sum_{t \in HT_b} \lambda_s^{grid}(t) \cdot P_s^{grid}(t) \cdot \Delta t + \sum_{t \in T_b} \lambda_s^{EV} \cdot P_s^{EV}(t) \cdot \Delta t \quad (21)$$

The initial outstanding loan amount was defined as:

$$LL_s^0 = 0.7 \cdot IC_s^0$$

Assuming a fixed annual loan instalment during the repayment period, the annual instalment amount was calculated as:

$$Inst_s = \frac{\tau \cdot LL_s^0}{1 - (1 + \tau)^{-n_L}}$$

where τ is the loan rate of interest, and n_L is the loan repayment period in years.

The annual interest payment of the loan for year y $Il_{s,y}$ was calculated as:

$$Il_{s,y} = \tau \cdot LL_{s,y-1}$$

and the remaining loan amount $LL_{s,y}$ evolved according to:

$$LL_{s,y} = LL_{s,y-1} - (Inst_s - Il_{s,y})$$

where $Inst_s - Il_{s,y}$ represents the principal repayment in year y .

Based on the above:

$$FCFE_{s,y} = (R_{tot,s,y} - OM_s - In_s - Ad_s - Il_{s,y}) \cdot (1 - \Phi) + Ad_s - (Inst_s - Il_{s,y}) - IC_{s,y}^{rep}$$

and finally, NPV was calculated as:

$$NPV_s = \sum_{y=1}^n \frac{FCFE_{s,y}}{(1 + r_e)^y} - 0.3 \cdot IC_s^0 \quad (22)$$

where OM is the annual operation and maintenance cost, In is the insurance cost, Ad is the annual depreciation, Φ is the income tax coefficient, $IC_{s,y}^{rep}$ is the replacement expenditure incurred in year y where applicable and based on T_s^{rep} , r_e is the cost of equity and n is the project lifetime (=20 years).

Routine labour was included within the annual OM allowance. Therefore, no separate daily labour-cost term was included in the FCFE calculation. Tax losses were not carried forward between years. The project residual value at the end of the 20-year horizon was assumed to be zero. Battery-module replacements were treated as equity-funded capital outflows in the year in which replacement was triggered.

The representation of the developed sizing methodology of the BESS is depicted in Figure 6, where the calculated curtailed energy from the wind farm (see Figure 3) is used as input along with the set constraints including SoC, the stored energy in the BESS, and the dispatched energy to the electricity grid and/or EV charging facility (Figures 4 and 5).

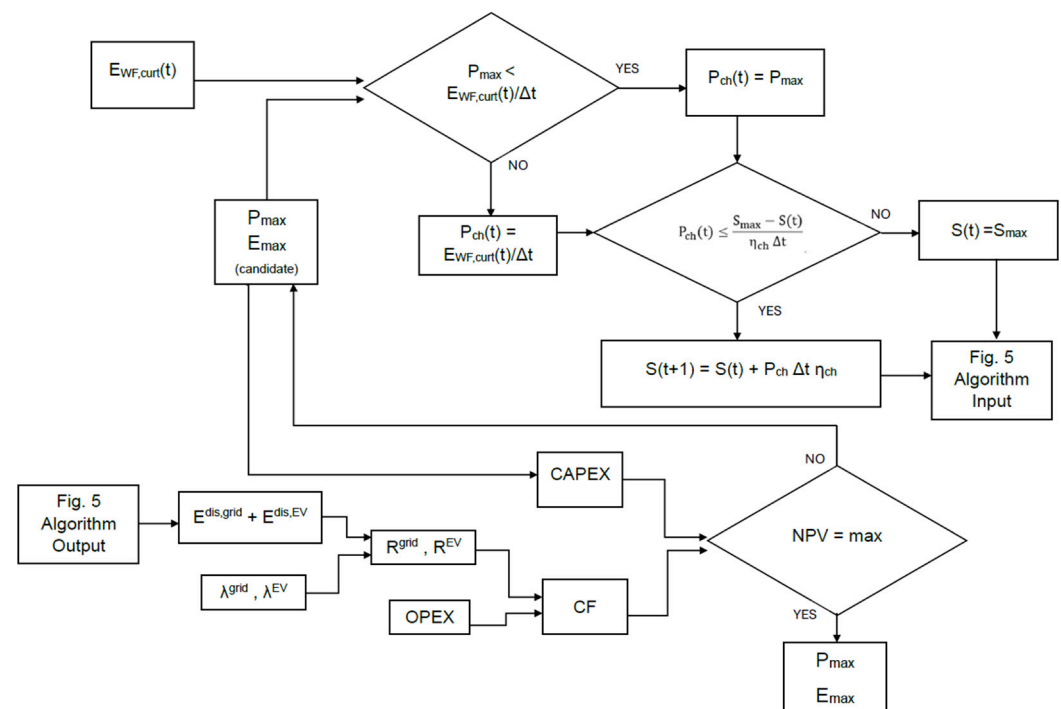


Figure 6. Algorithm used for sizing the BESS for all SCs to maximise the investment NPV.

The available common dataset comprised only two annual historical profiles. Consequently, the block-bootstrap procedure was not interpreted as an estimate of a fully representative 20-year empirical distribution. Instead, it was used as a conditional within-sample uncertainty analysis that preserved the observed within-block dependence between curtailed-energy availability, electricity prices, wind-farm output and traffic-derived EV-demand conditions. Each Monte Carlo realisation sampled complete paired annual blocks with replacement and concatenated them over the 20-year project horizon. The

reported Monte Carlo statistics must therefore be interpreted as conditional on the limited observed sample.

Future-curtailment conditions were addressed separately through deterministic pathways rather than being inferred from the two historical blocks. The tested curtailment multipliers were $\gamma_{\text{curt}} = 0.5, 1.0, 1.5$ and 2.0 . The hourly charging-energy input was calculated as:

$$E_{WF, \text{curt}}^{(\gamma)} = \min \left\{ \gamma_{\text{curt}} \cdot E_{WF, \text{curt}}^{\text{base}}(t), \max[0, \hat{E}_{WF, \text{net}}(t) - E_{WF, \text{msr}}(t)] \right\} \quad (23)$$

where $E_{WF, \text{curt}}^{(\gamma)}$ denotes the curtailment-energy input applied in the future-curtailment sensitivity case γ_{curt} . The base series $E_{WF, \text{curt}}^{\text{base}}(t)$ had already been calculated using the event-hour allowance $\varepsilon \cdot P_{WF, \text{rated}} \cdot \Delta t$ in the base curtailment-estimation procedure. Therefore, the allowance is not deducted again. γ_{curt} scales the conservatively estimated base series, whereas the second term imposes a physical upper-bound equal to the gross positive difference between calibrated expected net generation and measured wind-farm energy. This upper-bound prevents the scaled sensitivity series from exceeding the hourly energy shortfall available under the observed wind conditions.

3.6. Sensitivity Cases

A structured sensitivity and robustness analysis was performed in order to distinguish between uncertainty in the historical curtailment estimate, deterministic future-curtailment pathways, dispatch-affecting technical assumptions, EV-demand and EV-remuneration assumptions, and finance-only valuation parameters. In all cases, the no-investment alternative, defined by $(E_{\text{max}}, P_{\text{max}}) = (0, 0)$, was retained in the candidate set. The reported investment decision was therefore the candidate with the highest expected NPV over the full candidate set. Consequently, the no-investment option was selected whenever all non-zero BESS candidates yielded negative expected NPV.

Curtailment-estimation uncertainty was first assessed through the event-hour shortfall allowance ε . The tested values were $\varepsilon = 1\%$ and 3% with a base case of 2% (see Table 1). Each ε value generated a different event-conditioned curtailed-energy input series and was propagated through the dispatch, BESS-sizing and financial-evaluation stages.

Dispatch-affecting technical sensitivities were then evaluated through full MILP re-optimisation because they change the feasible hourly operation of the BESS. These cases included the SoC operating range and the round-trip efficiency. The SoC bounds were tested at $10\text{--}90\%$, $20\text{--}80\%$ (Base) and $30\text{--}70\%$, while the BESS round-trip efficiency was tested at $\eta_{\text{rt}} = 85\%, 92\%$ (Base) and 95% . In each case, all BESS candidates were re-dispatched and re-ranked by expected NPV.

EV-demand and EV-outlet robustness cases were evaluated only for SC2 and SC3, because SC1 does not use the EV outlet. The traffic-to-demand conversion was tested by varying $p_{\text{stop}} = 0.05, 0.10$ (Base) and 0.20 while keeping e_{session} fixed at 0.04 MWh/session, and by varying $e_{\text{session}} = 0.02, 0.04$ (Base) and 0.06 MWh/session while keeping p_{stop} fixed at 0.10 . The EV outlet-capacity robustness cases used $P_{EV, \text{max}} = 0.55$ (Base), $1, 2$ and 5 MW. These cases were solved through full MILP re-optimisation, because EV demand and outlet capacity directly constrain the feasible discharge to the EV facility.

The base EV remuneration was defined as the monthly average day-ahead electricity price plus a fixed EV service premium. To test whether this monthly averaging affected dispatch allocation, an additional hourly market-linked EV-remuneration case was evaluated using $\lambda_{EV}(t) = \lambda_{\text{grid}}(t) + p_{EV}$, while retaining the same EV service premium. This robustness case was also solved through full MILP re-optimisation for SC2 and SC3.

Finance-only sensitivity cases were evaluated separately from the dispatch-affecting cases. These parameters affect FCFE, NPV and replacement timing, but do not change the hourly dispatch feasibility or the operating revenue obtained from a given dispatch solution. Therefore, they were evaluated by reusing the exported baseline dispatch metrics for every BESS candidate and recalculating FCFE and NPV. The tested finance-only parameters were the installed BESS CAPEX multiplier $k_{CAPEX} = 0.8, 1.0$ (Base) and 1.2, the replacement-cost fraction $\alpha_{rep} = 0.50, 0.62$ (Base) and 0.75, the cost of equity $r_e = 6\%, 8\%$ (Base) and 10%; the loan interest rate $\tau = 3.5\%, 4.7\%$ (Base) and 6.0%, the calendar-life threshold $T_{cal} = 12, 15$ (Base) and 18 years; and the cycle-life threshold $N_{life} = 6000, 8000$ (Base) and 10,000 equivalent full cycles.

Finally, two complementary EV-viability diagnostics were performed for the EV-related scenarios SC2 and SC3. First, an EV-service-premium analysis was carried out over the range $p_{EV} = 50\text{--}1400$ €/MWh, starting from the base EV service premium. A discrete full re-optimisation sweep was performed at $p_{EV} = 50, 100, 200, 400, 600, 800, 1000, 1200$ and 1400 €/MWh. A breakeven search was then performed over the same interval in order to identify the EV service premium at which the highest-expected-NPV non-zero BESS candidate first achieved a non-negative expected NPV. Unlike the finance-only cases, the EV-service-premium cases required full MILP re-optimisation, because p_{EV} changes the hourly value of discharging to the EV outlet and can therefore affect both the dispatch allocation and the NPV-maximising BESS size. At each tested premium, the full BESS candidate set was re-dispatched and re-ranked, so the reported breakeven premium was associated with the corresponding re-optimised BESS energy and power capacities rather than with a fixed baseline BESS size.

Second, an EV-demand breakeven diagnostic was defined in order to test how much the realised EV charging demand would have to increase, relative to the base traffic-derived demand profile, for the BESS investment to become financially viable under the base EV service premium. For this purpose, a dimensionless EV-demand multiplier, κ_{EV} , was applied to the raw traffic-derived EV-demand profile before imposing the EV outlet-capacity limit:

$$D_{EV,raw,\kappa}(t) = \kappa_{EV} \cdot D_{EV,raw,base}(t)$$

$$D_{EV,\kappa}(t) = \min[D_{EV,raw,\kappa}(t), P_{EV,max}]$$

where $D_{EV,raw,base}$ is the base raw traffic-derived EV charging-demand profile before applying the EV outlet-capacity limit, $D_{EV,raw,\kappa}$ is the scaled raw EV demand under the EV-demand multiplier κ_{EV} , and $D_{EV,\kappa}$ is the EV demand made available to the dispatch model after applying the EV outlet-capacity constraint. The case $\kappa_{EV} = 1$ corresponds to the base traffic-derived EV-demand profile. The diagnostic therefore represented a combined increase in realised EV charging activity, without assigning the increase exclusively to EV fleet share, stopping probability, traffic volume, or charging energy per session. The EV-demand breakeven search was performed at the base EV service premium, with all other technical and financial assumptions kept at their base values. As with the EV-premium breakeven analysis, the full BESS candidate set was re-dispatched and re-ranked at each tested κ_{EV} value. Therefore, the reported EV-demand breakeven threshold was associated with the corresponding re-optimised BESS energy and power capacities rather than with a fixed baseline BESS size.

Potential additional revenue streams, such as balancing-market participation, ancillary services, subsidies or capacity payments, were not parameterised as sensitivity cases. Their inclusion would require product-specific reserve, activation, availability and eligibility data, as well as additional constraints to avoid double-counting revenues from the same stored

energy. They were therefore treated as outside the quantitative modelling boundary and are discussed as potential extensions rather than as part of the base-case investment assessment.

3.7. Computational Implementation

The dispatch optimisation, financial evaluation, and sensitivity analyses were implemented in the ‘Spyder’ version 6 software platform through a developed ‘Python 3.12.11’ code. The workflow was organised into sequential scripts in order to make each modelling stage auditable and reproducible.

The MILP matrices were assembled in sparse form and solved using ‘HiGHS’ version 1.12.0, an open-source high-performance optimisation solver for linear and mixed-integer programming, through ‘Python’. The final reported runs used a relative mixed-integer optimality-gap target of 0.5%. Candidate ranking was based on the expected NPV computed after the annual dispatch outputs had been passed to the FCFE valuation routine.

The baseline optimisation was initially run on a workstation equipped with an ‘Intel Core i5-12600H’ processor and 16 GB of RAM. Because the full re-optimisation sensitivity cases required substantially longer runtimes, those cases were executed on a higher-specification workstation equipped with an ‘Intel Core i7-13700’ processor and 48 GB of RAM. Dispatch-affecting sensitivity cases, EV-remuneration cases and EV-demand multiplier cases were re-solved through the same MILP procedure, while finance-only sensitivity cases reused the exported dispatch metrics and recalculated FCFE and NPV without re-solving the hourly dispatch problem.

- A preparation stage imported all source datasets harmonised to a common UTC end-of-interval hourly timeline, and created the complete annual operational blocks used in the dispatch model.
- The baseline optimisation stage solved SC1, SC2 and SC3 over the full discrete BESS candidate grid, including the explicit no-investment alternative. For each non-zero candidate and each annual block, the deterministic MILP dispatch was solved, and the resulting annual revenues, energy allocation and cycling metrics were exported. These annual metrics were then used in the Monte Carlo FCFE valuation.
- A one-at-a-time constraint-relaxation diagnostic was applied to the highest-expected-NPV non-zero BESS candidate in each scenario. This diagnostic did not change the investment decision; instead, it quantified the marginal operational effect of relaxing individual constraints such as charging power, discharge power, usable energy capacity, SoC range, EV demand, EV outlet capacity and residual grid-export headroom.
- The sensitivity and robustness analyses were executed as separate scripts. Cases that changed the hourly curtailed-energy input, such as BESS operating feasibility, EV demand, EV outlet capacity, EV-remuneration timing or EV service premium, were solved through full MILP re-optimisation. In contrast, finance-only cases were evaluated by reusing the exported baseline dispatch metrics and recalculating FCFE and NPV for every BESS candidate. This separation ensured that computationally intensive MILP runs were repeated only when the parameter under examination changed hourly feasibility or hourly operating revenues.
- Subsequently, the EV-service-premium analysis was implemented as a dedicated re-optimisation step for SC2 and SC3. A discrete sweep was first performed over $p_{EV} = 50, 100, 200, 400, 600, 800, 1000, 1200$ and 1400 €/MWh. At each tested premium, the full BESS candidate set was solved again through the MILP and re-ranked by expected NPV. This procedure identified the EV service premium required for the highest-expected-NPV non-zero BESS candidate to reach a non-negative expected NPV, together with the corresponding re-optimised BESS energy and power capacities.

- An EV-demand multiplier breakeven diagnostic was also implemented as a complementary re-optimisation step for SC2 and SC3. In this diagnostic, the raw traffic-derived EV charging-demand profile was multiplied by κ_{EV} before applying the EV outlet-capacity limit. The EV service premium and all other base-case assumptions were kept fixed. At each tested κ_{EV} value, the full BESS candidate set was solved again through the MILP and re-ranked by expected NPV. This diagnostic identified the realised EV-demand scaling required for the highest-expected-NPV non-zero BESS candidate to reach a non-negative expected NPV, together with the corresponding re-optimised BESS size.

All output workbooks reported both the global NPV-maximising solution, including the no-investment alternative, and the best non-zero BESS candidate.

4. Results and Discussion

The financial evaluation and dispatch optimisation were implemented in the ‘Spyder’ version 6 software platform through a developed ‘Python 3.12.11’ code. The workflow produced the event-conditioned curtailed-energy time series, solved the MILP dispatch problem for all BESS options and scenarios, computed the FCFE-based NPV for the project period, and produced the baseline, Monte Carlo, sensitivity, constraint diagnostic and EV viability analysis outputs. The output data is presented and analysed in five stages.

First, the calibration of the expected generation and curtailed-energy estimation is discussed. Second, the baseline BESS sizing and dispatch allocation findings are analysed among the three scenarios. Third, the long-term financial performance and the results of Monte Carlo uncertainty analysis are considered. Next, the sensitivity analysis is employed to determine the parameters having the strongest effect on the optimal non-zero BESS investment. Finally, the EV premium and EV-demand diagnostics are employed to assess if the EV outlet will be a sufficient value stream for the curtailed wind energy.

4.1. Characteristics of Wind Potential and Energy Curtailment

The initial analysis involved assessing the wind potential of the geographical area under consideration. Figure 7 presents the wind-speed time series for the period from February 2024 to February 2026, which reveals significant temporal variability, with continuous fluctuations between low and high levels. During the period under consideration, multiple peaks are recorded, ranging from low wind speeds to instances where speeds approach 12–13 m/s.

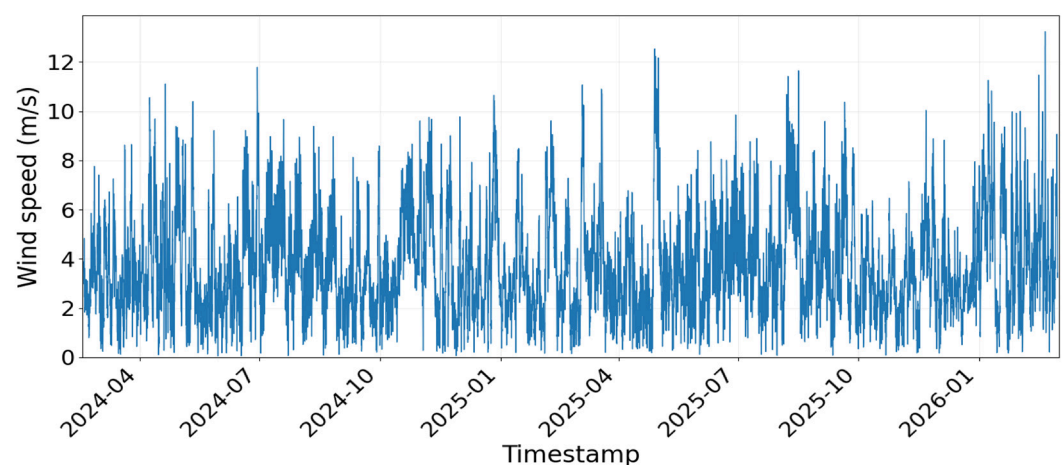


Figure 7. Temporal variation in wind potential at the location of the examined wind farm during the period February 2024–February 2026.

The expected-generation model was evaluated using 17,807 matched hourly observations spanning from 18 February 2024 to 1 March 2026. The matched dataset contained 2233 IPTO-event hours and 15,574 eligible non-IPTO-event observations (N_{normal}). The chronological training subset contained $k = 10,901$ observations, and the independent holdout subset contained 4673 observations.

Table 3 reports the temporal holdout validation results. The raw ERA5-plus-manufacturer-curve index produced an MAE of 5.513 MWh, RMSE of 9.472 MWh, MBE of -4.309 MWh, normalised RMSE of 21.92% of rated hourly wind-farm energy, and Pearson correlation coefficient of 0.565. After isotonic calibration, the MAE decreased to 5.196 MWh and the RMSE decreased to 7.704 MWh. The calibrated model exhibited an MBE of 0.117 MWh, normalised RMSE of 17.83%, and Pearson correlation coefficient of 0.658. These results indicate that the calibration did not eliminate all uncertainty in the expected-generation estimate, but it materially improved the representation of normal wind-farm production compared with the unadjusted ERA5/manufacturer-curve index.

Table 3. Independent chronological holdout validation of the expected-generation model.

Model on Holdout Sample	Hours, N	MAE (MWh)	RMSE (MWh)	MBE (MWh)	nRMSE (% of Rated Energy)	Pearson r
Raw ERA5	4673	5.513	9.472	-4.309	21.92	0.565
Calibrated net generation	4673	5.196	7.704	0.117	17.83	0.658

This validation step is central to the interpretation of the curtailment results. The available data did not include a directly metered curtailed-energy series. Therefore, the estimation of the curtailed energy was performed only for the reported event-hours based on the difference between the calibrated expected non-curtailed energy and the actual wind-farm generation while considering the event-hour deficit adjustment factor. Consequently, the series should be interpreted as the estimate of the recoverable curtailed energy conditioned by events, but not as the metered amount of the curtailment itself. This nuance is important since there might still be deviations between the expected and actual productions due to various plant-level factors.

Under the base-case shortfall allowance of $\varepsilon = 2\%$, which is equal to 0.864 MWh for every event hour, there were 1537 out of 2233 matched IPTO-event hours with positive estimated curtailment. This led to an estimated curtailed energy of 10,260 MWh. It can be seen from Table 4 that when the allowance is decreased to ($\varepsilon = 1\%$), there were more hours with positive curtailment, totalling 1606, and a total of 10,942 MWh of estimated curtailed energy. When the allowance is increased to ($\varepsilon = 3\%$), the positive estimated hours fell to 1468 and estimated curtailed energy was only 9612 MWh.

Table 4. Sensitivity of the event-conditioned curtailment estimate to the event-hour shortfall allowance.

ε	Allowance (MWh h ⁻¹)	Positive Estimated Event Hours	Estimated Curtailed Energy (MWh)
1%	0.432	1606	10,942
2%	0.864	1537	10,260
3%	1.296	1468	9612

Figure 8 demonstrates the expected net energy after calibration, actual wind-farm energy and the estimated curtailed energy conditional on events during the two-year time period under consideration. It can be seen from Figure 8 that the curtailment happened sporadically and not constantly. This temporal clustering is a key result for the subsequent BESS analysis. Even though the two-year period contains more than 10 GWh of estimated

recoverable curtailed energy in the base case, the BESS cannot necessarily capture and utilise this energy efficiently. There are several constraints imposed on the BESS dispatching model, including BESS power capacity and energy capacity, SoC constraints, no grid charging, inability to export to the grid during IPTO events, shared point-of-connection capacity and EV demand.

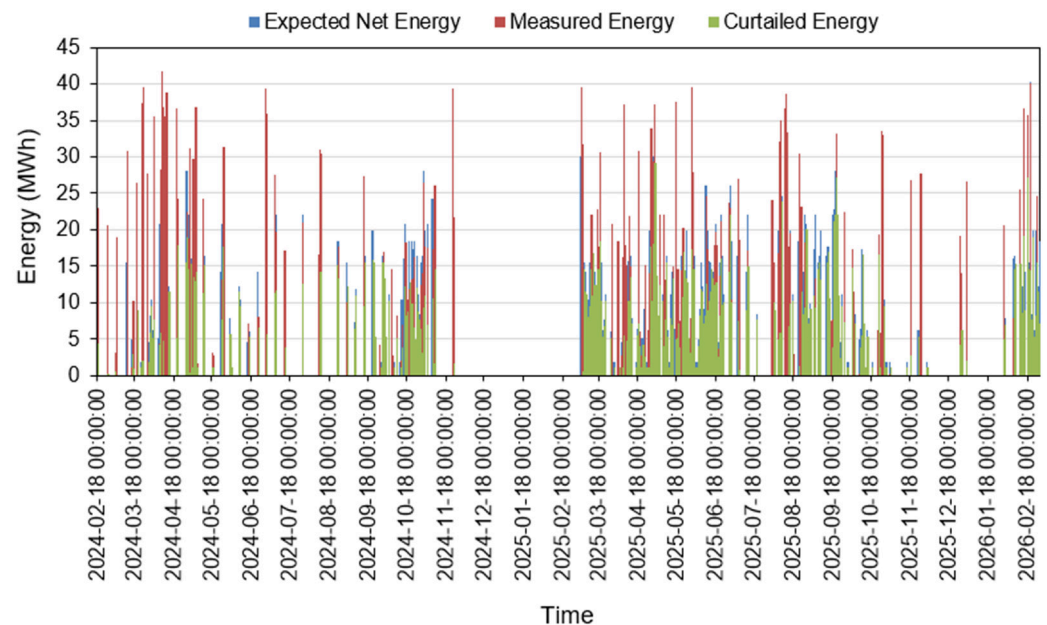


Figure 8. Hourly calibrated expected net energy, measured wind-farm energy, and event-conditioned estimated curtailed energy over the study period ($\varepsilon = 2\%$).

4.2. Baseline BESS Sizing and Dispatch Allocation

The dispatch operation of the battery energy storage system was examined based on three distinct operational scenarios: (SC1) exclusive feeding of stored energy into the power grid, (SC2) exclusive use of energy for charging electric vehicles, and (SC3) combined use for the grid and EV charging infrastructure.

Figure 9 illustrates the expected NPV achieved for the examined BESS energy and power capacities in the three dispatch scenarios. An alternative corresponding to no investment, ($E_{max} = 0$) and ($P_{max} = 0$), was included in the candidate set and had an NPV of zero. It is an important financial consideration because otherwise, the optimisation procedure could choose an unprofitable BESS simply because all candidates have non-zero parameters.

The globally optimising solution in all three scenarios was no investment. It means that, based on the initial assumptions and observed curtailment and market conditions, all non-zero BESS candidates had a negative expected NPV. Consequently, the economically optimal investment decision was not to build a BESS. It is stated explicitly in Table 5 and needs to be distinguished from the best non-zero BESS. The best non-zero BESS is a useful tool for diagnosis purposes since it is the least unfavourable investment in terms of BESS storage and provides an opportunity to compare the technical parameters between scenarios, but not the global optimum with no-investment alternative included.

Among non-zero candidates (see Figure 9), the best one was the case of $E_{max} = 0.5$ MWh and $P_{max} = 0.25$ MW in all three scenarios. The expected NPV of the best non-zero BESS was equal to -332.6 k€ in SC1, -356.3 k€ in SC2 and -321.0 k€ in SC3. It is clear that the best performance among the non-zero BESSs was provided by the combined grid-plus-EV case, followed by the grid-only operation and the EV-only case, respectively.

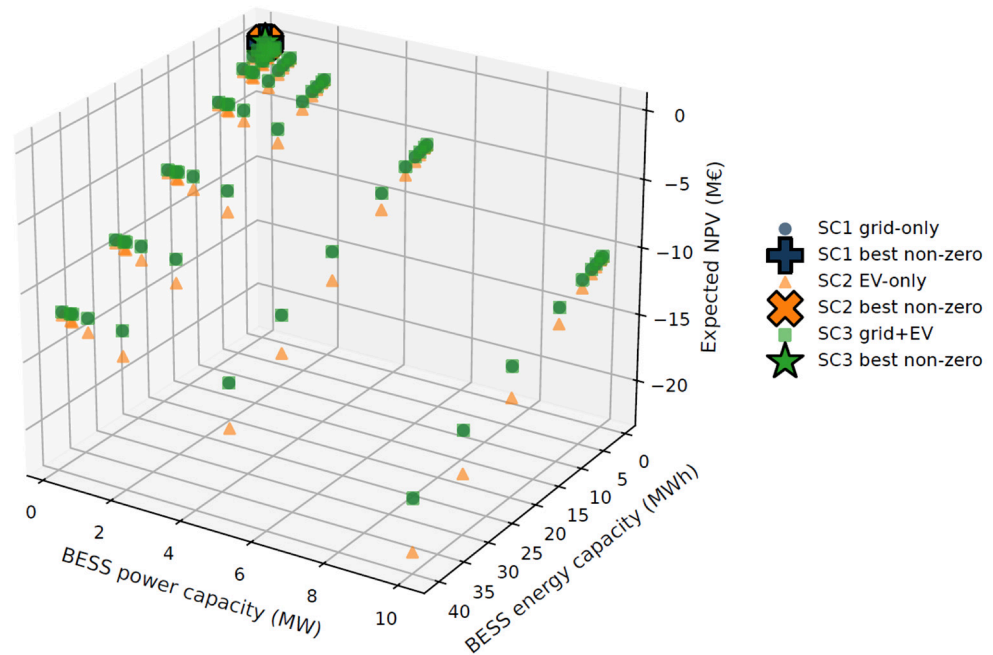


Figure 9. Sizing algorithm output of the BESS.

Table 5. BESS sizing optimisation results: optimum and best non-zero BESS in all SCs.

Scenario	Optimum $P_{\max}$ (MW)	Optimum $E_{\max}$ (MWh)	Best Non-Zero $P_{\max}$ (MW)	Best Non-Zero $E_{\max}$ (MWh)	NPV (k€)
SC1: Grid-only	0	0	0.25	0.5	−332.6
SC2: EV-only	0	0	0.25	0.5	−356.3
SC3: Grid + EV	0	0	0.25	0.5	−321

It is worth noting that the optimal non-zero BESS capacity turned out to be the smallest one among all tested energy–power combinations. While larger configurations were able to collect more energy during some hours of the year, they also required much greater initial investments. Considering the distribution of curtailment events, the benefit brought about by the larger storage capacity was not sufficient to offset the extra costs. Hence, the outcome demonstrates that the limiting factor was not just the existence of the curtailed energy but its ability to be collected often enough and then sold at the appropriate price.

Figure 10 demonstrates the monthly division of the dispatched BESS energy between grid export and EV charging in SC3. As can be seen, the allocation pattern proves that the combined case did not work as an EV-only or grid-only scheme. Instead, the algorithm chose the energy outlet that maximised operating profits, taking into account the scenario constraints, the grid-export availability, and the EV load limit. Grid export accounted for the majority of the dispatched energy in most months, while EV charging served as an additional profitable outlet. The role of the latter was especially important in the months when the EV remuneration was higher than that of the delayed grid export or grid export itself was limited.

Table 6 provides a summary of the average annual dispatch results for the best non-zero BESS. In SC1, the BESS charged 40.8 MWh/year and discharged 37.5 MWh/year to the grid, earning approximately 7387 €/year. In SC2, the BESS charged 37.8 MWh/year and discharged 34.8 MWh/year to the EV outlet, earning approximately 4948 €/year. In SC3, the BESS charged 49.5 MWh/year, discharged 31.4 MWh/year to the grid and 14.1 MWh/year to EV charging, earning approximately 8633 €/year. Hence, SC3 generated the greatest annual earnings since it had two market outlets at its disposal.

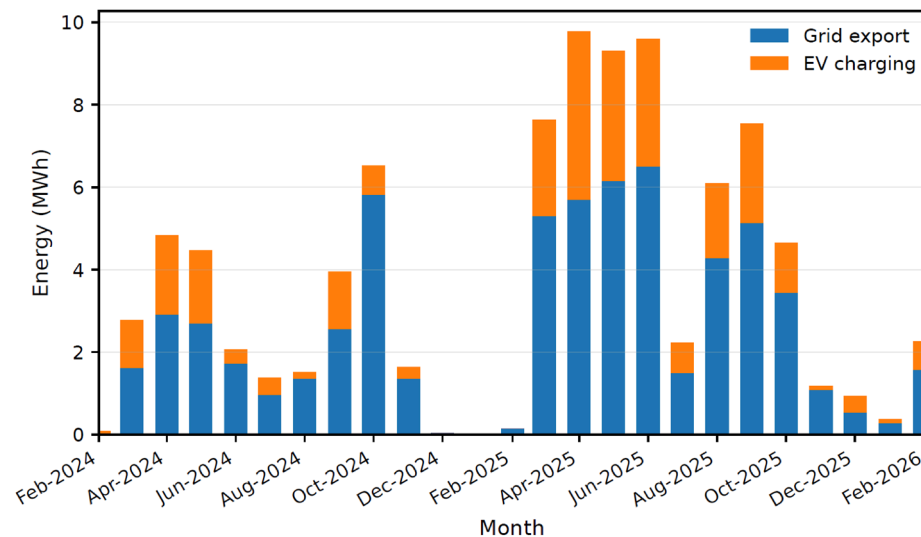


Figure 10. Monthly allocation of dispatched BESS energy between electricity-grid export and EV charging demand during the examined period for SC3.

Table 6. Baseline dispatch and energy allocation of the best non-zero BESS.

Scenario	Average Annual Charge (MWh)	Average Annual Grid Discharge (MWh)	Average Annual EV Discharge (MWh)	Average Annual Revenue (€)	Average BESS Annual Cycles
SC1: Grid-only	40.8	37.5	-	7387	125
SC2: EV-only	37.8	-	34.8	4948	116
SC3: Grid + EV	49.5	31.4	14.1	8633	152

Nevertheless, the dispatch numbers also show the reasons why the investment was still unprofitable. The best non-zero BESS managed to collect only a tiny fraction of the total curtailment-energy estimation. The problem was not in the insignificance of the latter, but in the limitations of the BESS (charging from the curtailment only), temporal clustering of the event hours and discharge constraints imposed by the SCs. During IPTO-event hours, grid export was forbidden, and hence the BESS could either charge from the curtailment or, in EV-related scenarios, discharge the collected energy to the EV outlet, but not both.

To further explain why the best non-zero BESS captured only a limited fraction of the estimated curtailed energy, a one-at-a-time constraint-relaxation diagnostic was applied to the best non-zero BESS configuration (see Table 7). The diagnostic was not used to change the investment decision and did not re-size the BESS. Instead, it kept the selected non-zero configuration fixed at $E_{max} = 0.5$ MWh and $P_{max} = 0.25$ MW and relaxed one operational constraint at a time. The resulting increments should therefore be interpreted as marginal diagnostic effects, rather than as additive contributions or as an alternative optimal design.

The output from the diagnostic indicates that the factors of usable energy capacity and EV-demand availability were the dominant operational restrictions. In SC1, relaxing the constraint of usable energy capacity resulted in an increase in the delivered energy from 75.1 MWh to 331.3 MWh, and the increase in operating revenue was approximately 63.1 k€. Relaxing the restriction on SoC operating range also increased delivered energy, but to a much smaller degree—from 75.1 MWh to 122.2 MWh. On the other hand, relaxing the constraint of charge–discharge power and grid-export headroom led to no changes in results. Thus, it can be concluded that for the chosen small BESS, the restriction on storing energy in the curtailment-event period is tighter than on immediate grid-export headroom.

Table 7. Constraint-relaxation diagnostic for the best non-zero BESS.

Scenario	Diagnostic Case	Charged Energy (MWh)	Grid Energy (MWh)	EV Energy (MWh)	Operating Revenue (€)	Incremental Delivered Energy (MWh)	Incremental Operating Revenue (€)
SC1	Base case	81.6	75.1	0	14,773.7	0	0
SC1	Charging-power limit relaxed	82.4	75.8	0	14,897.2	0.8	123.5
SC1	Discharge-power limit relaxed	81.6	75.1	0	15,011.6	0	237.9
SC1	Usable energy capacity relaxed	360.1	331.3	0	77,874.6	256.3	63,100.9
SC1	SoC operating range relaxed	132.8	122.2	0	23,049.6	47.1	8276
SC1	EV demand relaxed	81.6	75.1	0	14,773.7	0	0
SC1	EV outlet capacity relaxed	81.6	75.1	0	14,773.7	0	0
SC1	Grid-export headroom relaxed	81.6	75.1	0	14,773.7	0	0
SC2	Base case	75.6	0	69.6	9895.1	0	0
SC2	Charging-power limit relaxed	76.6	0	70.5	10,018.1	0.9	123
SC2	Discharge-power limit relaxed	75.6	0	69.6	9895.1	0	0
SC2	Usable energy capacity relaxed	177.5	0	163.3	25,100	93.7	15,204.8
SC2	SoC operating range relaxed	89.7	0	82.5	11,775.9	12.9	1880.8
SC2	EV demand relaxed	214.6	0	197.4	27,869.1	127.8	17,974
SC2	EV outlet capacity relaxed	75.6	0	69.6	9895.1	0	0
SC3	Base case	98.9	62.8	28.2	17,266	0	0
SC3	Charging-power limit relaxed	100	63.5	28.4	17,411.3	1	145.4
SC3	Discharge-power limit relaxed	98.9	63.8	27.2	17,460.9	0	194.9
SC3	Usable energy capacity relaxed	360.1	296.8	34.5	78,161.7	240.3	60,895.7
SC3	SoC operating range relaxed	147	106.3	28.9	25,249.3	44.3	7983.3
SC3	EV demand relaxed	214.6	52.5	144.9	32,444.9	106.4	15,178.9
SC3	EV outlet capacity relaxed	98.9	62.8	28.2	17,266	0	0
SC3	Grid-export headroom relaxed	98.9	62.8	28.2	17,266	0	0

In the SC2 scenario, the EV-only option was primarily restricted by EV-demand profile and usable energy capacity. The relaxation of the EV demand resulted in an increase in

delivered EV energy from 69.6 MWh to 197.4 MWh and operating revenue of about 18.0 k€. Relaxing usable energy capacity also led to an increase in delivered energy to 163.3 MWh. At the same time, relaxing the EV outlet capacity constraint resulted in no changes, which shows that the chosen 0.55 MW outlet capacity is not limiting for the base traffic-derived demand profile. Hence, it can be said that the limitation of the EV-only case scenario is not the capacity of the charger, but the availability of EV demand.

In SC3, the hybrid grid + EV strategy demonstrates similar results. Relaxing the restriction of usable energy capacity resulted in an increase in total delivered energy from 91.0 MWh to 331.3 MWh and operating revenue of about 60.9 k€. At the same time, relaxing the constraint of EV demand resulted in an increase in delivered energy to 197.4 MWh due to an increase in EV energy delivered from 28.2 MWh to 144.9 MWh. Relaxing EV outlet capacity and grid-export headroom did not affect the results. It proves that the restriction on the hybrid strategy implementation is not the installed charger capacity, but the combination of limitations listed above.

Thus, the constraint-relaxation diagnostic provides an explanation of why the total estimated volume of curtailed energy did not result in proportional BESS revenue. In other words, the main limitations for the results of the analysis were not just the curtailed-energy volume and installed EV outlet capacity, but the combination of small economically selected BESS capacity, usable energy capacity, SoC range, timing mismatch of curtailment and EV demand, and charging only during curtailment events.

4.3. Basic Financial Assessment of the Scenarios and Monte Carlo Uncertainty

Figure 11 shows the evolution of the cumulative discounted NPV of the optimum non-zero BESS in the three baseline scenarios over the project period of 20 years. In all three scenarios, the cumulative discounted NPV of the BESS was consistently negative over the entire period of 20 years. The initial outflow of the equity resulted in the negative starting point of the project. Moreover, the revenues earned each year were not enough to cover the cost of the project.

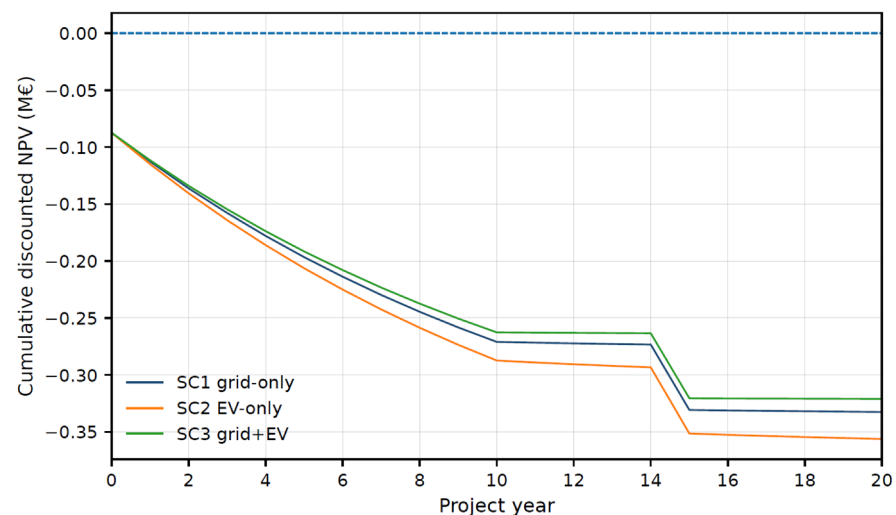


Figure 11. Cumulative NPV evolution of the three examined dispatch scenarios using the optimal BESS configuration (0.25 MW/0.5 MWh) over the 20-year project horizon.

It can be clearly seen that there is an evident deterioration in the cumulative NPV curve due to the replacement outflow. This replacement outflow causes the NPV of the project to go down sharply. It is especially true given the fact that the base of the revenue is rather small. Despite the fact that the BESS earns a positive operating revenue, the amount

of the annual revenue is not enough to cover both initial and replacement costs of the project over the period of 20 years.

The Monte Carlo analysis shown in Figure 12 confirms that the NPV being negative is robust within the annual block-bootstrapping uncertainty scenario. The uncertainty bands are quite small relative to the distance from zero, and the P05–P95 range remains strictly negative in all three scenarios. In other words, considering the two observed annual blocks and the underlying modelling assumptions, the annual block sequencing uncertainty does not lead to a realistic path to a positive NPV for the best non-zero BESS.

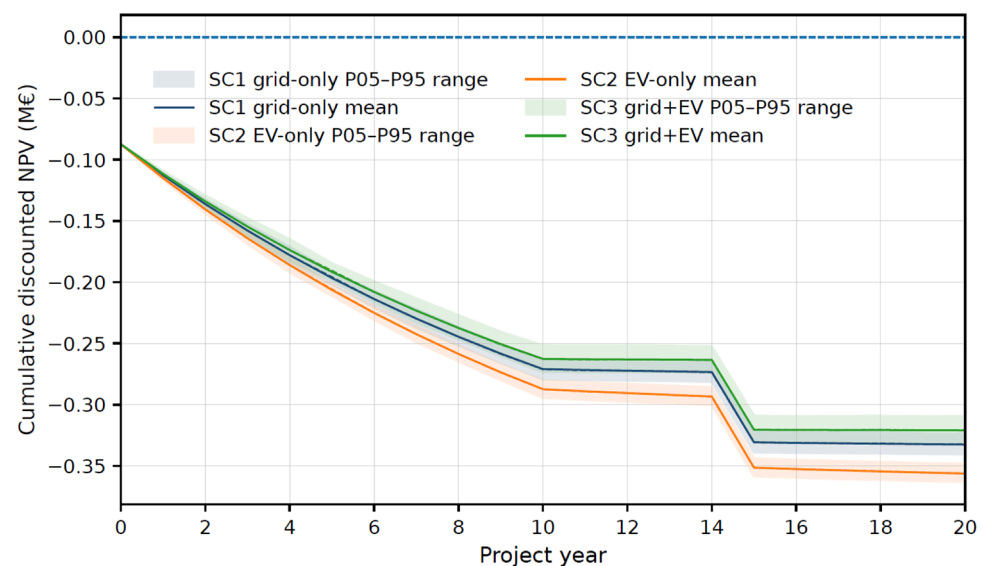


Figure 12. Monte Carlo simulation results of cumulative NPV for the three examined dispatch scenarios, including uncertainty bands over the 20-year project horizon.

The NPV statistics for the Monte Carlo simulation are shown in Table 8. The median NPV is −332.3 k€ for SC1, −356.0 k€ for SC2 and −320.8 k€ for SC3. The P05–P95 ranges are from −340.6 to −323.6 k€ for SC1, from −363.1 to −348.5 k€ for SC2 and from −331.5 to −309.5 k€ for SC3. The probability of having a positive NPV was equal to zero for all three baseline scenarios. SC3 had the highest expected and median NPV and the smallest negative upper percentile, which indicates better financial performance due to market diversification.

Table 8. Monte Carlo NPV statistics of the best non-zero BESS.

Scenario	BESS System ($P_{\max}/E_{\max}$)	Mean NPV (k€)	Median NPV (k€)	Std. dev. NPV (k€)	P05 NPV (k€)	P95 NPV (k€)	Probability NPV > 0 (%)
SC1: Grid-only	0.25 MW/ 0.5 MWh	−332.6	−332.3	5.3	−340.6	−323.6	0
SC2: EV-only	0.25 MW/ 0.5 MWh	−356.3	−356	4.5	−363.1	−348.5	0
SC3: Grid + EV	0.25 MW/ 0.5 MWh	−321	−320.8	6.8	−331.5	−309.5	0

This result answers the main financial question of this study. Based on the base assumptions, the curtailed wind energy does not provide sufficient income for a standalone BESS business, even in the case of allocating stored energy between wholesale grid export and EV charging. The combined strategy reduced the economic loss relative to the EV-only case and slightly outperformed the grid-only case as confirmed by Rancilio et al. [48], but the improvement was not enough to make the best non-zero BESS economically viable.

4.4. Sensitivity Analysis

Changes in expected NPV related to deviations from the base best non-zero BESS parameters are presented in Figure 13 and Table 9. Sensitivity analysis involved distinguishing between three kinds of effects: curtailment-input effects, technical dispatch effects and finance-only valuation effects. It is essential to distinguish between the kinds of effects since different parameters can influence the BESS result via different mechanisms. Curtailment allowance and future-curtailment multipliers affect the amount of available charging input. SoC and round-trip efficiency affect dispatch feasibility and losses. EV demand, EV session energy, EV outlet capacity and EV remuneration affect the EV-related scenarios. CAPEX, replacement cost, loan rate, cost of equity, calendar life and cycle-life influence the financial evaluation.

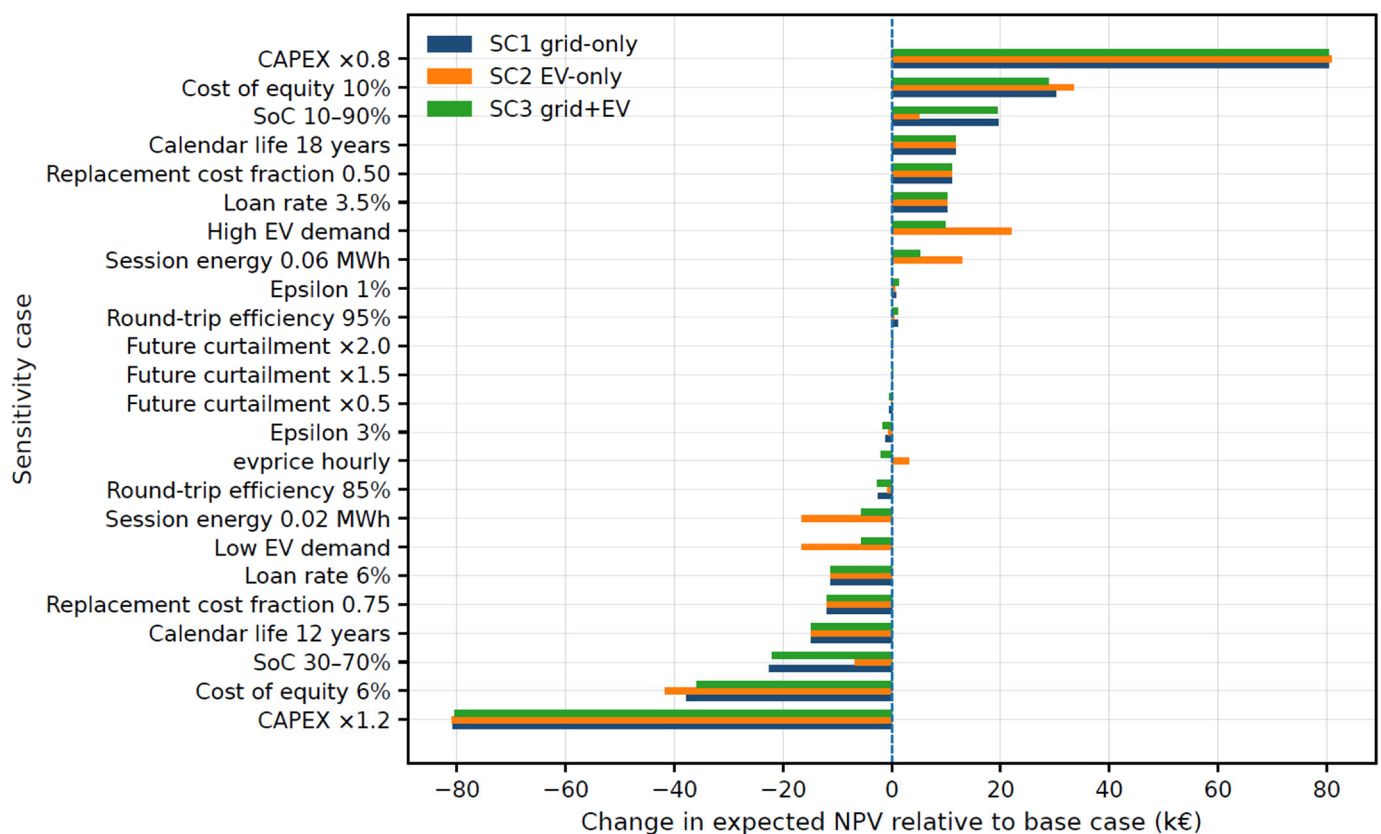


Figure 13. Sensitivity analysis for all SCs.

Table 9. Sensitivity summary: change in best non-zero expected NPV for SC1, SC2 and SC3.

Sensitivity Group	Case	Best Non-Zero BESS ($P_{\max}/E_{\max}$)	SC1 Expected NPV (k€)	Δ NPV vs. Base SC1 (k€)	SC2 Expected NPV (k€)	Δ NPV vs. Base SC2 (k€)	SC3 Expected NPV (k€)	Δ NPV vs. Base SC3 (k€)
Curtailment allowance	$\varepsilon = 1\%$	0.25 MW/0.5 MWh	−331.9	0.7	−355.7	0.5	−319.8	1.2
Curtailment allowance	$\varepsilon = 3\%$	0.25 MW/0.5 MWh	−333.7	−1.1	−356.8	−0.6	−322.7	−1.7
Future curtailment	$\gamma_{\text{curt}} = 0.5$	0.25 MW/0.5 MWh	−333.0	−0.4	−356.4	−0.1	−321.5	−0.5
Future curtailment	$\gamma_{\text{curt}} = 1.5$	0.25 MW/0.5 MWh	−332.4	0.1	−356.2	0.1	−320.8	0.2
Future curtailment	$\gamma_{\text{curt}} = 2.0$	0.25 MW/0.5 MWh	−332.4	0.1	−356.2	0.1	−320.8	0.2

Table 9. Cont.

Sensitivity Group	Case	Best Non-Zero BESS ($P_{\max}/E_{\max}$)	SC1 Expected NPV (k€)	Δ NPV vs. Base SC1 (k€)	SC2 Expected NPV (k€)	Δ NPV vs. Base SC2 (k€)	SC3 Expected NPV (k€)	Δ NPV vs. Base SC3 (k€)
SoC range	10–90%	0.25 MW/ 0.5 MWh	−313.0	19.5	−351.3	5.0	−301.7	19.3
SoC range	30–70%	0.25 MW/ 0.5 MWh	−355.0	−22.5	−363.0	−6.8	−343.0	−22.0
Round-trip efficiency	85%	0.25 MW/ 0.5 MWh	−335.1	−2.5	−357.1	−0.8	−323.7	−2.7
Round-trip efficiency	95%	0.25 MW/ 0.5 MWh	−331.5	1.1	−355.9	0.3	−319.9	1.1
EV demand	Low EV demand	—	—	—	−372.8	−16.5	−326.6	−5.6
EV demand	High EV demand	—	—	—	−334.2	22.0	−311.1	9.9
EV session energy	0.02 MWh/ session	—	—	—	−372.8	−16.5	−326.6	−5.6
EV session energy	0.06 MWh/ session	—	—	—	−343.3	13.0	−315.8	5.2
EV outlet capacity	1 MW	—	—	—	−356.3	0.0	−321.0	0.0
EV outlet capacity	2 MW	—	—	—	−356.3	0.0	−321.0	0.0
EV outlet capacity	5 MW	—	—	—	−356.3	0.0	−321.0	0.0
EV-remuneration timing	Hourly price mode	—	—	—	−353.1	3.2	−323.0	−1.9
CAPEX	$k_{CAPEX} = 0.8$	0.25 MW/ 0.5 MWh	−252.2	80.4	−275.3	80.9	−240.7	80.4
CAPEX	$k_{CAPEX} = 1.2$	0.25 MW/ 0.5 MWh	−413.3	−80.7	−437.2	−80.9	−401.4	−80.4
Replacement cost	$\alpha_{rep} = 0.50$	0.25 MW/ 0.5 MWh	−321.5	11.0	−345.2	11.0	−310.0	11.0
Replacement cost	$\alpha_{rep} = 0.75$	0.25 MW/ 0.5 MWh	−344.5	−11.9	−368.2	−11.9	−332.9	−11.9
Cost of equity	$r_e = 6\%$	0.25 MW/ 0.5 MWh	−370.3	−37.7	−397.9	−41.6	−356.9	−35.9
Cost of equity	$r_e = 10\%$	0.25 MW/ 0.5 MWh	−302.3	30.3	−322.9	33.4	−292.2	28.8
Loan interest rate	3.5%	0.25 MW/ 0.5 MWh	−322.5	10.1	−346.2	10.1	−310.9	10.1
Loan interest rate	6.0%	0.25 MW/ 0.5 MWh	−343.8	−11.3	−367.5	−11.3	−332.3	−11.3
Calendar life (years)	12	0.25 MW/ 0.5 MWh	−347.3	−14.8	−371.0	−14.8	−335.8	−14.8
Calendar life (years)	18	0.25 MW/ 0.5 MWh	−320.8	11.7	−344.5	11.7	−309.3	11.7
Cycle life (full cycles)	6000	0.25 MW/ 0.5 MWh	−332.6	0.0	−356.3	0.0	−321.0	0.0
Cycle life (full cycles)	10,000	0.25 MW/ 0.5 MWh	−332.6	0.0	−356.3	0.0	−321.0	0.0

The change in the event-hour shortfall allowance has a relatively small impact on the economic outcome of BESS. Transition from $\varepsilon = 1\%$ to 2% increased expected NPV by 0.7 k€ in SC1, 0.5 k€ in SC2 and 1.2 k€ in SC3. Transition to $\varepsilon = 3\%$ decreased expected NPV by 1.1 k€ in SC1, 0.6 k€ in SC2 and 1.7 k€ in SC3. Despite the total curtailment estimate changing by approximately $\pm 6\%$, NPV reacts more mildly to the change. That means

that only a certain share of the additional curtailed-energy estimate can be captured and monetised with the help of the best non-zero BESS.

The future-curtailement multiplier affects the NPV quite mildly despite the whole range of variation being explored. Reduction in the amount of curtailment input to $\gamma_{\text{curt}} = 0.5$ has caused only a loss of 0.4 k€ in SC1, 0.1 k€ in SC2 and 0.5 k€ in SC3. An increase in the amount of curtailment input to $\gamma_{\text{curt}} = 1.5$ or 2.0 led to an increase in expected NPV of about 0.1–0.2 k€. Such a mild reaction of NPV to the input change does not indicate that the curtailment is not valuable at all. Instead, it means that, for the chosen best non-zero BESS, under certain operational limitations, additional curtailment availability did not lead to additional profitable discharge. Curtailed-energy availability was only one aspect of the profitability problem; timing of discharge and value of delivered energy were equally important.

On the other hand, the SoC range effect turned out to be more significant. Extending the range of possible SoC values from 20 to 80% to 10–90% increased the expected NPV by 19.5 k€ in SC1, 5.0 k€ in SC2, and 19.3 k€ in SC3. Constraining the SoC range to 30–70% decreased the expected NPV by 22.5 k€ in SC1, 6.8 k€ in SC2 and 22.0 k€ in SC3. The effect demonstrates the significance of usable capacity as an operational limitation. However, the extended SoC range did not make any non-zero BESS profitable despite the improvement in the performance metric. The gains from extra usable capacity were significant but insufficient to offset investment and replacement costs.

Round-trip efficiency turned out to be even less significant than the SoC range effect. Decreasing the round-trip efficiency from the baseline value to 85% decreased the expected NPV by 2.5 k€ in SC1, 0.8 k€ in SC2 and 2.7 k€ in SC3, whereas increasing it to 95% increased the expected NPV by 1.1 k€ in SC1, 0.3 k€ in SC2 and 1.1 k€ in SC3. The limited extent of the effect reflects the small annual energy throughput of the most profitable non-zero BESS. Efficiency improvements are certainly desirable from a technical perspective but cannot compensate for limited utilisation and revenue generation.

Finally, only SC2 and SC3 proved sensitive to EV-demand parameters. Lower EV demand decreased the expected NPV by 16.5 k€ in SC2 and 5.6 k€ in SC3, whereas higher EV demand increased the expected NPV by 22.0 k€ in SC2 and 9.9 k€ in SC3. Similarly, decreasing the average energy per EV session to 0.02 MWh/session decreased the expected NPV by 16.5 k€ in SC2 and 5.6 k€ in SC3, while increasing it to 0.06 MWh/session increased the expected NPV by 13.0 k€ in SC2 and 5.2 k€ in SC3. The analysis reveals that the EV-only scenario is more sensitive to assumptions concerning EV demand compared to the combined one, as SC2 lacks another grid-export channel. SC3, in its turn, is relatively less vulnerable to variations in EV demand, as it can switch to the grid when EV demand is lower.

Increasing the outlet capacity to 1, 2 or 5 MW from the baseline value of 0.55 MW had no significant effect on the expected NPV in either SC2 or SC3. It means that the outlet capacity installed at the base level was not the binding constraint for the optimal BESS deployment in the analysed situations. What defined the performance of the system was the realised EV demand, stored energy and its utilisation, and remuneration of EV services, but not the installed charger capacity. This insight matters because the increase in charger capacity will not necessarily increase the value of BESS investment without higher EV demand or remuneration.

Finally, changing the EV-remuneration case had a relatively modest impact as well. Switching from monthly EV remuneration to an hourly EV price based on the market rate increased the expected NPV in SC2 by 3.2 k€, while reducing it in SC3 by 1.9 k€. Opposite signs of effects resulted from the difference in the allocation logics in the two cases. In SC2, all discharge should go to EV charging, and thus hourly remuneration allows improving

the match between the discharge and remuneration. In SC3, the model can freely allocate discharge between grid and EV, and the hourly remuneration might change their relative attractiveness, which does not necessarily lead to higher profit.

Among all parameters tested, financial parameters showed the most significant impact on expected NPV. A reduction in CAPEX by 20% improved the expected NPV by approximately 80 k€ in all scenarios, whereas an increase in CAPEX by 20% reduced expected NPV by approximately 80 k€. A reduction in the replacement-cost fraction (α_{rep}) to 0.50 improved NPV by 11 k€, and an increase in the replacement-cost fraction to 0.75 decreased NPV by 12 k€. Also, a decrease in the loan interest rate by 2% increased the expected NPV by 10 k€, whereas an increase in the loan interest rate by 2% decreased the expected NPV by 11 k€. Furthermore, a decrease in the calendar life to 12 years reduced the expected NPV by 14.8 k€, while its increase to 18 years increased the expected NPV by 11.7 k€.

No effect of the cycle-life threshold on the result was observed within the tested range from 6000 to 10,000 equivalent full cycles. It means that replacement was triggered by calendar ageing rather than by cycling within the case of the optimal non-zero BESS. The observation is justified by the low annual energy throughput of the battery. The battery was not cycled enough to make the cycle-life be the triggering condition.

The cost of equity sensitivity test returned a result not following the same pattern for the tested values. A decrease in the cost of equity to 6% made the expected NPV more negative, while its increase to 10% improved the expected NPV. Such an effect appears due to the negative or weakly positive net equity cash flows of the project over the whole lifetime, including replacement cost. The higher discount rate lowers the present value of the negative cash flows, while the initial outflow of equity remains undiscounted.

In general, the sensitivity analysis showed that the negative result of the investment is not caused by a single model parameter. The widening of SoC limits, increase in the EV demand, increase in the session energy, decrease in CAPEX, decrease in replacement cost, increase in calendar life, and decrease in the cost of debt all increase the result of the best non-zero BESS, yet none of the one-at-a-time changes makes the base non-zero BESS viable. The result is therefore robust: under the present market boundary, curtailed-energy-only charging does not create sufficient value to support a dedicated BESS investment.

4.5. Analysis of the EV-Premium Margin and EV Demand Diagnostics

The final analysis focused on the EV service premium required to achieve a non-negative NPV. The two EV-related scenarios were investigated with the help of two viability diagnostics. The first diagnostic varied the EV service premium (p_{EV}), while the second diagnostic varied the realised EV-demand multiplier (κ_{EV}) at the base EV service premium.

Figure 14 presents the expected NPV of the best non-zero BESS in SC2 and SC3 as a function of increasing EV service premium from 50 to 1400 €/MWh. For each EV-premium, the full BESS candidate set was re-dispatched and re-ranked. As such, the curves presented in the figure cannot be regarded as a post-processing calculation for a fixed-size candidate set. The curves represent the results of re-optimisation of the BESS for every EV premium assumption. Expected NPV is almost monotonically increasing with the EV service premium in both EV-related scenarios. Thus, it confirms that the EV remuneration is one of the major factors driving the financial result.

However, the required premium is very high. The breakeven search revealed that the EV-only scenario needs an EV service premium of about 1207.5 €/MWh, while the combined grid and EV scenario needs approximately 1186.4 €/MWh. The values of these breakeven premiums are much higher than the base premium of 50 €/MWh and thus show that the current EV outlet remuneration assumption is far below the required level to make

a non-zero BESS investment feasible. SC3 reaches breakeven at a lower premium since it can utilise grid export and EV charging, while SC2 relies on EV outlet only.

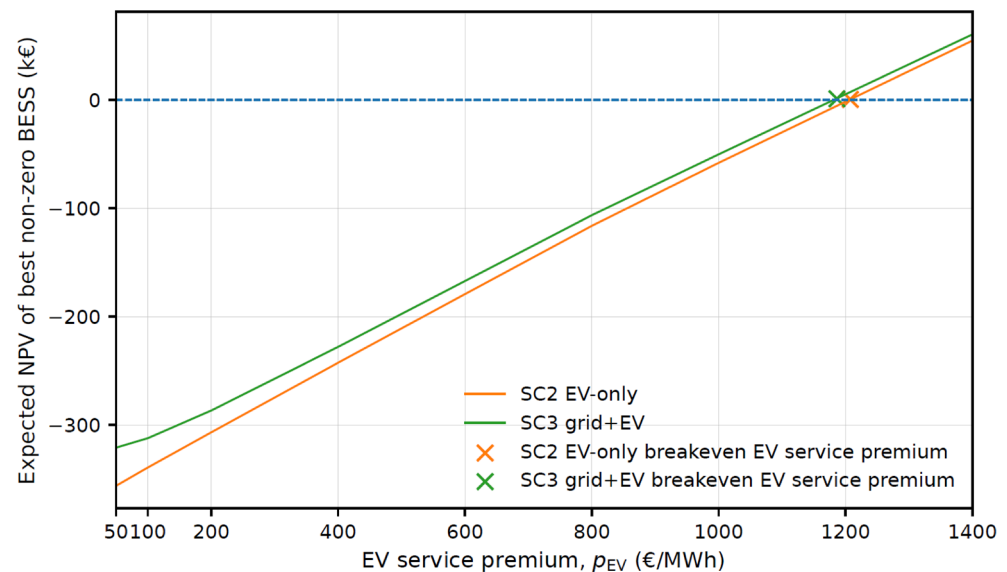


Figure 14. Expected NPV variation in the EV-based dispatch scenarios (SC2 and SC3) under different EV-premium values.

The premium for EV services mentioned earlier does not reflect the actual cost of charging, but rather the extra compensation needed to make use of surplus wind energy that would otherwise go to waste. To put this into perspective, public DC charging points in Greece usually charge between 0.49 and 0.67 €/kWh [49], while the minimum premium required to make battery energy storage a viable investment is around 1.19 to 1.21 €/kWh. This disparity underscores the substantial difference between the revenue needed to justify investing in battery storage and the current market rates for EV charging.

As reported in Table 10, the EV-only case reached breakeven at an EV service premium of approximately 1208 €/MWh, with an expected NPV of 0.45 k€. The combined grid-plus-EV case reached breakeven at a slightly lower premium of approximately 1186 €/MWh, with an expected NPV of 1.05 k€. In both cases, the re-optimised best non-zero BESS system remained $P_{max} = 0.25$ MW and $E_{max} = 0.5$ MWh. This indicates that the high EV premium did not justify a larger BESS under the observed curtailed-energy availability and operational constraints. Instead, the increased remuneration made the smallest non-zero BESS marginally viable.

Figure 15 shows the cumulative NPV trajectory at the EV-premium breakeven values. At these premiums, the cumulative NPV tends to zero during 20 years horizon. The form of the curves is still impacted by the same investment and replacement scheme as in the baseline case; however, the higher remuneration of EV makes the annual income sufficient to cover the investment costs. This result demonstrates that the key problem is not the technical impossibility of dispatching the curtailed wind energy to the EV outlet. The key problem is the level of remuneration of EV outlets in comparison to the cost of investment and replacement of BESS.

An alternative analysis of the issue is provided by the EV-demand multiplier diagnostic. Here, the EV service premium is left unchanged at the base value of 50 €/MWh, and the raw traffic-derived EV-demand profile is multiplied by the factor κ_{EV} before imposing the EV outlet-capacity limit. As Table 10 illustrates, there was no EV-demand breakeven achieved in either of the two studied scenarios, SC2 and SC3, over the tested

range $\kappa_{EV} = 1\text{--}100$. Specifically, at the top end of the tested range, $\kappa_{EV} = 100$, the best non-zero BESS has an expected negative NPV of -271.86 k€ in SC2 and -250.91 k€ in SC3.

Table 10. EV service-premium and EV-demand breakeven diagnostics.

Scenario	Diagnostic	Tested Parameter Range	Re-Optimised BESS System ($P_{\max}/E_{\max}$)	Breakeven Parameter	Expected NPV at Breakeven (k€)
SC2: EV-only	EV service premium	50–1400 €/MWh	0.25 MW/0.5 MWh	1207.5 €/MWh	0.45
SC3: Grid + EV	EV service premium	50–1400 €/MWh	0.25 MW/0.5 MWh	1186.4 €/MWh	1.05
SC2: EV-only	EV demand multiplier	$\kappa_{EV} = 1\text{--}100$	0.25 MW/0.5 MWh	No breakeven ($\kappa_{EV} = 100$)	-271.86
SC3: Grid + EV	EV demand multiplier	$\kappa_{EV} = 1\text{--}100$	0.25 MW/0.5 MWh	No breakeven ($\kappa_{EV} = 100$)	-250.91

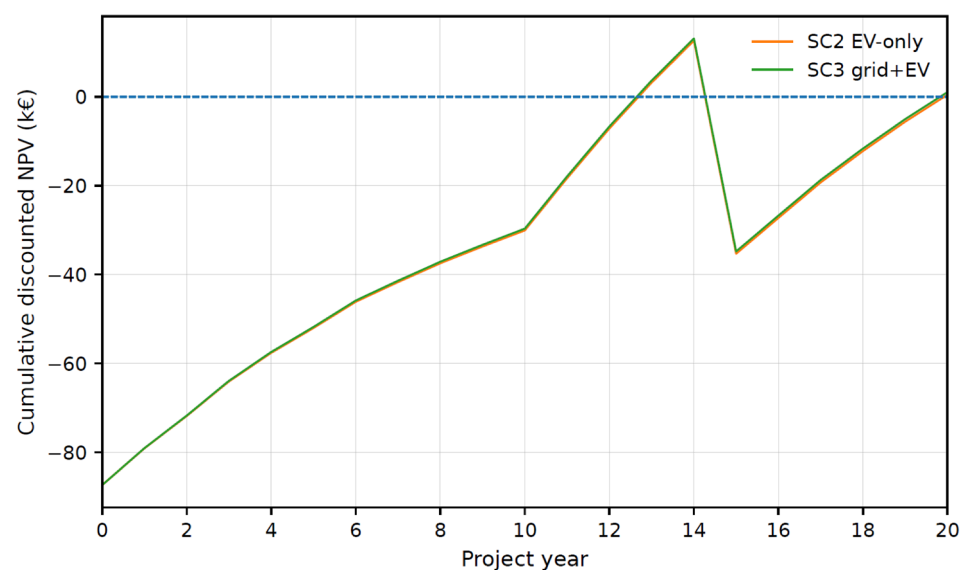


Figure 15. Cumulative NPV evolution of the EV-based dispatch scenarios (SC2 and SC3) at the breakeven EV-premium values over the 20-year project horizon.

This means that increasing the demand for EV charging is not enough, as the EV service premium stays at the base value of 50 €/MWh. Increasing κ_{EV} leads to an increase in the potential EV demand to absorb the discharged energy, but it does not lead to an increase in the revenue generated per MWh. After relaxing the EV-demand constraint, the investment is constrained by the amount and timing of curtailed energy available, by the assumption of charging from curtailment only, by the EV outlet-capacity limit, SoC and power limitations, and by the cost of the BESS.

The comparison of the two scenarios demonstrates once again the importance of market diversification. SC3 requires a smaller EV service premium than SC2 and generates a less negative NPV for the case of the high EV-demand multiplier. This happens because the stored energy can be utilised for grid export and EV charging in SC3, while in SC2, solely for the latter. However, even the benefit offered by this strategy was not enough to make the investment viable in the case of the base EV service premium.

Overall, it is clear from Table 10 that the problem is more about the remuneration than about the availability of demand. A high enough EV service premium can bring the best non-zero BESS to near breakeven, but very significant growth in EV demand cannot do so with the EV service premium staying at the base level. It means that the economic viability of the use of curtailed wind energy for EV charging would require not only increased

demand for such charging but also significantly increased price for the energy delivered to the EV outlet, decreased cost of the BESS, or extra revenue streams.

4.6. Discussion of the Research Outcome

The results provide a coherent response to the three research questions of the study and clarify the techno-economic conditions under which curtailed wind energy can be recovered through battery storage. The analysis showed that the proposed MILP dispatch framework was able to allocate stored curtailed wind energy between wholesale grid export and EV charging while respecting the main operational restrictions of the system, including battery power and energy limits, SoC bounds, curtailment-only charging, grid-export restrictions during IPTO-event hours, and EV-demand constraints. With regard to the first research question, the result means that the proposed model framework can identify not only how much curtailed energy will be stored and discharged, but also how this energy should be distributed between different streams. Among all BESS installations with non-zero values, the SC3 strategy produced the highest expected NPV as it could select one of the two value streams based on hourly conditions. Nevertheless, the no-investment scenario revealed that in all considered scenarios the decision of no BESS installation was the globally maximising NPV decision under the base assumptions.

Regarding the second research question, the results show that combining grid-export and EV charging leads to a more economically advantageous approach of curtailed-energy utilisation compared to single-outlet approaches. In particular, SC3 yielded the highest expected NPV, the highest average annual revenue, and the most flexible dispatch allocation among all BESS installations. SC2 was the weakest baseline scenario because of its dependence on EV demand and remuneration of the charge service; i.e., when EV demand was unavailable or not sufficient, there was no other way to utilise the stored energy. While SC1 performed better than SC2 due to greater discharge opportunity of the grid-export stream, it lacked additional value stream related to EV charging. Hence, the combined strategy generated some economic advantages, but they were not large enough to make it financially feasible. The main point is that market diversification improves BESS economics, but diversification itself is not sufficient when the charging stream is limited to the event-conditioned curtailed wind energy only.

Regarding the third research question, the sensitivity analysis helped to identify the parameters having the greatest influence on the maximisation of NPV. According to the results, the expected NPV was influenced most of all by CAPEX, SoC operating range, EV demand, EV session energy, replacement cost, loan interest rate, and calendar life. Round-trip efficiency, the allowance for curtailment estimation, and EV outlet capacity had less influence. It is especially important to note the weak response to an increase in EV outlet capacity because it shows that installation of higher power chargers is not enough when actual EV demand, curtailed-energy availability, and EV remuneration are limited. Similarly, the negligible influence of the cycle-life threshold means that in the best non-zero BESS configuration, the replacement of the unit was determined by calendar ageing rather than intensive cycling. It corresponds to relatively low utilisation of the asset per year.

One of the broader implications of these results is that even the event-conditioned curtailed energy should not be regarded as a sufficient resource for profitable investment just because it does not have any purchase cost. In spite of the fact that BESS charges only from energy, which is otherwise curtailed, it should cover the investment in the BESS unit, its replacement, financing, and operational costs through discharge revenue streams. The event-conditioned curtailment profile was intermittent and temporally clustered, while the dispatch model incorporated constraints on charging, discharging, grid-export, and EV delivery. Therefore, only a limited part of the estimated curtailed energy could be

monetized. This explains why despite the relatively high estimate of event-conditioned curtailed energy, the corresponding BESS investment is not financially feasible.

At the same time, the results stress the importance of policy and market design for the implementation of BESS projects aimed at curtailment recovery. When recovered curtailed energy is valued solely through day-ahead wholesale prices and moderate EV service premiums, a dedicated BESS is likely to remain uneconomic. EV-premium and EV-demand diagnostics confirmed that EV charging could add to the value of stored curtailed energy, but a significantly higher EV-remuneration level is required to reach break-even under the current assumptions. Therefore, profitability of the project would likely need a higher EV-remuneration level, lower BESS installation costs, longer calendar life of the BESS, lower replacement cost, additional revenues, or specific incentives. Additional revenues were not taken into account in the current study because they require detailed market information and additional constraints to avoid double-counting, but they are important extensions for further studies.

Because the available curtailment dataset did not identify whether each reported curtailment event was caused by local point-of-connection congestion, upstream transmission constraints, or system-level operational measures, the residual point-of-connection headroom used in non-event hours should be interpreted as a local upper-bound proxy rather than as a full network-feasibility assessment. If upstream constraints also limited BESS export during some non-event hours, the grid-export revenues of SC1 and SC3 could be overestimated. This would further reduce the already negative NPVs of the non-zero BESS candidates.

Finally, it should be noted that the results should be interpreted in light of the limitations of the used data and modelling boundary. The estimated curtailed-energy series was event-conditioned and model-based, not metered. The Monte Carlo analysis used two observed blocks of years and thus represents the conditional within-sample uncertainty assessment, not climatological or market price distribution. Nonetheless, the combination of holdout validation, allowance sensitivity, no-investment benchmarking, Monte Carlo statistics, full re-optimisation sensitivity analysis, and EV viability diagnostics provides a solid foundation for the main result of the study. In particular, under the observed curtailment pattern and base market assumptions, the curtailed wind energy alone was not enough for a profitable BESS investment, but a combined grid-plus-EV strategy yielded better results than single-outlet dispatch strategies.

4.7. Novelty

The novelty of this study lies in the development of a techno-economic optimisation framework that views curtailed wind energy not just as lost renewable generation but as a constrained energy resource that can be recovered, stored, and assigned to other value streams. While many studies explore ways to reduce renewable curtailment through storage, grid improvements, demand response, or market involvement, this work specifically targets the economic use of wind energy that would otherwise be curtailed. Thus, the available charging energy of the BESS is not assumed to be freely available from the grid; instead, it is determined by when, how much, and for how long curtailment events occur.

Another contribution is the simultaneous consideration of BESS sizing and dispatch allocation between two competing uses: exporting to the wholesale electricity market and supplying EV charging. Conventional battery storage studies often look at either electricity market arbitrage or curtailment reduction as separate uses, while EV charging is usually seen as a flexible load rather than a separate market channel for stored renewable energy.

In contrast, this study treats the EV charging facility as an alternative revenue stream for curtailed wind energy. It has its own demand profile, installed charging capacity,

power limits, and market-based payment signal. This approach helps quantify whether EV charging can enhance the value of curtailed wind energy compared to conventional grid export. The proposed framework does not evaluate profitability only after selecting a specific BESS size. Instead, the battery energy capacity and rated power are treated as decision variables that are re-optimised for each dispatch scenario and sensitivity case. This is crucial because the best BESS setup for economic purposes may differ from the most efficient setup that maximises curtailed-energy absorption. By clearly linking sizing, dispatch, battery cycling, replacement needs, financing assumptions, and long-term NPV, the study offers a more realistic view of whether curtailed wind energy can justify a dedicated storage investment on its own.

5. Conclusions

This study assessed whether event-conditioned curtailed wind energy from a 43.2 MW wind farm could support a co-located BESS that allocates stored energy to wholesale grid export, EV charging, or both outlets. The workflow combined expected-generation calibration, curtailment estimation, MILP dispatch, discrete BESS sizing, FCFE-based valuation, Monte Carlo uncertainty, sensitivity analysis, constraint-relaxation diagnostics, and EV-viability diagnostics. Under the base shortfall allowance of $\varepsilon = 2\%$, 1537 IPTO-event hours returned positive estimated curtailment, corresponding to approximately 10.26 GWh of estimated recoverable curtailed energy over the examined period.

Despite this available resource, the no-investment alternative proved to be the global maximum of NPV for all baseline cases. The best non-zero BESS was 0.25 MW/0.5 MWh of P_{max} and E_{max} respectively, with expected NPVs of -332.6 k€ for grid-only operation, -356.3 k€ for EV-only operation, and -321.0 k€ for the combined grid-plus-EV strategy. SC3 therefore improved the economics relative to the single-outlet cases, but the improvement was not sufficient to make the investment profitable. The Monte Carlo results also remained negative across the P05–P95 ranges, with zero probability of positive NPV under the baseline assumptions. Thus, charging the BESS exclusively from curtailed wind energy did not yield positive economic results under the observed curtailment pattern and base market conditions.

The constraint-relaxation and sensitivity results support this outcome. The estimated curtailment was intermittent and temporally clustered, grid export was prohibited during IPTO-event hours, and the BESS could not charge and discharge within the same hourly interval. Utilisation was further limited by usable energy capacity, SoC bounds, temporal mismatch between curtailment and EV demand, and the small economically selected BESS size. CAPEX, SoC operating range, EV demand, EV session energy, replacement cost, loan interest rate, and calendar life had the strongest influence on expected NPV, whereas EV outlet capacity and cycle-life were not binding under the base utilisation pattern.

The EV diagnostics showed that remuneration was more limiting than demand availability alone. Non-negative expected NPV required very high EV service premiums of approximately 1208 €/MWh in SC2 and 1186 €/MWh in SC3, while increasing realised EV demand up to $\kappa_{EV} = 100$ did not reach breakeven at the base premium of 50 €/MWh. The financial feasibility of a battery energy storage system that relies solely on excess wind energy hinges on a delicate balance of factors. For such a venture to be successful, several key elements must align, including a significant increase in the amount of recoverable surplus energy, more lucrative incentives for electric vehicle owners, reduced upfront costs for the storage system, and the ability to tap into supplementary sources of income. Simply boosting demand for electric vehicle charging or expanding charging infrastructure is not enough to tip the scales in favour of economic viability. Ultimately, unless there are concurrent improvements in both the revenue streams and the fundamental economics of

the project, harnessing wasted wind energy through a dedicated storage system remains a financially unviable proposition under current market and operational conditions.

Future research should therefore examine hybrid operating strategies in which the BESS can also charge during non-curtailment periods, such as low-price or high-renewable-output hours, while explicitly accounting for charging costs and avoiding revenue double-counting. Further extensions should include directly metered curtailment data, longer weather and market datasets, dynamic EV tariffs, observed charging-station utilisation, and stacked revenues from balancing or ancillary-service markets.

Author Contributions: Conceptualization, D.A. and E.G.; methodology, D.A.; software, D.A.; validation, D.A.; formal analysis, D.A. and E.G.; investigation, D.A. and E.G.; resources, D.A. and E.G.; data curation, D.A.; writing—original draft preparation, D.A. and E.G.; writing—review and editing, D.A. and E.G.; visualisation, D.A.; supervision, D.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Publicly available datasets were analysed in this study, including ERA5 hourly reanalysis wind fields (Copernicus Climate Change Service) and a day-ahead electricity price dataset for Greece from the Hellenic Energy Exchange S.A. (HEEx S.A.). The turbine power curve was taken from the cited Vestas V117 documentation/reference. The processed hourly wind–price time series and the Spyder version 6 workflow used to generate the results are available from the corresponding author upon reasonable request.

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

Abbreviations

The following abbreviations are used in this manuscript:

AFIR	Alternative Fuels Infrastructure Regulation
BESS	Battery Energy Storage System
CAPEX	Capital Expenditure
Eq	Equation
EV	Electric Vehicle
FCFE	Free Cash Flow to Equity
G2V	Grid-to-Vehicle
MAE	Mean Absolute Error
MBE	Mean Bias Error
NPV	Net Present Value
POC	Point of Connection
RES	Renewable Energy Sources
RMSE	Root Mean Square Error
RQ	Research Question
SC	Scenario
SoC	State of Charge
V2G	Vehicle-to-Grid

References

1. European Council. European Green Deal. Available online: <https://www.consilium.europa.eu/en/policies/european-green-deal/> (accessed on 5 June 2026).
2. European Commission. The European Green Deal. Available online: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en (accessed on 5 June 2026).
3. UNFCCC. The Kyoto Protocol. Available online: <https://unfccc.int/process-and-meetings/the-kyoto-protocol> (accessed on 5 June 2026).

4. UNFCCC. The Paris Agreement. Available online: <https://unfccc.int/process-and-meetings/the-paris-agreement> (accessed on 5 June 2026).
5. European Union. Official Journal of the European Union, L 243. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=oj:JOL_2021_243_R_TOC (accessed on 5 June 2026).
6. IPCC. *Climate Change 2023: Synthesis Report*; Lee, H., Romero, J., Eds.; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2023.
7. Gryparis, E.; Papadopoulos, P.; Leligou, H.C.; Psomopoulos, C.S. Electricity Demand and Carbon Emission in Power Generation under High Penetration of Electric Vehicles. A European Union Perspective. *Energy Rep.* **2020**, *6*, 475–486. [\[CrossRef\]](#)
8. Fang, X.; Misra, S.; Xue, G.; Yang, D. Smart Grid—The New and Improved Power Grid: A Survey. *IEEE Commun. Surv. Tutor.* **2012**, *14*, 944–980. [\[CrossRef\]](#)
9. Luo, X.; Wang, J.; Dooner, M.; Clarke, J. Overview of Current Development in Electrical Energy Storage Technologies and the Application Potential in Power System Operation. *Appl. Energy* **2015**, *137*, 511–536. [\[CrossRef\]](#)
10. EMBER. Electricity Data Explorer. Available online: <https://ember-energy.org/data/electricity-data-explorer> (accessed on 5 June 2026).
11. Syranidou, C.; Linssen, J.; Stolten, D.; Robinius, M. Integration of Large-Scale Variable Renewable Energy Sources into the Future European Power System: On the Curtailment Challenge. *Energies* **2020**, *13*, 5490. [\[CrossRef\]](#)
12. Kies, A.; Schyska, B.U.; Von Bremen, L. Curtailment in a Highly Renewable Power System and Its Effect on Capacity Factors. *Energies* **2016**, *9*, 510. [\[CrossRef\]](#)
13. Bundesnetzagentur SMARD. Congestion Management in the Second Quarter of 2024. Available online: <https://www.smard.de/page/en/topic-article/5892/215186/congestion-management-in-the-second-quarter-of-2024> (accessed on 5 June 2026).
14. Schermeyer, H.; Vergara, C.; Fichtner, W. Renewable Energy Curtailment: A Case Study on Today's and Tomorrow's Congestion Management. *Energy Policy* **2018**, *112*, 427–436. [\[CrossRef\]](#)
15. Frysztacki, M.; Brown, T. Modeling Curtailment in Germany: How Spatial Resolution Impacts Line Congestion. In Proceedings of the 2020 17th International Conference on the European Energy Market (EEM), Stockholm, Sweden, 16–18 September 2020; pp. 1–7.
16. Syranidou, C.; Linssen, J.; Stolten, D.; Robinius, M. On the Curtailments of Variable Renewable Energy Sources in Europe and the Role of Load Shifting. In Proceedings of the 2020 55th International Universities Power Engineering Conference (UPEC), Turin, Italy, 1–4 September 2020; pp. 1–6.
17. Villamor, L.V.; Avagyan, V.; Chalmers, H. Opportunities for Reducing Curtailment of Wind Energy in the Future Electricity Systems: Insights from Modelling Analysis of Great Britain. *Energy* **2020**, *195*, 116777. [\[CrossRef\]](#)
18. Möst, D.; Ladwig, T.; Gunkel, D. How Does Renewable Curtailment Influence the Need of Transmission and Storage Capacities in Europe? In Proceedings of the 13th European IAAE Conference 2013, Düsseldorf, Germany, 18 August 2013.
19. Root, C.; Presume, H.; Proudfoot, D.; Willis, L.; Masiello, R. Using Battery Energy Storage to Reduce Renewable Resource Curtailment. In Proceedings of the 2017 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 23–26 April 2017; pp. 1–5.
20. Klinge Jacobsen, H.; Schröder, S.T. Curtailment of Renewable Generation: Economic Optimality and Incentives. *Energy Policy* **2012**, *49*, 663–675. [\[CrossRef\]](#)
21. Mohan, V.; Suresh, M.P.R.; Singh, J.G.; Ongsakul, W.; Kumar, B.K. Online Optimal Power Management Considering Electric Vehicles, Load Curtailment and Grid Trade in a Microgrid Energy Market. In Proceedings of the 2015 IEEE Innovative Smart Grid Technologies—Asia (ISGT ASIA), Bangkok, Thailand, 3–6 November 2015; pp. 1–6.
22. Lee, J.; Lee, J.; Wi, Y.-M.; Joo, S.-K. Stochastic Wind Curtailment Scheduling for Mitigation of Short-Term Variations in a Power System with High Wind Power and Electric Vehicle. *Appl. Sci.* **2018**, *8*, 1684. [\[CrossRef\]](#)
23. Alkhalidi, A.; Alqarra, K.; Abdelkareem, M.A.; Olabi, A.G. Renewable Energy Curtailment Practices in Jordan and Proposed Solutions. *Int. J. Thermofluids* **2022**, *16*, 100196. [\[CrossRef\]](#)
24. Szinai, J.K.; Sheppard, C.J.R.; Abhyankar, N.; Gopal, A.R. Reduced Grid Operating Costs and Renewable Energy Curtailment with Electric Vehicle Charge Management. *Energy Policy* **2020**, *136*, 111051. [\[CrossRef\]](#)
25. Hersbach, H.; Bell, B.; Berrisford, P.; Biavati, G.; Horányi, A.; Muñoz Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Rozum, I.; et al. ERA5 Hourly Data on Single Levels from 1940 to Present. Available online: <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download> (accessed on 26 January 2026).
26. The Wind Power. Vestas V117/3600—Manufacturers and Turbines—Online Access. Available online: https://www.thewindpower.net/turbine_en_1809_vestas_v117-3600.php (accessed on 30 March 2026).
27. IPTO. RES Curtailments. Available online: <http://www.admie.gr/systima/leitourgia/periorismoi-ape> (accessed on 7 April 2026).
28. Craig, E.A. Uncertainty Quantification in Wind Plant Energy Estimation. In Proceedings of the AIAA SciTech 2019 Forum, San Diego, CA, USA, 7–11 January 2019.

29. Castano, S.; Gauchia, L.; Voncila, E.; Sanz, J. Dynamical Modeling Procedure of a Li-Ion Battery Pack Suitable for Real-Time Applications. *Energy Convers. Manag.* **2015**, *92*, 396–405. [CrossRef]
30. Cole, W.; Ramasamy, V.; Turan, M. *Cost Projections for Utility-Scale Battery Storage: 2025 Update*; Technical Report NREL/TP-6A40-93281; National Renewable Energy Laboratory: Golden, CO, USA, 2025.
31. IPTO S.A. Specification No SS-25/20: Three-Phase Transformers 150/20 kV. Available online: https://www.admie.gr/sites/default/files/inline-files/groups/ADMIE_DAPM/406501/406501_el_PRODIAGRAFI.pdf (accessed on 3 July 2026).
32. IEA. Electric Vehicle Charging—Global EV Outlook 2025—Analysis. Available online: <https://www.iea.org/reports/global-ev-outlook-2025/electric-vehicle-charging> (accessed on 5 April 2026).
33. Rupnik, B.; Wang, Y.; Kramberger, T. Hybrid Model for Motorway EV Fast-Charging Demand Analysis Based on Traffic Volume. *Systems* **2025**, *13*, 272. [CrossRef]
34. Anadón Martínez, V.; Sumper, A.; Saldaña-Gonzalez, A.E.; Gadelha, V. Planning Fast-Charging Stations along Highways Using Probability Distribution Functions and Traffic Data. *Sustain. Energy Technol. Assess.* **2025**, *82*, 104547. [CrossRef]
35. European Alternative Fuels Observatory Vehicles and Fleet: Greece. Available online: <https://alternative-fuels-observatory.europa.eu/transport-mode/road/greece/vehicles-and-fleet> (accessed on 3 July 2026).
36. Data-Gov.gr. Traffic Data from Toll Stations in Hellastron Network. Available online: <https://staging.data.gov.gr/en/dataset/data-pan-gov-gr-traffic-data-from-toll-stations-in-hellastron-network> (accessed on 14 April 2026).
37. Hecht, C.; Figgenger, J.; Sauer, D.U. Analysis of Electric Vehicle Charging Station Usage and Profitability in Germany Based on Empirical Data. *iScience* **2022**, *25*, 105634. [CrossRef] [PubMed]
38. ENEX Group. Electricity Market Results. Available online: <https://www.enexgroup.gr/dam-idm-archive> (accessed on 5 June 2026).
39. Gnann, T.; Funke, S.; Jakobsson, N.; Plötz, P.; Sprei, F.; Bennehag, A. Fast Charging Infrastructure for Electric Vehicles: Today's Situation and Future Needs. *Transp. Res. Part D Transp. Environ.* **2018**, *62*, 314–329. [CrossRef]
40. Kim, S.H.; Shin, Y.-J. Optimize the Operating Range for Improving the Cycle Life of Battery Energy Storage Systems under Uncertainty by Managing the Depth of Discharge. *J. Energy Storage* **2023**, *73*, 109144. [CrossRef]
41. Lis, M.; Mądział, M. A Simulation-Based Decision-Support Framework for EV Charging Infrastructure Development Along a TEN-T Corridor. *Appl. Sci.* **2026**, *16*, 4902. [CrossRef]
42. Apostolou, D.; Xydis, G. Sustainable Integration of Offshore Wind Energy with Green Ammonia Production Systems. *Sustainability* **2026**, *18*, 2938. [CrossRef]
43. Trading Economics. Greece Corporate Tax Rate. Available online: <https://tradingeconomics.com/greece/corporate-tax-rate> (accessed on 31 March 2026).
44. Garttan, G.; Alahakoon, S.; Emami, K.; Jayasinghe, S.G. Battery Energy Storage Systems: Energy Market Review, Challenges, and Opportunities in Frequency Control Ancillary Services. *Energies* **2025**, *18*, 4174. [CrossRef]
45. Hulten, E.-C. *Depreciation, Inflation, and the Taxation of Income from Capital*; Urban Institute Press: Washington, DC, USA, 1981.
46. Bank of Greece. Interest Rates on Bank Deposits and Loans: January 2026. Available online: <https://www.bankofgreece.gr/en/news-and-media/press-office/news-list/news?announcement=73029d42-ed8e-4fa0-b509-c09530c297e1> (accessed on 31 March 2026).
47. Roth, A.; Brückmann, R.; Jimeno, M.; Dukan, M.; Kitzing, L.; Breitschopf, B.; Alexander-Haw, A.; Lucia, A.; Blanco, A.; Resch, G.; et al. *Renewable Energy Financing Conditions in Europe: Survey and Impact Analysis*; AURES II Project Report D5.2; European Commission: Brussels, Belgium, 2021.
48. Rancilio, G.; Dimovski, A.; Bovera, F.; Moncecchi, M.; Falabretti, D.; Merlo, M. Service Stacking on Residential BESS: RES Integration by Flexibility Provision on Ancillary Services Markets. *Sustain. Energy Grids Netw.* **2023**, *35*, 101097. [CrossRef]
49. Incharge. Drivers' Club. Available online: <https://www.incharge.gr/el/drivers-club/> (accessed on 15 July 2026).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.