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Technical Modelling and Market Feasibility of V2X Services for Enhanced Grid Stability and Efficiency in Renewable-Rich Distribution Networks

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ABSTRACT:

This thesis evaluates the techno-economic role of electric vehicle (EV) battery participation in a renewable-integrated distribution-network context using the Vaasa/Sundom area in Finland as the case study. The study focuses on how EV-based flexibility can support a local wind–photovoltaic (PV) storage system by improving renewable-energy utilization, reducing dependence on the external grid, lowering curtailment and influencing the levelized cost of energy (LCOE). The techno-economic analysis was carried out using the Hybrid Optimization and Performance Platform (HOPP) in a Python code workflow. The model was based on electricity demands from three substations J06 Sulva, J07 Sundom and J09 Vaskiluoto, wind-resource data, PV capacity factors, electricity spot prices, stationary battery assumptions, EV battery assumptions and technology cost parameters. The annual simulation was performed over 8760 hourly time steps. Three cases of EV participation were considered: NoEV, BEV50 and BEV80. For these cases there are four different TargetUnmet presenting the maximum share of annual demand that the external grid can supply with the remaining demand supplied by local wind generation, PV generation, stationary battery storage and EV battery if applicable. The lowest configuration was Target80Unmet_NoEV with an LCOE of 89.32 €/MWh, clearly showing that the zero-EV case was the most viable one when the local renewable supply was the lowest. But things changed when a higher percentage of the demand had to be met from local sources. In the Target40Unmet and Target20Unmet cases use of BEV50 and BEV80 led to lower LCOE compared to NoEV demonstrating that EV flexibility is more important with more stringent local-supply requirements. It was also observed that there is a strong trade-off between grid dependence, renewables overbuilding, storage need, curtailment and the system cost. Several scenarios achieved curtailment reduction with stationary battery and even in a few cases battery storage did not entirely replace stationary storage. The price-based dispatch analysis also showed that the EV batteries can provide added value, by being charged at low prices and discharged at high prices. In conclusion, all results indicate that V2G should not be treated as a standalone solution, but rather as a flexibility resource to be used in combination with a larger wind–PV–storage system.

KEYWORDS: (Electric vehicle, Vehicle to Grid, bidirectional charging, renewable energy integration, techno-economic analysis, Simulink simulation, battery storage, LCOE).

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Abbreviations

AC	Alternating Current
APEX	Annualized Capital Expenditure
BEV	Battery Electric Vehicle
CAPEX	Capital Expenditure
CF	Capacity Factor
CRF	Capital Recovery Factor
DC	Direct Current
DC-link	Direct Current Link
DER	Distributed Energy Resource
DSO	Distribution System Operator
EV	Electric Vehicle
FCR-D	Frequency Containment Reserve for Disturbances
G2V	Grid-to-Vehicle
HOPP	Hybrid Optimization and Performance Platform

IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
ISO	International Organization for Standardization
kV	Kilovolt
LCOE	Levelized Cost of Energy
LV	Low Voltage
MV	Medium Voltage
MW	Megawatt
MWh	Megawatt-hour
OPEX	Operational Expenditure
P	Active Power
PV	Photovoltaic
PWM	Pulse Width Modulation
Q	Reactive Power
RES	Renewable Energy Source
SOC	State of Charge
THD	Total Harmonic Distortion
TSO	Transmission System Operator
V2B	Vehicle-to-Building
V2C	Vehicle-to-Community
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
V2L	Vehicle-to-Load
V2Q	Vehicle-to-Quarter
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
WT	Wind Turbine
€/MWh	Euro per Megawatt-hour

1 Introduction

1.1 Background and Motivation

Transport electrification and a high rate of renewable electricity generation are altering how present-day power systems are planned and operated. Electric vehicles are no longer just transport technologies, as their batteries can also communicate with the electricity system through controlled charging and bidirectional charging (Acharige et al., 2022). Meanwhile, wind and solar generation amplify the necessity of flexibility due to variations in their output because of weather conditions and a lack of correspondence between their generation and electricity demand (Jung & Broadwater, 2014). A high level of renewable penetration thus necessitates flexible resources that can move energy over time and lessen the gap between the generation and demand (Solomon et al., 2019). In this regard, EV batteries can be used to support the grid by charging during the excess renewable generation and discharging or reducing demand during peak times (Wang et al., 2024).

However, EV charging has the potential to impose new stresses in the distribution networks, unless coordinated effectively. Unregulated charging can lead to higher peak demand, deviation in voltages, loading of the transformer, congesting feeder and network losses (Ibrahim et al., 2024). The planning of charging infrastructure has also demonstrated that the location of chargers, charger power capacity and the local grid capacity must be considered as a group since the needs of charging affect both the transport system and the system of power distribution (Unterluggauer et al., 2022). To mitigate some of these effects, smart charging can shift charging to less expensive or more renewable times (Szinai et al., 2020). Nevertheless, smart charging merely regulates the time when EV use electricity, whereas V2G allows EV to also provide electricity back to the grid as long as this is technically and economically feasible(Acharige et al., 2022).

Vehicle-to-Grid and broader Vehicle-to-Everything services are thus coming under more scrutiny as a flexibility option in future smart grids. V2G enables EV to serve as distributed storage resources that can support the peak-shaving, the voltage regulation, the frequency regulation, the balancing of renewable energy and ancillary services (Mastoi et al., 2023). Also, in V2X are applications such as Vehicle-to-Home, Vehicle-to-Building, Vehicle-to-Community and Vehicle-to-Load where the EV battery supports local energy requirements rather than solely providing exports to the grid (Wang et al., 2024). Research carried out at building- and community-level demonstrates that bidirectional EV batteries have the potential of enhancing local PV self-consumption and reducing reliance on external grid imports (Börchers et al., 2025). This is demonstrated through these applications indicating that EV batteries can be converted into flexible energy resources once they are connected using the appropriate chargers, control systems and market arrangements.

Technical value of V2G is highly dependent on the converter performance, battery capacity and the power quality over the grid. Bidirectional chargers should control the DC-link voltage, current of the batteries, current of the grids and synchronization with the AC system during its charging and discharging process (Adhikary et al., 2023). Converter-oriented research reveals the fundamental importance of a stable DC-link control with harmonic reduction to ensure the reliability of V2G operation (Fu et al., 2025). Studies of grid-forming V2G chargers also indicate that EV chargers have the capability to support voltage and frequency when active power, reactive power and SOC are coordinated accordingly (Ordono et al., 2024). So the entire V2G does not simply represent an energy-management concept; it represents a power-electronic and distribution-network control paradigm.

V2G has uncertainties in terms of economic value, which relies on the market structure, price variation, battery degradation, charger cost and user participation. Studies of V2G profitability reveal that EV will be able to generate revenue through energy-market participation and ancillary services (Zheng et al., 2023). Aggregator experiments demonstrate that profit of V2G use each year depends on the availability of EV, as well as the availability of service windows, imbalance penalties and user-satisfaction limits (De Caro et al., 2025). Studies of user-acceptance indicate that EV owners are worried about loss of flexibility, battery degeneration and privacy even with financial incentives (Bakhuis et al., 2025). These results indicate that V2G feasibility should be researched under both technical and techno-economic aspects.

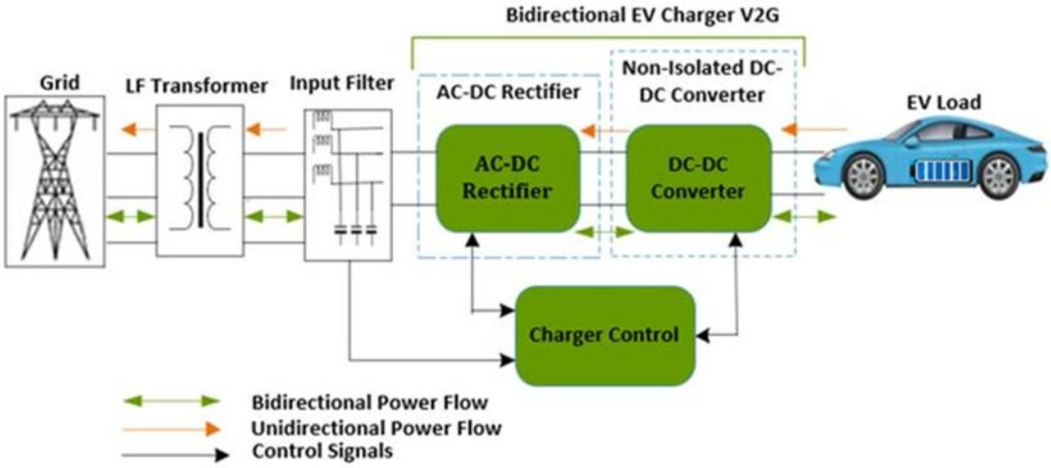

Figure 1. Basic concept of bidirectional V2G EV charging Operation (Zentani et al., 2024).

1.2 Research Gap

The key research problem that is to be discussed in the framework of the current thesis is as follows: the technical potential of V2G is widely known, yet it is still unclear how it can be practically implemented into the framework of renewable-rich distribution networks. The voltage problems, losses and congestion that may be experienced in the distribution networks are not due to EV charging and renewable generation not being coordinated (Ibrahim et al., 2024). V2G could alleviate some of these issues by engaging EV batteries to provide grid support but this would require appropriate SOC control, how to operate the chargers and the quality of the current on the grid side (P. P. Singh et al., 2023). Converter studies indicate that bidirectional operation should ensure the stable DC-link voltage and were simultaneously acceptable power quality in both G2V and V2G conditions (Islam et al., 2025). So, one of the aspects of the issue is technical: the EV battery should be capable of charging and discharging without causing any disruption to the grid and load.

The second component of the problem is the economic one. Although V2G may technically be a possibility, it might not be an appealing alternative unless the value of the service is greater than the value of battery degradation, investment in chargers and the complexity of operation. Studies of battery degradation indicate that repeated V2G operation can accelerate battery degradation and may need to compensate EV owners (Sagaria et al., 2025). According to market research, revenues of V2G are linked to the price differences of electricity, the regulations of the ancillary service and the involvement of aggregators (Wan et al., 2024). According to the Nordic reserve-market research, the flexibility of EV can generate value but must participate in the market provided that probabilistic availability and collective aggregation on the portfolio level (Lunde et al., 2025). Consequently, based on the technical operation only, the techno-economic feasibility of V2G cannot be concluded.

The third section of the issue relates to the integration of renewables. Wind and solar generation are associated with the need to have flexibility due to the surplus generation during certain periods and deficit during others (A. A. et al., 2020). Investigations into wind solar complementary reveal that storage requirements are highly dependent on the renewable mix and timing of generation against demand (Solomon et al., 2016). V2G can assist the renewable systems by storing the excess electric power to minimize the curtailment particularly when the availability of the EV are consistent with the renewable production and demand curves (Fachrizal et al., 2024). Nonetheless, EV batteries can primarily fit short-term and day-to-day flexibility and therefore should be considered as a single component of a greater flexibility portfolio and not a full replacement of all storage technologies.

1.3 Research Aim and Objectives

This thesis is aimed at assessing how EV-based V2G flexibility may contribute to grid stability, integration of renewable energy sources and techno-economic performance in a wind- and solar-integrated distribution-network scenario. The technical section explores the dynamic behaviour of an EV charging/discharging station that is connected to a wind turbine, transformer, grid and dynamic load. It concentrates on battery current direction, response of SOC, control of DC-link voltage and three-phase voltage/current behaviour. All these variables are directly relevant since studies on battery current control, DC-link stability and the quality of grid current outline as the fundamental requirements of V2G operation (Adhikary et al., 2023; Fu et al., 2025). The technical objective is thus to validate the performance of the simulated EV interface to operate in a charging mode and a discharging mode without apparent instability in the grid and load waveforms.

The techno-economic section explores the impact of wind, solar PV, stationary battery storage and EV battery storage on annual demand supply, unmet demand, curtailment and LCOE. Techno-economic V2G researchers indicate that the value of EV storage is dependent on renewable availability, price indications, market participation and limitations associated with the use of battery (Arsalan et al., 2025). It is also demonstrated in integrated microgrid studies that EV batteries can save the cost of the system as well as increase the reliability of the system when it is integrated with renewable generation and demand response (Yu et al., 2026). The economic objective hence is to assess whether EV involvement enhances system performance as compared to situations that do not involve EV storage. This enables the thesis to tie the short-term technical feasibility with the annual system-level performance.

The initial goal is to model the short-term technical response of a V2G-capable EV battery which is linked to a renewable-integrated grid system. Such purpose is justified by research indicating that the V2G operation needs to be controlled by stable converters, as well as by SOC (Ordono et al., 2024). The second goal is to compare charging and discharging behaviour of EV using the following variables; battery voltage, current, SOC, DC-link voltage, grid voltage/current and load voltage/current. This is needed since the change of battery current direction and SOC trend helps to verify the bidirectional operation (Adhikary et al., 2023). The third objective is to determine the annual techno-economic impact of EV battery participation using system KPIs of served energy, unmet demand, curtailment and LCOE. This form of integrative technical, as well as economic analysis, is in line with other studies that relate V2G scheduling, market value, renewable integration and battery degradation (Yang et al., 2024; Zheng et al., 2023).

1.4 Research Questions

There are three research questions which this thesis answers. The first research question will require how the EV charging/discharging station will behave technically when it relates to the wind-integrated grid system. This question is significant as V2G operation cannot be claimed to have any economic benefit before having stable converter and grid-interface behaviour (Fu et al., 2025). The second research question will be how the system response varies with EV charging and EV discharging modes. This difference is needed due to the opposite current direction on the battery and the reverse SOC movement in G2V and V2G, respectively (Acharige et al., 2022). The third research question entails the impact of participation in EV battery on the annual technical-economic performance of an energy system based on renewable sources. The importance of this question is that V2G value is determined based on annual renewable generation, demand profile, storage operation, electricity price, as well as system cost (Nagel et al., 2024).

These research questions are related since technical feasibility and economic feasibility are not independent. Even in case there is theoretical revenue a technically unstable V2G converter is incapable of offering reliable market services. Correspondingly, technical stability of the V2G system may not be very appealing in case price spreads are too shallow, or the degradation of the battery is excessively high, or the end user does not engage in it. The literature on V2G barriers indicates that technical, economic, regulatory and behavioural factors should be volunteered as one to deploy practically (Goncearuc et al., 2024). Thus, the thesis relies on a simulation-based technical analysis as well as on techno-economic analysis.

1.5 Scope and Limitations

This thesis is restricted to a scope of distribution-level V2G operation relying on renewable generation and storage. The technical simulation is an analysis of a short-periodic dynamic model of a wind turbine, transformer, dynamic load and EV charging/ discharging station. It lacks in-depth electrochemical battery ageing, long run thermal modelling and hardware in the loop validation. In-depth battery ageing models are significant as final profitability analyses; however, they do not belong to the direct scope of the technical simulation (M. Mosammam et al., 2024). The simulation thus confirms the short-term operation and not the entire life product battery degradation.

The techno-economic section provides annual energy balance, storage dispatch, unmet demand, curtailment and LCOE of the selected renewable and EV cases with annual energy balance. It is not a complete electricity-market bidding model or process of detailed aggregator settlement. Aggregator-based studies reveal that V2G profit is determined by services windows, bidding strategies, imbalanced penalizing and market regulations (De Caro et al., 2025). These factors matter but are simplified in this thesis due to the focus on the system-level comparison of the wind and solar participation, stationary battery and EV battery participation. As such, the economic outcomes would be viewed as scenario-based techno-economic proxies and not definitive commercial investment decisions.

User behaviour is even simplified. Practically, the availability of V2G depends on the parking time, plug-in behaviour, the required departure SOC, access to chargers and willingness to participate (F. Liu et al., 2025). According to user-acceptance studies, financial incentives, concerns with battery degradation and loss of flexibility are strongly influencing factors impacting participation (Bakhuis et al., 2025). These behavioural aspects are addressed in the literature but are not fully modelled in technical simulation. This weakness states the thesis approximates the technical and techno-economic potential in defined assumptions as opposed to forecasting specific real-world participation.

1.6 Structure of the Thesis

Chapter 1 introduces the background and motivation of the research, identifies the research gap, and presents the aim, objectives, research questions, scope and limitations of the thesis. Chapter 2 reviews the relevant literature on V2G and V2X, EV charging impacts, bidirectional charging control, battery limitations, renewable-energy integration, market participation, user acceptance, infrastructure requirements, cybersecurity, communication standards and the Sundom Smart Grid context. Chapter 3 describes the HOPP-based techno-economic methodology, including data preparation, scenario development, system modelling, optimization, LCOE calculation and sensitivity analysis. Chapter 4 presents the techno-economic results, focusing on demand and renewable-resource characteristics, LCOE performance, EV contribution, curtailment, grid interaction and price-based dispatch. Chapter 5 presents the Simulink model of the Sundom Smart Grid distribution branch and analyses the charging, discharging, PV and wind output results. Chapter 6 concludes the thesis by summarizing the main findings, outlining the limitations and proposing directions for future research.

2 Literature Review

2.1 An Overview of V2G and V2X Concepts

Vehicle-to-Grid (V2G) refers to bidirectional power exchange between an electric vehicle (EV) battery and the electricity grid. In grid to vehicle (G2V) mode the EV battery absorbs electricity from the grid or from local renewable generation, while in V2G mode the battery discharges electricity back to the grid or to a local load through a bidirectional charger (Acharige et al., 2022). Such bidirectional functionality enables EV to transition their electricity consumption from passive to flexible distributed storage resource (Wan et al., 2024). Vehicle to X (V2X) applications involve Vehicle to Home (V2H), Vehicle to Building (V2B), Vehicle-to-Load (V2L), Vehicle-to-Community (V2C) and Vehicle to Vehicle applications (V2V) (Wang et al., 2024). These concepts are relevant for this thesis because the technical simulation investigates the behaviour of EV for charging and discharging and the techno-economic model investigates EV batteries as an extra storage resource in wind-PV-storage scenarios.

The technical and economic potential of V2G relies on the capacity of EV to store electricity during periods of low demand or fewer costs and to release it during periods of high demand or high costs. This in Renewable Based systems implies that EV batteries take excess PV or wind generation and release electricity when generation falls short. Multiple research studies have demonstrated V2G's potential benefits in services such as peak shaving, valley filling, frequency regulation, voltage support, renewable-energy integration and provision of ancillary services (Mastoi et al., 2023; Sovacool et al., 2020). These services clearly relate to the motivation of the present thesis, where a test is performed to see if EV flexibility can reduce grid dependence, curtailment, stationary battery requirement, or levelized cost of energy (LCOE) as compared to NoEV scenarios.

Applications to V2X are also significant as they demonstrate that the value offer of EV batteries can be at different system levels. V2H can enhance household resilience during Power Outages (Einolander et al., 2024) and V2B can help lower Building Peak Demand

and local PV Self-Consumption (AC et al., 2025). However, V2X can also help to increase the energy self-sufficiency of communities by aggregating multiple EV as shared flexible storage(Börchers et al., 2025). These studies argue for considering EV batteries as local flexibility resources and not simply transport resources.

2.2 EV Charging Effects on Distribution Networks

Uncontrolled EV charging can pose technical challenges for distribution networks. This significant demand for EV charging can lead to peak load, overload the distribution transformers, cause feeder congestion, induce voltage deviation and cause distribution losses (Ibrahim et al., 2024). Many EV accumulating in the neighbourhood and charging at the same time can pose challenges in low voltage and medium voltage networks, when charging happens at the same time the vehicles enter the parking lot, for example after work (Unterluggauer et al., 2022). Additionally, fast charging may induce peak stress of short duration and high magnitude locally due to the high-power consumption of chargers (Lai et al., 2022). Both problems or issues warrant the examination of EV integration beyond only as an energy resource but rather as a problem in the distribution network's plan and operation.

Smart charging is a suggested first step to minimise the adverse effects of EV charging. Smart charging involves modifying charging times to either avoid the peak period or take advantage of periods when renewable generation is significant. Numerous large-scale charging-management studies demonstrate that smart charging can lead to fewer costs at the power grid and less curtailment of renewables than unmanaged charging (Szinai et al., 2020). Electricity-pricing studies also indicate that dynamic, using hourly or specific time of day pricing can have a greater effect than the use of fixed time of use tariffs (Schwarz et al., 2020). This is relevant in the price-based dispatch portion of this thesis, where EV charging is permitted when the price is below a certain threshold and EV discharge/sell is allowed when the price is above a certain threshold.

However, smart charging and V2G are not the same. Smart charging only changes the timing of electricity consumption, while V2G allows EV batteries to inject electricity back to the grid or local system. This implies that V2G not only aids in reducing energy demand but also contributes to active energy supply in times of energy shortages or high electricity pricing. This distinction is critical for the techno-economic results presented in this thesis, since EV batteries are not generating energy, but are merely moving energy around in time from when there is excess energy to when there is energy shortage.

The impact of EV on the distribution-network also relates to the technical simulation result. EV charging and discharging shall not create unacceptable voltage distortion, current distortion or instability into the connected grid and load. The impacts of EV in distribution systems have demonstrated that EV, if not managed, can cause power-quality problems and voltage unbalances and that coordinated V2G can help decrease stress on the local distribution grid if well-controlled (Hassan et al., 2024; Ibrahim et al., 2024).

2.3 Bidirectional Charger and Converter Control

The key element in V2G is the bidirectional charging of the battery, which requires a bidirectional charger to facilitate controlled power flow between the EV battery and the AC grid. The components of a typical bidirectional EV charger are an AC–DC converter, DC–DC converter, DC-link capacitor, grid synchronization, pulse-width modulation (PWM) and battery current control (Adhikary et al., 2023). During G2V operation the converter functions as a rectifier and charges the battery via a regulated DC stage. During the V2G mode, the energy from the battery is sent through the inverter and DC-link to the AC grid (Acharige et al., 2022; Adhikary et al., 2023). This is in direct relation with the technical simulation model studied in this thesis: to determine charging/discharging based on current direction, battery voltage response, SOC trend and DC-link voltage behaviour.

One of the technical requirements of most import for the bidirectional charging is DC-link voltage regulation. When the DC-link voltage is not stable the current of grid-side inverter and battery-side current may also be unstable (Islam et al., 2025). In V2G converter studies using power quality improvement techniques, it is emphasized that the control in DC link, grid current tracking and harmonic reduction is crucial for safe operation of V2G (Fu et al., 2025). Converter topology may also influence the voltage ripple, the transient response and efficiency during charging and discharging (Mamidala & Kumar, 2025). These findings further justify that usage of DC-link voltage as an important technical result indicator in this thesis, as it is aimed for the power quality of the DC bus to be closely followed the reference after the initial transients.

Safe V2G operation also requires the grid synchronization and current control. The V2G converters need to synchronize with the AC grid and control the active and reactive component of the current properly (Islam et al., 2025). Studies on a grid-forming V2G charger indicate its ability to provide voltage and frequency support in situations where the charger active power, reactive power and SOC are coordinated (Ordono et al., 2024). Further, by designing the converter to provide grid-support functions, frequency/voltage support from EV fleets during disturbances has been demonstrated via real-time V2G simulation studies (Anany et al., 2024). These studies help the interpretation of the behaviour of the voltage and current on the grid side, particularly in case of visibility of the current phase and the possible exchange of reactive power.

2.4 Battery SOC, Degradation and Mobility Limitations

Technical or techno-economic V2G modelling requires a SOC management as a key element. Not all EV batteries are suited to be used as stationary storage and there are operating limits that must be kept within to ensure safe operation. The studies of V2G scheduling determine the feasibility of the operation through arrival time, departure time, minimum SOC, desired SOC and available discharge energy (Zheng et al., 2023). The other studies (Singh et al., 2023) use SOC thresholds for deciding upon charging/discharging and idle modes of EV for priority based V2G planning studies. They can directly support the methodology in this thesis operation with both EV and storage between 50% and 85% and stationary battery between 20% and 90% .

Another significant constraint for the V2G operation is the degradation of batteries. The combination of SOC range, charging/discharging currents, depth of discharge, temperature and frequency of charging/discharging operations can contribute to the accelerated ageing of the batteries (Sagaria et al., 2025). The results of the electrothermal analysis of batteries indicate that voltage, temperature, impedance, heat generation, SOC and capacity loss should be considered when considering V2G feasibility in the long term (Arsalan et al., 2025). From the multi-objective V2G studies, increasing V2G revenue can increase the battery ageing due to unmanaged charging and discharging (M. Mosammam et al., 2024). This also justifies the limitation of present thesis to not fully monetize the detailed battery degradation cost in the LCOE or dispatch analysis.

On top of this, mobility creates an even bigger limitation on the real availability of EV batteries. Existing V2G studies indicate that the amount of available flexibility is related to parking time, accessibility of chargers, driving patterns and locations, as well as departure SOC (F. Liu et al., 2025). Driver heterogeneity is also a concern for V2G participation as different drivers have varying levels of willingness to connect, discharge and to accept compensation (Yun et al., 2025).

2.5 V2G to Integrate Renewable Energy

V2G is emerging as especially significant in power systems with growing penetration rates of wind and solar power. Renewables can fluctuate with the tides and aren't necessarily always in alignment with electricity needs. Surplus and deficits of electricity loading can occur at different times related to wind and PV generation. EV batteries can be used to alleviate this imbalance by loading during times of renewables surplus and unloading during high demand or low renewables output (Yang et al., 2024). Together, this enables EV storage to be a potentially useful flexibility resource in renewable-rich distribution systems.

Multiple studies have been carried out demonstrating that the coordinated charging and discharging of EV can lead to a better utilization of renewables. EV batteries can boost the use of wind power by storing electricity during high wind generation and releasing it during peak demand or renewable-deficit times, as demonstrated in wind-based V2G scheduling studies (Shang et al., 2023). PV-focused studies also demonstrate that coordinated operation of EV with PV influence on local energy use and voltage issues to enhance PV penetration (Hassan et al., 2024). The results indicate that V2G can have a positive impact on both wind and solar integration, but the net benefits are highly dependent on renewable output time, demand and storage availability and network conditions.

Wind–solar complementarity is also important in renewable-energy system design. Wind and solar generation are temporally different and it is possible to decrease the mismatch between renewable output and demand when mixing wind and solar generation than just using one resource alone (Solomon et al., 2020). Nevertheless, as both wind and solar are variable resources, complementarity will not eliminate the need for storage or for grid service. Thus the high renewable systems must be flexible in terms of the ability to move energy around in time and diminish the impact from the generation-demand mismatch. This flexibility can be partly achieved with EV batteries, particularly of short duration and daily balancing.

Another important issue of renewable integration is Curtailment. Renewable capacity brings benefits of decreased external electricity reliance, but can also decrease the ability to use, store, or export electricity production. These studies on systems with high renewable share indicate that the variables of curtailment, storage capacity, overbuilding on renewable and system cost are closely related (Al-Rasheedi et al., 2021; Solomon et al., 2019). Some curtailment may be acceptable on an economic basis as it may be too much to invest in storage to prevent all curtailment. So, the planning for renewable systems must consider the possible trade-offs between the installed capacity of renewables, storage capacity, curtailment and cost.

From the literature investigated in the renewable-integration context, it was observed that with adequate surplus energy, EV batteries could increase renewable energy utilization, provided there is demand for discharging during times of energy shortages. But EV batteries do not produce any new energy; these are merely moving available energy by reshaping it. These then have battery size limitations and can only be charged and discharged at a limited rate, only operate for a limited amount of times and the user must participate and have a vehicle available. Therefore, it is more appropriate to think of V2G as a flexibility mechanism, or one possible mechanism, when looking at the larger potential of a renewables-based system.

2.6 V2G in Microgrids, Buildings and Communities

V2G has been well investigated in microgrids, buildings and community energy systems, which also include likely local demand, renewable generation, storage, controllable loads. A PV microgrid study demonstrated that with smart charging and V2G, PV self-consumption could be increased and grid peaks could be reduced, compared to uncontrolled charging (Van der Kam and van Sark, 2015). Studies on renewable microgrid optimization further indicate the potential of EV parking, G2V/V2G operation, demand response and storage to lower the operating costs and boost reliability (Yu et al., 2026). As further studies show, EV batteries can be used to aid local energy management if their charging and discharging operations coincide with local renewable energy generation and demand, respectively.

V2B applications are specific as commercial or fleet EV may be more available than private vehicles. Bidirectional charging studies reveal that it can lead to a decrease in electricity costs, boost PV self-consumption, lower peak demand and in some cases, replace stationary battery capacity (Antretter et al., 2025). This indicates in some situations, such as when vehicles are left plugged in for extended periods and a charging station is provided, the need for separate stationary storage may be eliminated. The amount of EV substitution varies, however, depending on the size of the EV fleet, connection time, power rating, battery availability and the demand profile of the site.

V2X studies at the community level are also being used to demonstrate the use of EV batteries as ‘aggregated flexibility resources. Based on residential community studies, the storage capacity of EV can be shared as a community and thus higher institutional self-sufficiency, if EV availability is sufficient (Börchers et al., 2025). In addition, an urban-level study revealed a positive effect of having aggregated EV batteries to enhance load matchability of wind and solar power in an urban power system (Fachrizal et al., 2024). It is important because while EV batteries are small in themselves, an EV fleet, if large enough, can be significant from a community or distribution-network perspective.

Another limitation of EV flexibility is discussed in the literature on micro grids and communities. EV batteries can primarily enable short time shifts of energy when renewables are available to charge and when there is a discharge requirement later in the day. They may not be adequate to accommodate long duration or seasonal balancing. Storage-portfolio studies have demonstrated that often, high-renewable storage systems are best provided through a mix of short-duration storage, long-duration storage, demand response, curtailment and grid support (Al-Rasheedi et al., 2021). Thus, V2G should not be the sole storage solution, but considered as a flexible resource in a larger energy-system design.

2.7 Aggregators, Virtual Power Plant and Energy Markets

V2G is significant due to the small size of EV batteries and their uncertainty. An aggregator can coordinate the operation of many EV, thus turning them into a flexible resource for energy markets, reserve markets or local flexibility markets (Sovacool et al., 2020). When it comes to the coordination of distributed EV batteries, renewables and storage, virtual power plant (VPP) concepts enable this coordination of a controllable portfolio (Sun & Jiao, 2014). This is a necessary aggregation method because generally, the market will need some capacity, predictability and control which an EV could not offer on its own.

There are several potential value streams for EV batteries, because of market participation. V2G can have energy arbitrage revenues, ancillary services, demand response, flexibility services and shifting of renewable energy (Wan et al., 2024). Based on aggregator profit studies, the revenue from V2G is seen to be dependent on arrival time, departure time, SOC of EV, desired SOC, service window and variation in market price (De Caro et al., 2025). The above indicate that the economic value of V2G can be influenced by any combination of battery availability and a variable price of electricity.

Nordic V2G studies can be especially mentioned in the context of Finland. Nordic frequency containment reserve market research into EV aggregation reveals that EV flexibility can lower electricity costs and generate value for EV owners if the reserve-market profit is passed back to them (Lunde et al., 2025). Nordic modelling studies in Norway and Denmark also indicate that large-scale V2G can helps to reduce renewable curtailment and system operating cost, particularly when engaged in high renewable penetration systems (Nagel et al., 2024). Based on these findings, Nordic electricity-market structures could offer possibilities for EV flexibility, provided proper aggregation, availability and market-rules are in place.

However, market-based V2G value is not guaranteed. The profitability of V2G is based on the spread of price between charging and discharging periods, charging efficiency, user compensation, battery degradation cost, the cost of the charger, market accessibility and type of aggregator control strategy (De Caro et al., 2025; Zheng et al., 2023). A low-price difference, or the lack of availability of cars in profitable times or a high degradation compensation could result in a weaker economic promoting case for

V2G. Hence, assessing the market participation of V2G Lightnings will need to consider not only technical aspects, but also economic aspects.

The aggregator and the market literature indicates that on a vehicle level operation must be coordinated for V2G. By aggregating EV Storage, value can be created by connecting it to electricity prices, renewables, reserve markets or local flexibility needs. Meanwhile, aggregator bidding, imbalances, user compensation, market settlement and regulation all play a major role in influencing the practicality in a detailed way. Therefore, these factors are crucial when analysing simplified V2G dispatch models based on price, as they indicate an economic potential but do not reflect actual market operation.

2.8 User Acceptance and Behavioural Barriers

User acceptance is a very important requirement for the implementation of V2G capabilities as EV owners must agree to keep the vehicle connected to the grid, accept some external control and accept bidirectional battery cycling. Financial incentives are found to have a positive impact on participation in V2G, with the potential of battery degradation, loss of flexibility, privacy concerns and range anxiety during the usage as reported factors that can be detrimental to participation in V2G (Bakhuis et al., 2025). In addition to these, the Technology-acceptance reviews highlight that trust, contract design, charging infrastructure, expected revenue and user control are crucial factors that will influence V2G adoption (F. Liu et al., 2025). The results indicate that ensuring V2G participation in practice goes beyond technical feasibility.

Mobility behaviour has a high influence on EV availability. The duration of parking, the location of chargers, arrival and departure times, the kind of trips and SOC (Chance of arrival) at the time of departure are found to have an impact on the V2G potential in data-driven studies (C. Liu et al., 2025). Research on driver heterogeneous provides evidence that compensation, connection duration, guaranteed SOC, flexibility requirements are different for different drivers (Yun et al., 2025). This indicates that there may not be as much EV flexibility available to the power system as the total number of batteries that all EV in an area hold.

User behaviour also affects the economic value of V2G. The theoretical capacity to store electricity to discharge would not be available if EV are not connected during high price or high demand times. The more guaranteed SOC users require, the less energy that can be supplied to the grid. V2G may not be so profitable if the battery degradation compensation is too high. The State of Charge (SOC) eligibility and willingness to discharge for fast charging V2G depend on the V2G available discharge power based on optimization studies of user willingness (G. Li et al., 2025). Hence, V2G analysis should consider both technical constraints of batteries and behavioural constraints of participation.

This user-acceptance literature suggests a guarded assessment of the potential of V2G. There is no direct correlation between EV penetrations and flexibility on the grid as flexibility relies on plug-in behaviour, connection duration, user willingness, battery condition and access to chargers. Assumptions regarding EV capacity should thus not assume a 100 per cent availability of the EV population. In techno-economic studies, this is particularly relevant as the actual deployment of EV is assumed to be higher than it is, leading to an overestimation of the potential relevance of V2G for integration of renewables, storage change and cost reduction.

2.9 Charging-Infrastructure and Planning Requirements

Charging infrastructure determines where and when V2G can be used. Smart planning of transport networks and distribution networks indicates that the location of charging stations will have an impact on travel distances, waiting times, grid losses, voltage deviations and grid reinforcement requirements (Unterluggauer et al., 2022). Further studies on charging-station planning demonstrate that the uncertainty in charging demand and renewable generation will impact annual costs, voltage stability and the utilization of renewables locally (C. Li et al., 2022). This research indicates that charging infrastructure is not a transport issue but also a distribution-network-planning issue.

Bi-Directional charging structure is more complicated than the normal charging structure. It must necessarily have bidirectional power-electronic capability, communication and metering, control, protection and compliance to the grid-interconnection rules (Acharige et al., 2022). V2G barrier studies highlight charger costs, limited number of V2G-capable vehicles, lack of certainty in revenue recognition, market entry barriers and a scarcity of large-scale demonstration projects (Goncearuc et al., 2024). These factors are important as the economic worth of EV flexibility may be diminished if investment costs of the charger are expensive or bidirectional chargers are not accessible.

The nature of charging stations has also a significant impact on the feasibility of V2G. Fast charging stations might not work well for V2G due to the short charging time favoured by users and potential reluctance to leave their cars plugged in for grid services (Zheng et al., 2023). Typically, home, workplace and fleet as well as long stay parking sites are better suited as vehicles are less frequently disconnected at these sites for longer periods (Gschwendtner et al., 2021). V2G potential might also be offered by public parking areas, where a long dwell time could enable potential savings.

Cost assessment is also impacted by charging-infrastructure planning. The economic potential of V2G might be compromised if the bidirectional chargers are costly. If the chargers are used by several users and/or for several services, the cost can be distributed more optimally. Such techno-economic estimates should thus consider the expense of chargers, which per the literature is not driven by the use case of V2G but still cost estimates should be included in the techno-economic assessments. At the same time, charger cost should be interpreted together with utilization rate, service value and expected lifetime.

2.10 Cybersecurity, Communication and Standards

V2G necessitates secure communication involving the EV, chargers, aggregators, grid operators and market platforms. Reviews of the cybersecurity show that spoofing, denial-of-service attacks, false data injection, weak authentication and insecure communication protocols are the main risks in V2G systems (Razzaque et al., 2025). These risks may impact technical operation, as well as financial settlement. When price signals or a meter data is manipulated, V2G trading and grid-service delivery might lose credibility (Chen et al., 2024). Thus, V2G feasibility includes cybersecurity.

The interoperability also requires the presence of communication standards. According to the reviews of EV charging technology, ISO 15118, IEC 61851, IEC 62196, IEEE 1547 and other standards are important in terms of charging and grid interaction (Acharige et al., 2022). Incomplete standards and charger-control protocols are also found as barriers to extensive deployment by V2G barrier studies (Goncearuc et al., 2024). Devoid of standardisation, V2G systems can only be restricted to charger models, vehicle classes or pilot projects. Standards are hence required to take V2G out of demonstrations.

The idea of cybersecurity and privacy also affects user acceptance. The user studies indicate that privacy and data security dispose decrease the willingness to engage in V2G (Bakhuis et al., 2025). Trust and privacy constitute other crucial factors of adoption through technology-acceptance reviews (C. Liu et al., 2025). This puts secure communication not as a technical solution but as a social and business one. When the interacting of energy transactions, battery control and personal data is carried out transparently, the user is more likely to participate.

2.11 Finland and Sundom Smart Grid

Finland smart-grid environment is applicable to the thesis since the follow-up project is a Vaasan renewable and EV system. The studies on Sundom Smart Grid describe a real MV smart-grid environment in Vaasa that has wind generation, distributed resources, measurement infrastructure and microgrid management functional units (Sirviö et al., 2020a). Such studies indicate the active distribution networks should have functions like voltage control, reactive power management, demand response, protection and market interaction (Sirviö et al., 2020a). This helps to justify the importance of research on V2G as a future flexibility resource within the same type of distribution-network environment.

Reactive power control factor is significant in the Finnish context of distribution-grids. Research on DSO TSO reactive power control in the Sundom Smart Grid demonstrates that reactive power control based on converters can be managed to stay within the limits of reactive power windows (Sirviö et al., 2019). Studies on active network management demonstrate that, depending on their location in relation to an HV/MV interface, DERs can have different reactive-power roles (Laaksonen et al., 2019). The concept of FlexZone, as well, demonstrates that EV, storage, distributed generation and controllable loads can contribute to local DSO services and system-wide TSO services (Laaksonen & Hovila, 2016). These observations reinforce the notion that the EV chargers of the future could be involved in the active distribution-network flexibility.

The network evolution studies, which are of low voltage, also demonstrate the position of EV in the future smart grids. The classic distribution networks have been passive and primarily deliver unidirectional power to consumers (Sirviö et al., 2019). Further phases of the microgrids and intelligent-networks are future outlooks incorporating the EV, smart meter, demand response, local generation, storage as well as the aggregator-based market participation (Sirviö et al., 2020b). This is directly related to V2G since EV batteries can be turned into an active resource with the assistance of bidirectional charging and control. Thus, the literature on Vaasa/Sundom offer a powerful local context to the thesis model.

2.12 Research Gap from Literature

The literature indicates that V2G is technologically feasible but implementation is challenging. Converter studies indicate bi-directional power transfer, DC-linking and currents monitoring (Adhikary et al., 2023). Studies on distribution-networks have demonstrated that V2G can enhance the following aspects: voltage, hosting capacity and management of peak loads (Hassan et al., 2024). Economic research indicates that V2G can bring revenue opportunities by exploiting arbitrage, reserve services and flexibility market opportunities (Wan et al., 2024). Nevertheless, studies of these areas typically focus on each of them separately rather than in one combined technical and techno-economic problem.

The first gap is the relationship between the short-term technical functioning on the one hand and the annual techno-economic operation on the other hand. Voltage, current, SOC and converter behaviour can be observed in seconds or even minutes in terms of stable behaviour. A techno-economic model on cost, LCOE, curtailment, unmet demand and value of storage in a year can be illustrated by annual models. Nonetheless, in many studies there is no clear connection between these two levels. That gap is taken care of in this thesis using a technical simulation of EV charging/discharging behaviour and an annual techno-economic model (wind, PV, stationary battery and EV battery scenarios).

The other gap is the local distribution-network context. The use of standard test systems, national energy-system models, or generic cases of microgrids are often used as general V2G literature. The studies by Vaasa and Sundom offer local smart-grid expertise but they do not directly assess the EV-to-grid simulation and techno-economic condition that has been developed as a part of this thesis (Sirviö et al., 2020b). Thus, this thesis is significant as it connects the operation of V2G with a renewable-built-in context of the distribution-network, in the context of Vaasa. This renders the work helpful in the awareness of technical behaviour, as well as of system-level feasibility.

Generally, literature encourages the need to use a combined V2G evaluation. V2G presupposes stable operation of bidirectional chargers, SOC protection, grid-side, power-quality control, renewable-conscious, dispatch, user intervention, coordination among the aggregators and viable market structures. There is no one single factor that can be used to determine feasibility. Thus, this thesis appraises the results of both technical simulation and techno-economic system to offer a more comprehensive perspective of V2G in renewable rich distribution systems.

3 Methodology

3.1 Techno-Economic Modelling Framework Using HOPP

The techno-economic analysis was performed using Hybrid Optimization and Performance Platform (HOPP) in Python workflow. HOPP is an open-source modelling and optimization tool, created by the National Renewable Energy Laboratory (NREL), for analysing hybrid energy systems. It is designed to assess hybrid power plants consisting of different technologies, including wind generation, PV generation, battery storage, grid connection, site-resource data and economic inputs. In this thesis, HOPP was used to model and compare wind–PV–storage configurations for the selected Vaasa/Sundom case area. Electric vehicle (EV) battery participation, stationary battery storage, electricity prices, renewable-resource inputs and local electricity demand were inputs into the model, along with assumptions related to technology costs. Main outputs were renewable generation, energy locally served, demand served by the grid, curtailment, storage operation, annualised cost and levelized cost of energy (LCOE). HOPP is an appropriate model for this analysis as it enables the assessment of hybrid wind and solar and storage system configurations in the same modelling environment (NREL, 2024).

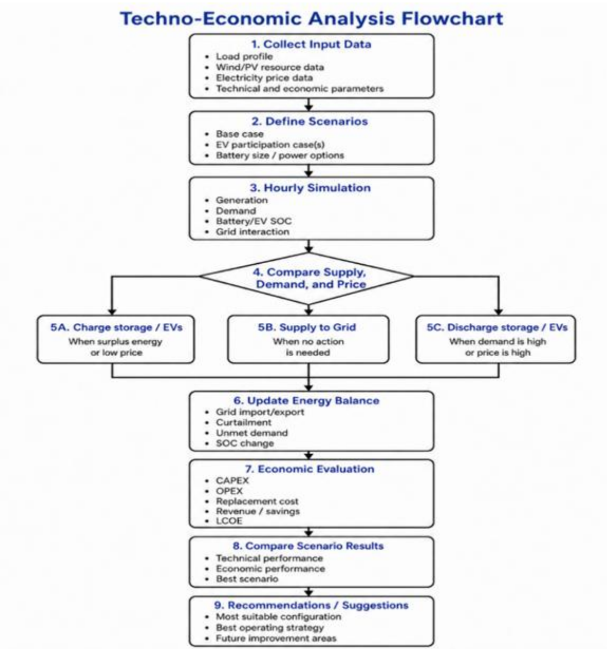

Figure 2. Techno-Economy analysis flow chart for decision making and scenario evaluation.

HOPP was chosen as it used an integrated modelling tool instead of standalone calculations for wind and PV generation, storage dispatch and economic performance. The goal of the techno-economic analysis was to investigate impact of specific contributions of renewable power generation, stationary battery storage and EV battery storage on both local renewable energy consumption, the external grid dependency and curtailment as well as the overall system cost. This was needed as the importance of EV flexibility is not only related to how many renewables are installed but also related to when the electricity is being used, the load demand, the availability of storage and the variation of electricity prices. The model was set up to be an annual hourly simulation of 8760-time steps. The model calculated renewable generation, local demand, battery charging and discharging, curtailment, grid demand fed, local demand served and economic factors at every hour. The hourly approach was followed since, in high-renewable electricity systems, annual average cannot fully capture the mismatch in timings for renewable generation and electricity demand (Solomon et al., 2019).

Three EV participation cases were used in the modelling process: NoEV, BEV50 and BEV80. Selected TargetUnmet cases were performed with various combinations of wind capacity, PV capacity, stationary battery energy capacity and stationary battery power capacity, for each EV case. A configuration was identified as feasible if the percentage of total annual demand met by the grid was less than or equal to the chosen TargetUnmet value. A model with the minimum LCOE was selected among the other configurations that were feasible. The procedure enabled the study to determine whether EV battery participation improved renewable utilization, reduced dependence on the grid, altered stationary battery requirements, or had an impact on economic performance relative to the NoEV reference case.

3.2 Study System, Data Sources and Input Preparation

The case study was taken from the Sundom Smart Grid area in Vaasa, Finland. Three substations, J06 Sulva, J07 Sundom and J09 Vaskiluoto, were used for the representation of the local electricity demand. Figure 2 illustrates the schematic structure of the

Sundom Smart Grid and the electrical background for the chosen demand model for the substation. The figure also justifies the choice of the Vaasa/Sundom area as the study system, as it represents the local distribution-network environment, where the renewable generation, demand and flexibility resources can be considered and analysed (Sirviö et al., 2020).

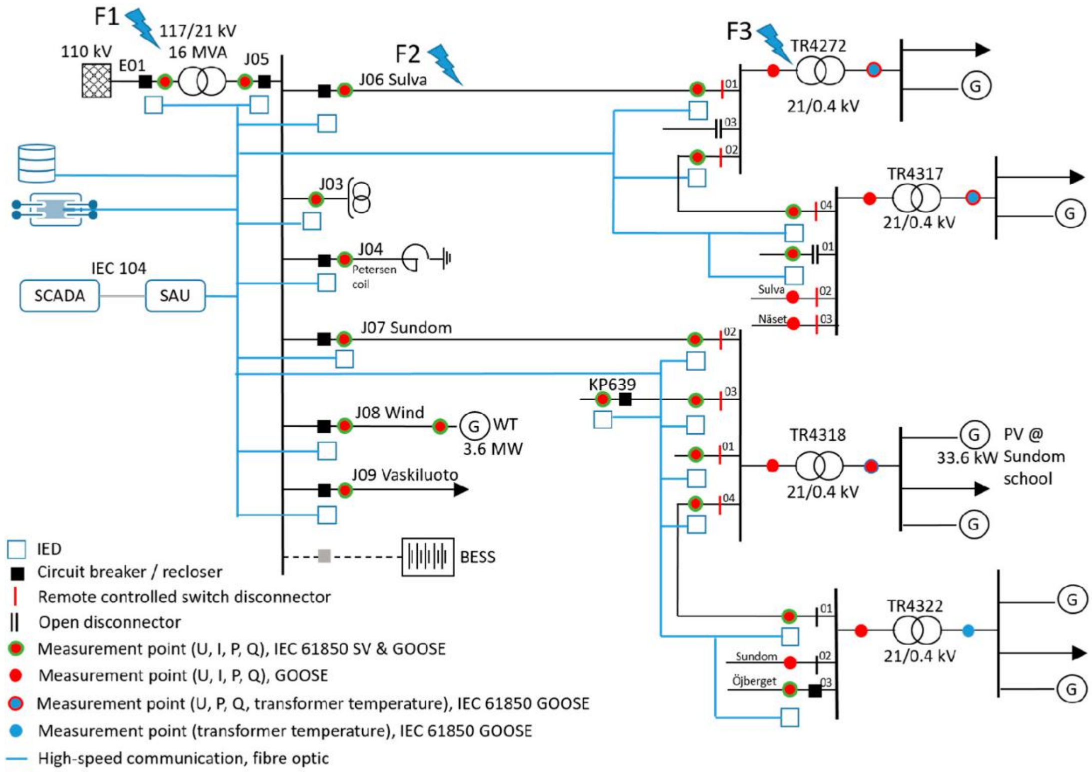

Figure 3. Schematic presentation of the Sundom smart grid and chosen substation area (Sirviö et al., 2020).

The reason for choosing the Sundom/Vaasa system is that substation load data was available resulting from past time series and the area is interesting for studying the integration of renewable-energy sources and distribution-level flexibility. Not all of the physical elements of the Sundom Smart Grid were represented in the techno-economic model. Rather, it relied on available substation level demand data and local renewable-resource inputs to assess annual techno-economic performance of wind generation, solar photovoltaic (PV) generation, stationary battery storage and electric vehicle (EV) battery participation.

The techno-economic model was prepared with the main input data mentioned in the Table 1. Past electricity consumption was acquired from the Sundom Smart Grid data for the year of 2018 and scaled to 2025 study year. Electricity spot-price data was provided by Fingrid and the data covered the hours. Data on wind speed and solar resources was collected from Finnish Meteorological Institute (FMI), while PV capacity factor data was collected. The major sources for technology cost assumptions were those from the International Renewable Energy Agency (IRENA) and the hybrid system analysis was carried out by using the Hybrid Optimization and Performance Platform (HOPP).

Table 1. Main data sources used in the techno-economic model.

Data type	Source	Use in the model
Local electricity demand	Sundom Smart Grid 2018 data	Historical hourly load profiles for J06 Sulva, J07 Sundom and J09 Vaskiluoto (Sirviö et al., 2020).
Forecasted peak demand	2025 substation peak-demand assumptions	Rescaling 2018 load profiles to the 2025 study year
Electricity spot price	Fingrid	Hourly price input for dispatch and economic evaluation
Wind resource	Finnish Meteorological Institute	Wind-speed input for wind generation estimation
Solar resource	Finnish Meteorological Institute and PV capacity-factor data	PV generation estimation
Technology cost assumptions	IRINA	Capital expenditure, operational expenditure and lifetime assumptions
Hybrid system modelling	NREL HOPP	Wind-PV-storage techno-economic modelling

Each input data was set up in the time series for hour basis before simulation. The substation load was scaled to the forecasted peaks for 2025. Each wind speed data set was converted to wind capacity factors and each PV data set into hourly PV capacity factors. Electricity price data were sorted into an annual hourly price series and then utilized in dispatch analysis using an electricity price. This preparation allowed to evaluate the demand, renewable generation, storage operation and variation of electricity price data at the same hourly level of detail.

3.3 Scenario Design and Main Assumptions

Three cases of EV participation were used: NoEV, BEV50 and BEV80. For the NoEV case the system was analyzed for the reference case without EV battery participation. BEV50 and BEV80 represented two levels of available EV battery capacity and bidirectional charging/discharging power. These cases were added on to consider if EV-Flexibility would impact external grid dependence, renewable-energy utilization, levelized cost of energy (LCOE) or stationary battery capacity.

The scenario framework can be separated into two dimensions: EV participation level and TargetUnmet level. The EV participation cases determine if EV battery storage is excluded or included at BEV50 and BEV80 levels, and the TargetUnmet cases determine the maximum percentage of annual demand that can be met by the outside electrical grid. Four cases of TargetUnmet were used here: Target80Unmet, Target60Unmet, Target40Unmet, and Target20Unmet. The difference in local-supply requirement impacts the wind and PV sizes, the stationary battery size, the amount of curtailment and the system cost among these cases to be compared. The scenario logic and the combined scenario names are provided in Tables 1 and 2.

Table 2. Scenario dimensions and assumptions used in the techno-economic model.

Scenario dimension	Scenario option	Meaning	Main assumption
EV participation	NoEV	No EV battery support	Only wind, PV and stationary batteries are used
EV participation	BEV50	Medium EV participation	One third of 50% of EV users participate
EV participation	BEV80	High EV participation	One third of 80% of EV users participate
Grid-supply target	Target80Unmet	Up to 80% of demand may be supplied by grid	At least about 20% supplied locally
Grid-supply target	Target60Unmet	Up to 60% supplied by grid	At least about 40% supplied locally
Grid-supply target	Target40Unmet	Up to 40% supplied by grid	At least about 60% supplied locally
Grid-supply target	Target20Unmet	Up to 20% supplied by grid	At least about 80% supplied locally

Table 3. Combined TargetUnmet and EV participation scenarios used in the techno-economic model.

EV case	TargetUnmet level	Combined scenario name
NoEV	80%	Target80Unmet_NoEV
NoEV	60%	Target60Unmet_NoEV
NoEV	40%	Target40Unmet_NoEV
NoEV	20%	Target20Unmet_NoEV
BEV50	80%	Target80Unmet_BEV50
BEV50	60%	Target60Unmet_BEV50
BEV50	40%	Target40Unmet_BEV50
BEV50	20%	Target20Unmet_BEV50
BEV80	80%	Target80Unmet_BEV80
BEV80	60%	Target60Unmet_BEV80
BEV80	40%	Target40Unmet_BEV80
BEV80	20%	Target20Unmet_BEV80

The TargetUnmet level and the EV participation case are the two dimensions used in the scenario design. The TargetUnmet value represents the annual load demand that is served by the external grid with remaining share being served by local resources. For instance, "Target80Unmet_NoEV" indicates an 80/20 split between the contribution of local renewables (e.g. wind generation and PV generation) and stationary battery storage (no EV batteries) and the contribution of the grid. In contrast, Target60Unmet_BEV50 means that 60% of the annual load demand is supplied by the grid, while 40% is supplied by local resources, including wind generation, PV generation, stationary battery storage and EV battery participation.

BEV 50 and BEV80 represent 50% and 80% of the passenger cars in the Sundom area, respectively, being battery electric vehicles (BEV). The population of Sundom is approximately 2,500 and based on the Finnish average of 492 passenger cars per 1,000 inhabitants, the total number of passenger cars in Sundom is estimated to be about 1,230. Therefore, the BEV50 scenario includes 615 BEV and the BEV80 scenario includes 984 BEV. Assuming that 1/3 of BEV are available for battery storage at any given time, the available BEV are estimated as 205 cars for BEV50 and 328 cars for BEV80. The total available battery storage capacity is the number of available BEV's times the assumed average battery capacity of one BEV.

Table 4. EV participation assumptions used in the techno-economic model (Electric Vehicles Database, 2026).

EV case	Available EV	Total EV battery capacity	Usable EV capacity	EV power
NoEV	0	0 MWh	0 MWh	0 MW
BEV50	205	11.275 MWh	3.946 MWh	3.383 MW
BEV80	328	18.040 MWh	6.314 MWh	5.412 MW

The EV assumptions used in the model are presented below in the table 4. In this study, BEV50 represents a scenario in which 50% of the passenger cars are BEV, while BEV80 represents a scenario in which 80% of the passenger cars are BEV. The storage capacity of the EV batteries was calculated by assuming a total number of BEV, an average BEV battery capacity of 55 kWh, and a charging/discharging capacity of 16.5 kW/battery. The EV storage was operating within a 50% to 85% SOC range so it was determined that only 35% of the EV battery was usable. So, the EV usable capacity was estimated as 3.946 MWh for BEV50 and 6.314 MWh for BEV80 with EV power capacities of 3.383 MW and 5.412 MW, respectively. The BEV80 case delivers 60% more available EV, total EV battery capacity, usable EV capacity, and available EV power when compared to BEV50. These scenarios represent the EV flexibility level for charging during renewable energy surplus and electricity price low periods, and discharging during renewable energy deficit and electricity price high periods.

All batteries for EV batteries were operated in the range of 50% to 85% and stationary batteries were operated in the range of 20% to 90% state of charge (SOC). This SOC range was implemented to limit full depth cycling of the batteries and to maintain a well defined battery storage SOC range. The SOC constraint plays a key role in vehicle-to-grid (V2G) modelling as battery availability, user mobility needs and battery degradation concerns limit EV flexibility (Sagaria et al., 2025; Zheng et al., 2023).

The main economic assumptions used in the model are summarized in Table 5. The discount rate was kept as 7% in all scenarios. Wind and PV capital costs were normalized using the exchange-rate normalisation in the model (USD to EUR). The same cost parameters, including uniform economic assumptions, were adopted for all the three cases NoEV, BEV50 and BEV80 to compare the effect of EV participation in the economical same conditions.

Table 5. Main economic assumptions used in the techno-economic model (IRINA, 2024).

Parameter	Value used in the model
Wind CAPEX	1640 USD/kW × 0.92
PV CAPEX	767 USD/kW × 0.92
Stationary battery CAPEX	192 €/kWh
Fast-charger CAPEX	500 € per 22 kW charger port
Wind OPEX	40 €/kW-year
PV OPEX	15 €/kW-year
Battery OPEX	8 €/kWh-year
Fast-charger OPEX rate	3%
Discount rate	7%
Wind lifetime	25 years
PV lifetime	25 years
Stationary battery lifetime	20 years
Fast-charger lifetime	15 years

3.4 Renewable Generation and Load Modelling

The annual load profile was created from the three representative substation load profiles. Each of the available load profile was scaled to match with the forecast peak load of the respective substation for 2025 which is the year of the Techno-economic analysis. This approach retained the hourly demand shape of the measured demand and it updated the load magnitude for the chosen study year.

$$P_{L,i}^{2025}(t) = \frac{P_{L,i}^{2018}(t)}{P_{L,i,\mathrm{peak}}^{2018}} \times P_{L,i,\mathrm{peak}}^{2025}$$

Where,

$P_{L,\mathrm{i}}{}^{2025}(t) = \ scaled\ 2025\ load\ of\ substation\ i\ at\ time\ t.$

$P_{L,\mathrm{i}}{}^{2018}(t) = \ original\ 2018\ load\ of\ substation\ i\ at\ time\ t.$

$P_{L,\mathrm{i},\mathrm{peak}}{}^{2018} = \ measured\ 2018\ peak\ load\ of\ substation\ i.$

$P_{L,\mathrm{i},\mathrm{peak}}{}^{2025} = \ forecasted\ 2025\ peak\ load\ of\ substation\ i.$

The total aggregated load was then calculated as:

$$P_L(t) = \sum_{i=1}^{N} P_{L,i}^{2025}(t)$$

Where,

$P_L(t) = \ aggregated\ load\ at\ time\ t.$

$N \ = \ number\ of\ substations\ included\ in\ the\ analysis.$

Wind and PV generation were calculated from installed capacity and hourly capacity factors. Wind and solar input data was provided by the Finnish Meteorological Institute and has been used to reflect the local renewable resources. Wind generation was calculated as:

$$P_{WT}(t) = C_{WT} \times CF_{WT}(t)$$

Where,

$P_{WT}(t) = \ wind\ generation\ at\ time\ t.$

$C_{WT} = \ installed\ wind\ capacity.$

$CF_{WT}(t) = \ wind\ capacity\ factor\ at\ time\ t.$

Specific yield was also determined from the model and compared to reference specific yields to validate that the specific yield value simulated was reasonable for the annual specific yield.

Solar PV generation was calculated as:

$$P_{PV}(t) = C_{PV} \times CF_{PV}(t)$$

Where,

$P_{PV}(t) = \ PV\ generation\ at\ time\ t$

$C_{PV} = \ installed\ PV\ capacity$

$CF_{PV}(t) = \ PV\ capacity\ factor\ at\ time\ t$

Total renewable generation was calculated as:

$$P_{RES}(t) = P_{WT}(t) + P_{PV}(t)$$

Where,

$P_{RES}(t) = \ total\ renewable\ generation\ at\ time\ t.$

$P_{WT}(t) = \ wind\ generation\ at\ time\ t.$

$P_{PV}(t) = \ PV\ generation\ at\ time\ t.$

An hourly renewable generation profile was compared to the hourly load profile and periods of surplus and deficit were compared. This was a critical move as the PV and wind power generation timing impacts storage operation, curtailment and utilization of renewables. The wind-solar complementarity has also been observed to have an impact on storage needs and balancing requirements for renewable-energy systems (Solomon et al., 2020).

3.5 Storage Dispatch, SOC Control and Optimization Procedure

The storage dispatch was simulated on an hourly basis. Total renewable generation was compared to local electricity demand at every time step. The hourly renewable surplus or deficit was calculated as:

$$P_{net}(t) = P_{RES}(t) - P_L(t)$$

Where,

$P_{net(t)} = \ hourly\ renewable\ surplus\ or\ deficit.$

$P_{RES}(t) = \ total\ renewable\ generation\ at\ time\ t.$

$P_L(t) = \ aggregated\ load\ at\ time\ t.$

A positive value indicates surplus renewable generation, while a negative value indicates that renewable generation is not sufficient to meet local demand.

EV storage was prioritised as the first flexibility resource in the EV participation scenarios. Model on charging the EV battery during the surplus periods first, then added more according to the EV power, usable capacity, SOC limit and efficiency. Additional energy was absorbed by the stationary battery when there was surplus renewable generation as part of the tested configuration that stationary battery capacity was considered. Curtailment was any surplus after storage charged was recorded.

When the EV is being used in the deficit mode, the EV battery supplied first based on the available EV energy, EV power, SOC and efficiency parameters. If the EV battery could not fully cover the deficit and stationary battery capacity was available, the stationary battery supplied the remaining deficit. If there was still a demand deficit upon departing some of the electricity stored in EV and stationary batteries, it was grid demand. This dispatch order is in line with the model implementation: EV flexibility was assumed as the priority in the EV scenarios and stationary storage was assumed as an additional storage alternative if EV flexibility was still insufficient. The SOC constraint for both EV and stationary battery storage was implemented as:

$$SOC_{min} \leq SOC(t) \leq SOC_{max}$$

Where,

$SOC_{\min} = \ 50\%, (For\ EV)$

$SOC_{\max} = \ 85\%$

$SOC_{\min} = \ 20\%, (For\ Stationary\ Battery$

$SOC_{\max} = \ 90\%$

Therefore, in the techno-economic model, EV storage was operated within an SOC range of 50% to 85%, while stationary battery storage was operated within an SOC range of 20% to 90%.

The optimization objective was to identify the feasible configuration with the lowest LCOE for each EV case and TargetUnmet level. The objective can be expressed as:

$$min\ LCOE$$

subject to:

$$S_{grid} \leq S_{target}$$

where S_{grid} is the annual share of demand supplied by the external grid after local wind, PV, EV storage and stationary battery contributions are applied and S_{target} is the selected TargetUnmet level.

$$S_{grid} = \frac{E_{grid}}{E_{demand}}$$

where S_{grid} is the annual share of demand supplied by the external grid after local wind, E_{grid} is the annual electricity demand supplied by the external grid and E_{demand} is the annual electricity demand.

A grid-search procedure was performed to test fixed combinations of wind, PV, stationary battery energy and stationary battery power. All combinations were simulated for a 0-8760 hour year. A configuration was determined to be feasible only if the share of demand supplied by the grid was equal or less to the selected TargetUnmet value. The selected model was the model whose configuration had the lowest LCOE among all feasible configurations. The model chose a fallback case for lack of adequate configuration to meet the targeted case, minimising the grid supplied demand first and the LCOE second.

3.6 Economic Evaluation and LCOE Calculation

Economic analysis compares the various system configurations using LCOE. Wind, PV, stationary battery and EV charging-infrastructure costs are all included in the annual cost. The annualization of capital costs is done in the capital recovery factor since every one of the technologies has a dissimilar lifetime. The result is then to add annual operation and maintenance costs to get the annualized cost of the system.

The capital recovery factor:

$$CRF = \frac{r(1+r)^n}{(1+r)^n - 1}$$

Where:

CRF = $capital\ recovery\ factor$

r = $discount\ rate$

n = $technology\ lifetime\ in\ years$

Annualized cost of capital is calculated as:

$$C_{cap,ann} = C_{WT}CRF_{WT} + C_{PV}CRF_{PV} + C_{BESS}CRF_{BESS} + C_{EVch}CRF_{EVch}$$

Where:

$C_{cap}, ann\ =\ annualized\ capital\ cost$

$C_{WT}\ =\ wind\ turbine\ capital\ cost$

$C_{PV}\ =\ solar\ PV\ capital\ cost$

$C_{BESS}\ =\ stationary\ battery\ capital\ cost$

$C_{EVch}\ =\ EV\ charging - infrastructure\ capital\ cost$

$CRF_{WT}\ =\ capital\ recovery\ factor\ for\ wind\ turbines$

$CRF_{PV}\ =\ capital\ recovery\ factor\ for\ solar\ PV$

$CRF_{BESS}\ =\ capital\ recovery\ factor\ for\ stationary\ battery\ storage$

$CRF_{EVch}\ =\ capital\ recovery\ factor\ for\ EV\ charging\ infrastructure$

Annual operation and maintenance are calculated as:

$$C_{opex,ann} = C_{opex,WT} + C_{opex,PV} + C_{opex,BESS} + C_{opex,EVch}$$

Where:

$C_{opex}, ann\ =\ annual\ operation\ and\ maintenance\ cost$

$C_{opex}, WT\ =\ annual\ wind\ turbine\ operation\ and\ maintenance\ cost$

$C_{opex}, PV\ =\ annual\ solar\ PV\ operation\ and\ maintenance\ cost$

$C_{opex}, BESS\ =\ annual\ stationary\ battery\ operation\ and\ maintenance\ cost$

$C_{opex}, EVch \ = \ annual\ EV\ chargin\ infrastructure\ operation\ and\ maintenance\ cost$

The total annualized system cost is then:

$$C_{ann,total} = C_{cap,ann} + C_{opex,ann}$$

Where:

$C_{ann}, total \ = \ total\ annualized\ system\ cost$

$C_{cap}, ann \ = \ annualized\ capital\ cost$

$C_{opex}, ann \ = \ annual\ operation\ and\ maintenance\ cost$

Lastly, the LCOE can be estimated as:

$$LCOE = \frac{C_{ann,total}}{E_{served}}$$

Where:

$LCOE \ = \ levelized\ cost\ of\ energy$

$C_{ann}, total \ = \ total\ annualized\ system\ cost$

$E_{served} = \ annual\ served\ electricity\ demand$

This expression is the same format as in the Python code, where the annualized capital cost and annual operation and maintenance cost are added together, then divided by the annual energy served. The denominator serves energy since the objective of the system is to serve useful local demand. Curtailed renewable generation is left out since it is not routed to the load. This sensitivity of LCOE to investment cost and system operation.

In the cases of EV, the cost of EV charging-infrastructure is also a component of LCOE. Thus, EV participation is considered not just as a technical resource of flexible use but an economic investment. This is significant since BEV50 or BEV80 can decrease unmet demand, or curtailment as compared to NoEV but the incremental cost of charging-infrastructure can also influence the resultant LCOE. LCOE can then be used as an economic indicator to balance out the technical benefit and cost effect on V2G/G2V participation.

3.7 Profit-Based Dispatch and Sensitivity Analysis

The price-based dispatch analysis is conducted once the main scenario is selected. This step would assess the potential business worth of EV flexibility at hourly electricity spot rates. The LCOE provides the average cost of beneficial supplied energy, whereas the price-based dispatch demonstrates that EV batteries and renewable generation could generate the value under the varying prices in the market.

The dispatch employs two thresholds depending on the chosen scenario LCOE:

$$c_{ch} = 0.90 \times LCOE$$
$$c_{sell} = 1.10 \times LCOE$$

Where:

$c_{ch} = \; charging\ price\ threshold$

$c_{sell} = \; selling\ price\ threshold$

$LCOE \; = \; levelized\ cost\ of\ energy\ of\ the\ selected\ scenario$

When the spot price is lower than the charging level, charging of the EV occurs where the energy is present. At the point where the spot price is higher than the selling threshold, the renewable production and the available EV energy is sold to the grid. The model considers local demand the most important thing between the two thresholds and only sells when there is excess generation.

This discussion validates the business-model explanation of V2G. There must be technical flexibility to support a viable V2G case, the value also requires price differentials, the cost of charging, revenue derived on discharging, the cost of infrastructure and the availability of EV. The price-based dispatch thus offers another economic point of view on top of the LCOE comparison.

3.8 Sensitivity Analysis

The sensitivity analysis will evaluate the impact of variations in important cost assumptions on the LCOE. The parameters that were tested are the wind CAPEX, PV CAPEX, stationary battery cost, EV charger cost and the level of EV participation. The main cost parameters are determined by low, reference and high values, whereas NoEV, BEV50 and BEV80 are contrasted with EV participation.

This discussion is needed as the results of techno-economics are subject to the future cost assumptions. The costs of the batteries and chargers can reduce as days pass by and the wind and PV costs can also fluctuate with market conditions and location of the project. The studies of storage reveal that cost-effectiveness of storage varies depending on renewable penetration, storage time and technology assumptions.

The sensitivity analysis assists in determining the most influential parameters in making the final LCOE. It also explains whether EV participation is as attractive or not with changes in charger or battery costs assumptions. Particularly when it comes to V2G, since the technical value of EV flexibility might demand at least an economic value due to energy arbitrage or grid support or evaded investment in stationary storage.

3.9 Methodological Summary

This methodology utilized a Python workflow using HOPP, local demand data, renewable-resource inputs, assumptions for EV batteries, stationary battery options, electricity price data and assumptions of technology costs. The aggregated Vaasa load profile was prepared from the J06 Sulva, J07 Sundom and J09 Vaskiluoto substations with the model first. It was then used to calculate hourly wind and PV generation, dispatch for EV-first storage, apply SOC constraints and calculate curtailment, grid-supplied demand, locally served energy, LCOE.

Four TargetUnmet levels were analysed for the scenario comparison, involving NoEV, BEV50 and BEV80. In the EV scenarios EV battery storage was utilized first, followed by stationary battery storage as an extra storage option if needed. Only those configurations where a feasible was found for the selected TargetUnmet level were considered. The lowest-LCOE case was chosen from amongst feasible configurations.

This approach enabled the thesis to analyse the impact of EV batteries on renewable utilization, grid dependency, curtailment, stationary battery requirement, LCOE and price-based dispatch value in the selected case for the distribution network in Vaasa.

4 Results

4.1 Overview of Scenario Outputs

The techno-economic outcomes are calculated for three different electric vehicle (EV) participation cases: NoEV, BEV50 and BEV80. There are four TargetUnmet levels for these cases: Target80Unmet, Target60Unmet, Target40Unmet and Target20Unmet. The TargetUnmet name in the scenarios indicates the maximum percentage of annual demand load that can be met by the external grid, with the remaining percentages met by local resources like wind generation, photovoltaic (PV) generation and stationary battery storage (EV battery storage applies, where applicable). For instance, Target80Unmet_NoEV is a scenario where local resources supply at least some 20% of local demand and the remaining 80% is supplied by the grid, without considering EV storage. Target60Unmet_BEV50, on the other hand, incorporates participation of EV battery sources into local supply share.

The NoEV scenarios are important because they provide the zero-EV reference case for the whole techno-economic comparison. They demonstrate the performance of the wind–PV–stationary-battery configuration in absence of EV batteries as flexible storage. This allows the potential added value of BEV50 and BEV80 to be determined for each EV, separately from each NoEV case with the same TargetUnmet value. This is particularly valuable comparison because results indicate that NoEV provides the lowest-cost configuration in the most relaxed situation yet EV participation is increasingly favourable when higher percentage of load needs to be locally supplied by the system.

The results are presented using the main output indicators from the HOPP-based techno-economic model. These indicators consist of locally served energy, energy served by the grid, renewable served share, wind and PV installed capacity, stationary battery demand, dispatch revenue from price, EV battery contribution, LCOE sensitivity, energy curtailed. This structure is consistent with the modelling logic applied in the methodology, with hourly references in each wind, PV, storage and EV configuration of these demand, renewable generators, storage dispatch, TargetUnmet constraints and cost assumptions.

4.2 Annual Demand and Renewable Resource Characteristics

The annual electricity demand and the peak electricity demand of the chosen Sundom distribution-network case were equal to 33,366.56 MWh and 9.53 MW, respectively. All the load inputs for NoEV, BEV50 and BEV80 scenarios followed this demand profile. Fully year hourly electricity price data, with an average spot price of 81.63 €/MWh and the 75th percentile of the spot price of 117.38 €/MWh, were also applied to the model. These two price values are later to be used as reference levels in the LCOE comparison and as a starting point to interpret the price-based dispatch results.

The wind and solar resource quality applied in the Sundom model is shown in Figure 5. Its annual wind capacity factor data was around 0.227 with the PV capacity factor of 0.1071. Thus, it demonstrates that the production potential of the wind resource is higher than PV in the input data selected. This may be explained by the higher wind capacity factor and reflects the importance of wind capacity in many selected configurations when high TargetUnmet cases require a higher local renewable contribution.

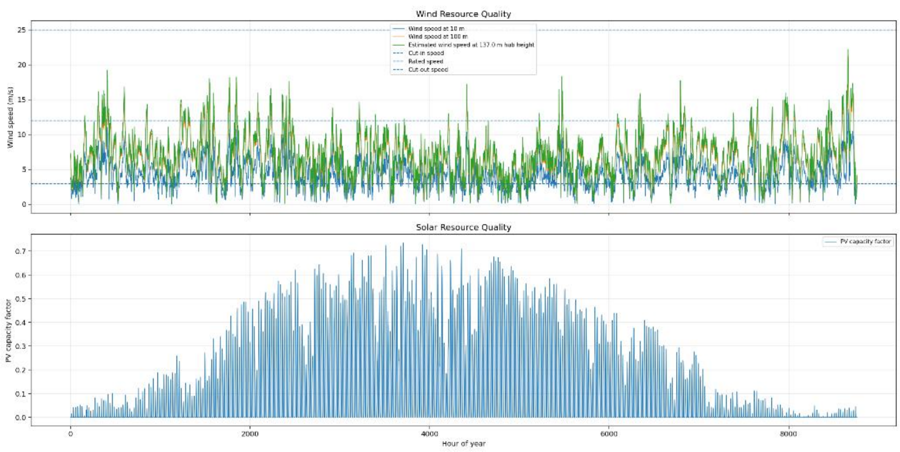

Figure 4. Quality of the wind resources and solar resources adopted in the Sundom techno-economic model.

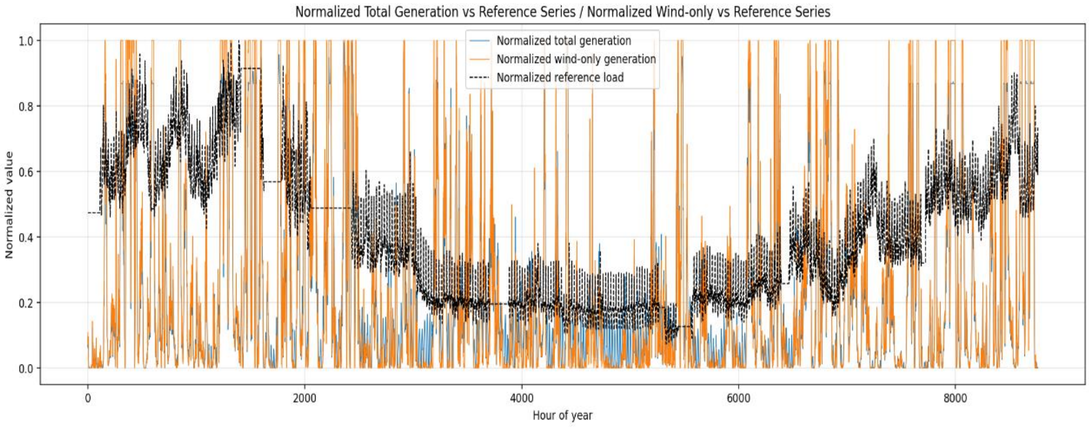

Figure 5. Normalized Profiles of Renewable Generation and Reference Load.

However, the PV resource still affects the model due to its renewable daytime generation profile and varying renewable mix when increasing PV sizes. For example, Target20Unmet_BEV80 selected 25 MW of PV, compared with 15 MW in Target20Unmet_NoEV and Target20Unmet_BEV50. This means PV can still be used in certain arrangements, despite having a smaller annual capacity factor (ACF) compared to wind.

4.3 LCOE Comparison Across Scenarios

The LCOE differences are shown between the TargetUnmet/EV participation scenarios in Figure 6. There are also average spot price and 75 percentile spot price lines drawn as a reference. The lowest LCOE was achieved in Target80Unmet_NoEV with an LCOE value of just 89.32 €/MWh. This finding is significant as it means the zero-EV case is the most cost effective when the local-supply requirement is the lowest. Target80Unmet_BEV50 was the best wind–PV–EV case: the LCOE was 89.53 €/MWh. These values fall close together, suggesting that the cost increase for BEV50 participation is insignificant in the case with the lowest Target for being undone.

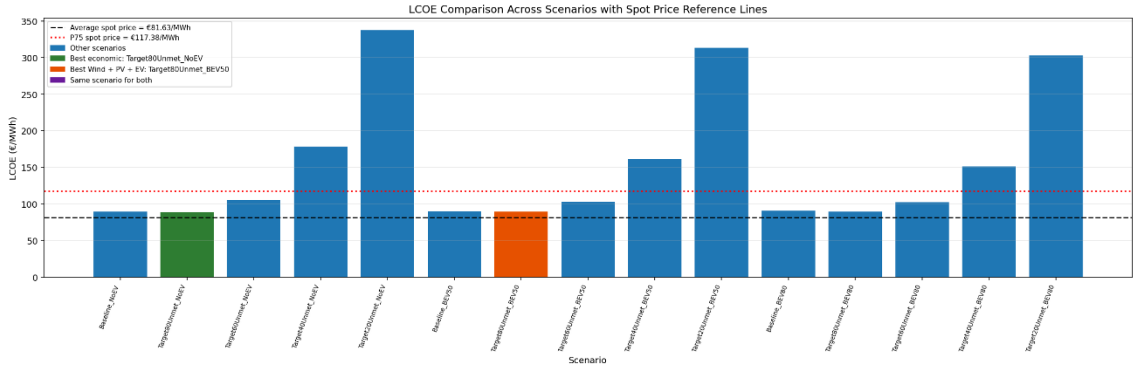

Figure 6. Comparison of LCOE with TargetUnmet and EV participation scenarios and electricity price reference lines.

The LCOE increased as the TargetUnmet level became stricter. For the NoEV case, LCOE at Target80Unmet was 89.32 €/MWh and at Target20Unmet was 337.11 €/MWh. In the BEV50 case, LCOE increased from 89.53 €/MWh to 313.04 €/MWh. In the BEV80 case, LCOE increased from 89.86 €/MWh to 302.83 €/MWh. This trend happens as lower TargetUnmet values mean a higher proportion of the annual demand must be met through local resources. This means that larger wind, PV and storage capacities are needed for the selected configurations, which yields higher annualised costs of the systems.

The comparison with the NoEV baseline shows where EV participation becomes useful. NoEV was again the cheapest case at Target80Unmet. However, at Target40Unmet, LCOE decreased from 178.84 €/MWh in NoEV to 161.06 €/MWh in BEV50 and 151.42 €/MWh in BEV80. This equates to a reduction in LCOE of approximately 9.9% for BEV50 and 15.3% for BEV80 compared to the zero-EV case. At Target20Unmet, LCOE decreased from 337.11 €/MWh in NoEV to 313.04 €/MWh in BEV50 and 302.83 €/MWh in BEV80. This equates to one of the reductions being 7.1% and the other being 10.2%. These indicate that EV storage isn't very economic when there's a small local-supply requirement, but it becomes more helpful when there's a high flexibility requirement.

The spot-price reference lines provide an additional economic interpretation. The lowest LCOE values are above the average spot price (81.63 €/MWh), but below the 75th percentile price (117.38 €/MWh). This indicates that the lowest cost local renewables configuration is not competitive with the average market electricity rate, although may be more relevant in periods of costly electricity. This is significant for the price-based dispatch results because the amount of EV charging and discharging will rely on the amount of low-price and high-price hours.

4.4 EV Role in Different Scenarios

Figure 7 shows the selected wind capacity, PV capacity, stationary battery capacity and EV battery capacity across the scenario set. As it can be seen in the figure, the size of system grows as the TargetUnmet value decreases. For the NoEV case, Target80Unmet identified 3.6 MW of wind and 1 MW of PV without stationary battery storage. Target20Unmet_NoEV opted for 40 MW of wind energy, 15 MW of PV and 50 MWh of stationary battery storage. This Zero EV Progression demonstrates the necessary capacity expansion in the presence of only wind, PV and stationary battery storage to decrease dependence on the grid.

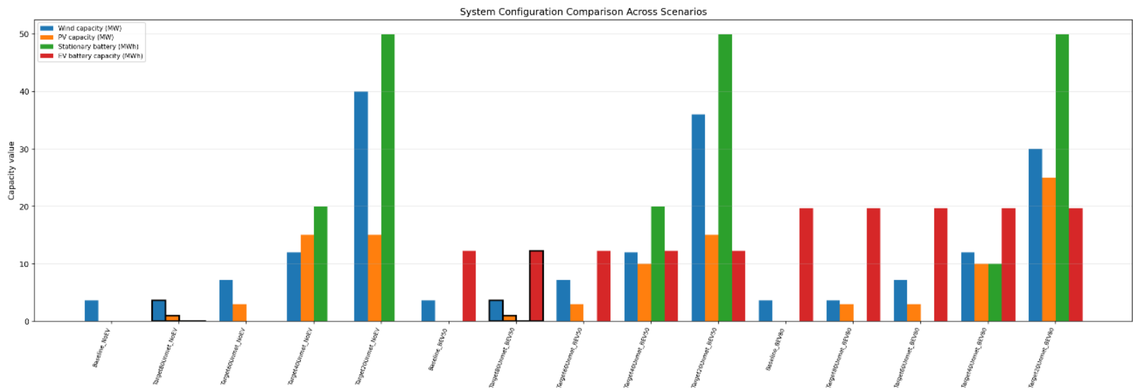

Figure 7. System configuration comparison across TargetUnmet and EV participation scenarios.

Table 5 indicates which system configurations were chosen for each of the TargetUnmet and EV participation cases. The table provides the distribution of the selected wind, PV and stationary battery capacities when EV participation is used. The effect of adding EV battery flexibility to the same TargetUnmet levels is seen in cases BEV50 and BEV80, respectively.

Table 6. Effect of EV participation on selected wind, PV, stationary battery and EV battery configurations under different TargetUnmet cases (HOPP).

TargetUnmet case	EV case	Wind capacity (MW)	PV capacity (MW)	Stationary battery (MWh)	EV battery capacity (MWh)	Main observation
Target80 Unmet	NoEV	3.6	1	0	0	Lowest-cost zero-EV configuration, no stationary battery required
Target80 Unmet	BEV50	3.6	1	0	12.30	EV participation adds flexibility without changing wind or PV capacity
Target80 Unmet	BEV80	3.6	3	0	19.68	Higher EV participation is paired with higher PV capacity
Target60 Unmet	NoEV	7.2	3	0	0	Local supply increases without stationary battery storage
Target60 Unmet	BEV50	7.2	3	0	12.30	EV participation adds flexibility without changing selected wind/PV size
Target60 Unmet	BEV80	7.2	3	0	19.68	Higher EV participation gives additional flexibility with the same wind/PV capacity
Target40 Unmet	NoEV	12	15	20	0	Reference case without EV storage

TargetUnmet case	**EV case**	**Wind capacity (MW)**	**PV capacity (MW)**	**Stationary battery (MWh)**	**EV battery capacity (MWh)**	**Main observation**
Target40 Unmet	BEV50	12	10	20	12.30	EV participation reduces required PV capacity compared with NoEV
Target40 Unmet	BEV80	12	10	10	19.68	Higher EV participation reduces the stationary battery requirement
Target20 Unmet	NoEV	40	15	50	0	Strict target requires large renewable and stationary battery capacity without EV support
Target20 Unmet	BEV50	36	15	50	12.30	EV participation reduces required wind capacity compared with NoEV
Target20 Unmet	BEV80	30	25	50	19.68	Higher EV participation changes the renewable mix, but stationary battery requirement remains high

The table indicates low impact of EV participation for the least strict Target80Unmet and Target60Unmet cases. In these cases, the choice of stationary battery becomes 0 MWh for every EV participation level. This also implies that the local-supply requirement can largely be fulfilled by wind and PV capacity alone without any explicit stationary storage. However, without selecting stationary storage, BEV80 at Target80Unmet shows that 3

MW PV is chosen along with 1 MW PV in NoEV and BEV50, indicating that higher EV availability shifts the mix of renewables needed.

The effect of EV participation becomes clearer in the stricter Target40Unmet case. In the absence of EV storage, the selected configuration is composed of 12 MW wind, 15 MW PV and 20 MWh stationary battery storage. BEV50 involves a reduction of the PV installed capacity from 15 MW to 10 MW and stationary battery storage capacity remains at 20 MWh. By using BEV80, the stationary battery size can be reduced from 20 MWh to 10 MWh, as wind power is still 12 MW and PV power is 10 MW. This means that to the extent that there is EV storage capacity, stationary battery storage can be reduced.

The strictest Target20Unmet case shows that EV participation can reduce or reshape renewable capacity, but it does not remove the need for large stationary battery storage. For the NoEV case, 40 MW wind, 15 MW PV and 50 MWh stationary battery storage is required. The BEV50 case's specifications are that wind is reduced to 36 MW, PV remains at 15 MW and stationary battery storage is still 50 MWh. Wind so far gets virtually cut in half in the BEV80 scenario (30 MW) and static batteries are still at 50 MWh, though PV generation increases to 25 MW. Thus, EV batteries are providing flexibility, but cannot fully substitute stationary battery storage when the local-supply condition is the most stringent.

The configuration results demonstrate overall that the zero-EV scenarios are vital to the understanding of the added value of EV participation. NoEV represents the baseline system requirement while BEV50 and BEV80 demonstrate alternative reductions in PV capacity, reductions in wind capacity, or reductions in stationary battery capacity for different levels of TargetUnmet. The most noticeable is the storage-substitution effect reflected in Target40Unmet_BEV80: The stationary battery capacity drops from 20 MWh (NoEV) to 10 MWh (BEV80). This indicates that EV batteries can serve as a side-wind-PV-storage flexibility resource, particularly under higher proportions of local supply.

4.5 Curtailment, Grid-Supplied Demand and Renewable Overbuilding

This comparison of curtailment share and grid-supplied demand share between the scenarios is shown in Figure 8. The figure makes it obvious that there will be a trade-off between the grid supplied demand share and the curtailment. This is because the wind, PV and storage requirements are greater at more restrictive TargetUnmet values. These larger systems serve higher local demand, while generating higher levels of excess energy during hours in which the local demand is satisfied and when storage is either full or does not exist.

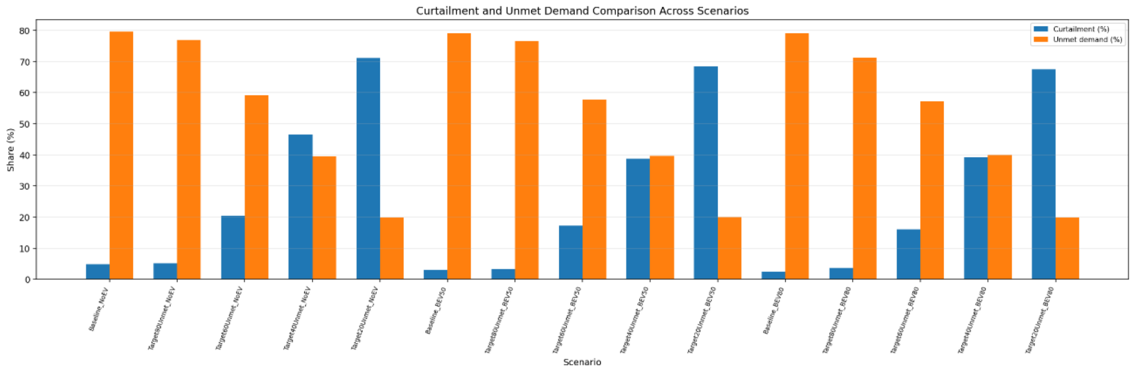

Figure 8. Curtailment and comparison of the grid supplied demand for scenarios.

The NoEV cases represent the baseline case without EV flexibility. In the NoEV case, the grid-supplied demand share decreased from 76.99% in Target80Unmet to 19.81% in Target20Unmet. During this change curtailment went up from 5.19% to 71.16%. This outcome demonstrates the high level of renewable overbuilding needed to achieve a grid dependence reduction from approximately 77% to approximately 20% (excluding EV batteries). While the additional renewable supply enhances local supply, a major portion of the additional production cannot be consumed locally.

Curtailment was decreased in several similar cases involving EV participation. At Target60Unmet, curtailment decreased from 20.36% in NoEV to 17.28% in BEV50 and 16.13% in BEV80. This corresponds to a curtailment reduction of about 15.1% for BEV50 and 20.8% for BEV80 compared with NoEV. At Target40Unmet, curtailment decreased from 46.46% in NoEV to 38.82% in BEV50 and 39.19% in BEV80. The numbers indicate that part of the renewable oversupply can be stored in EV batteries and that the storage can reduce unused renewable generation.

However, EV participation did not eliminate curtailment in the strictest cases. In all scenarios the level of curtailment was high: 71.16% in NoEV, 68.52% in BEV50 and 67.44% in BEV80 for curtailment. At this target, curtailment was reduced by BEV80 by only approximately 5.2% as compared to NoEV. The finding indicates that the EV storage can have a positive impact on increasing the utilization of renewables, but when the renewable generator is strongly oversized the available storage power and size are not sufficient to accommodate all surplus generation.

The demand values obtained from the grid show that in general the chosen configurations provide the desired TargetUnmet values. Target80Unmet_NoEV was at 76.99% with Target60Unmet_NoEV in second at 59.11%, Target40Unmet_NoEV in third at 39.50% and Target20Unmet_NoEV in fourth at 19.81%. These trends are seen for BEV50 and BEV80. This indicates that the grid-search method found viable configuration not far from the desired grid-supply constraints.

4.6 Annual Renewable Production and Local Demand Served

LCOE is compared to annual wind and PV production for all the scenarios in the scenario set in Figure 9. The figure helps explain why LCOE increases when the TargetUnmet level becomes stricter. Switching from Target80Unmet to Target20Unmet leads to higher annual renewables productions as the wind and PV capacities are now much larger. But not all extra generation is delivered to local demand because curtailment does go up as well.

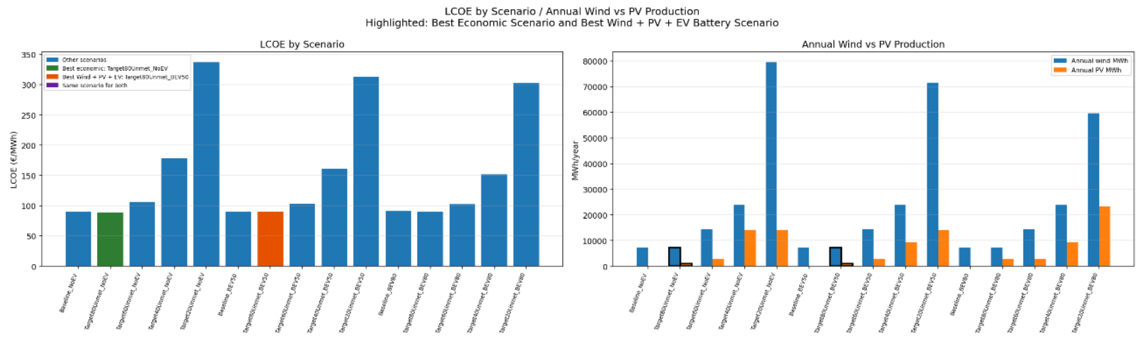

Figure 9. LCOE and annual Wind/PV production between the different scenarios.

The NoEV cases include no EV storage and thus serve as a reference to understand how much demand can be met without EV storage. In Target80Unmet_NoEV, the local system served 7,676.61 MWh, equal to 23.01% of the annual demand. The energy supplied for Target 60 Unmet_NoEV increased to 13,643.15 MWh, representing 40.89% of energy demanded. In Target40Unmet_NoEV, 20,186.63 MWh was supplied, which was 60.50% of demand. Served energy in Target20Unmet_NoEV was 26757.30 MWh, which is 80.19% of the demand. This shows that the NoEV system can meet stricter local-supply targets, but only by increasing renewable and stationary battery capacity.

In several cases, participation resulted in an increase in locally served energy. In Target80Unmet, BEV50 served 7,818.09 MWh, equal to 23.43% of demand, while BEV80 served 9,566.58 MWh, equal to 28.67%. In Target60Unmet, NoEV served 13,643.15 MWh, BEV50 served 14,118.52 MWh and BEV80 served 14,295.36 MWh. This means the local served share increased from 40.89% in NoEV to 42.31% in BEV50 and 42.84% in BEV80. These values indicate that EV penetration could enhance local renewables utilization if the supply of renewables for storage is sufficient.

Due to the similar local-supply requirement, served energy was similar across all EV cases of the selected configurations at Target20Unmet. Target20Unmet_NoEV served 26,757.30 MWh, Target20Unmet_BEV50 served 26,694.62 MWh and Target20Unmet_BEV80 served 26,760.13 MWh. These values represent around 80% of the yearly demand. This means that the most significant difference in the most stringent target does not lie in the served share but rather in the system configuration and LCOE needed to achieve that share.

This outcome helps to better understand role of EV batteries in techno-economic model. There is no net increase in renewable generation from EV batteries. Rather, they allocate some of the available renewable generation from surplus hours to deficit hours. This effect will be most significant if there is adequate renewable oversupply to charge the EV batteries and sufficient periods of renewable undersupply for discharging to reduce grid supply.

4.7 Price-Based Dispatch Results

The price-based dispatch analysis was conducted following the main dispatch scenario selection based on LCOE. It was done to investigate the effect of hourly electricity price variation on selected configurations. The dispatch rule parameters were a charging threshold of 90% of the selected scenario LCOE and selling threshold of 110% of the selected scenario LCOE. This analysis is not a comprehensive optimization of the market bidding. It is a simple dispatch test to illustrate the periods where system dispatching of energy charges EV batteries, meets local demand, sells generation and/or extracts energy from EV over selected 30-day periods.

Figure 10 shows the first 30 days dispatch result by price for Target80Unmet_BEV50 which is the best combination for wind-PV-EV case. This case had an LCOE of 89.53 €/MWh, a charging threshold of 80.58 €/MWh and a selling threshold of 98.49 €/MWh. In this period, the EV battery was charged when the spot price was below the charging threshold and EV battery was discharged/selling was supported when the spot price was above the selling threshold.

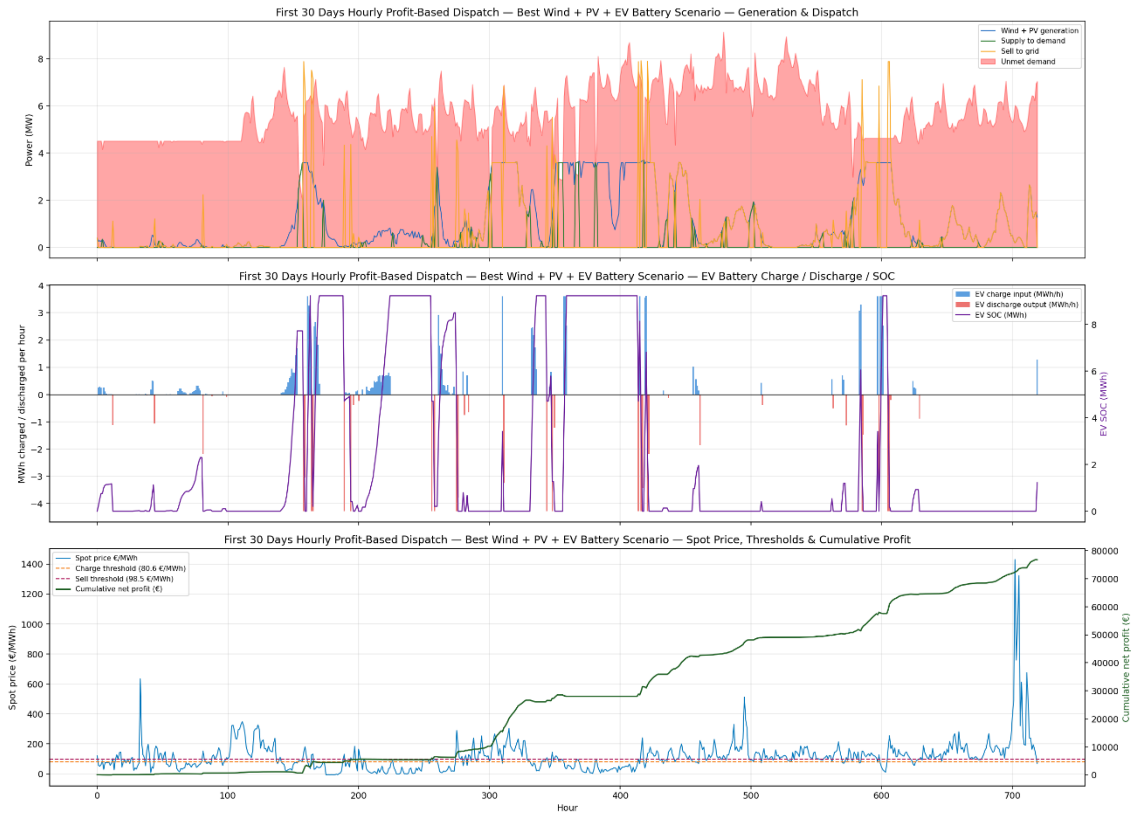

Figure 10. The amount of Target80Unmet_BEV50 that has been dispatched in the first 30 days by price.

In the first 30-day period the BEV50 case charged 114.38 MWh, stored 108.51 MWh and discharged 101.78 MWh in the EV battery. For any EV discharge, the contribution for selling revenue is €15,541.91. Total selling revenue was €82,738.06, while charging cost was €5,984.33. The amount of profit overall was €76,753.73. The average electrical revenue for selling was 161.86 €/MWh and the average charging price was 52.32 €/MWh. The rule-based dispatch demonstrates this impression of a distinct difference in pricing for the charging hours versus selling hours within these values.

The final 30-day dispatch window for the same Target80Unmet_BEV50 case is provided in figure 11. During the period, EV battery generated 145.90MWH and discharged 131.31MWH while 138.41MWh were charged. EV discharge helped in selling revenue to the extent of €18,598.78. Total selling revenue was €56,043.47, while charging cost was €6,747.93, giving a net profit of €49,295.54. The average price of charging was 46.25 €/MWh while the average price of selling was 144.73 €/MWh.

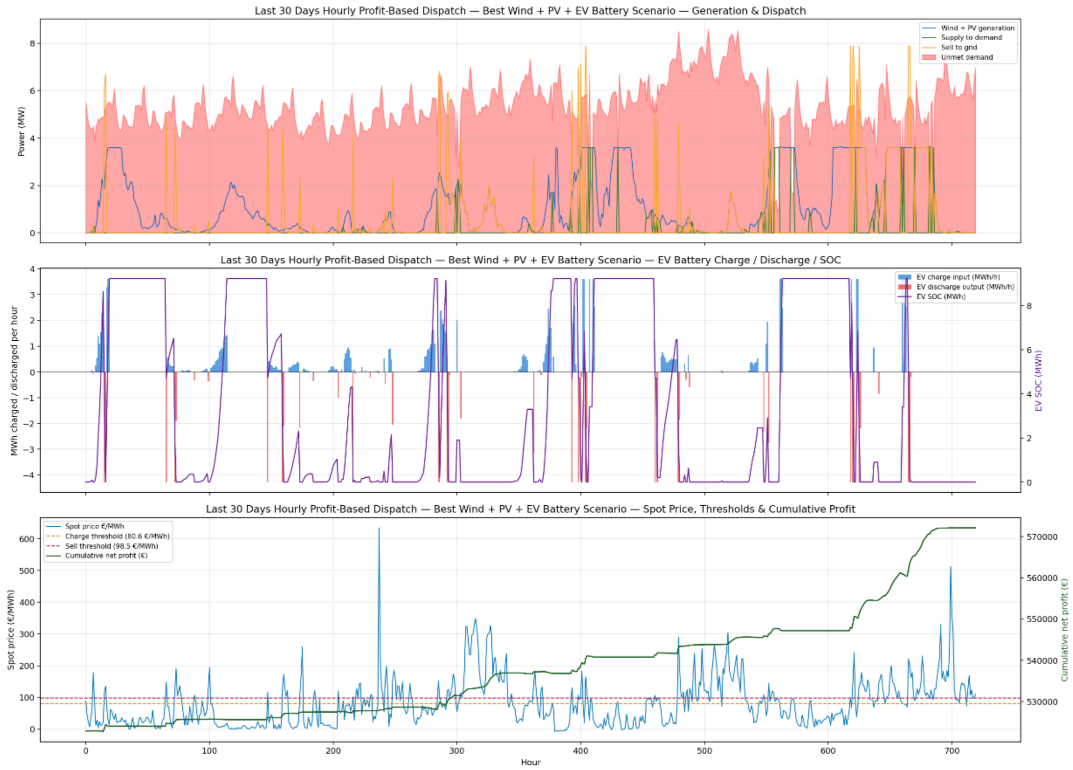

Figure 11. The amount of Target80Unmet_BEV50 that has been dispatched in the last 30 days by price.

While there was more discharge energy in the final 30-day window, than in the first 30-day window, the overall net profit was lower. Lower total selling revenue is the reason for this difference as well as the varying price hours for the selected period. As a result, the initial and final 30-day periods should be viewed as illustrative examples of dispatch for the selected time only only.

The NoEV dispatch results are helpful as a reference point as they represent excluding renewable export but still show EV battery arbitrage. There are two NoEV periods in place and in the initial 30-day period, 409.38 MWh were sold to the grid and the revenue generated was €67,196.21. In the last 30-day NoEV window, it sold 255.91 MWh and earned €37,444.70. The BEV50 case is compared to NoEV, which does not include the EV flexibility service as an extra price responsive flexibility service.

4.8 Sensitivity Analysis

The sensitivity analysis of the LCOE is shown in Figure 12. Several cost assumptions were investigated to see the impact on LCOE. The parameters tested included battery cost, wind CAPEX, PV CAPEX, charger cost and EV participation. The basic rate was 7% throughout the discount. An individual sensitivity test was carried out with each parameter at a time varying and the others maintained at their reference values.

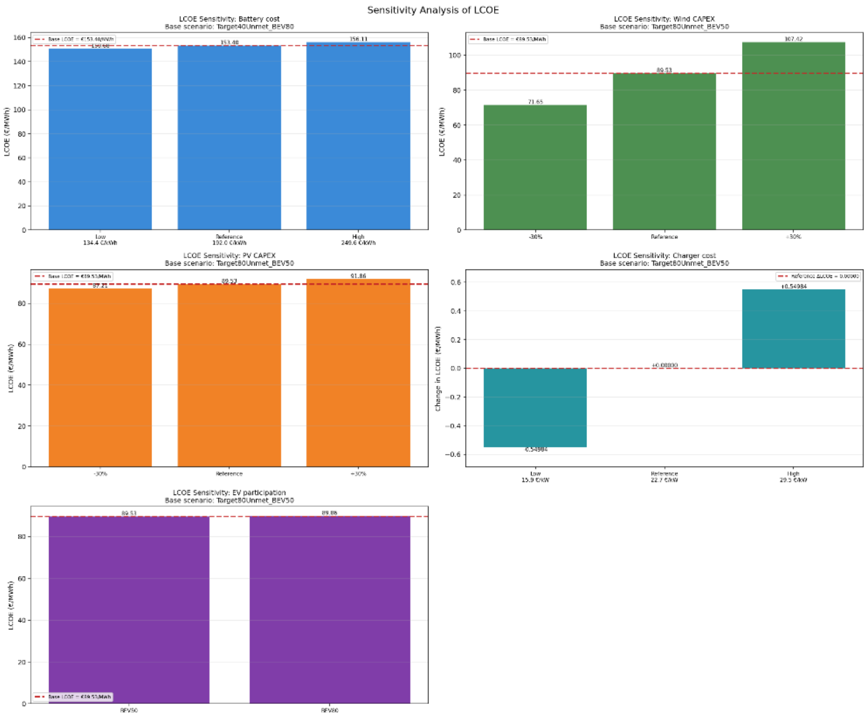

Figure 12. Selected techno-economic assumptions include sensitivity analysis of LCOE.

Wind CAPEX showed the highest impact among all the cases considered: Target80Unmet_BEV50. LCOE was able to be reduced from 89.53 €/MWh to 71.65 €/MWh when wind CAPEX was lowered by 30%. As one may have expected, the higher the wind CAPEX, the greater the LCOE; when wind CAPEX rose by 30%, LCOE rose to 107.42 €/MWh. This result is in line with the chosen configuration: in the least-cost wind–PV–EV case, the most significant part of the annual renewable produced was due to wind generation.

In the same case, PV CAPEX resulted in a smaller effect. A 30% reduction in PV CAPEX reduced LCOE from 89.53 €/MWh to 87.21 €/MWh, while a 30% increase raised it to

91.86 €/MWh. The input assumptions to the reference input also had a not so strong impact on Charger cost. The cost of charging when reduced from the reference cost reduced LCOE to 88.98 €/MWh whilst increased cost of charging increases the LCOE to 90.08 €/MWh. That does not imply that changing cost is not significant in actual practice, simply that it had less of an impact than wind Capex within the cost assumptions made in this model.

Cost sensitivity of battery was tested with Target40Unmet_BEV80. In this case, reducing stationary battery cost from 192 €/kWh to 134.4 €/kWh decreased LCOE from 153.40 €/MWh to 150.68 €/MWh. Raising the battery cost to 249.6 €/kWh lead to a LCOE of 156.11 €/MWh. This impact is moderated by the approach used: the case study employs both EV storage and stationary battery storage, permitting the total cost to be split between multiple system components.

Participation sensitivity of the EV indicates that more EV implies LCOE does not necessarily be lowered in every case. In Target80Unmet, BEV50 had an LCOE of about 89.53 €/MWh, while BEV80 had 89.86 €/MWh. But the previous LCOE comparison indicates that BEV80 helps in more severe Targets (Target40Unmet and Target20Unmet). This means that the value of what EV participation can bring to the economy depends on the local-supply requirement and the actual renewables surplus produced for storage.

4.9 Overall Techno-Economic Interpretation

The techno-economic results show a consistent trade-off between grid dependence, local renewable supply, curtailment, storage requirement and LCOE. The zero-EV baseline makes this trade-off clear. The lowest LCOE was 89.32 €/MWh for LCOE_Target80_NoEV, although the external grid was still needed for 76.99% of the annual demand. Target20Unmet_NoEV, on the other hand, provided approximately 80% of local demand, but necessitated 40 MW wind, 15 MW PV and 50 MWh / 10 MW stationary battery storage, which added up to a LCOE of 337.11 €/MWh.

The techno-economic results were enhanced with EV participation, especially for the high local-supply requirements. The LCOE was only slightly affected by BEV50 and BEV80 for the least strict Target80Unmet case. However, in the Target40Unmet and Target20Unmet cases, EV participation led to a reduction in LCOE and a modification of the chosen split between storage and renewables. The most obvious example is to look at Target40Unmet_BEV80, where stationary battery size reduced from 20 MWh / 10 MW in NoEV case to 10 MWh / 5 MW in BEV80 case. This indicates that under certain conditions, EV storage will be able to partially replace stationary battery storage.

Curtailment grew significantly as the model chose higher additions of renewable energy to lower dependency on the grid. When it came to percentage of curtailment, this was most pronounced in the Target20Unmet cases – with curtailment rate of more than 67% in all EV cases. Compared with NoEV the reduced curtailment with EV batteries did not result in the removal of curtailment. This shows that EV flexibility is valuable for short-term shifting of energy, but it's not enough when renewable energy is massively oversized.

The price-based dispatch results demonstrate that batteries can contribute value on the level of a sufficient price differential between charging and selling hours for EV. The Target80Unmet_BEV50 dispatch windows resulted in an EV battery energy source being charged during the lower priced period and discharged when the price was higher generating extra EV discharge revenue. But these results must be understood as giving a simplified view of dispatch test based on profit, instead of a full market participation model. In practice, EV dispatch value would also depend on battery degradation, user participation, charging infrastructure cost, aggregator operation, market rules and grid constraints.

Overall, the Sundom techno-economic results show that EV battery participation can increase renewable utilization, increase dispatch value in some situations, decrease grid dependence under certain circumstances, mitigate curtailment and lower LCOE where strict local-supply requirements are enforced. But local renewable supply will not be high if just EV are storing the energy. If the share of demand from the grid is significantly reduced, still a tremendous amount of renewable capacity and stationary battery storage are needed. So don't consider V2G as a stand-alone solution, rather as part of a whole-wind-PV-storage solution.

5 Simulink Model of the Sundom Smart Grid Distribution Branch Using Optimal HOPP Data

5.1 MATLAB Simulink Model

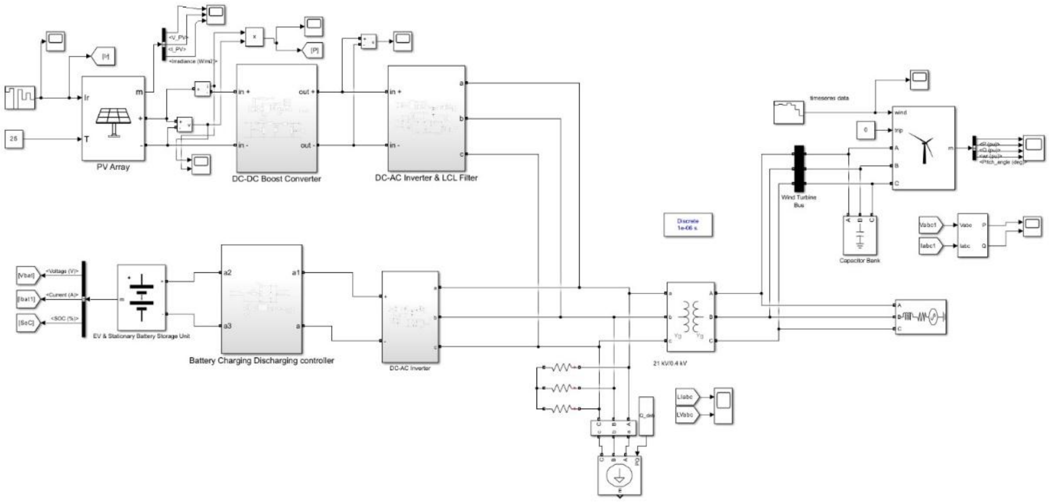

Figure 13. The simulated model.

MATLAB/Simulink was used to create the technical simulation of a distribution branch of the Sundom Smart Grid. The model includes a 21 kV, 50 Hz AC source, a 3.6 MW wind turbine connected at the medium-voltage side, a 21 kV/400 V transformer, a low-voltage distribution load, a 1 MW PV plant, an EV bidirectional charging/discharging station and stationary battery storage. The PV capacity, wind turbine rating, EV battery capacity and stationary storage size were selected from the best-scenario output of the techno-economic model. Therefore, the technical simulation is linked with the techno-economic analysis by applying the selected optimal configuration in a detailed Simulink distribution-network model.

The system involves a 3.6MW wind turbine connected to the 21kV side and a transformer that reduces voltage to 400V on the low voltage distribution branch. The low voltage side consists of the local load, PV plant, local EV charging station and stationary battery storage. The load is based on an annual demand of 7808 MWh/year, which corresponds to an average daily demand of approximately 21.39 MWh/day. The 1

MW PV plant is installed with DC-DC boost converter, DC-AC inverter and LCL filter. The PV DC bus voltage is approximately 600 V before conversion to AC power.

EV station and stationary battery are connected at the end side of the low-voltage distribution branch. The total DC storage capacity is around 12.3MWh. The bidirectional converter allows for operation in charging, discharging and idle modes for the storage system with a battery-side DC bus voltage of 800 V and a charging or discharging current reference of maximum 80 A. In charging, the power goes from the AC side to the DC power storage system. In the discharge, the power goes from the storage system towards the AC side. Idle mode is when no charging or discharging current is called for.

The charging and discharging decision are controlled by electricity spot price and battery state of charge. The capital cost of production is 89,53 €/MWh. The high price threshold is 110% of this value, the low-price threshold is 90% of this value. When the spot price is high and the SOC is at least 55%, the battery discharges with a current reference of −80 A. The battery charges with a current reference of +80 A when the spot price is low with an SOC below 85%. The discharge is not allowed when SOC is below 55%. Charging is blocked if the SOC is above 85%. In any other case, the battery is idle.
The implemented control logic is expressed as follows:

$$B = \begin{cases} 0, & if\ P_{spot} \geq P_{high}\ and\ SOC\ < 55 \\ 0, & if\ P_{spot} < P_{high}\ and\ SOC\ \geq 85 \\ -80, & if\ P_{spot} \geq P_{high}\ and\ SOC\ \geq 55 \\ 80, & if\ P_{spot} \leq P_{low}\ and\ SOC\ < 85 \\ 0, & otherwise \end{cases}$$

Where,

$B_{current}\ = battery\ current\ reference.$

$P_{spot} =\ electricity\ spot\ price.$

$P_{high} = high - price\ threshold.$

$P_{low} =\ low - price\ threshold.$

$SOC = battery\ state\ of\ charge.$

A discrete solver was used for modelling the model with the purpose of capturing the transient behaviour within a short time horizon in the converter-based distribution system. The response of PV converter, battery interface, inverter current, DC bus voltage, grid voltage and battery SOC under charging and discharging operation were tensile stress points.

5.2 Charging Mode Output Results

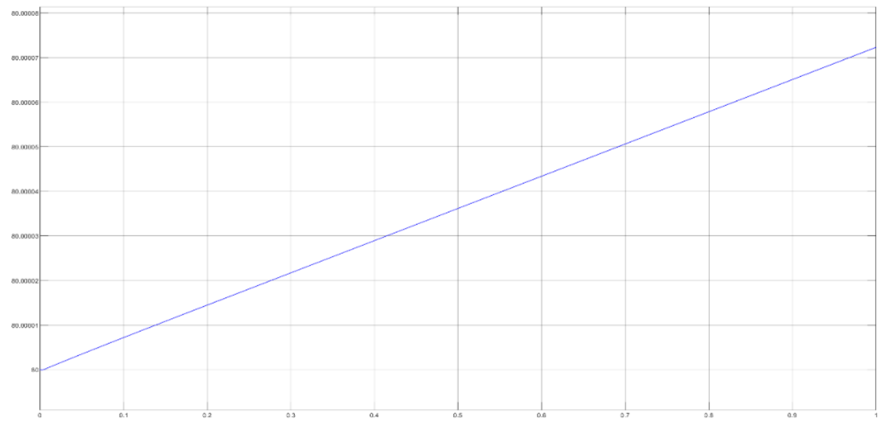

Figure 14. Battery SOC during charging mode.

During charging mode, the battery SOC curve increases slightly from approximately 80%. Although the change is small because of the short simulation time, the upward trend confirms that the battery is receiving energy and operating in charging mode.

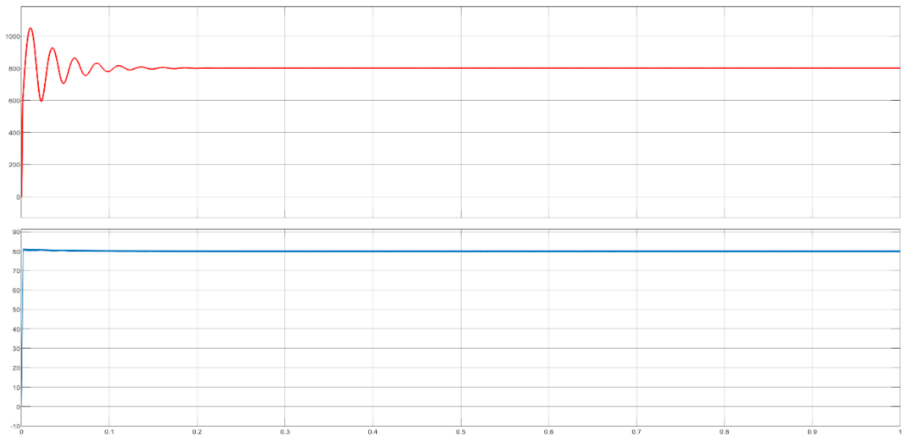

Figure 15. DC voltage and DC current during charging mode.

The second figure shows the DC-side response of the battery/converter system during charging operation.

The DC-side voltage and current response also verifies the charging operation. The transient oscillating characteristics are observed on the DC bus voltage and eventually settle near 800 V. The DC current is increased to about +80 A, corresponding to the charging current reference to be used in the control logics. The result on the DC side indicates that the storage system is charged on command current.

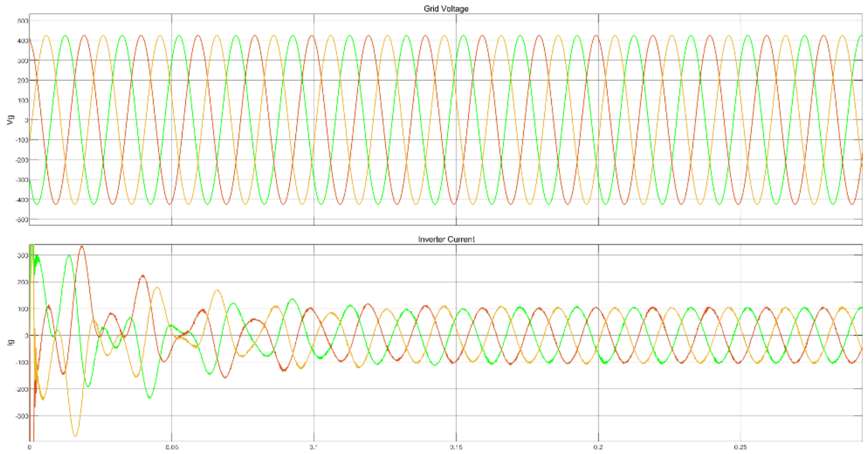

Figure 16. Grid voltage and inverter current during charging mode.

The AC-side behaviour during charging is demonstrated in the grid voltage and inverter current curves. The 3-phase grid voltage maintains its sinusoidal shape with a shift between phases of around 120°. Initially the current in the inverter has transients and then during the steadystate, it is relatively stable with a three-phase sinusoidal form. This means that the inverter is also actively handling the current during the battery charging cycle.

5.3 Discharging Mode Output Results

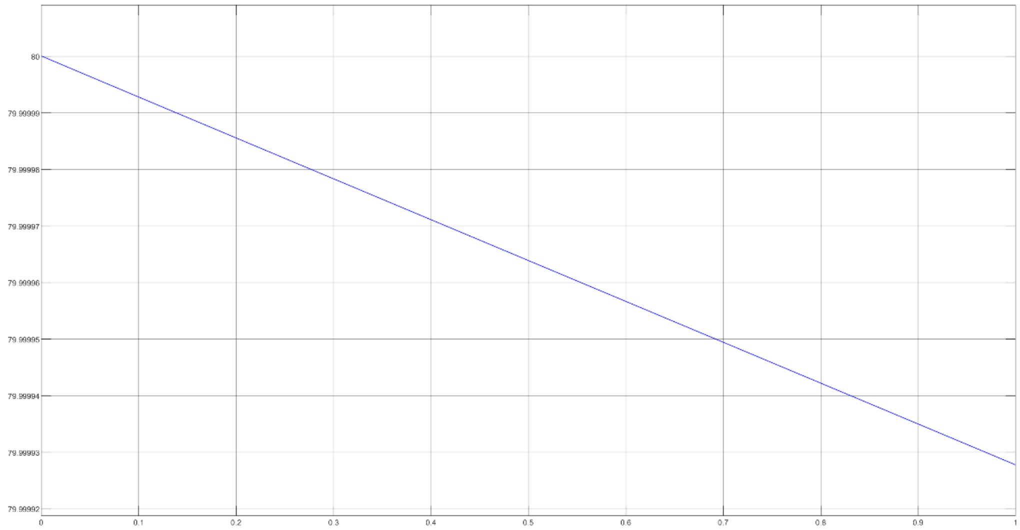

Figure 17. Battery SOC during discharging mode.

The battery SOC curve drops down a little bit from approximately 80% when the battery is in discharging mode. This is a small decrease because the simulation time is small, but the tendency is downward, indicating the release of energy from the battery.

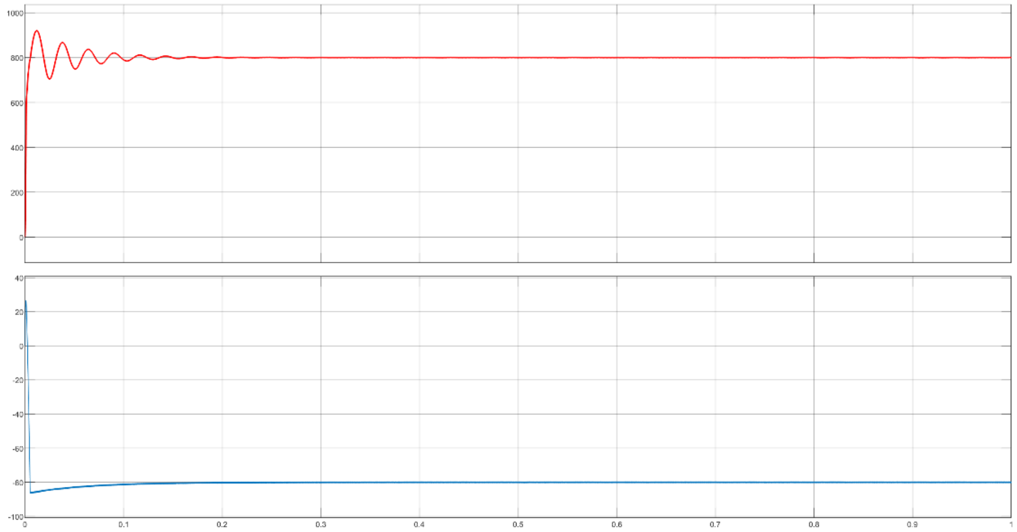

Figure 18. DC voltage and DC current during discharging mode.

The discharging behaviour is seen in the response of the DC side voltage and current of the figure 17. The transient oscillation is initially present in the DC bus voltage and then settles near 800 V. The DC current tends to stabilize around −80 A, corresponding to the discharging current reference of the control logic. The negative current thus verifies that in the defined sign convention the battery is in discharging mode.

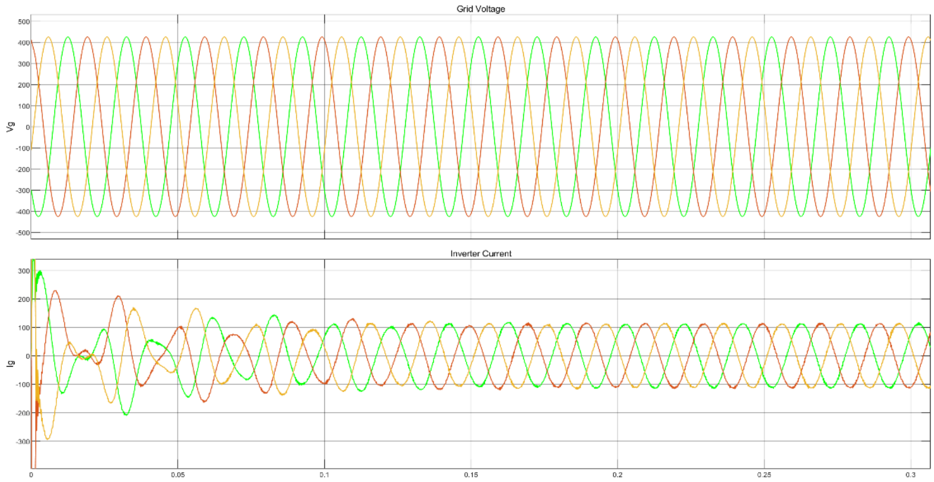

Figure 19. Grid voltage and inverter current during discharging mode.

In this figure 18, the grid voltage and inverter current curves show the AC-side response during discharging. Grid voltage is balanced and sinusoidal and consists of three phases approximately 120 degrees apart. The inverter current contains transient oscillations at the beginning and then becomes more stable. During the discharging time, however, the current fed into the inverter and the voltage of the grid cannot be synchronized as same as those in the charging time. This phase difference indicates the inverter current response during discharging of the battery. The current curve thus reflects the behaviour of the inverter current on the AC side and the negative current on the DC side verifies the discharge state.

5.4 PV Plant Output Results

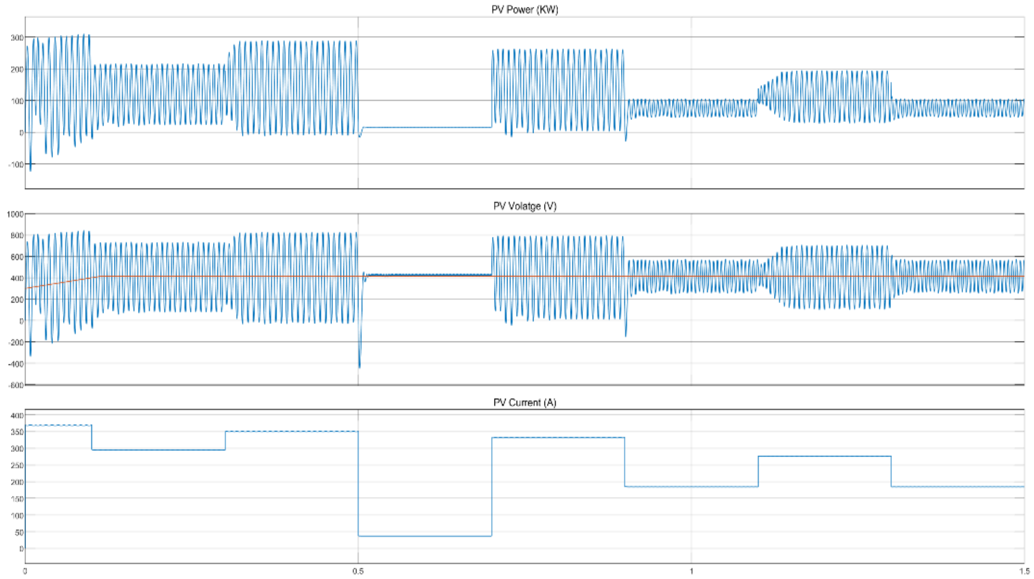

Figure 20. PV power, PV voltage and PV current.

Figure 19 shows the PV-side output of the 1 MW PV plant, including PV power, PV voltage and PV current. The PV power curve changes with time due to the varying value of the input of irradiance over the time of simulation. As irradiance increases PV output power increases and when irradiance decreases PV output power decreases. Therefore, the fluctuation in the PV power curve mainly represents the effect of time-varying irradiance on the PV plant output.

The voltage curve of PV array and converter is illustrated in the same figure as PV voltage curve. The voltage varies based on PV operating condition and the visible ripple is due to power electronic conversion phase. There is also a change of PV current curve as irradiance changes. The higher the irradiance, the higher the PV current and the lower the irradiance, the lower the PV current. Therefore, the PV current variation supports the changes observed in the PV power curve.

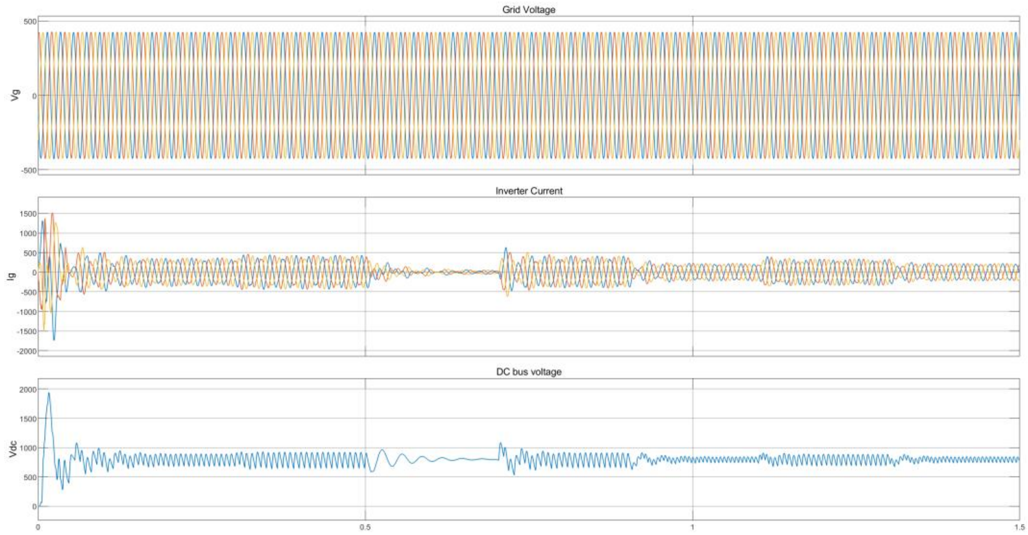

Figure 21. Grid voltage, inverter current and DC bus voltage.

Figure 20 demonstrates the AC-side output of the PV inverter system, showing the grid voltage, inverter current and DC bus voltage. The voltage to the grid appears balanced and sinusoidal and the three phases are approximately 120 degrees apart. Inverter current presents transient response, followed by the steady state three-phase sinusoidal current. It is not constant as the PV power varies with time being dependent on solar irradiance. The transient response of the DC bus voltage has also initially a high peak and oscillation and then a DC bus voltage oscillating around its operating voltage range with some ripples arising from converter and inverter operations.

5.5 Wind Turbine output

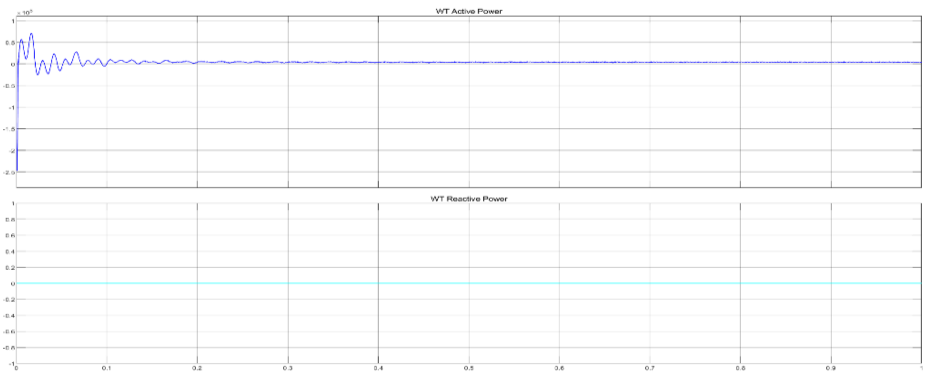

Figure 22. Wind turbine active and reactive power output during the simulation period.

Wind Turbine active and reactive power output is shown in figure 21. The upper plot is the active power of the WT which oscillates during the transient phase and remains approximately steady with small oscillations afterwards. The lower plot is the reactive power of the WT, which has a near zero level during the simulation period. This means that mainly the wind-turbine produces active power and reactive power contribution is negligible as its contribution is very low.

6 Conclusion

This thesis assessed the participation of electric vehicle batteries in a renewable integrated power system, the techno-economic case evaluation was performed on the case of the distribution-network in Sundom Smart Grid. The analysis was conducted via a Python workflow in the Hybrid Optimization and Performance Platform (HOPP) which evaluated wind generation, PV generation, stationary battery storage, EV battery participation, electricity demand, electricity prices and technology costs all in one. The comparison was made between three cases of EV participation (NoEV, BEV50, BEV80) and four TargetUnmet cases. The NoEV case was particularly meaningful as it enabled the specificity of the value of EV participation to be judged against a NoEV baseline. This allowed to explore and understand if the EV storage resulted in increased utilization of renewables, less dependence on the power grid, reduced curtailment, altered stationary battery needs, or decreased levelized cost of energy.

Results indicated that minimum cost configurations were not necessarily those with the highest EV participation. The lowest LCOE was obtained in the Target80Unmet_NoEV case, with an LCOE of 89.32 €/MWh. This finding indicates that, even with the least-stringent local renewables supply requirement, the zero-EV case was the cheapest because it involved limited supplies of renewables and no stationary battery storage. However, as demand for locally provided supply increased, the participation of EV increased in value. For the Target40Unmet and Target20Unmet scenarios, the decrease in LCOE for BEV50 and BEV80 with respect to NoEV includes the benefit of flexibility offered by the EV Battery.

The results also revealed a definite trade-off between grid dependence, renewable overbuilding, renewable curtailment, renewable energy storage needs and system cost. Overall, the model selected larger sizes for wind, PV and battery while removing energy from the external grid, as the TargetUnmet lowered. This boosted local supply from renewables but also led to higher levels of renewable generation curtailment, due to uneven generation and storage availability. In some cases, EV participation reduced curtailment by using part of the renewable surplus and did not avoid curtailment in more extreme cases. The results thus show that EV storage can help bring up renewables' contribution, but it does not eliminate the need for proper renewables sizing, stationary battery storage and support from the grid.

This was most noticeable in the selected system configurations, which highlighted the role of EV batteries. Using both the stationary battery demands and EV storage physical supply data, from the Target40Unmet case, BEV80 found a reduction in the need for stationary battery units compared with the NoEV case, indicating that EV storage competitively can somewhat replace stationary battery storage if sufficiently large volumes of EV storage are available. However, in the Target20Unmet scenario, even with EV participation, a large stationary battery storage was still necessary. This implies that EV batteries provide a valuable service for short duration energy shifting, but they are not the only solution in such a system designed to provide a very high percentage of the annual energy demand from a very short supply-line. The key finding is that V2G is a flexibility resource in the broader context of a wind–PV–storage system than as a stand-alone technology.

The dispatch analysis based on prices also indicated that due to the price spread between charging and selling hours, there is a potential gain in additional economic value if the EV batteries are used in the dispatch. The results here were that in the Target80Unmet_BEV50 dispatch case the EV battery was being charged during lower-priced periods and discharged during higher priced periods with this creating additional EV discharge revenue. This indicates that EV storage can not only help with shifting renewables but can also help with price-responsive operation. But the dispatch analysis was simplified and thus cannot be regarded as a comprehensive electricity-market bidding model. The economic viability of the practical implementation of V2G would, in addition, depend on battery degradation, user compensation, the cost of the chargers, market access, the operation of aggregators and the availability of real electric vehicles.

The main contribution of this analysis is the comparison between the NoEV, BEV50 and BEV80 under the different levels of local-supply requirements. This comparison demonstrates that accounting for the zero-EV case is critical since it exposes the fundamental performance of the wind, PV and stationary-battery power system without EV flexibility. Also, the results demonstrate that the more strongly the system needs to be reduced dependence on the grid, the more valuable EV flexibility is. Consequently, with more stringent scenarios, V2G can also contribute to achieving renewable integration and supporting lower system costs but it must be designed in concert with stationary storage systems, sizing of renewable power and electricity generation, curtailment control and realistic EV participation assumptions. In summary, EV battery participation can enhance renewable utilization, minimize curtailment, lower LCOE in the presence of more stringent local-supply requirements and generate extra dispatch value but must be viewed as part of a larger flexibility portfolio.

To assess the short-term feasibility of the proposed EV bidirectional charging and discharging interface in the renewable-integrated distribution model, a technical simulation was carried out. It is noted that the battery current direction and SOC can easily indicate the charging and discharging modes: charging mode in which the battery current followed the positive reference and discharging mode in which the battery current followed the negative reference, with a small increase of SOC in the charging mode and with a small decrease of SOC in the discharging mode. After the transient, the DC bus voltage was close to the reference voltage of 800 V, which showed stable DC-side operation by the converter interface in both G2V and V2G modes. The sinusoidal grid-side voltage was well-preserved over the entire time, though the voltage level varied accordingly based on the volume of EV charging and discharging. PV output fluctuated with irradiance variability, while wind turbine contributed primarily active power with negligible amount of reactive power. Overall, the technical results have proven that the model can simulate the forward and reverse operation of EV under control and could serve as a reasonable technical basis to correlate with EV battery techno-economic analysis.

6.1 Limitations

There are several limitations that need to be considered when interpreting the techno-economic results of this study. The model was based on fixed participation cases for EV and not on stochastic EV availability. Within the practical domain, the availability of EV relies on the length of parking time, the plug-in behaviour, the daily mobility needs, the access to chargers, the willingness to plug in and the desired departure SOC of the EV. Therefore, the BEV50 and BEV80 scenarios are critical, technical potential cases and not an absolute benchmark for participation. This implies that the estimated contribution of EV to the distribution grid is not necessarily consistent with the actual V2G availability in a real distribution-grid context.

The effects of battery degradation were not fully monetised in the LCOE and dispatch calculation. Either EV batteries or stationary batteries were run between 50% SOC and 85% SOC, which was far short of unrealistic full-depth cycling, but not necessarily a full representation of battery ageing. It is in real V2G operation that degradation cost could impact user compensation, dispatch and profitability. The price-based dispatch analysis was also simplified since it was not a market-optimization or an aggregator bidding approach, but rather operating thresholds based on LCOE for charging and selling. The outcomes in dispatch should thus be viewed as an indicative estimate of the potential value of V2G responsive pricing and an approximation of a commercial V2G profitability estimate.

A range of capacities and assumptions were selected within which the chosen configurations were identified. The model was tested with a range of wind, PV and stationary battery and EV configurations; however the result is not necessarily a global optimum outside those tested ranges. The model also primarily concentrated on annual energy balance, curtailment, grid-supplied demand and LCOE and detailed distribution-network constraints did not fully capture the annual techno-economic optimization. In fact, factors such as feeder limits, transformer loading, voltage constraints, reactive power flows and protection constraints were not considered in the annual assessment based on HOPP. For this reason, the techno-economic findings should be taken as planning indicators for a system, rather than definitive engineering design decisions.

The technical simulation only covered short time dynamical analysis and was not a full day or full year of operation. The duration of simulation was not long enough, so the battery SOC did not reach the lower 55% and upper 85% limits. The storage control was also based only on electricity spot price and SOC, while real-time load demand, PV generation, wind generation and grid import/export measurements were not yet included in the control decision. Thus, the model is a basic converter and battery response and do not represent a complete automatic operation energy-management system. A drawback is that the wind turbine block was phasor-type compared with the other system's solved using a discrete solver, meaning that transient parameters of the wind turbine could not be solved in detail.

6.2 Future Work

Further studies should use a more realistic representation of EV availability. Instead of using fixed BEV50 and BEV80 cases only, future models could include stochastic plug-in and plug-out times, parking duration, daily driving demand, charger location and required departure SOC. This would bring the calculated EV flexibility nearer to actual driving conditions. Solely user willingness may be integrated as well, through a connection with money, degradation of the battery and guaranteed mobility needs. This would aid to ascertain the actual EV battery-based capacity that could be utilized for V2G operation.

A more detailed battery degradation and compensation model should also be included in future work. The SOC range, depth of discharge, charge/discharge power, cycling frequency, energy throughput and battery lifetime assumptions could be considered to estimate battery ageing. This would make the dispatch results obtained by the LCOE and the profit-based dispatch more feasible as there would be a cost to EV cycling. Finally, fixed LCOE-based thresholds in the price-based dispatch model could be replaced by an optimization-based approach. A more advanced dispatch model could consider future price forecasts, renewable generation forecasts, storage availability, grid-export limits, battery degradation cost and user SOC requirements together.

Electricity market and grid-export modelling could also be further enhanced in the techno-economic assessment. A possible future extension would be electricity prices to the consumer, grid tariff, taxes, as well as explicit revenue from selling excess electricity generated by renewables to the grid. A second consideration is that excess export revenues may provide a lower effective system costs in high export renewable scenarios when large curtailments occur. To further investigate, the sensitivity analysis can be extended to other cost scenarios, such as low wind cost and low battery cost, or high PV cost and high charger cost, or other EV participation assumptions. This would broaden the understanding of the sensitivity of the techno-economic conclusions when an alternative technology cost and market condition are considered.

In the future, the Simulink model needs to be further improved by integrating real-time load demand, PV generation, wind generation, grid exchange, electricity price and battery SOC into a supervisory control system. This would provide flexibility to the battery to choose either charging, discharging or idle mode, as per price and local system conditions. The simulation period should also be extended so that the battery can reach the defined SOC limits and the stopping logic at 55% and 85% can be fully verified. If such a model exists, it should be used so a fully discrete model of the wind turbine can be created, allowing the transient behaviour of the wind turbine to be checked in a more consistent manner to the converter-based system. Future work should also involve power factor analysis, Active Reactive Power and Harmonic Analysis, which can play an important role in a proper, detailed, evaluation of the phase shift of the current observed at the inverter during a discharging mode.

References

A. A., S., Child, M., Caldera, U., Breyer, C., & LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland. (2020a). Exploiting wind-solar resource complementarity to reduce energy storage need. *AIMS Energy*, *8*(5), 749–770. https://doi.org/10.3934/energy.2020.5.749

A. A., S., Child, M., Caldera, U., Breyer, C., & LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland. (2020b). Exploiting wind-solar resource complementarity to reduce energy storage need. *AIMS Energy*, *8*(5), 749–770. https://doi.org/10.3934/energy.2020.5.749

Acharige, S. S. G., Haque, M. E., Arif, M. T., & Hosseinzadeh, N. (2022). *Review of Electric Vehicle Charging Technologies, Configurations, and Architectures*. https://doi.org/10.48550/ARXIV.2209.15242

Adhikary, S., Biswas, P. K., Sain, C., Thanikanti, S. B., & Nwulu, N. I. (2023). Bidirectional converter based on G2V and V2G operation with time of usage-based tariff analysis and monitoring of charging parameters using IoT. *Energy Reports*, *9*, 5404–5419. https://doi.org/10.1016/j.egyr.2023.04.358

Al-Rasheedi, M., Al-Khayat, M., Gueymard, C. A., Ellen Haupt, S., Kosović, B., Al-Qattan, A., & Lee, J. A. (2021). Performance analysis of a 10-MW wind farm in a hot and dusty desert environment. Part 1: Wind resource and power generation evaluation. *Sustainable Energy Technologies and Assessments*, *47*, 101487. https://doi.org/10.1016/j.seta.2021.101487

Antretter, M., Oberfeier, P., Surmann, A., Schäfer, M., & Kühnbach, M. (2025). Bidirectional battery electric vehicle fleets in commercial applications: Exploring synergies and substitutions with stationary battery storage. *Applied Energy*, *402*, 126884. https://doi.org/10.1016/j.apenergy.2025.126884

Arsalan, M., Jacob, E., Nie, Z., & Farzaneh, H. (2025). Analyzing the impact of battery technical performance and driving conditions on the overall economic feasibility of a Vehicle-to-Grid (V2G) system implemented in the Japan electric power exchange (JEPX) market. *Energy Conversion and Management: X*, *26*, 100980. https://doi.org/10.1016/j.ecmx.2025.100980

Bakhuis, J., Barbour, N., & Chappin, É. J. L. (2025). Exploring user willingness to adopt vehicle-to-grid (V2G): A statistical analysis of stated intentions. *Energy Policy*, *203*, 114619. https://doi.org/10.1016/j.enpol.2025.114619

Börchers, L., Stötzer, F., Becker, T., Hanfeld, M., & Schwarz, J. (2025). *A Simulation Based Study for Estimating the V2g Potentials for and Effects on Autarky in German Energy Communities and Quarters*. SSRN. https://doi.org/10.2139/ssrn.5096935

Chen, Y., Lei, X., Niu, S., & Jian, L. (2024). Trustworthy V2G scheduling and energy trading: A blockchain-based framework. *eTransportation*, *22*, 100376. https://doi.org/10.1016/j.etran.2024.100376

De Caro, F., Graber, G., Calderaro, V., Vaccaro, A., & Galdi, V. (2025). Exploring economic profit of EV aggregators in supplying flexibility services through V2G. *Sustainable Energy, Grids and Networks*, *43*, 101851. https://doi.org/10.1016/j.segan.2025.101851

Einolander, J., Kiviaho, A., & Lahdelma, R. (2024). Valuing the household power outage self-sustainment capabilities of bidirectional electric vehicle charging. *Applied Energy*, *374*, 124071. https://doi.org/10.1016/j.apenergy.2024.124071

Fachrizal, R., Qian, K., Lindberg, O., Shepero, M., Adam, R., Widén, J., & Munkhammar, J. (2024). Urban-scale energy matching optimization with smart EV charging and V2G in a net-zero energy city powered by wind and solar energy. *eTransportation*, *20*, 100314. https://doi.org/10.1016/j.etran.2024.100314

Fu, J., Chen, Y., Wang, Z., Li, X., Liu, Y., Sun, B., & Li, J. (2025). Power-quality-enhanced control scheme applied in V2G converters: Unified gains optimization for previewable reference feedforward, repetitive learning, and state feedback. *International Journal of Electrical Power & Energy Systems*, *172*, 111274. https://doi.org/10.1016/j.ijepes.2025.111274

Goncearuc, A., De Cauwer, C., Sapountzoglou, N., Kriekinge, G. V., Huber, D., Messagie, M., & Coosemans, T. (2024). The barriers to widespread adoption of vehicle-to-grid: A comprehensive review. *Energy Reports*, *12*, 27–41. https://doi.org/10.1016/j.egyr.2024.05.075

Gschwendtner, C., Sinsel, S. R., & Stephan, A. (2021). Vehicle-to-X (V2X) implementation: An overview of predominate trial configurations and technical, social and regulatory challenges. *Renewable and Sustainable Energy Reviews*, *145*, 110977. https://doi.org/10.1016/j.rser.2021.110977

Hassan, S. J. U., Mehdi, A., Song, J.-S., Shin, G.-S., Alamgir, S., Kim, H.-Y., & Kim, C.-H. (2024). An efficient modelling and hosting capacity analysis of a distribution system integrating PVs supported by the V2G technology. *Electric Power Systems Research*, *236*, 110959. https://doi.org/10.1016/j.epsr.2024.110959

Ibrahim, R. A., Gaber, Ibrahim. M., & Zakzouk, N. E. (2024). Analysis of multidimensional impacts of electric vehicles penetration in distribution networks. *Scientific Reports*, *14*(1), 27854. https://doi.org/10.1038/s41598-024-77662-6

Islam, M. M., Yu, T., Scala, M. L., Wang, J., & Ruan, Z. (2025). Robust nonlinear control design with optimal coordination methodology for bidirectional BEV chargers in V2G/G2V applications. *Journal of Energy Storage*, *113*, 115612. https://doi.org/10.1016/j.est.2025.115612

Jung, J., & Broadwater, R. P. (2014). Current status and future advances for wind speed and power forecasting. *Renewable and Sustainable Energy Reviews*, *31*, 762–777. https://doi.org/10.1016/j.rser.2013.12.054

Laaksonen, H., & Hovila, P. (2016). Flexzone concept to enable resilient distribution grids—Possibilities in sundom smart grid. *CIRED Workshop 2016*, 11 (4 .)-11 (4 .). https://doi.org/10.1049/cp.2016.0611

Laaksonen, H., Sirviö, K., Aflecht, S., & Hovila, P. (2019). *Multi-objective active network management scheme studied in Sundom smart grid with MV and LV network connected DER units*.

Lai, C. S., Chen, D., Zhang, J., Zhang, X., Xu, X., Taylor, G. A., & Lai, L. L. (2022). Profit maximization for large-scale energy storage systems to enable fast EV charging infrastructure in distribution networks. *Energy*, *259*, 124852. https://doi.org/10.1016/j.energy.2022.124852

Li, C., Zhang, L., Ou, Z., Wang, Q., Zhou, D., & Ma, J. (2022). Robust model of electric vehicle charging station location considering renewable energy and storage equipment. *Energy*, *238*, 121713. https://doi.org/10.1016/j.energy.2021.121713

Li, G., Yang, Y., Wang, C., Lei, H., Xu, Z., & Wang, Y. (2025). User Willingness-Incorporated V2G Optimization Method for Active Distribution Networks. *2025 International Conference on Electrical Engineering, Automation and Information Science (EEAIS)*, 70–74. https://doi.org/10.1109/EEAIS66172.2025.11171293

Liu, C., Guo, Y., Qian, X., Li, X., Liu, H., & Zhong, M. (2025). Understanding spatiotemporal dynamics of V2G participation in megacities: A data-driven study. *Applied Energy*, *401*, 126866. https://doi.org/10.1016/j.apenergy.2025.126866

Liu, F., Wei, Z., Lin, Y., Huang, X., Li, Y., Huang, Y., & Lim, M. K. (2025). Vehicle-To-Grid Technology Acceptance for Electric Vehicle Users: A Systematic Literature Review and Future Research Agenda. *International Journal of Consumer Studies*, *49*(3), e70065. https://doi.org/10.1111/ijcs.70065

Lunde, G. A., Damm, E. V., Gade, P. A. V., & Kazempour, J. (2025). *Aggregator of Electric Vehicles Bidding in Nordic FCR-D Markets: A Chance-Constrained Program* (arXiv:2404.12818). arXiv. https://doi.org/10.48550/arXiv.2404.12818

M. Mosammam, Z., Ahmadi, P., & Houshfar, E. (2024). Multi-objective optimization-driven machine learning for charging and V2G pattern for plug-in hybrid vehicles: Balancing battery aging and power management. *Journal of Power Sources*, *608*, 234639. https://doi.org/10.1016/j.jpowsour.2024.234639

Mamidala, S., & Kumar, Y. V. P. (2025). Zeta converter integration for improved power quality in bidirectional V2G energy charging stations. *Results in Engineering*, *28*, 107346. https://doi.org/10.1016/j.rineng.2025.107346

Mastoi, M. S., Zhuang, S., Munir, H. M., Haris, M., Hassan, M., Alqarni, M., & Alamri, B. (2023). A study of charging-dispatch strategies and vehicle-to-grid technologies for electric vehicles in distribution networks. *Energy Reports*, *9*, 1777–1806. https://doi.org/10.1016/j.egyr.2022.12.139

Nagel, N. O., Jåstad, E. O., & Martinsen, T. (2024). The grid benefits of vehicle-to-grid in Norway and Denmark: An analysis of home- and public parking potentials. *Energy*, *293*, 130729. https://doi.org/10.1016/j.energy.2024.130729

Ordono, A., Asensio, F. J., Cortajarena, J. A., Zamora, I., González-Pérez, M., & Saldaña, G. (2024). A grid forming controller with integrated state of charge management for V2G chargers. *International Journal of Electrical Power & Energy Systems*, *157*, 109862. https://doi.org/10.1016/j.ijepes.2024.109862

Razzaque, M. A., Khadem, S. K., Patra, S., Okwata, G., & Noor-A-Rahim, Md. (2025). Cybersecurity in vehicle-to-grid (V2G) systems: A systematic review. *Applied Energy*, *398*, 126364. https://doi.org/10.1016/j.apenergy.2025.126364

Sagaria, S., Van Der Kam, M., & Boström, T. (2025). Vehicle-to-grid impact on battery degradation and estimation of V2G economic compensation. *Applied Energy*, *377*, 124546. https://doi.org/10.1016/j.apenergy.2024.124546

Schwarz, M., Auzépy, Q., & Knoeri, C. (2020). Can electricity pricing leverage electric vehicles and battery storage to integrate high shares of solar photovoltaics? *Applied Energy*, *277*, 115548. https://doi.org/10.1016/j.apenergy.2020.115548

Shang, B., Dai, N., Cai, L., Yang, C., Li, J., & Xu, Q. (2023). V2G Scheduling of Electric Vehicles Considering Wind Power Consumption. *World Electric Vehicle Journal*, *14*(9), 236. https://doi.org/10.3390/wevj14090236

Singh, P. P., Das, S., Wen, F., Palu, I., Singh, A. K., & Thakur, P. (2023). Multi-objective planning of electric vehicles charging in distribution system considering priority-based vehicle-to-grid scheduling. *Swarm and Evolutionary Computation*, *77*, 101234. https://doi.org/10.1016/j.swevo.2023.101234

Sirviö, K., Kauhaniemi, K., Ali Memon, A., Laaksonen, H., & Kumpulainen, L. (2020a). Functional Analysis of the Microgrid Concept Applied to Case Studies of the Sundom Smart Grid. *Energies*, *13*(16), 4223. https://doi.org/10.3390/en13164223

Sirviö, K., Kauhaniemi, K., Ali Memon, A., Laaksonen, H., & Kumpulainen, L. (2020b). Functional Analysis of the Microgrid Concept Applied to Case Studies of the

Sundom Smart Grid. *Energies*, *13*(16), 4223. https://doi.org/10.3390/en13164223

Sirviö, K., Mekkanen, M., Kauhaniemi, K., Laaksonen, H., Salo, A., Castro, F., Ansari, S., & Babazadeh, D. (2019). Controller Development for Reactive Power Flow Management Between DSO and TSO Networks. *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 1–5. https://doi.org/10.1109/ISGTEurope.2019.8905578

Solomon, A. A., Bogdanov, D., & Breyer, C. (2019). Curtailment-storage-penetration nexus in the energy transition. *Applied Energy*, *235*, 1351–1368. https://doi.org/10.1016/j.apenergy.2018.11.069

Solomon, A. A., Kammen, D. M., & Callaway, D. (2016). Investigating the impact of wind–solar complementarities on energy storage requirement and the corresponding supply reliability criteria. *Applied Energy*, *168*, 130–145. https://doi.org/10.1016/j.apenergy.2016.01.070

Sovacool, B. K., Kester, J., Noel, L., & Zarazua De Rubens, G. (2020). Actors, business models, and innovation activity systems for vehicle-to-grid (V2G) technology: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *131*, 109963. https://doi.org/10.1016/j.rser.2020.109963

Sun, Z. W., & Jiao, J. (2014). A Survey of Vehicle-to-Grid Implementation through Virtual Power Plants. *Applied Mechanics and Materials*, *631–632*, 314–317. https://doi.org/10.4028/www.scientific.net/AMM.631-632.314

Szinai, J. K., Sheppard, C. J. R., Abhyankar, N., & Gopal, A. R. (2020). Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management. *Energy Policy*, *136*, 111051. https://doi.org/10.1016/j.enpol.2019.111051

Unterluggauer, T., Rich, J., Andersen, P. B., & Hashemi, S. (2022). Electric vehicle charging infrastructure planning for integrated transportation and power distribution networks: A review. *eTransportation*, *12*, 100163. https://doi.org/10.1016/j.etran.2022.100163

Wan, M., Yu, H., Huo, Y., Yu, K., Jiang, Q., & Geng, G. (2024). Feasibility and Challenges for Vehicle-to-Grid in Electricity Market: A Review. *Energies*, *17*(3), 679. https://doi.org/10.3390/en17030679

Wang, S., Cabrera, J. A., & Fitzek, F. H. P. (2024). *Bidirectional Charging Use Cases: Innovations in E-Mobility and Power-Grid Flexibility* (arXiv:2412.17814). arXiv. https://doi.org/10.48550/arXiv.2412.17814

Yang, K., Zhang, Q., Wang, G., Li, H., & McLellan, B. (2024). A new model for comprehensively evaluating the economic and environmental effects of vehicle-to-grid(V2G) towards carbon neutrality. *Journal of Energy Storage*, *98*, 113067. https://doi.org/10.1016/j.est.2024.113067

Yu, F., Bi, S., & Zhang, E. (2026). Optimizing electric vehicle-based renewable energy microgrids with V2G technology: An integrated approach for grid efficiency and sustainability. *Journal of Energy Storage*, *141*, 119156. https://doi.org/10.1016/j.est.2025.119156

Yun, S., Woo, J., & Kwak, K. (2025). Unlocking peak shaving: How EV driver heterogeneity shapes V2G potential. *Energy*, *329*, 136773. https://doi.org/10.1016/j.energy.2025.136773

Zentani, A. T., Almaktoof, A. M. A., & Kahn, M. (2024). *A Comprehensive Review of Electric Vehicles Fast Charging Developments and Technology*. Engineering. https://doi.org/10.20944/preprints202404.1355.v1

Zheng, Y., Shao, Z., Shang, Y., & Jian, L. (2023). Modeling the temporal and economic feasibility of electric vehicles providing vehicle-to-grid services in the electricity market under different charging scenarios. *Journal of Energy Storage*, *68*, 107579. https://doi.org/10.1016/j.est.2023.107579

Fingrid. (n.d.). Open data on the electricity market and the power system. Retrieved May 8, 2026, from https://data.fingrid.fi/en

Finnish Meteorological Institute. (n.d.). Data sets made available. Retrieved May 8, 2026, from https://en.ilmatieteenlaitos.fi/open-data-sets-available

International Renewable Energy Agency. (2025). Renewable power generation costs in 2024. International Renewable Energy Agency.

https://www.irena.org/Publications/2025/Jun/Renewable-Power-Generation-Costs-in-2024

National Renewable Energy Laboratory. (n.d.). Welcome to the HOPP documentation. HOPP: Hybrid Optimization and Performance Platform. Retrieved May 8, 2026, from https://hopp.readthedocs.io/en/latest/intro.html

Electric Vehicles Database. (2026). Useable battery capacity of full electric vehicles. https://ev-database.org/cheatsheet/useable-battery-capacity-electric-car