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Deliverable D2.1 Control Strategies for V2X Integration in Houses

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Deliverable D2.1
Control Strategies for V2X Integration in Houses

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[1] https://ev4eu.eu/

Executive Summary

The *Control Strategies for V2X Integration in Houses* deliverable aims to create a decision-making model capable of integrating Vehicle-to-Everything (V2X) and Distributed Energy Resources (DER) / Renewable Energy Sources (RES) aspects in a Home Energy Management System (HEMS). The resulting decision-making model will be considered in the Portuguese demonstrator of the EV4EU project, in São Miguel Island, Azores, to test Vehicle-to-Home (V2H) smart charging and discharging techniques that benefit both Electric Vehicle (EV) using homeowners and utilities.

The methodology for the design and development of the proposed decision-making model includes the following steps:

1. Data Collection: Post-processing information on EV usage behaviours, load demand profiles, network tariff frameworks, grid service activation, and weather conditions specific to the case of São Miguel Island. The aforementioned data serve as input for the decision-making model.
2. Forecast Module: The decision-making model includes a forecast module that features machine learning capabilities to predict EV user behaviour, weather conditions (*i.e.*, solar PV power output), household energy consumption, and grid service activation. This module generates predictive day-ahead data.
3. Daily Planning Module: The decision-making model also includes a daily planning module computationally rooted in optimization algorithms. This module aims to produce control instructions that optimize a predefined goal, such as minimizing the overall operating cost of a household with an EV.
4. Real-time operation Module: Based on real-time data, previous control decisions, and the control instructions from the daily planning module, this module leverages information exchange and communication capabilities to control and monitor multiple EV charging and discharging actions.

To that effect, the main findings of this work are related to the capabilities of the decision-making algorithm for the integration of EVs into the energy system, with a focus on V2X integration in houses. The inclusion of a forecast and an optimization module can boost economic benefits for distinct parameters, namely, EV usage, load demand, and grid service participation. These benefits are enhanced as the flexibility and complexity of variables increase. Nevertheless, the computation time can escalate, which may limit the attainment of global optimums within the designated time window.

The capabilities of the developed control strategies have shown promising results in achieving substantial cost reductions. These optimization-based approaches have proven to be particularly effective, especially in terms of leveraging the sale of exported energy to the power grid. Implementing such algorithms can lead to enhanced financial benefits for the stakeholders involved in load flexibility. Also, this V2X integration into the energy system can reduce carbon emissions and promote sustainable energy practices.

Two main recommendations emerge as the inclusion of comprehensive studies on the overall operational cost (*e.g.*, battery degradation) and forms of compensation for participation in grid services. The results of these studies on battery degradation would not only strengthen existing know-how relative to the techno-economic feasibility of V2X technology but also support the creation of new rules and penalties to be respectively integrated into the rule-based and optimization algorithms of the daily planning module, enabling a more complete decision-making model. Different forms of compensation are also envisaged, particularly those of economic nature, for the provision of EV

supported grid services, which should preferably be conducted in association with flexibility operators and EV users.

These conclusions highlight the potential benefits, challenges, and areas for further research and development in the integration of EVs into the energy system, namely within the household scope, using the proposed decision-making algorithm.

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Acronym

DER	Distributed Energy Resources
DHI	Diffuse Horizontal Irradiance
DNI	Direct Normal Irradiance
EDA	Eletricidade dos Açores
EV	Electric Vehicle
GHI	Global Horizontal Irradiance
HEMS	Home Energy Management System
NSRD	National Solar Radiation Database
OF	Objective Function
PDF	Probability Distribution Function
PV	Photovoltaic
RES	Renewable Energy Sources
SOC	State of Charge
SS	Secondary Substation
V2H	Vehicle-to-Home
V2X	Vehicle-to-Everything

Nomenclature

Δt	Time step
η	Overall efficiency of the EV and charger joint system
E	Energy instructed to be charged/discharged into/from the EV
E_{EV}^{CH}	Energy to be effectively charged into the EV
E_{EV}^{DCH}	Energy to be effectively discharged from the EV
$\bar{E}_{EV}$	EV battery capacity
$\underline{E}_{EV}$	User-defined minimum battery level
$\underline{\underline{E}}_{EV}$	Algorithm-defined minimum battery level
E_t^{SOC}	SOC at time t
E_{thrsh}	Algorithm-defined threshold within S4 – energy export simulator
I_{soc_e}	Expected SOC at the time of the next EV exit instance
$\bar{P}_C$	Contracted power
$\bar{P}_{CS}^{CH}$	Maximum charger charge power
$\bar{P}_{CS}^{DCH}$	Maximum charger discharge power
$\bar{P}_{EV}^{CH}$	Maximum EV charge power
$\bar{P}_{EV}^{DCH}$	Maximum EV discharge power
$P_t^{CongRelax}$	Relaxation variable related to non-participation in congestion management services
P_t^{export}	Power exported to the power grid at time t
P_t^{import}	Power imported from the power grid at time t
$P_t^{CurtRelax}$	Relaxation variable related to non-participation in wind curtailment services
P_L	Household load
P_{PV}	PV power output
P_U	Unsupplied power
$price_t^{buy}$	Energy import price at time t
$Price_{thr}$	User-defined electricity price threshold
$price_t^{sell}$	Energy export price at time t
$pricesignal_t^{Cong\_buy}$	Energy purchase price signal for active congestion management service participation
$pricesignal_t^{Cong\_sell}$	Energy sale price signal for active congestion management service participation
$pricesignal_t^{Curt\_buy}$	Energy purchase price signal for active wind curtailment service participation
$Penalty_t^{Cong}$	Penalty for an unsuccessful response to a congestion management service participation request
$Penalty_t^{Curt}$	Penalty for an unsuccessful response to a wind curtailment service participation request

1 Introduction

The combination of V2H smart charging and discharging techniques with DER, such as solar PV, has been proven to be a viable energy management design for residential applications, effectively covering a typical household's load profile. V2H technology may serve as a practical backup power system, enabling EV users to optimize their houses' energy consumption in a cost-effective manner, combining volatile solar PV production with distinct driving behavioural patterns. Furthermore, coupling V2H technology and DER provides additional flexibility to the power grid, making it more robust to unexpected demand-side and supply-side imbalances [1].

1.1 Scope and Objectives

This document presents a newly created decision-making model towards the integration of V2X and DER aspects in a HEMS. The model considers a plurality and heterogeneity of data, pertaining to solar PV power output, household energy consumption, EV usage behaviour, grid service activation, electricity market pricing, and weather conditions.

In this context, the main objective herein is to design, develop, and preliminarily evaluate the performance of the decision-making model in the context of several residential demonstration sites in São Miguel Island, Azores, Portugal. In particular, the model must be capable of effectively leveraging advanced forecast capabilities, rule-based and optimisation algorithms, as well as real-time control techniques, to minimize the overall cost of operation of a household with an EV, while considering the potential activation of grid services, such as wind curtailment and congestion management, as well as the export of energy to the power grid.

To achieve these goals, extensive data collection was initially performed, either by retrieving real data, or – in case that was not possible – by generating new datasets based on reasonable assumptions. Following, the decision-making model was designed and developed considering three different modules – forecast, daily planning, and real-time operation. Finally, that same decision-making module was evaluated via a benchmark comparison between real data and the simulated results of multiple scenarios considering different input data variables and algorithm architectures.

1.2 Structure

The remainder of the current document is divided into 4 sections. Section 2 introduces an overview of the data that will feed the forecast module of the decision-making model. Section 3 addresses the design and development – including in terms of implementation setup – of the decision-making algorithm. Its performance is then discussed in Section 4, while the main conclusions of the present document are outlined in Section 5.

1.3 Relationship with Other Deliverables

The scenarios considered for the simulation of the proposed decision-making model are partly rooted in the insights regarding the evolution of the Portuguese electromobility market – available in *D1.1 Electric Road Mobility Evolution Scenarios* [2]. On the other hand, the Portuguese regulatory framework for pricing and compensation – available in *D1.3 Regulatory opportunities and barriers for V2X deployment in Europe* [3] – not only impacts the scenarios, but also the algorithms underlying the daily planning module of the decision-making model. Moreover, the grid services considered are based on the business models and subsequent business use cases applicable to the Portuguese electromobility market – available in *D1.4 Business models centred in the V2X value chain* [4] and *D1.5 V2X Use-cases repository* [5], respectively.

Downstream, the decision-making model resulting from the current deliverable will be installed, configured, commissioned, operated, and monitored in the residential sites of the Portuguese demonstrator. Thus, the present deliverable will serve as the basis for a part of the implementation procedures detailed in deliverable *D6.1 Implementation plan for the Azores demo*.

2 Data Pre-Processing

The present work envisions the design, development, and preliminary evaluation of a suitably performing decision-making model enabling the integration of V2X and DER aspects in the HEMS of several residencies in São Miguel Island (at least one of which includes a solar PV system). In this context, it is fundamental to ensure that the model is fed with data which are representative and extensive scope-wise.

On that account, a comprehensive dataset has been developed, either through direct data collection or assumption-based data generation, namely:

- EV usage behavioural data – generated based on previously compiled data [6]–[9];
- Load demand profile data:
  - PV power output data – collected via the database of the Azorean electrical system operator, Eletricidade dos Açores (EDA) [10];
  - Household energy consumption data – collected via the Horizon 2020 SMILE project's database [11].
- Network tariff data – collected via EDA's current electricity pricelist [12], as well as via the current electricity market daily and weekly cycling on the part of the Portuguese energy regulating authority, Entidade Reguladora dos Serviços Energéticos [13];
- Grid services data:
  - Wind curtailment data – collected via EDA's database [14];
  - Congestion management data – collected via EDA's database [15].[2]
- Weather data – collected via the National Solar Radiation Database (NSRD) [16].

2.1 EV Usage Behaviour

Given the inherent difficulty underlying the prediction of specific individual EV usage behaviour, two opposing EV usage behavioural patterns were introduced based on previously compiled data [6]–[9], namely: i) "car at work"; and ii) "car at home".

2.1.1 Temporal Availability

Based on [6]–[9], the "car at work" EV usage pattern considers that the EV mostly remains at an office during the day, assuming its user has a 95% chance to commute to and from work during any weekday. Accordingly, the following Probability Distribution Functions (PDFs) shown in Figure 1 are assumed for the EV users' departure and arrival times.

[2] The primary objective of including this data is to evaluate the decision-making model's effectiveness in curtailing EV charging sessions when a congestion management service participation request is received.

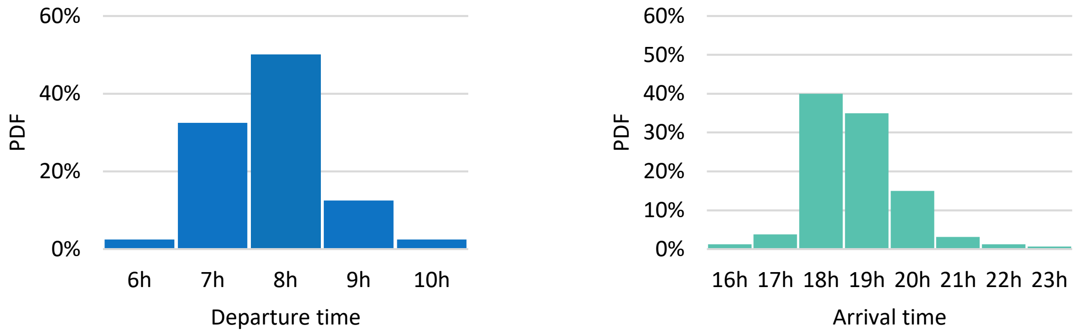


Figure 1. PDFs of the departure (left) and arrival (right) times for the “car at work” on weekdays

During the weekend, EV usage is naturally more erratic: an 80% chance is assumed for the EV user to conduct a round trip [2]–[5]. In this context, a uniform distribution PDF was assumed for the EV users’ departure time (between 08:00 and 15:00) and trip duration (between 3 hours and 8 hours) during any weekend day.

On the other hand, the “car at home” EV usage pattern considers that the EV mostly remains at home during the day, assuming its user has a 95% chance to conduct a round trip on any weekday (*e.g.*, to get children to and from school) [2]–[5]. The departure time is assumed to be identical to that of the “car at work” EV usage pattern in Figure 1 (*i.e.*, two daily trips, one of which during the morning, and the other during the afternoon or evening), while the trip duration is assumed to follow a uniform distribution (between 0.5 hours and 1 hour).

Moreover, during the weekend, the departure time, trip duration, and round-trip probability are considered identical to the case of the “car at work” EV usage pattern.

These scenarios provide a simplistic yet representative characterisation of possible mobility behaviours at the Portuguese demonstration sites. Their primary purpose is to incorporate stochastic behaviour in the EV usage behaviour considered in the proposed decision-making model.

2.1.2 Energy Consumption

The previously introduced EV usage patterns enable the precise characterisation of EV availability for charging/discharging actions. Nevertheless, the proposed decision-making model requires data concerning EV energy consumption, which can be indirectly derived through the vehicles’ covered distance.

Considering the local context of the Portuguese demonstrator in São Miguel Island, an average daily covered distance of around 30 km is assumed, which is roughly below the national average (46 km) [17]. On the other hand, the assumed dispersion is based on the data compiled in [6]–[9]. EV energy consumption is assumed to be about 15 kWh / 100 km (implying an EV annual energy consumption of around 1.5 MWh), resulting in the “car at work” and “car at home” weekday and weekend day PDFs illustrated in Figure 2.

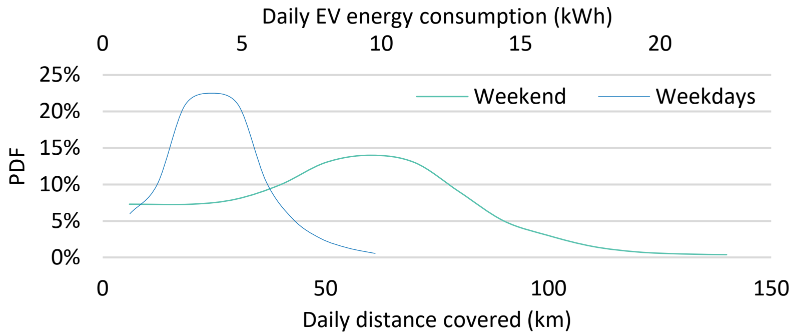


Figure 2. PDFs of the daily covered distance and EV energy consumption per type of day

It is estimated that, on any given weekday, the vast majority of EVs will cover around 10 km to 30 km, consuming approximately 1.5 kWh to 4.5 kWh. On the other hand, on any given weekend day, most EVs are assumed to cover around 50 km to 90 km, corresponding to an EV energy consumption of approximately 7.5 kWh to 13.5 kWh. It is important to emphasize that this is an assumed behaviour, implying that other EV users may follow different patterns.

2.2 Load Demand Profile

Load demand profiling implies the collection of two additional datasets: i) PV power output data; and ii) household energy consumption data.

2.2.1 PV Power Output

The power output of a 6-panel PV system with a peak power output of 2.22 kWp was retrieved from EDA's database [10], concerning a typical single-family house, in Ponta Delgada, São Miguel Island, Azores. The dataset represents data collected from 12/01/2022 to 20/12/2022, at 5-minute intervals. Missing data have been linearly interpolated considering the two most proximate data points. Concerning prolonged periods with no available data points, data have been duplicated considering the most proximate data points.

In this context, Figure 3 illustrates the average PV power output per time of day and season.

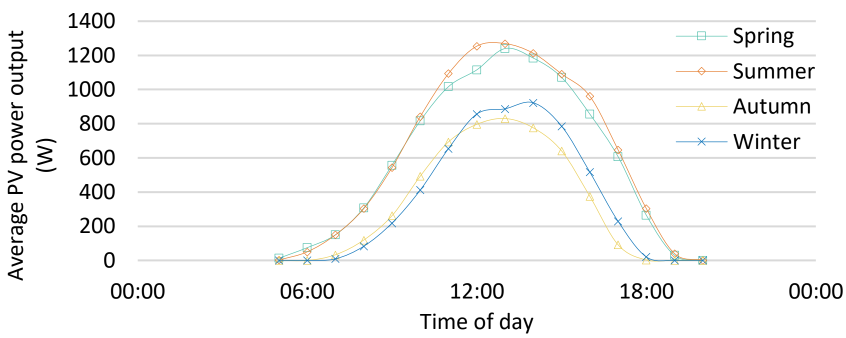


Figure 3. Average PV power output per time of day and season

Naturally, the spring and summer seasons encompass higher average PV power outputs. It is also relevant to remark the total annual energy produced, which amounted to approximately 2.72 MWh, resulting in an annual energy yield of about 1.2 MWh/kWp.

2.2.2 Household Energy Consumption

The energy consumption of a single-family household in Madeira Island, with an annual energy consumption of approximately 6 MWh and without an EV, was retrieved from the database of the Horizon 2020 SMILE project [11]. Even though data could not be obtained for the energy consumption of a house in São Miguel Island, it is important to highlight the similarities between the two locations at stake, such as the fact that both islands belong to Portuguese autonomous regions. The dataset represents data collected from 01/01/2019 to 30/12/2019, at 1-minute intervals. Missing data are subjected to a similar post-processing approach as outlined in the preceding section.

Figure 4 illustrates the average household energy consumption per time of day and season.

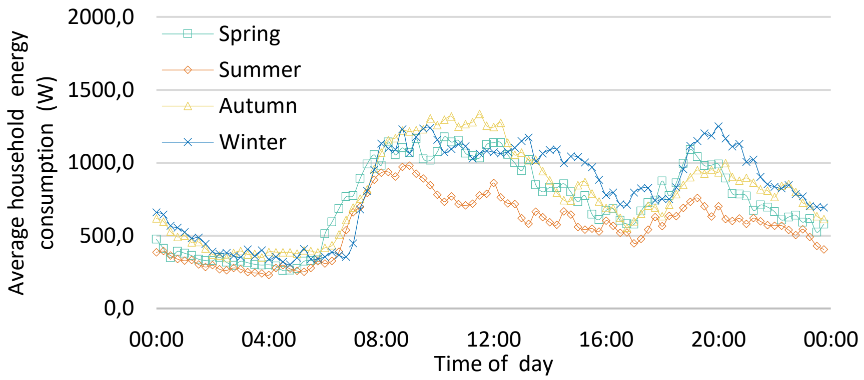


Figure 4. Average household energy consumption per time of day and season

As expected, the average household energy consumption was the lowest during the summer and the highest during the winter. Moreover, the average household energy consumption peaked during the morning and late evening periods, while it valleyed during the night.

2.3 Network Tariffs

In the Azores, electricity prices for low voltage clients (*i.e.*, clients with a contracted power between 2.3 kVA and 20.7 kVA) are fixed according to seasonally dependent time-of-use tariffs that vary according to a daily or a weekly cycle [12], which are represented in Figure 5.

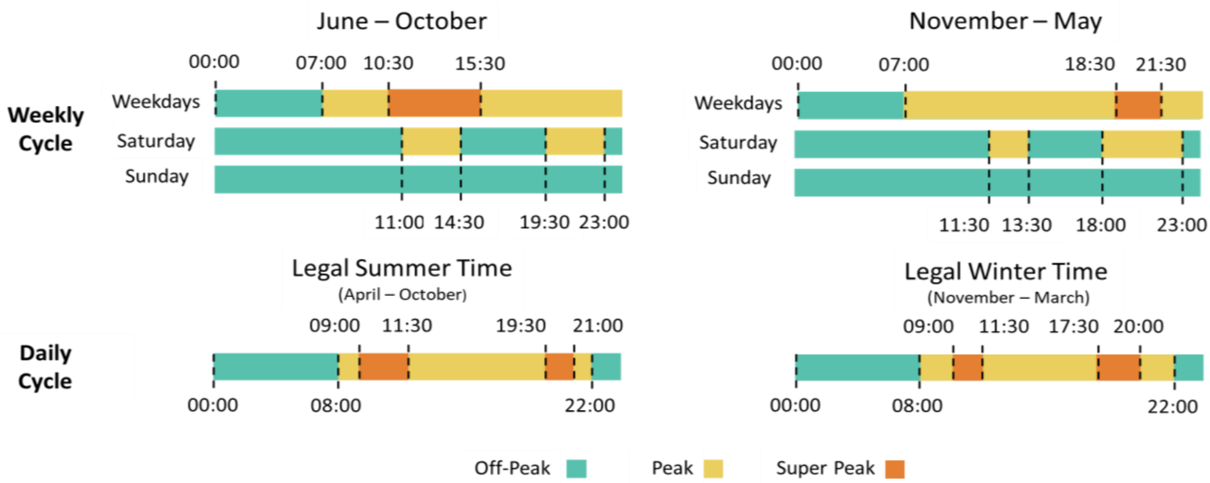


Figure 5. Azorean electricity market weekly cycle (top) and daily cycle (bottom) applicable to low voltage clients

Electricity prices currently practiced in the Azores are summarized in Table 1 [12]:

Table 1. Electricity prices in the Azores, by period, in €/kWh

<table>
<tr><th>Simple</th><th>Bi-hourly</th><th>Tri-hourly</th><th>Period</th></tr>
<tr><td rowspan="3">0.1707</td><td>0.1112</td><td>0.1112</td><td>Off-peak time</td></tr>
<tr><td rowspan="2">0.2031</td><td>0.1769</td><td>Peak time</td></tr>
<tr><td>0.2439</td><td>Super peak time</td></tr>
</table>

It is worth mentioning that the simulated scenarios for the proposed decision-making model consider a weekly cycle, as well as a tri-hourly network tariff structure. Furthermore, regard that the sale price for the electricity discharged from the solar PV system or EV to the power grid was assumed to be 80% of the tri-hourly electricity prices in Table 1.

2.4 Grid Services

Unmanaged EVs may lead to the surge of load demand beyond what is deemed acceptable when considering the local capacity constraints. However, V2H integration transforms an EV into a flexible load, unlocking the activation of grid services and hence various benefits for the homeowners and grid operator, with a strong emphasis on RES integration.

The present subsection will focus on assessing the relevance of EV charging and discharging actions towards providing grid services, namely: i) wind curtailment; and ii) congestion management.

2.4.1 Wind Curtailment

RES integration into power systems poses some challenges in terms of balancing generation with demand, given their inherent volatility. Due to grid safety and reliability issues, spinning reserves must be dimensioned to back up non-dispatchable sources such as RES. On isolated systems, as São Miguel Island, this represents a pivotal challenge, not only due to the system's dimension but also given the absence of interconnections with other systems.

For the upcoming years, an addition of around 20 MW of non-dispatchable power – divided between geothermal, wind, and solar PV power – is planned for the electrical system of São Miguel Island. In parallel to the resulting decarbonization of the island's power system, there will be a surging need to set up each tool that can help to integrate RES into the power system without compromising its safety and reliability.

Usually, curtailment in a wind farm occurs during the night period, matching the off-peak time. In parallel, the average home EV charging action takes place during night-time. Therefore, grid services seeking to coordinate EV charging actions and wind power generation could enable harnessing a significant amount of otherwise curtailed power.

In this context, an extensive dataset was retrieved from EDA's database [14] to support the assessment of the curtailed power at the Graminhais wind farm (the only wind farm on the island), with 9 MW of installed power. The collected sample extends from 12/01/2022 to 31/12/2022, at 10-minute intervals. Missing data were post-processed similarly to previous sections. In this regard, it is worth noting that, between the months of May and July, there were 16 days in which all wind turbines were switched off between 09:00 and 16:00, allowing for the maintenance of the downstream transmission line.

Figure 6 illustrates the average curtailed power at the Graminhais wind farm, per month and per time of day (focusing only on the night period, considered to be between 00:00 and 07:00).

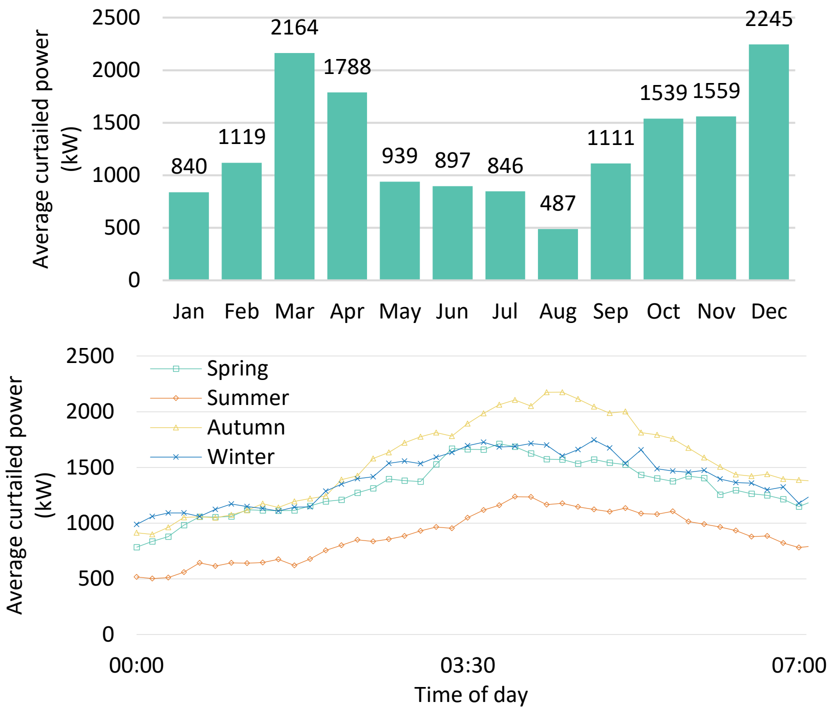


Figure 6. Average curtailed power at the Graminhais wind farm per month (top) and time of day (bottom)

As expected, wind curtailment is typically higher during autumn and winter, when wind is more abundant, whereas it is lower during spring and summer. Moreover, an average curtailed power peak is observable between around 03:50 and around 04:50, which is encompassed within the off-peak time.

Assuming wind curtailment occurrences are adequately predicted, the likelihood of an EV being called upon to participate in a grid service depends on the pool of participating EVs (in this deliverable, the assumed number of participating EVs is 500).

2.4.2 Congestion Management

Concerning congestion management, the decision-making model must be able to effectively engage in grid services by pausing a charging session, or even discharging. With a view to supporting the decision-making model in this regard, data pertaining to the active power of a 630 kVA Secondary Substation (SS) serving the urban area of Arcanjo Lar (a high load demand urban zone in Ponta Delgada) was retrieved via EDA's database [15], being collected from 01/01/2022 to 31/12/2022, at 10-minute intervals.

Figure 7 illustrates the usage rate (*i.e.*, ratio between load demand and total installed power), on average, per time of day, of the Arcanjo Lar SS.

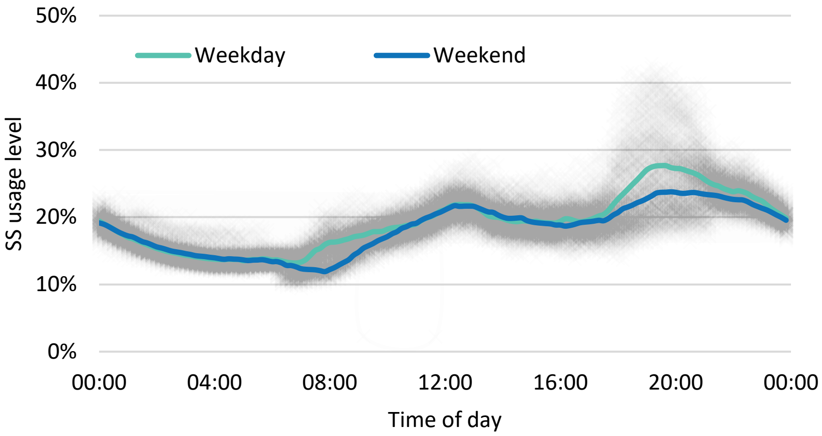


Figure 7. Usage rate of the Arcanjo Lar SS per type of day and time of day

Overall, the average usage rate of the SS is low. Peak consumption occurs during the morning and late evening periods, independently of the day. However, weekdays exhibit slightly more demand, especially at dinner time.

Usually, the period of highest demand starts around 18:00 and ends around 22:00. This is to be expected, since this daily period is typically characterized by higher load demands in urban areas. In fact, daily average capacity peaks at approximately 19:30 during weekdays (27.7%) and 19:50 during weekend days (23.8%). On the other hand, daily average capacity valleys at approximately 06:50 during weekdays (13.2%) and 07:50 during weekend days (11.9%).

It is worth stressing that São Miguel Island's power grid does not currently face any congestion issues at a local level. However, to properly assess the congestion management performance of the decision-making model, congestion was intentionally assumed at the SS. With that in mind, a N-1 criterion was adopted, implying the SS is able to withstand a transference of load from a nearby SS with identical characteristics and load demand. In other words, it was assumed that the SS needs to operate uncongested at double its current load demand.

Note that, based on the SS capacity results in Figure 7, a congestion threshold of 60% was considered for the simulation of the decision-making model.

2.5 Weather Conditions

Regarding the weather conditions in Ponta Delgada, São Miguel Island, Azores, Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), Global Horizontal Irradiance (GHI), air temperature, solar zenith angle, precipitable water, and relative humidity data were collected from 01/01/2019 to 31/12/2019, at 30-minute intervals, via the NSRD [16]. Missing data have been linearly interpolated considering the two most proximate data points.

Figure 8 illustrates the average DNI, DHI, GHI, and temperature per time of day [16].

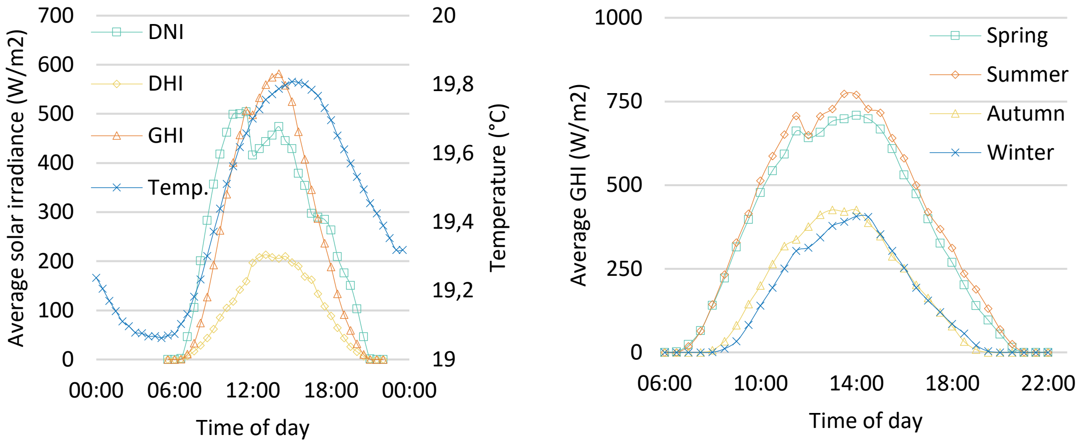


Figure 8. Average DNI, DHI, GHI and temperature per time of day (left), and average GHI per time of day and season (right)

The average DNI peaks at around 11:30 (504 W/m2), while the average DHI peaks at around 13:00 (213 W/m2) and the average GHI peaks at around 14:00 (582 W/m2). On the other hand, the average temperature peaks at around 15:00 and valleys at around 05:00.

As anticipated, the spring and summer seasons encompass the highest average GHI values. GHI peaks are observable around 14:00 in spring (709 W/m2), 13:30 in summer (772 W/m2), 13:00 in autumn (426 W/m2), and 14:00 in winter (406 W/m2).

The total annual solar irradiation amounted to approximately 1.55 MWh/m2.

3 Decision-Making Model Design and Development

3.1 Design

With the appearance of EVs and V2X technology, it was just a matter of time until major market players would start developing smart strategies for reducing energy consumption and related costs. In fact, in 2012, Japanese carmaker Nissan, conjointly with Nichicon Corp., developed the first commercially available V2H system platforms [18]. Since then, alternatives kept emerging. Seeing that there are limitless different ways to control an EV and manage household loads, scientific literature is brimming with different algorithms for the purpose, such as the rules in [19], which prioritize selling energy to the power grid instead of charging the EV. Another rule-based approach is defined in [20], where the authors have developed four different algorithms considering variables such as precipitable water, while also having conducted an in-depth study pertaining to user satisfaction: the results show considerable savings in the energy bills of end-users. In [21], the authors went a step further and identified several optimal State of Charge (SOC) thresholds according to the hour of the day and the energy import price, having designed and developed a purely rule-based approach that performs actions such as discharging the EV, charging the EV, maintaining the SOC, or injecting energy into the power grid. Other studies such as [22] include reinforcement learning models, while the authors in [23] and [24] employed a genetic algorithm to obtain optimal results for end-users. It is relevant to remark that, in [24], smart appliances were taken into consideration, which is not the case herein.

For the purpose of this deliverable, the proposed decision-making model comprises three main modules: forecast, daily planning, and real time operation. The architecture behind the decision-making model is exhibited in Figure 9.

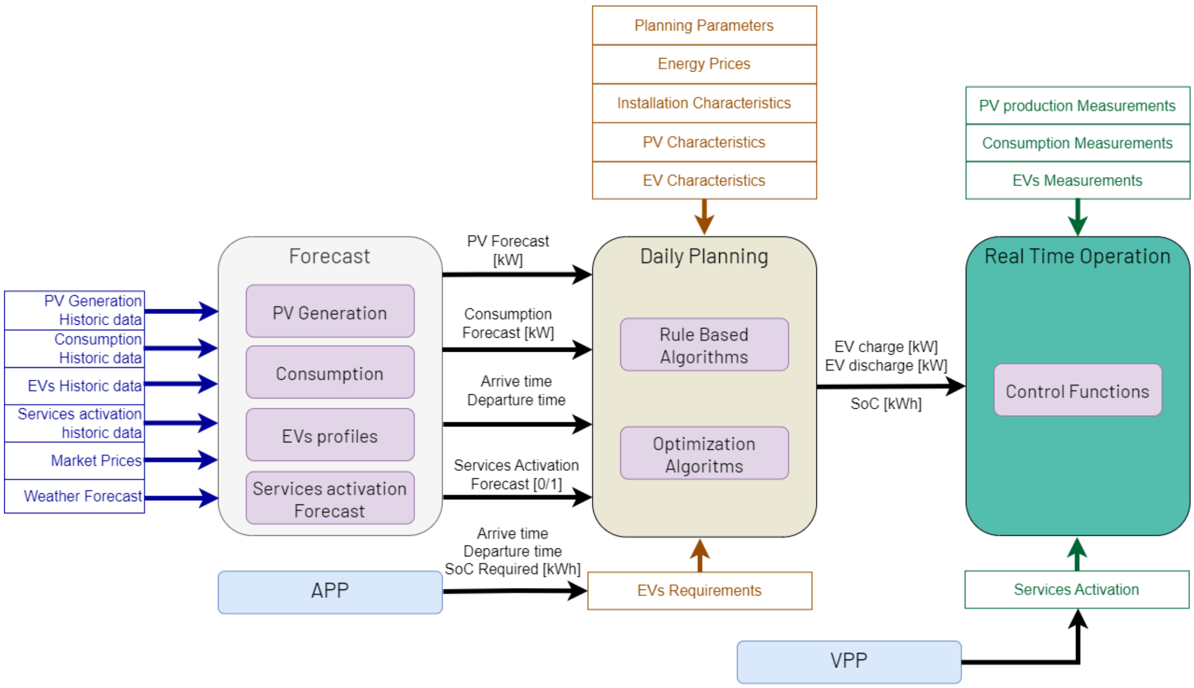


Figure 9. Decision-making model architecture

The forecast module uses historical data related to solar PV power output, household energy consumption, EV usage behaviour, grid service activation, electricity market pricing, and weather conditions. Resorting to this information, the forecast module can generate day ahead data that will feed the optimisation algorithms in the daily planning module. The daily planning module is responsible for leveraging the output of the forecast module to conceive a strategy that minimizes the overall cost of operation of a household with an EV, considering two types of algorithms, namely: i) rule-based algorithms; and ii) optimisation algorithms. The real time operation module is fed by the daily planning module's resulting strategy and resorts to real-time data to control the EV charging and discharging cycle according to previously made decisions, to either satisfy the household load or export surplus energy to the power grid. It is worth mentioning that households are considered not to have any dispatchable loads besides EV charging.

3.2 Development

The creation of the proposed decision-making model encompassed the development of three distinct EV control methods, namely: i) charge; (ii) discharge; and iii) last chance charge. The charge and discharge methods stipulate instructions meant to define the optimal period to respectively charge or discharge the EV – with a specific amount of energy to be either charged (E_{EV}^{CH}) or discharged (E_{EV}^{DCH}) –, considering operational limits such as the maximum EV charge ($\bar{P}_{EV}^{CH}$) and discharge ($\bar{P}_{EV}^{DCH}$) rate, maximum charger charge ($\bar{P}_{CS}^{CH}$) and discharge ($\bar{P}_{CS}^{DCH}$) rate, EV battery capacity ($\bar{E}_{EV}$), and overall efficiency of the EV and charger joint system (η). On the other hand, the last chance charge method charges the EV with available energy, considering the operational limits of the charger and of the EV, as well as contracted power ($\bar{P}_C$) limitations. Figure 10 demonstrates the instructions stipulated for each method. E indicates the specific amount of energy that is instructed to be charged into the EV or discharged from the EV, Δt indicates the time step, E_t^{SOC} indicates the SOC at time t, $\underline{E}_{EV}$ indicates the user-defined minimum battery level, and P_U indicates the unsupplied power.

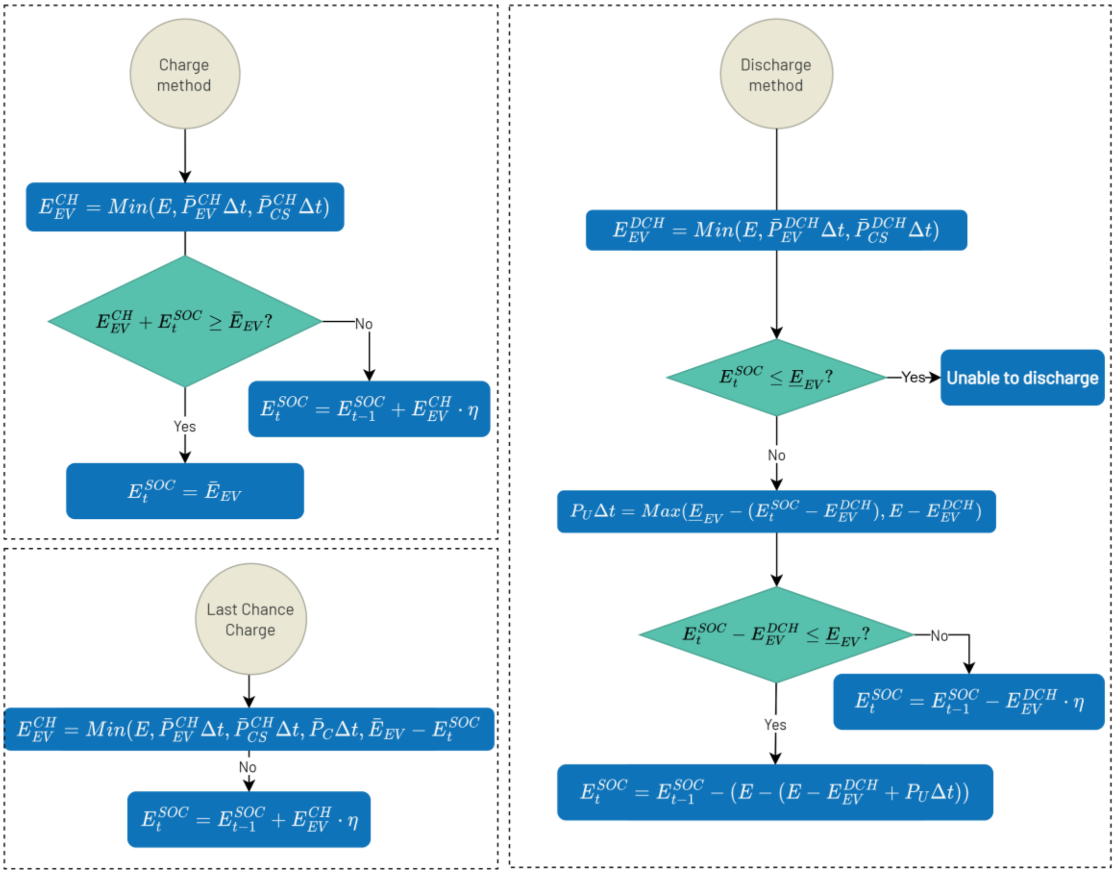


Figure 10. Charge (upper left), discharge (right) and last chance charge (bottom left) methods

3.2.1 Forecast Module

The forecast module comprises 5 stages, namely: i) inputs; ii) pre-processing; iii) feature engineering; iv) model implementation; and v) validation. This module is fed information pertaining to the connection status of the EV, solar PV generation, household energy consumption, as well as congestion management and wind curtailment service activation. In the context of the simulation of the proposed decision-making model, the forecast period corresponds to one month per season (21-05-2019 to 21-06-2019 for spring, 23-08-2019 to 23-09-2019 for summer, 21-11-2019 to 21-12-2019 for autumn, and 20-02-2019 to 20-03-2019 for winter).

In the pre-processing stage, weather data from the NSRD was integrated, while missing values and data outliers were handled. In the feature engineering stage, lag features (corresponding to past data for target variables) and date/time features (*e.g.*, season, month, weekday, weekend day, holiday, hour, minute) were created. In the model implementation stage, the optimal number of features was determined, and the best features were selected accordingly. Furthermore, a Random Forest algorithm (*i.e.*, machine learning method for classification and regression, which combines the output of multiple decision trees to reach a single result) was developed to generate precise predictions for each one of the output variables of the forecast module. In the validation stage, the forecast module's performance was determined via the calculation of its outputs' normalized root mean square error and R^2. Additionally, several *csv.* files containing the outputs of the forecast module were generated.

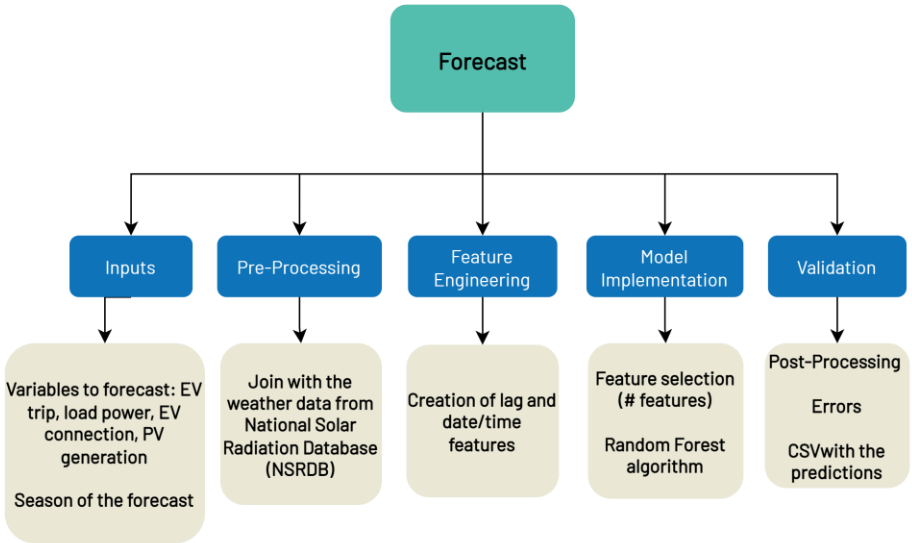


Figure 11. Forecast module diagram

3.2.2 Daily Planning Module

The daily planning module encompasses several distinct rule-based algorithms, which were developed to test diverse operating approaches, such as: i) instructions not considering pricing, service events, or net-metering – rule-based simulator; ii) instructions considering pricing but not service events or net-metering – price simulator; iii) instructions considering pricing and service events, but not net-metering – price and service events simulator; and iv) instructions considering pricing, service events, and net metering – energy export simulator. Moreover, an optimisation algorithm was developed and incorporated in the daily planning module (theoretically, the best results will be held by the optimisation algorithm).

S1 – Rule-based simulator: the first and simplest rule-based algorithm is the rule-based simulator, which only takes into consideration the solar PV power output (P_{PV}) and household load (P_L). This algorithm's behaviour, shown in Figure 12, is simple: when P_{PV} is higher than P_L, it charges the EV; otherwise, the EV is discharged until $\underline{E}_{EV}$. If the SOC is below $\underline{E}_{EV}$, the EV is charged according to the last chance charge method in Figure 10 (bottom left), using only energy from the power grid.

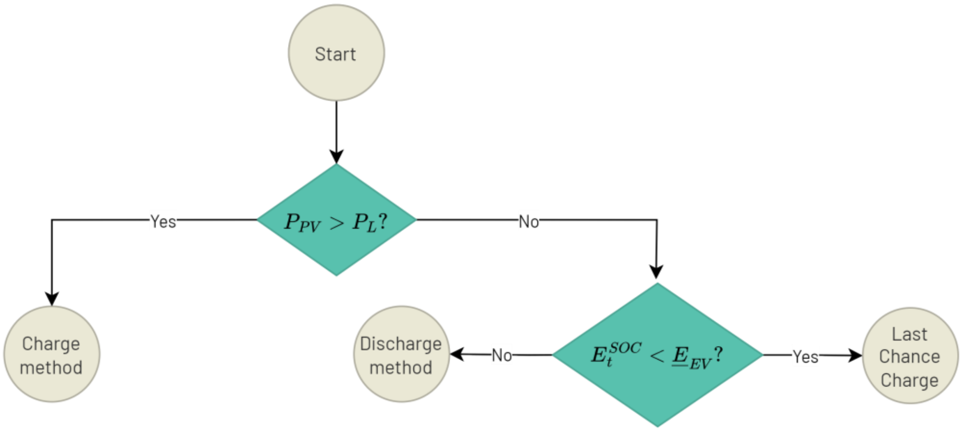


Figure 12. S1 – rule-based simulator diagram

S2 – Price simulator: an extension of the rule-based simulator, with the difference that it assumes a dynamic pricing tariff. As in Figure 13, when the grid import electricity price ($price_t^{buy}$) is higher than a user-defined price threshold ($Price_{thr}$) and the SOC is above $\underline{E}_{EV}$, the EV is discharged. However, if $\underline{E}_{EV}$ is reached, the algorithm will define a new minimum battery level ($\underline{\underline{E}}_{EV}$), which is dependent on how much energy can be can charged back into the EV at a price lower than $Price_{thr}$ before the next EV exit instance. Finally, if $\underline{\underline{E}}_{EV}$ is reached, the algorithm validates whether the SOC is lower than the expected SOC at the time of the next EV exit instance (I_{SOC_e}). In that case, the EV is charged until $\underline{\underline{E}}_{EV}$.

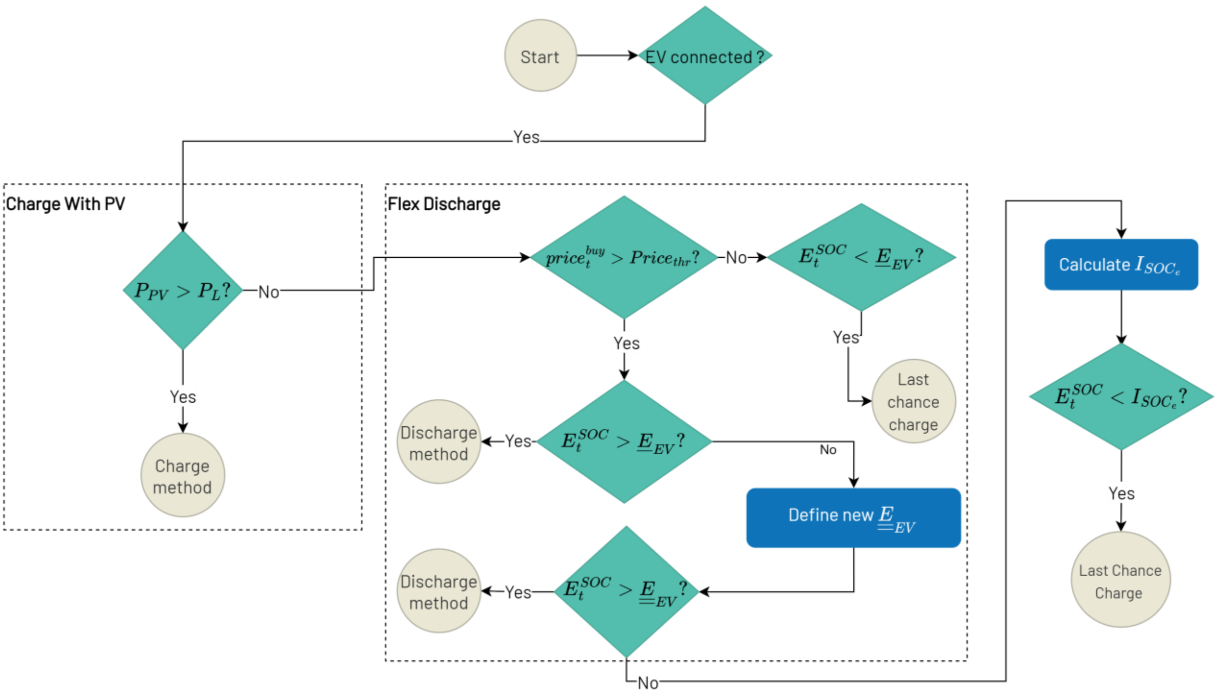


Figure 13. S2 – price simulator diagram

S3 – Price and service events simulator: an extension of the price simulator, which regards the existence of any service participation request and acts accordingly. If congestion management service participation is requested, the EV will be discharged until $\underline{E}_{EV}$. On the other hand, if wind curtailment service participation is requested, the EV will be charged until its maximum SOC, using only energy from the power grid (Figure 14).

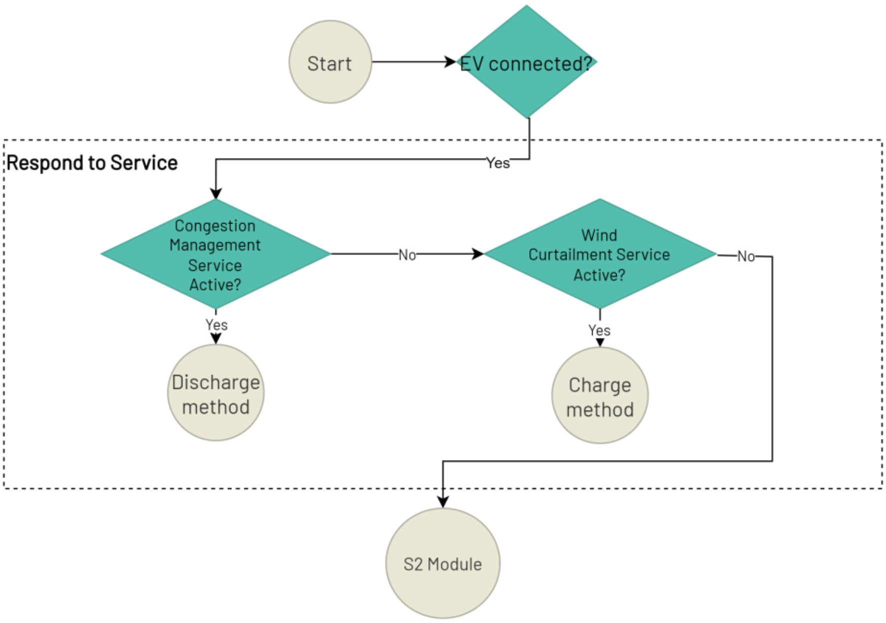


Figure 14. S3 – price and service events simulator diagram

S4 – Energy export simulator: a variation of the price and service events simulator, encompassing a key difference within the discharge method: to avoid wasting energy as a result of EV battery discharge efficiency, the EV is only allowed to discharge an amount of energy greater than an algorithm-defined threshold (E_{thrsh}) (Figure 15).

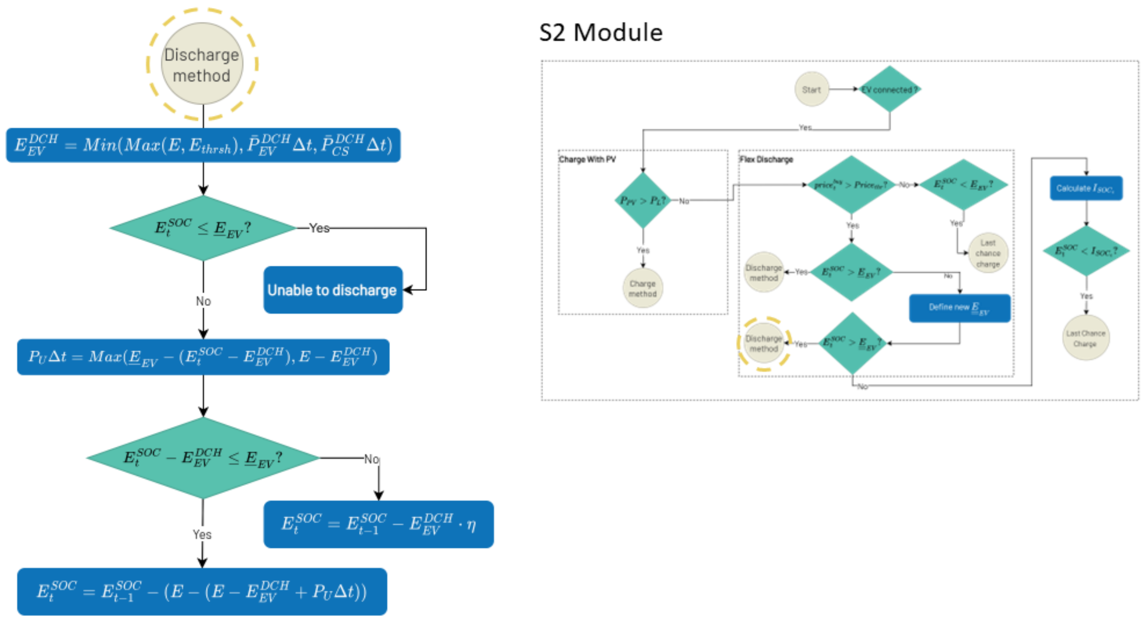


Figure 15. S4 – energy export simulator diagram

S5 – Optimisation: the optimisation algorithm is an implementation of a mixed integer linear programming mathematical framework, resorting to the CPLEX solver from IBM [25]. The proposed model is highly configurable: for instance, it is possible to indicate whether to use V2H, or if dynamic pricing tariffs should be considered. At the core of the optimisation algorithm is the Objective Function (OF). In this regard, two distinct approaches have been implemented. P_t^{import} and P_t^{export} indicate, respectively, the power imported/exported from/to the power grid, while $price_t^{sell}$ represents the energy export price, at time t.

Within the first approach (OF1), grid service participation is considered to be mandatory. Accordingly, relaxation variables have been introduced for the non-participation in congestion management services ($P_t^{CongRelax}$) and wind curtailment services ($P_t^{CurtRelax}$). Analogously, penalties have also been included for the non-participation in the grid services, respectively, $Penalty_t^{Cong}$ and $Penalty_t^{Curt}$. All simulations that have been tested follow this approach.

On the other hand, the second approach (OF2) regards grid service participation as voluntary. Grid services are activated via a price signal sent by the electrical system operator. As a result, in the case of excessive energy consumption or production within the electrical system, importing energy from the power grid will become correspondently more expensive or cheaper, while exporting energy to the power grid will become correspondently cheaper or more expensive. Consider that $pricesignal_t^{Cong\_buy}$ and $pricesignal_t^{Cong\_sell}$ indicate, respectively, the price signal for the purchase and sale of energy under active congestion management service participation, while $pricesignal_t^{Curt\_buy}$ represents the price signal for the purchase of energy under active wind curtailment service participation. Furthermore, it is worth stressing that, despite not having been included for the simulation of the proposed decision-making model, OF2 will be tested in the context of future deliverables.

$$OF1 = \min(cost\ system + services) \tag{1a}$$

$$cost\ system = \sum_{t=1}^{T} (P_t^{import}.\Delta_t.price_t^{buy} - P_t^{export}.\Delta_t.price_t^{sell}) \tag{1b}$$

$$services = \sum_{t=1}^{T} (P_t^{CongRelax}.\Delta_t\ .Penalty_t^{Cong} + P_t^{CurtRelax}.\Delta_t.Penalty_t^{Curt}) \tag{1c}$$

$$OF2 = \min(cost\ system) \tag{2a}$$

$$\begin{aligned} cost\ system = \sum_{t=1}^{T} (& P_t^{import}.\Delta_t.\left(price_t^{buy} \pm pricesignal_t^{Cong\_buy} - pricesignal_t^{Curt\_buy}\right) \\ & - P_t^{export}.\Delta_t.\left(price_t^{sell} \pm pricesignal_t^{Cong\_sell}\right)) \end{aligned} \tag{2b}$$

Moreover, regard that the optimisation problem is subject to constraints related to EV operation, EV and system energy balance, and grid operation.

3.2.3 Real Time Operation Module

To ensure all plausible real time operation instructions are contemplated, forecast results were worsened by 10%: the solar PV power output was considered to be 90% of the forecasted, household energy consumption was considered to be 110% of the forecasted, trips were considered to start one hour earlier than what was forecasted, and electricity prices were considered to be 110% of the forecasted[3].

The real time operation module can yield four distinct instructions: to initiate any one of the three previously mentioned methods (illustrated in Figure 10), or to remain idle. It is worth mentioning that, while the daily planning module resorts to a digital twin of the EV to undergo the charge, discharge, and last chance charge methods, the real time operation module calls upon a real EV for that effect. In this sense, the simulation of the decision-making model carried out in the present deliverable uses pre-defined real time operation data. Also, note that the real time operation module (Figure 16) verifies whether or not the EV is connected, given the possibility of error in this regard at the hand of the forecast module.

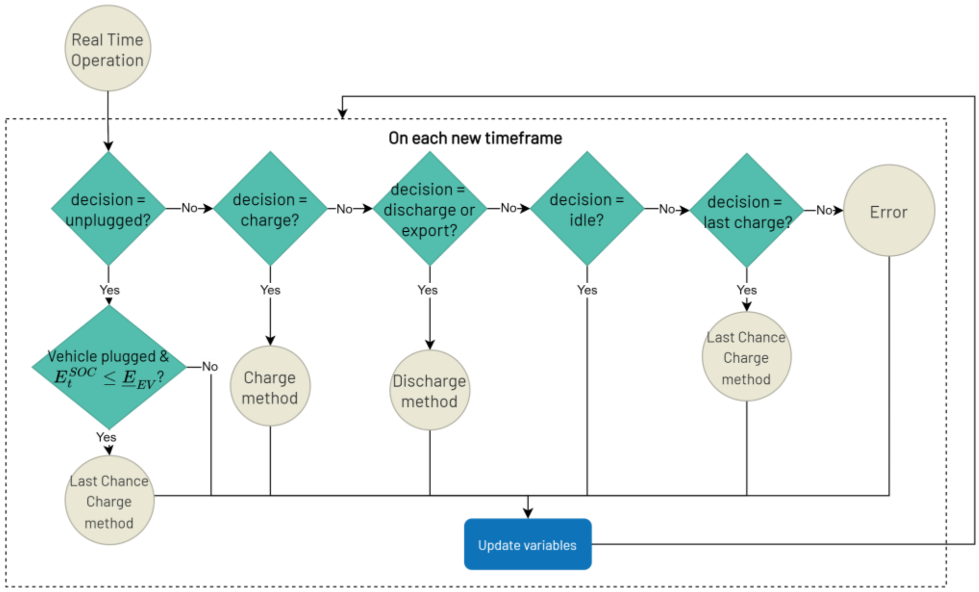


Figure 16. Real time operation module diagram

3.2.4 Implementation Setup

Figure 17 conceptually illustrates the implementation setup of the decision-making model. Information relating to the day ahead pricing, service participation requests, and weather conditions must be communicated in a way that allows for the appropriate functioning of the decision-making model. On that account, the implementation of the forecast module will be cloud-based and enable the collection of household and EV usage behaviour information in the interest of incrementally producing more precise predictions as the amount of available data grows. Additionally, a translator module will be developed to parse information from/to a smart controller module, which includes the

[3] In the case of fixed price energy markets, this assumption does not impact the electricity price.

daily planning and real time operation modules. It is important to point out that the implementation concept at stake is a preliminary version.

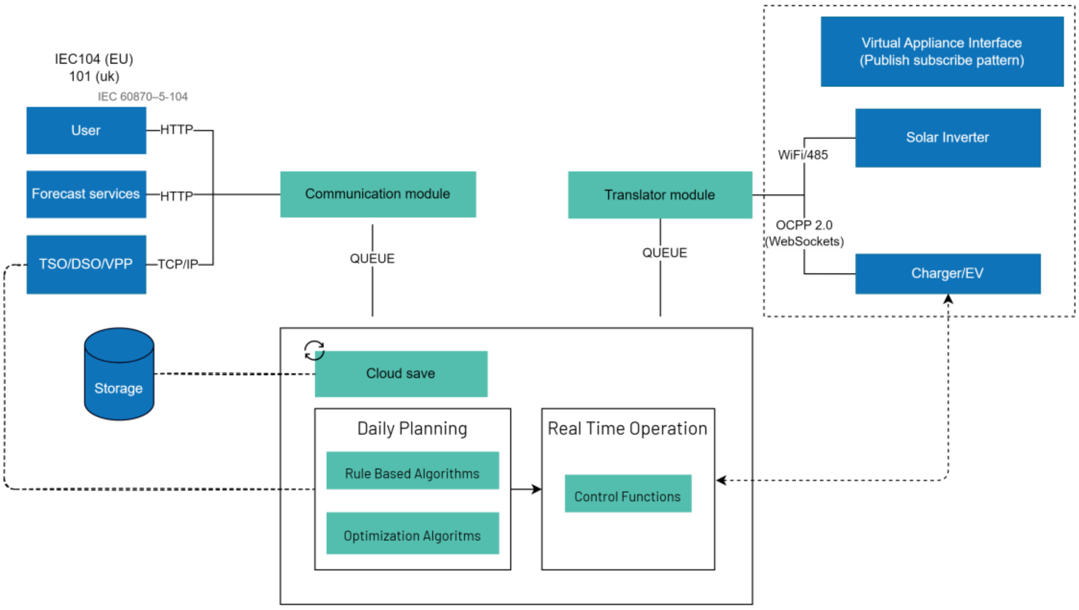


Figure 17. Conceptual implementation setup of the decision-making model

4 Decision-Making Model Simulation

4.1 Scenarios

Table 2 displays the behavioural, technical, and economic parameters underpinning the reference case scenario for the simulation of the forecast and daily planning modules of the decision-making model.

Table 2. Parameterisation of simulation scenario #1

Control Strategy	EV Usage Pattern	PV Power Output	Household Energy Consumption	Grid Service Participation	Energy Export	EV Battery Capacity	Daily Planning Module Algorithm
V2H	"Car at Home" (1750 kWh per year)	2.22 kWp (6 Panels)	4 MWh per year	None	None	40 kWh	S5 – Optimisation

Table 3 displays the remaining scenarios for the simulation of the forecast and daily planning modules of the decision-making model, detailing, for each scenario, how parameterisation is altered compared to Table 2.

Table 3. Decision-making model's simulation scenarios

Cluster	#	Description
Reference Case	1	See Table 2
Control Strategy	2	Smart Charging (No EV Discharge)
	3	Dumb Charging (No EV Discharge)
EV Usage Pattern	4	"Car at Work" (1550 kWh per year)[4]
PV Power Output and Household Energy Consumption	5	0 kWp (No PV)
	6	1.5 kWp (4 Panels)
	7	2.9 kWp (8 Panels)
	8	2 MWh per year
	9	6 MWh per year
Grid Service Participation and Energy Export	10	Wind Curtailment Services
	11	Wind Curtailment Services and Congestion Management Services
	12	Wind Curtailment Services, Congestion Management Services and Energy Export
EV Battery Capacity	13	20 kWh
	14	60 kWh
Daily Planning Module Algorithm	15	S1 – Rule-based Simulator
	16	S2 – Price Simulator
	17	S3 – Price and Service Events Simulator
	18	S4 – Energy Export Simulator

Importantly, some parameters are pre-defined in every simulation, namely the overall efficiency of the EV and charger system η – the product of the EV's efficiency (97%) and the charger's efficiency (97%) is approximately 94.09% –, initial SOC E_0^{SOC} (60%), User-defined minimum battery level $\underline{E}_{EV}$ (80%), contracted power $\bar{P}_C$ (7.2 kVA) and user-defined electricity price threshold $Price_{thr}$ (0.15€/kWh). Two main criteria were considered to evaluate the performance of the forecast and daily planning modules

[4] The average annual energy consumption varies among different EV usage patterns due to the stochastic nature of data generation.

of the decision-making model, namely: i) cost per unit of energy consumed; and ii) energy exchange between the PV system, household, EV, and power grid.

Moreover, computing time was assessed for each one of the simulation scenarios in Table 3. On this subject, it is worth noting that the scenarios based on the optimisation daily planning module algorithm evidenced larger computing times than its rule-based counterparts, given the computational effort which underlies the determination of the global minimum for equation (1).

4.2 Analysis and Discussion of Results

Table 4 presents the yearly results for each one of the simulation scenarios listed in Table 3.

Table 4. Simulation scenarios' yearly results

#	House from EV (kWh)	House from Grid (kWh)	House from PV (kWh)	EV from Grid (kWh)	EV from PV (kWh)	EV Mobility (kWh)	Export to Grid (kWh)	Total Cost (€)	Energy Cost (€/kWh)
1	951	1 748	1 371	1 812	981	1 750	370	471	0.0810
2	0	2 699	1 371	756	978	1 750	373	526	0.0903
3	0	2 699	1 371	1 491	91	1 750	1 260	665	0.1142
4	708	1 991	1 371	2 032	228	1 550	1 123	532	0.0947
5	1 697	2 373	0	3 611	0	1 750	2 722	754	0.1295
6	1 048	1 922	1 100	2 349	540	1 750	176	555	0.0954
7	926	1 652	1 493	1 352	1 435	1 750	650	416	0.0715
8	449	697	906	916	1 333	1 750	482	216	0.0569
9	1 804	2 673	1 684	2 956	775	1 750	262	722	0.0913
10	1 247	1 452	1 371	2 359	728	1 750	623	494	0.0848
11	1 279	1 420	1 371	2 389	730	1 750	621	489	0.0841
12	985	1 715	1 371	8 187	414	1 750	6 471	116	0.0200
13	924	1 775	1 371	1 872	954	1 750	397	483	0.0829
14	975	1 724	1 371	1 716	997	1 750	354	457	0.0786
15	1 422	1 277	1 371	2 475	930	1 750	421	566	0.0973
16	934	1 765	1 371	1 900	953	1 750	398	479	0.0823
17	968	1 731	1 371	2 312	591	1 750	760	516	0.0886
18	1 019	1 681	1 371	5 131	839	1 750	3 406	337	0.0579

Moreover, the results for the simulation of the proposed decision-making model under scenario #1 are exhibited for arbitrarily selected weeks during summer and winter (Figure 18 and Figure 19).

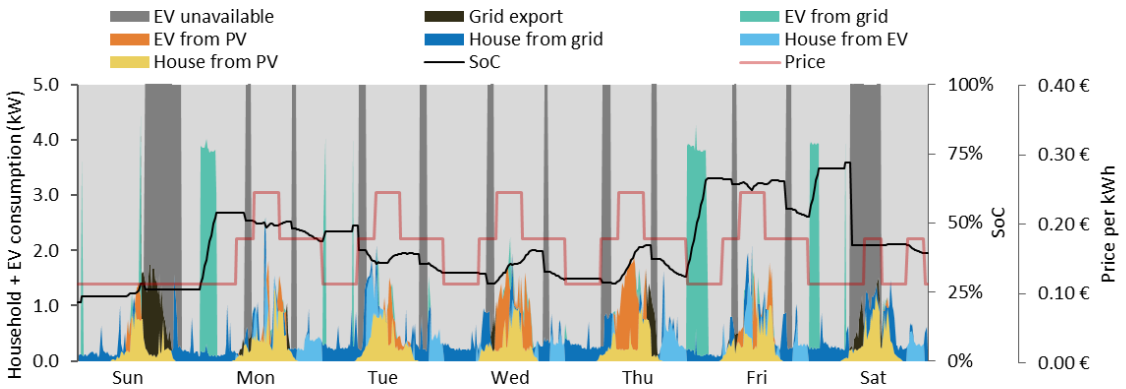


Figure 18. Summer daily results for simulation scenario #1

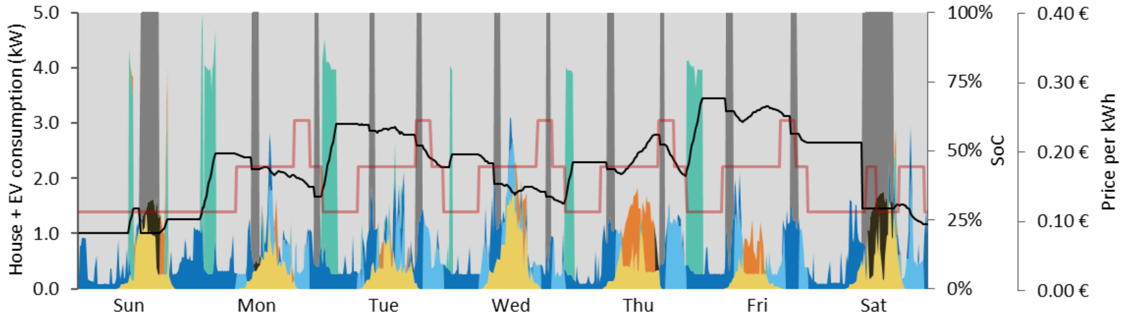


Figure 19. Winter daily results for simulation scenario #1

It is possible to observe that, to minimize the overall cost of operation of the household and EV joint system, the decision-making model consistently coordinates the delivery of energy to the household or EV with the existence of solar resource and off-peak times.

Another takeaway from the analysis of Figure 18 and Figure 19 corresponds to the distinction between EV charging requirements according to different seasons: more energy is required from the power grid into the EV in winter than in summer. During winter, household energy consumption and solar PV power output is respectively higher and lower than during summer. Thus, the EV relies more on the power grid for charging, and discharges more often to fulfil the house's energy requirements.

4.2.1 Control Strategy

Figure 20 illustrates the cost and energy exchange relative to the V2H (scenario #1), smart charging (scenario #2), and dumb charging (scenario #3) control strategies. A key point to highlight is that the energy exchange should not be mixed with the total sum of the yearly energy balance. Rather, it refers to the yearly flow of energy between different elements in the system.

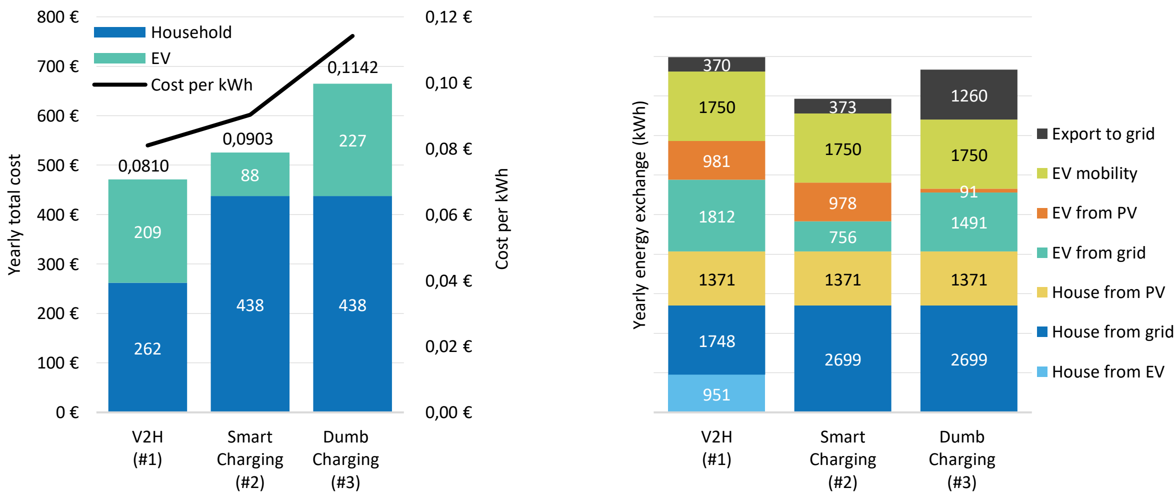


Figure 20. Cost (left) and energy exchange (right) for simulation scenarios #1, #2 and #3

Comparing the V2H control strategy with the smart charging control strategy, the former exhibits a reduction of about 10% for the cost per kWh consumed, since the discharge of energy from the EV into the household leverages low electricity market prices during off-peak times and costless solar PV energy to minimize the overall energy bill. This reduction of the cost per kWh consumed is the most significant during autumn and winter, when the share of solar PV energy in the total amount of energy fed into the household is the lowest, and thus the flexibility arising out of the V2H control strategy is the most impactful.

In comparison with the dumb charging control strategy, the smart charging scenario results in a reduction of about 21% for the cost per kWh consumed, since the amount of solar PV energy fed into the EV is around 91% lower in the former case than in the latter case. In fact, within the dumb charging control strategy, the EV is charged until its maximum battery capacity as soon as it is connected, often without taking full advantage of existent solar PV energy, which must then be exported free of charge to the power grid. The reduction of the cost per kWh consumed is particularly noticeable during spring and summer, when solar PV power output is the highest.

4.2.2 EV Usage Behaviour

In Figure 21, it is possible to observe the cost and energy exchange pertaining to the “car at home” (scenario #1) and “car at work” (scenario #4) EV usage behavioural patterns.

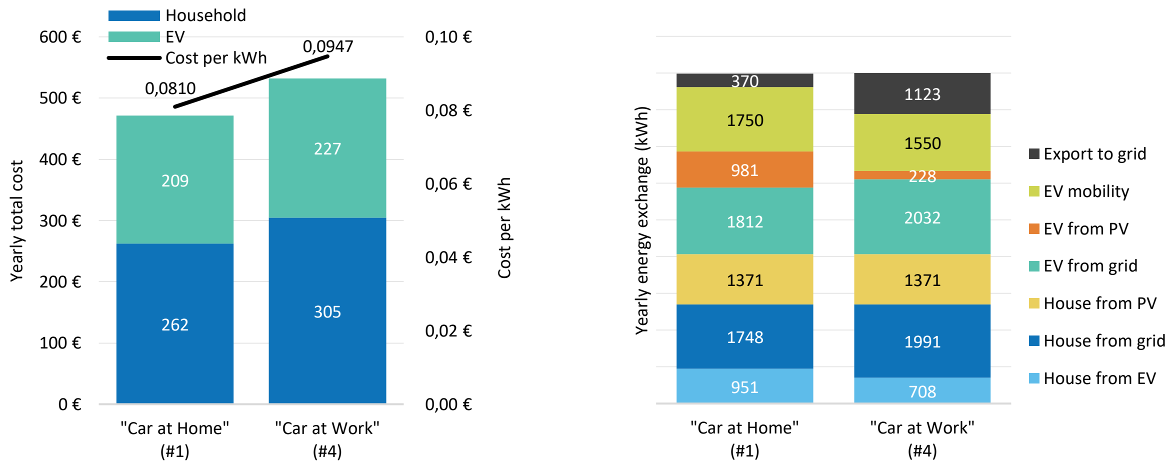


Figure 21. Cost (left) and energy exchange (right) for simulation scenarios #1 and #4

Comparing the “car at home” EV and “car at work” EV usage patterns, the former exhibits a reduction of about 14% for the cost per kWh consumed. This is so because the “car at work” EV usage pattern implies the EV is not connected for most of the day during weekdays, meaning that the amount of solar PV energy being exported free of charge to the power grid is about 3 times larger than in the case of the “car at home” EV usage pattern. The reduction of the cost per kWh consumed is the most significant during spring and summer, when solar PV power output is the highest.

4.2.3 PV Power Output and Household Energy Consumption

Figure 22 illustrates the cost and energy exchange relative to the absence of a solar PV system (scenario #5), as well as to the existence of a 1.5 kWp 4-panel solar PV system (scenario #6), a 2.22 kWp 6-panel solar PV system (scenario #1), and a 2.9 kWp 8-panel solar PV system (scenario #7).

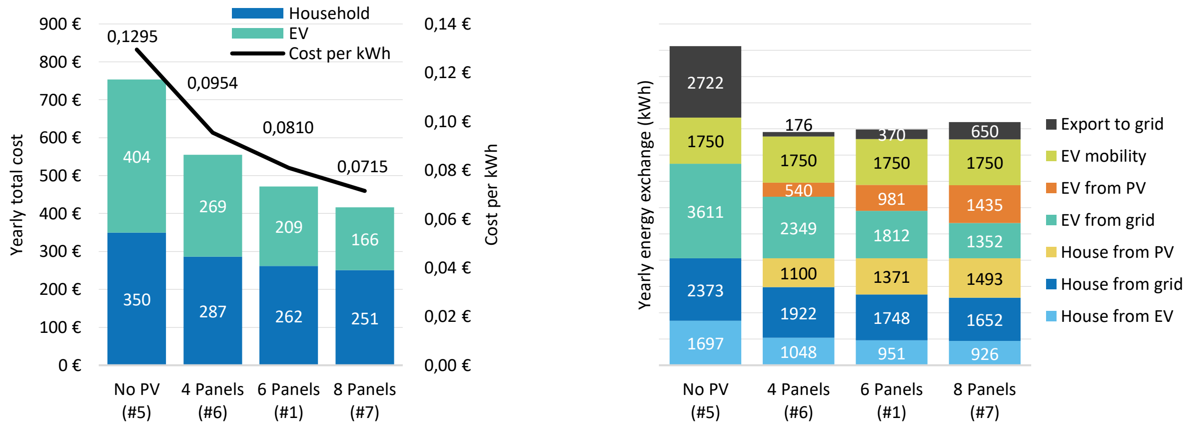


Figure 22. Cost (left) and energy exchange (right) for simulation scenarios #1, #5, #6 and #7

In comparison with the absence of a solar PV system and with a 1.5 kWp 4-panel solar PV system, a 2.22 kWp 6-panel solar PV system results in a reduction of about 37% and 15%, respectively, for the cost per kWh consumed. On the other hand, a 2.9 kWp 8-panel solar PV system results in a reduction of about 12% for the cost per kWh consumed when compared with a 2.22 kWp 6-panel solar PV system. Evidently, the cost per kWh consumed is inversely proportional to the share of solar PV energy in the total amount of energy fed into the household and EV, which amounts to around 24%, 34% and 43%, respectively, for a 1.5 kWp 4-panel, 2.22 kWp 6-panel and 2.9 kWp 8-panel solar PV system.

Figure 23 exhibits the cost per kWh consumed in relation to the share of solar PV energy in the total amount of energy fed into the household and EV, for scenarios #1, #5, #6, #7, #8, #9, #13, and #14.

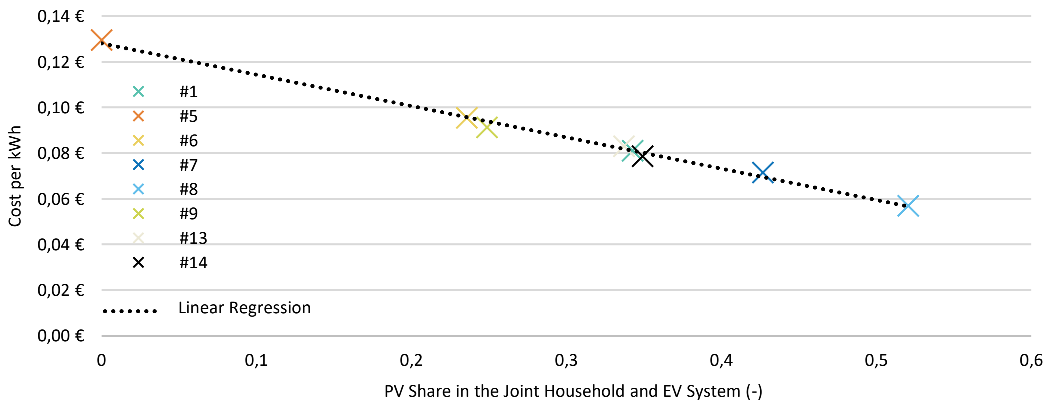


Figure 23. Cost per unit of energy consumed vs. solar PV share in the joint household and EV system for simulation scenarios #1, #5, #6, #7, #8, #9, #13 and #14

Regard that the cost per kWh consumed evolves approximately linearly with the solar PV share in the joint household and EV system, for any such value comprised in the [0,0.5] interval. This is due to the high availability of EVs for the majority of the time and their relatively large battery capacity for the scenarios in hand, which makes exporting solar PV energy to the power grid infrequent.

Additionally, in Figure 24, it is possible to observe the cost and energy exchange pertaining to a household with a yearly energy consumption of 2 MWh (scenario #8), 4 MWh (scenario #1), and 6 MWh (scenario #9).

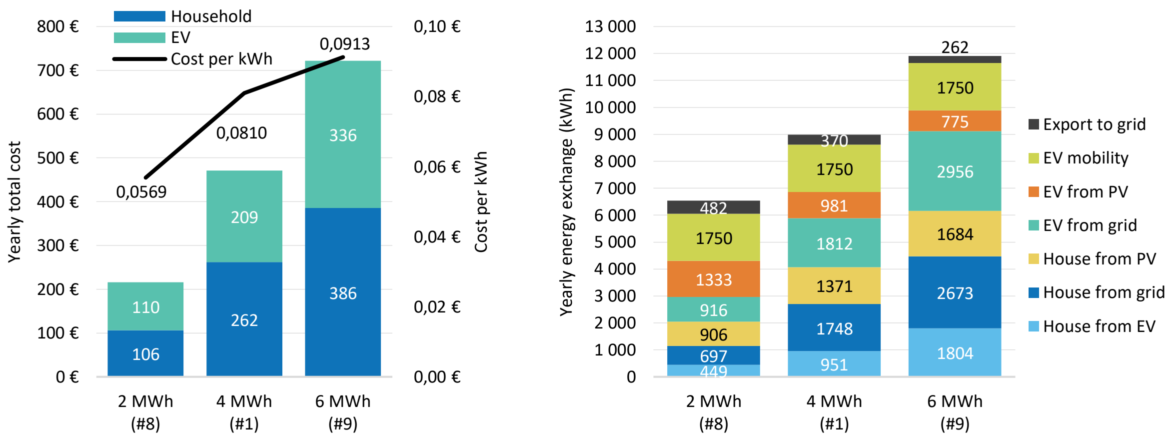


Figure 24. Cost (left) and energy exchange (right) for simulation scenarios #1, #8 and #9

Comparing households with a yearly energy consumption of 4 MWh and 2 MWh, the latter exhibits a reduction of about 30% for the cost per kWh consumed. On the other hand, a household with a yearly energy consumption of 4 MWh results in a reduction of about 11% when comparing with a yearly energy consumption of 6 MWh. It is possible to observe that the share of solar PV energy in the total amount of energy fed into the household and EV is somewhat similar between the case of a household with a yearly energy consumption of 2 MWh and a 2.9 kWp 8-panel solar PV system – around 52% and 43%, respectively –, as well as between the case of a household with a yearly energy consumption of 6 MWh and a 1.5 kWp 4-panel solar PV system – around 25% and 24%, respectively.

4.2.4 Grid Service Participation and Energy Export

Figure 25 illustrates the cost and energy exchange relative to the case of non-participation in grid services (scenario #1), participation in wind curtailment services (scenario #10), participation in both wind curtailment and congestion management services (scenario #11), as well as participation in both wind curtailment and congestion management services considering the sale of exported energy (scenario #12).

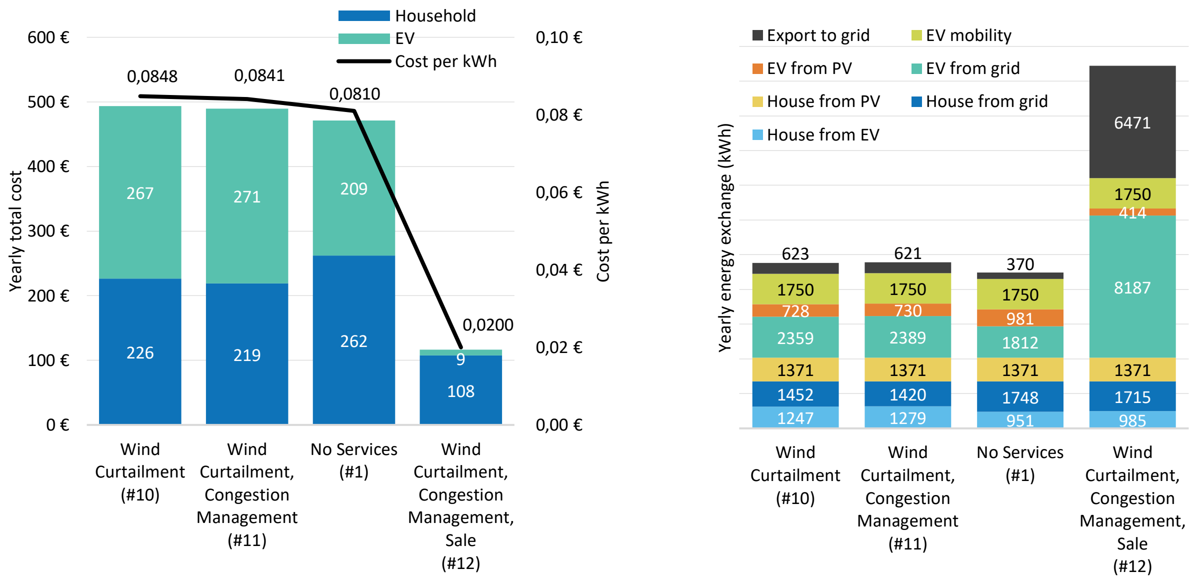


Figure 25. Cost (top) and energy exchange (bottom) for simulation scenarios #1, #10, #11 and #12

In comparison with the sole participation in wind curtailment services and the participation in both wind curtailment and congestion management services, not participating in grid services results, in comparison with one or the other, in an increase of about 4% for the cost per kWh consumed. For validation purposes, the proposed decision-making model imposes grid service participation whenever requested, which implies the negligence of less costly alternative decisions. Without any restrictions, the optimization module will exploit advantageous sale tariffs. Therefore, when considering different compensation strategies, the results can be expected to vary significantly.

Furthermore, comparing the participation in both wind curtailment and congestion management services with an analogous case which additionally encompasses the sale of exported energy, the latter exhibits a reduction of about 76% for the cost per kWh consumed, since the exported energy is assumed to be sold at 80% of the electricity market price, allowing for lucrative energy arbitrage actions. The prominent reduction in energy costs is primarily influenced by the ability to sell energy, rather than being directly impacted by participation in grid services. Solely participating in grid services leads to a more modest cost reduction of approximately 7%.

It is worth mentioning that a 20% electricity market price discount is considered for the purchase of electricity in the context of wind curtailment service participation, while the participation in congestion management services is compensated via the avoidance of extraordinary penalties for energy consumption during grid congested periods. It is also worth pointing out that wind curtailment and congestion management service participation is the most frequent during autumn and winter, when the imbalances between wind power output and load demand are the most significant and the power grid is the most congested due to a high load demand.

4.2.5 EV Battery Capacity

In Figure 26, it is possible to observe the cost and energy exchange concerning an EV battery with a capacity of 20 kWh (scenario #13), 40 kWh (scenario #1), and 60 kWh (scenario #14).

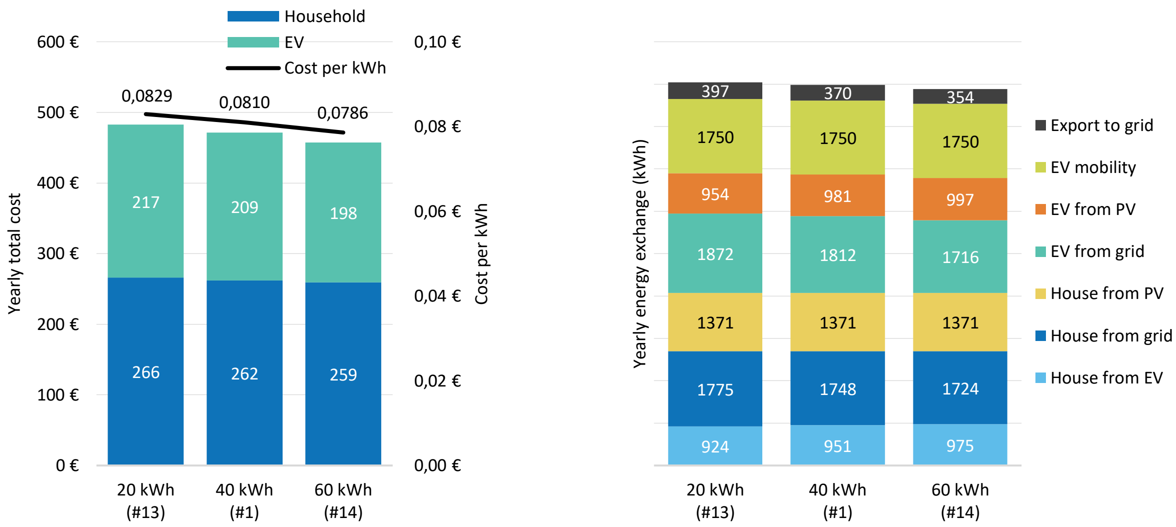
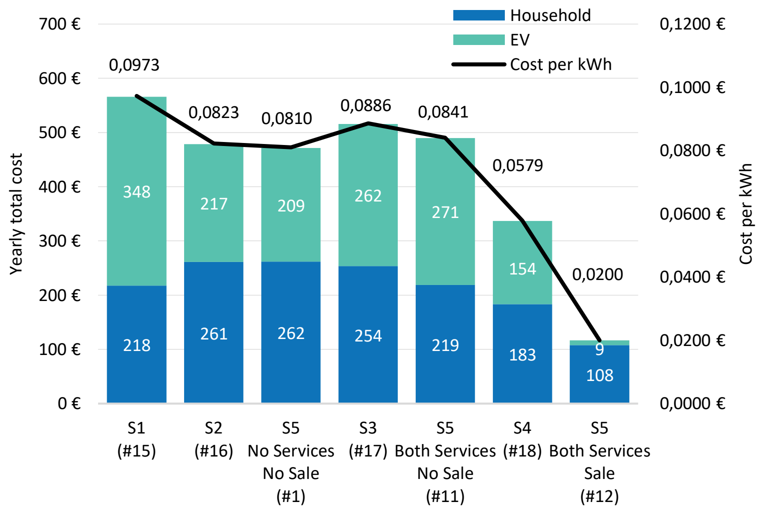


Figure 26. Cost (left) and energy exchange (right) for simulation scenarios #1, #13 and #14

In comparison with a 20 kWh EV battery, a 40 kWh EV battery results in a reduction of about 2% for the cost per kWh consumed. On the other hand, a 60 kWh EV battery results in a reduction of about 3% for the cost per kWh consumed when comparing with a 40 kWh EV battery. Naturally, the cost per kWh consumed is inversely proportional to the EV battery's capacity until a saturation limit, since the more energy can be stored, the more low-cost off-peak electricity and costless solar PV energy can be leveraged to minimize the overall energy bill. The reduction of the cost per kWh consumed is the most significant during summer, when solar PV power output is the highest, and thus the added flexibility arising out of the increased energy storage capacity is the most impactful.

4.2.6 Daily Planning Module Algorithm

Figure 27 illustrates the cost and energy exchange relative to S1 – rule-based simulator (scenario #15), S2 – price simulator (scenario #16), S5 – optimisation, with no grid service participation nor sale of exported energy (scenario #1), S3 – price and service events simulator (scenario #17), S5 – optimisation, with participation in both wind curtailment and congestion management services but no sale of exported energy (scenario #11), S4 – Energy export simulator (scenario #18), and S5 – optimisation, with participation in both wind curtailment and congestion management services and considering the sale of exported energy (scenario #12).



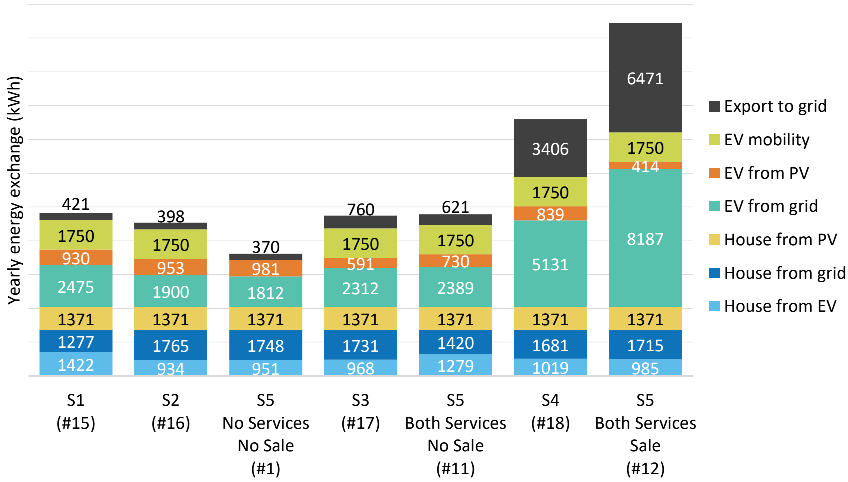


Figure 27. Cost (top) and energy exchange (bottom) for simulation scenarios #1, #11, 12, #15, #16, #17 and #18

Comparing the optimisation daily planning module algorithm with no grid service participation nor exported energy sale with the rule-based simulator daily planning module algorithm, the former exhibits a reduction of about 17% for the cost per kWh consumed, primarily given the fact that the rule-based simulator does not account for the electricity market price when deciding whether to charge the EV. In fact, the cost per kWh fed into the EV is approximately 40% lower for the optimisation daily planning module algorithm. The reduction of the cost per kWh consumed is the most significant during autumn and winter, when the share of solar PV energy in the total amount of energy fed into the household is the lowest, and thus the share of energy originating from the EV in the total amount of energy fed into the household is the highest.

Furthermore, in comparison with the price simulator, the optimisation daily planning module algorithm with no grid service participation nor exported energy sale results in a reduction of about 2% for the cost per kWh consumed, since the former does not account for any forecast capabilities. The reduction of the cost per kWh consumed is particularly noticeable during autumn and winter, when the share of solar PV energy in the total amount of energy fed into the household and EV is the lowest, meaning adequate predictions of forthcoming solar PV energy, household energy consumption, and EV departure and arrival times are the most impactful. In these scenarios, the EV exhibits high availability, and the market prices remain fixed. However, if these two variables were to become more erratic, it is expected that the performance difference between the rule-based and the optimization daily planning modules will increase in favour of the latter.

Comparing the optimisation daily planning module algorithm with participation in both wind curtailment and congestion management services but no sale of exported energy with the price and service events simulator, it is possible to observe that the former exhibits a reduction of about 5% for the cost per kWh consumed. The reduction of the cost per kWh consumed is the most significant during spring and summer, when grid service participation requests are the least frequent, and thus optimisation capabilities have less constraints.

Finally, in comparison with the export energy simulator, the optimisation daily planning module algorithm with grid service participation and exported energy sale results in a reduction of about 65% for the cost per kWh consumed. This is so due to the integrated forecast in the optimisation daily planning module algorithm, particularly in terms of EV usage, support the export of a larger amount of energy. In fact, the amount of energy exported from the solar PV system and EV to the power grid is approximately 90% higher for the optimisation daily planning module algorithm. The reduction of the cost per kWh consumed is particularly noticeable during spring and summer, when the share of solar PV energy in the total amount of energy fed into the household is higher.

In Figure 28, it is possible to observe the cost per kWh consumed for scenarios #11, #12, #15, #16, #17, and #18, in comparison with the scenario #1 benchmark.

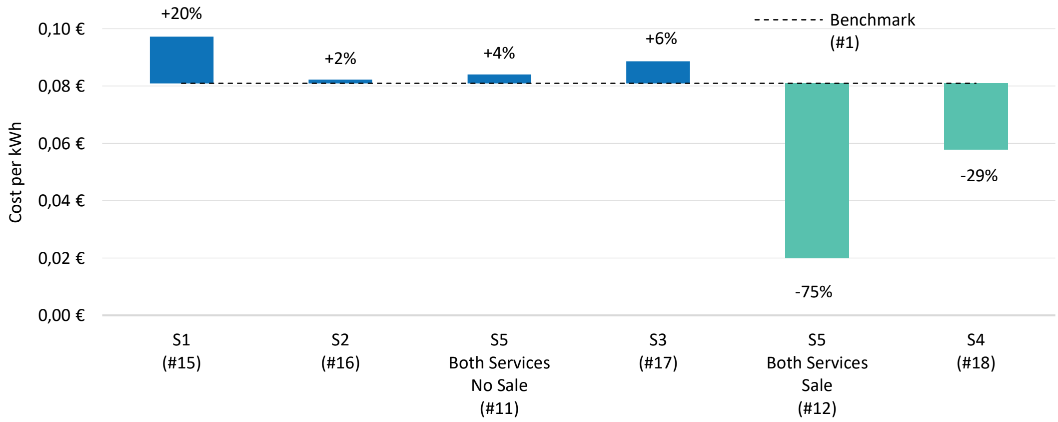


Figure 28. Comparative analysis of cost per unit of energy consumed for simulation scenarios #1, #11, #12, #15, #16, #17 and #18

In comparison with the benchmark case, grid service participation and exported energy sale results in a reduction of about 75% and 29% for the cost per kWh consumed, respectively, under an optimisation and rule-based daily planning module algorithm. Nevertheless, the former and latter cases encompass a respective increase of around 208% and 114% for the energy fed into the EV, which, for a 40 kWh EV battery, corresponds to approximately 145 and 79 added charge cycles per year.

5 Conclusions

This deliverable presents the design and development of a newly created decision-making model, to be considered in the Portuguese demonstrator of São Miguel Island, Azores. The proposed decision-making model enables the integration of V2X technology and DER/RES aspects in a HEMS and leverages either rule-based or optimisation algorithms to minimise the overall operating cost of a household with an EV. Moreover, it allows for the potential activation of wind curtailment and/or congestion management grid services, as well as the export of energy to the power grid.

Additionally, the deliverable submits the simulation and performance evaluation of the proposed decision-making model, in the context of various scenarios considering seasonality and distinct behavioural, technical, and economic specifications.

5.1 Key Findings

The primary focus of this deliverable is to test, calibrate, and validate the performance of the decision-making algorithm across various scenarios. When considering algorithm architecture and performance, the key findings are as follows:

- One notable feature is the forecast capability that utilizes machine learning techniques to accurately predict EV usage, solar PV production, household energy consumption, and grid service participation for different seasons. The forecast model then feeds into the optimization daily planning module, which can have a significant impact on the decision-making model's outcomes as the flexibility and complexity of variables increase. However, the algorithm at stake requires additional computational power, which may limit the attainment of global optimums within the designated time window for certain scenarios.
- The time step of the simulation, set at 15-minute intervals, plays a significant role in computation time. This time granularity is compatible with most available datasets and keeps the calculation times within reasonable limits. However, it is important to remark that this level of granularity could potentially influence the results of certain scenario combinations unfavourably.

Concerning, the algorithm results and the associated benefits for various stakeholders are outlined below:

- EV charging requirements differ substantially between seasons, given that, due to solar PV power output and household energy consumption variability, more energy is required to be fed from the power grid to the EV during winter than in summer.
- Another relevant finding is the decreasing cost per unit of energy consumed when comparing dumb charging, smart charging, and V2H control strategies. In this regard, smart charging outperforms dumb charging since it better leverages solar PV energy towards EV charging actions, while V2H outperforms smart charging given its inherent flexibility strengthens the share of solar PV energy in the total amount of energy fed into the household.
- The decision-making model enhances the integration of solar PV power output. The cost per unit of energy consumed was evidenced to be inversely proportional to the share of solar PV energy in the total amount of energy fed into the household and EV. This reduction follows an

approximately linear trend if no constraints are to be found on the EV's battery capacity and availability.

- It is worth noting that incorporating grid services into house energy management without compensation could adversely affect algorithm performance, potentially increasing energy costs by up to 5% based on the assumptions made in this case study. This imposition creates additional constraints that limit the amount of flexibility available for charging and discharging strategies. Simultaneously, from the perspective of the electricity provider, EV charging involuntarily participates in wind curtailment services for 15% of the requests in the base scenario. However, through voluntary participation in these services, the algorithm can accommodate 85% of the requests to integrate otherwise curtailed clean energy. Concerning congestion management, during power curtailment requests, the house relies on grid imports for approximately 59% of the required load in the base scenario. However, by actively participating in these requests, the energy imported during congestion decreases to 31% as the EV steps in by providing power to the house. The benefits for grid management are evident; however, the interactions between EV users and the electric system provider can prove advantageous for both parties. By compensating the requested consumption (wind curtailment services) and power curtailment (congestion management services) at 80% of the current time-of-use tariff, the overall annual cost for EV users can decrease by approximately 7%.

In conclusion, the adoption of daily planning module algorithms based on optimization has shown promising results in achieving substantial cost reductions per unit of energy consumed. When compared to rule-based algorithms, these optimization-based approaches have proven to be particularly effective, especially in terms of leveraging the sale of exported energy to the power grid. The findings suggest that the implementation of such algorithms can lead to enhanced financial benefits for stakeholders involved.

5.2 Future Research Recommendations

Firstly, it is of the utmost importance that studies are conducted on the relation between EV load curves and corresponding battery degradation, as well as on the costs arising out of said degradation from the perspective of the EV user. The results of these studies would not only strengthen existent knowledge relative to the techno-economic feasibility of V2X technology, but also support the creation of new rules and penalties to be respectively integrated into the rule-based and optimisation algorithms of the daily planning module, enabling a more complete decision-making model.

Another significant future research topic is the study of different forms of compensation, particularly those of economic nature, for the provision of EV supported congestion management grid services, which should preferably be conducted in association with distribution system operators, flexibility operators, and EV users.

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Appendix I – Decision-Making Model

The source code of the decision-making model was developed and hosted on the GitHub tool. It is available in https://github.com/EV4EU/house_demo_PT, as shown in Figure 29.

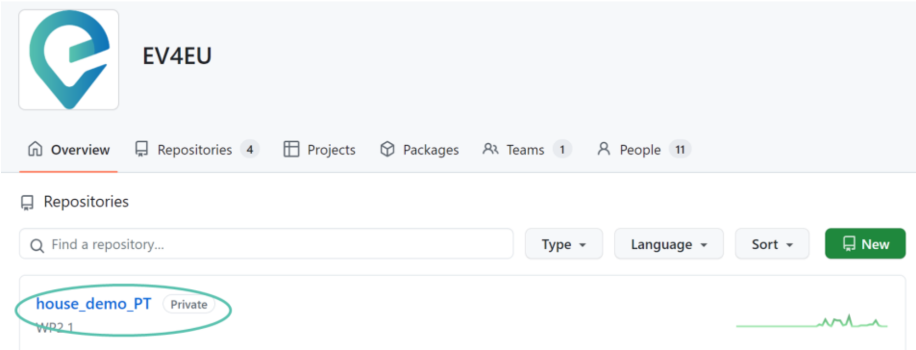

Figure 29. Repository for the decision-making model's source code, in EV4EU's GitHub

The repository includes the following folders and files:

- "README.md" – brief description of the simulators' functioning;
- "assets" – diagrams and other pertinent images utilized in README.md;
- "classes" – source code for the simulator's base implementation and specialisations, as well as other relevant files, such as the models for the functioning of the EVs and EV batteries;
- ".gitignore" – indicates the file should not be sent to the repository;
- "_init_.py" – indicates the folder is a Python package;
- "ev_sim.ipynb" – carried out examples and test cases, as well as simple visualisations;
- "requirements.txt" – description of the libraries used;
- "simulations.py" – script used for generating the simulation results in Section 4.2.