Deliverable D5.2: Virtual Demonstration Actions

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Contributors

Name	Organisation
Anna Eisner	Virtual Vehicle
Niccolò Pezzati, Lorenzo Berzi, Eleonora Innocenti, Massimo Delogu	UNIFI
Xinyuan Cao	RWTH Aachen
Nicolò Russo, Dario Giannelli	ABB

Formal Reviewers

Name	Organisation
Alois Steiner	Virtual Vehicle
Thomas Schade	FEV
Joshua Dalby	RICARDO
Iona Kirkpatrick	Virtual Vehicle

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Abbreviations and Definitions

BESS	Battery Energy Storge System
DER	Distributed Energy Resources
OBC	On-Board Charger
PV	Photovoltaic
REC	Renewable Energy Communities
RES	Renewable Energy Sources
SOC	State of Charge
V1G	Unidirectional charging
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home
V2B	Vehicle-to-Building

Executive Summary

The overarching goal of the XL-Connect project is the optimization of the complete charging chain – from energy supply to the end consumer. One main optimization aspect being the charging process and the utilization of smart charging and bidirectional charging functionalities. In order to maximize the potential of these functionalities, the development of adequate charging strategies is necessary and shall be realized within the XL-Connect project.

These strategies shall be tested in several virtual and real-world demonstrations, within work-package 5 of the XL-Connect project. The real-word demonstration provides the proof of feasibility of these strategies in a real context. Beside private demonstrations, that are more controllable regarding the access of users, public demonstrators will also be implemented in order to acquire realistic user-data and verify the technical feasibility of the EVSE and the algorithms with a wide range of EVs. In addition, virtual demonstrations will cover use-cases with a higher amount of EVs as well as more complex use-cases.

This deliverable provides an overview of the virtual demonstration actions treated in this project.

Keywords: smart charging, V2G, V2B, simulated use-cases

1. Introduction

As described in Figure 1 virtual and real use cases and the corresponding data are used to build a scalable digital twin of an energy system. As a result, it is possible to investigate the impacts on the grid, the environment, emissions, on electric vehicle (EV) batteries as well as on society. The real-world demonstrations give not only important insight regarding power-to-hydrogen and AC-microgrids for large parking areas. Another very important part of the real-world demonstrations is the communication between charging station and the vehicle, especially on the ISO 15118-20 which focuses on bidirectional charging. Although it is important to build and analyse real world demonstrations, especially in the context of new charging technologies, the simulated virtual use cases deliver valuable results and data for the digital twin.

In the following sections the three virtual use cases and their results of the project will be presented. The first virtual use case describes a renewable energy community (REC) in combination with EV charging. The results show in which extent it is possible to increase the self-sufficiency rate of all participants as well as reducing the energy exchange with the medium-voltage grid. Participating in these types of RECs could be applied at parking areas next to a university campus or even a company. The second virtual use case investigates if and how vehicle-to-building can be an alternative solution for a local storage for an industrial site that heavily invests in renewable energy. In addition, the usage of waste heat for the heating system is investigated. The third use case has a closer look on on-road parking in smart cities. Here an aggregator is trained with supervised learning to optimise the Vehicle-to-Grid (V2G) application for smart city applications. Therefore, different EV penetration rates as well as different level of willingness to use V2G are assumed.

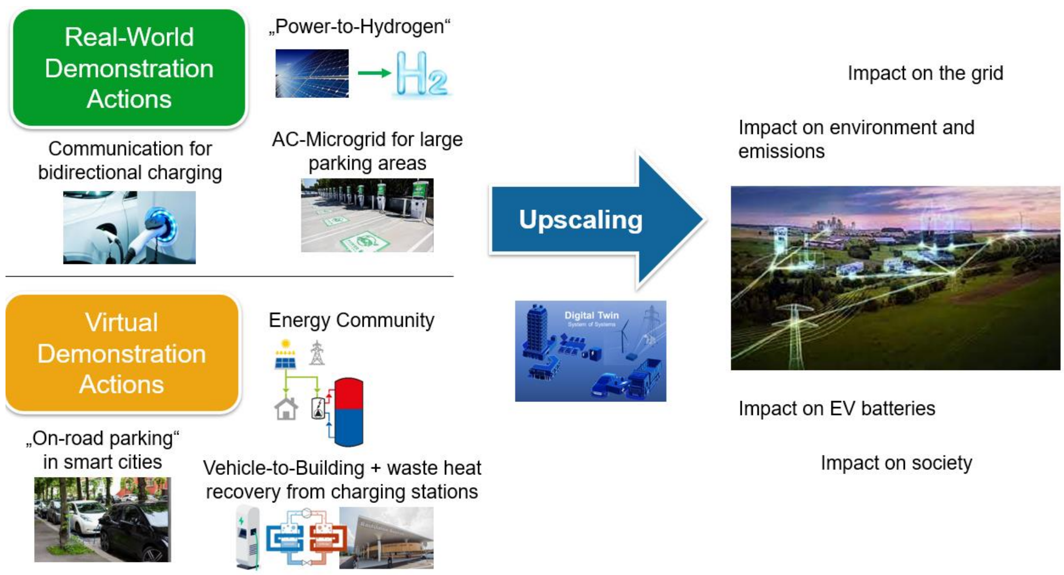


Figure 1: Overview on virtual and real Use Cases in XL-Connect

2. Scalable model for Energy Communities with charging park areas

The proposed model aims to study optimal energy dispatching methods within Renewable Energy Communities (REC) with possible EV charging events, and it is designed to be adaptable for different case studies, with a particular focus on real-world demonstration activities related to parking areas servicing point of interest such as University campus, or company parking. UNIFI.

REC are composed of various consumers and energy producers connected to the low voltage grid referring to the same medium-to-low voltage substation. Their members, by aligning production and consumption across different sites as much as possible, can potentially reduce overall power exchanges with the grid and optimize them based on the energy market price profile.

The model, built in *MATLAB-Simulink* environment (Figure 2), allows for the characterization of one or more locations. These locations exchange local data with an aggregator, which aims to schedule upcoming power flows based on each location's needs and forecast data. The main goals for the Communities include the optimization of the energy exchange between partners (at a very local level), overall reducing energy exchanges with the medium-voltage grid substation. This typically implies increasing the share of self-consumption of Renewable Energy Sources (RES); further grid services can be provided by Energy Communities. For the scopes of the demonstration action energy management has been assumed as main target. The model described in this paragraph implement an energy community comprehending two main locations and a planning system for energy management.

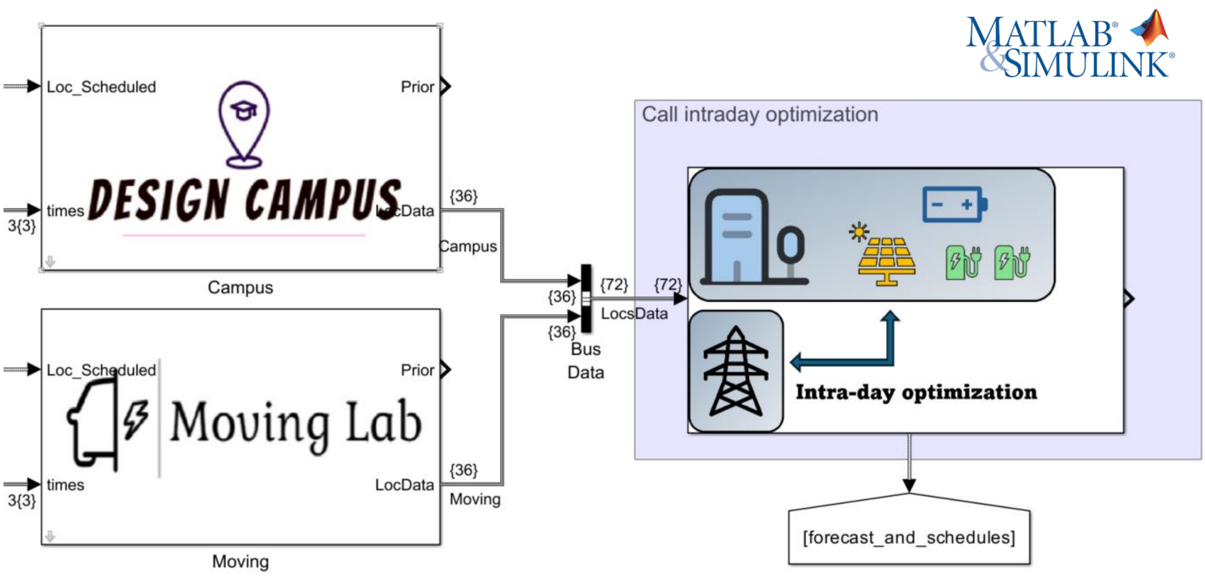


Figure 2: Simulink model with two locations: Design Campus Parking and Moving Unifi lab, along with a local aggregator for optimizing scheduled power flows. The proposed example is in accordance with the real case of UNIFI.

The model is intended to provide a technical solution for energy management and to verify data aggregation, system calibration and overall feasibility. The effective advantages in terms of economic benefit depend on boundary conditions such as local energy cost, business model adopted and local country existing regulation; in this phase, costs have been assessed using ENTSOE (i.e. a public database, as described in this chapter) data as main source. Each location can implement and configure the characteristics of the parking site, a potential Photovoltaic system (PV) coupled with a Battery Energy Storage System (BESS), and the power demand of a building. The complete list of parameters is shown in Table 1.

Parking: chargers characteristics		
	Number of chargers	
	Nominal powers	*[kW]*
	Chargers type	*"V1G" / "V2G"*
	Current type	*"AC" / "DC"*
Battery energy static storage		
	Nominal capacity	*[kWh]*
	Max charging rate	*[1/h]*
	Max discharging rate	*[1/h]*
	Mean estimated efficiency	*[%]*
Photovoltaic characteristics		
geo Properties		
	Latitude	*[°]*
	Longitude	*[°]*
	Tilt angle	*[°]*
	Azimuth angle	*[°]*
	Albedo factor	*[%]*
PV characteristics		
	Peak power	*[kW]*
	Mean estimated efficiency	*[%]*
Building/Home		
	Measured power demand	*[kW]*
	Max power *from* grid (bought)	*[kW]*
	Max power *to* grid (sold)	*[kW]*

Table 1: Parameters for defining a location of a REC.

2.1. Simulated timeframe of charging events

As input for the simulation, a simulated timeframe of possible charging events is generated in accordance with the expected arrivals for a specific parking area. For instance, an event generator for a business parking area (such as the UNIFI Moving lab) should create events with a high probability of arrivals in the early morning hours. Assuming that the derivative of load profile is proportional to the variation of the number of active stations, the probability curve of arrivals is based on the exponential of the derivative of the mean power absorbed by vehicles in a business cluster (Figure 3).

For every simulation a set of user and vehicle characteristics are generated. Assuming greater flexibility in scheduling the charge via APP, the user could specify the desired final State of Charge (SOC), estimated parking time, and whether they are open to V1G or V2G charging methods. Based on the information gathered, users can be classified into three main categories, *Priority, V1G and V2G,* as shown in Table 2: Classification of user types based on provided charging preferences.

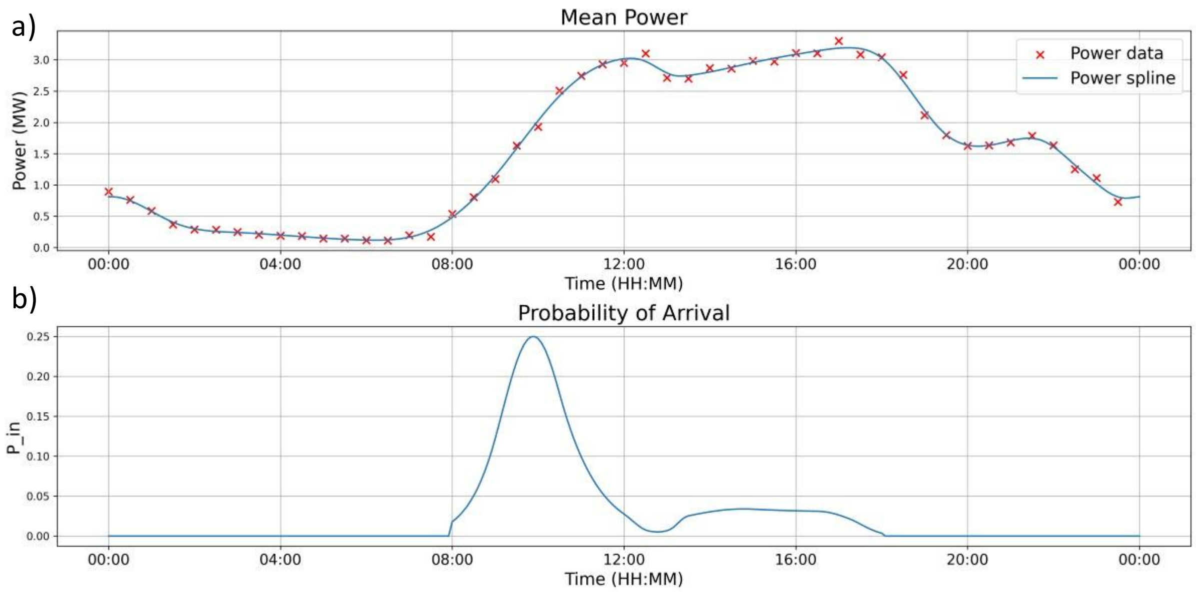


Figure 3: Arrival probability curve for a business parking area. This curve is derived from the exponential of the derivative of the mean power consumption profile absorbed by vehicles in a business cluster of ESTRA charging stations located in the peripheral area of Florence [1]. The probability is set to zero during closing hours.

User type	Description	SOC target	Estimated parking time
Priority			
Full charge	Charges at maximum power	Not required	Not required
Partial charge	Charges to a specific SOC at maximum power	Required	Not required
V1G	Allows modular charging	Optional	Required
V2G	Allows bidirectional charging	Optional	Required

Table 2: Classification of user types based on provided charging preferences.

2.2. Model description

Each location may include a charging park. The management of EVs arriving at the location is simulated using the *Sim Events* library, where vehicles are paired with chargers based on a simple matrix of load probabilities. In cases where a user and a charging station have different levels of flexibility (e.g. a priority user paired with a V2G-enabled charging station), the pairing mechanism constrains the charging method to the lower level of flexibility imposed.

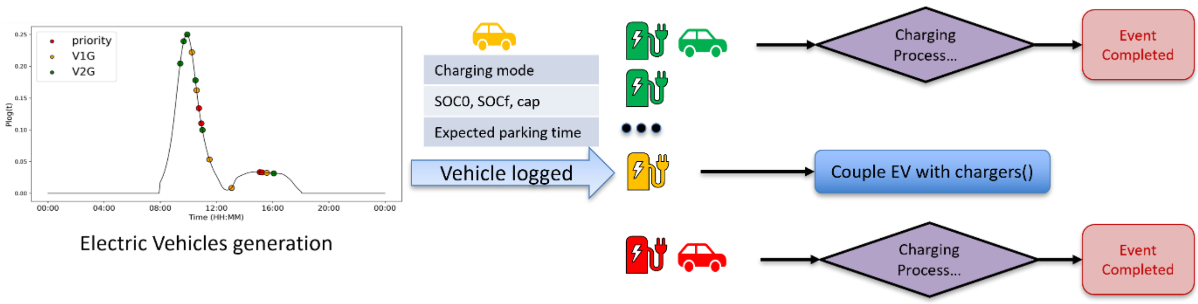


Figure 4: Schematic representation of vehicle generation and pairing with a preferable available charging station.

Each location model also includes high-level simplified sub-models for buildings, BESS and PV systems. These sub-models are responsible for updating internal state variables based on the power schedules. The full set of internal state variables is then passed as input to the main aggregator, enabling the optimization of power flows.

The Intra-Day Optimization process is triggered whenever a new charging event begins or ends before expected. This process determines the charging schedules for vehicles and BESSs, considering current charging events, forecasted energy consumption of REC buildings, forecasted photovoltaic production, and day-ahead energy prices retrieved via an API from the ENTSO-E Transparency Platform [2] (Figure 5).

The Intra-Day Optimization is structured by defining the following elements for each location:

- **Optimization Variables:**
  A set of variables id defined for each time step in the optimization horizon. These variables include [Table 3]:

  1. **Power** exchange with EVs (P_{EV}), with local BESS (P_{BESS}), and with local low-voltage grid (P_{GRID}).
  2. **SOC** evolution over time for EVs (SOC_{EV}) and for local BESS (SOC_{BESS}).
  3. **Sub-optimization variables** are defined to enable custom piecewise-linear cost functions for aging penalties: these ensure the optimization problem remains linear, avoiding the need for non-linear optimization methods, which are more computationally expensive. Specifically, for

each EV and BESS, a set of five variables is defined for Power ($P_{low_{dis}}$; $P_{high_{dis}}$; P_{medium}; P_{low_ch}; P_{high_ch}) and SOC (SOC_{low}; SOC_{min}; SOC_{medium}; SOC_{high}; SOC_{max}). These sub-variables are restricted to a limited range within the domain of the main variables and are designed to penalize extreme value of SOC and power. A similar approach is applied to the global power exchanged with the grid, penalizing deviations from the expected mean grid power to promote stability and efficiency.

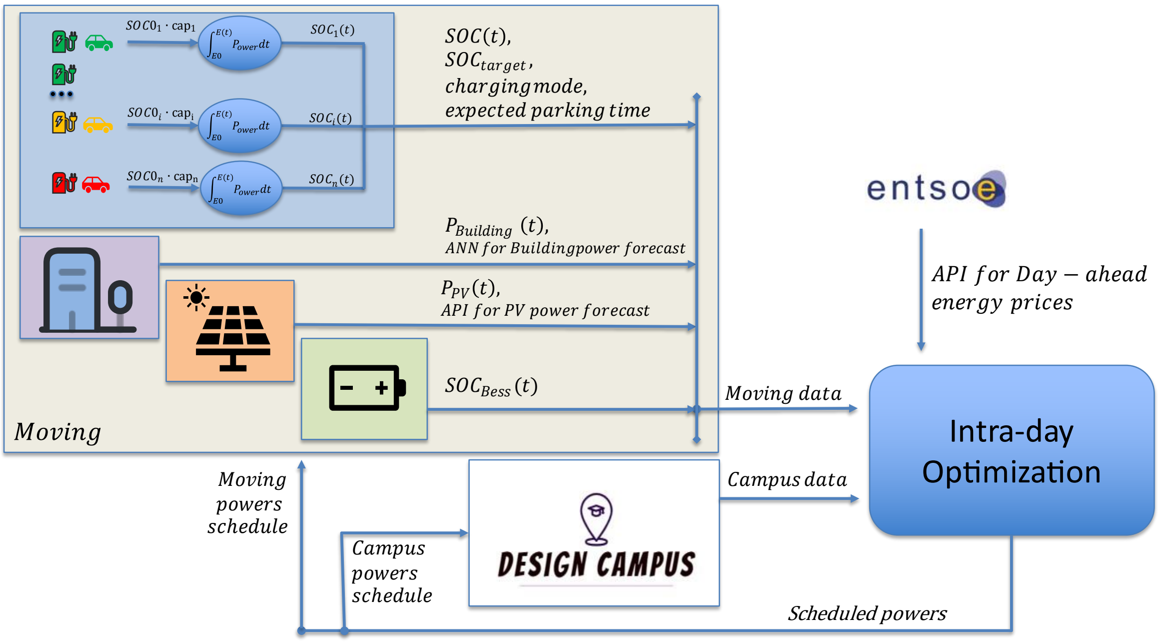


Figure 5: Location sub-components and state variables passed as input for the optimization.

	Variable Description	Symbol	
Local			
	Power to EV	P_{EV}	EV power sub-variables
	EV State of Charge	SOC_{EV}	EV SOC sub-variables
	Power to BESS	P_{BESS}	BESS power sub-variables
	BESS State of Charge	SOC_{BESS}	BESS SOC sub-variables
	Power to low-voltage Grid	P_{loc_GRID}	

Global			
	Power to medium-voltage grid	P_{gl_GRID}	Grid power sub-variables

Table 3: Variables defined for the optimization problem.

- **Problem Constraints:**
  These define the rules and limits which the optimization operates [Table 4], including:

1. **Power Balance Constraint** for ensuring that energy supply equals demand at each time step.
2. **User flexibility constraints** applied to the vehicle charging processes. These constraints reflect the user's preferences for the desired charging behaviour. For AC charging, they also account for the minimum power level required for the On-Board Charger (OBC) to convert power from to DC.
3. **Sub-Constraints** Applied to Sub-Optimization Variables: the sum of the sub-variables equals the corresponding main variable.

Constraint	**Equation**	
Local		
Power balance constraint	$P_{PV} + P_{GRID} = P_{Building} + \sum P_{EV_i} + P_{BESS}$	
User flexibility constraints	V1G user	$P_{EV} \geq 0$
	Priority user	$P_{EV} = P_{max}ch$
	OBC minimum power level constraint	$\begin{cases} P_{EV} \geq bP_{min}ch \\ P_{EV} \leq 100b \end{cases}$, b as a Boolean variable
	Target SOC user	$SOC_f(t_{estimated}) = SOC_{target}$
SOC evolution constraints	$\begin{cases} \Delta SOC_{EV} = \dfrac{\eta P_{EV}}{cap}, & P_{EV} \geq 0 \\ \Delta SOC_{EV} = \dfrac{P_{EV}}{\eta cap}, & P_{EV} \leq 0 \end{cases}$	

Sub-constraints	$SOC_{EV} = SOC_{medium} + SOC_{high} + SOC_{max} - SOC_{low} - SOC_{min}$
	$P_{EV} = P_{medium} + P_{low\_ch} + P_{high\_ch} - P_{low\_dis} - P_{high\_dis}$
Global	
Power balance constraint	$P_{gl\_grid} = \sum P_{loc\_grid_i}$
Sub-constraint	$P_{gl\_grid} = P_{gl\_medium} + P_{gl\_high} + P_{gl\_max} - P_{gl\_low} - P_{gl\_min}$

Table 4: Constraints defined for the optimization problem.

- **Cost Functions:**
  The optimization process uses *MATLAB's intlinprog* to minimize a weighted sum of cost functions while respecting constraint boundaries [Table 5-Table 6]. The cost functions include:

1. **Energy Cost Function** for minimizing energy costs based on day-ahead energy prices. Using energy price curve for power flow optimization not only results in cost savings, but also helps achieve hourly demand-supply balance and Distributed Energy Resources (DER) consumption within REC's zone. The energy price profile for the day-ahead market is typically established by Transmission System Operators (TSO): prices vary hourly and with specific geographic zones based on balance between local energy production, consumption and the capacity of the grid to transfer power along high-voltage lines with other areas.

2. **Aging Cost Functions,** designed to limit excessive battery usage, particularly at high power levels and extreme SOC values. Sub-variable values are penalized with progressive weights to discourage excessive power usage (reducing cycling aging) and prolonged maintenance at extreme SOC levels (reducing calendar aging), as shown in Figure 6.

3. **Grid Efficiency Cost Functions**, which are designed to achieve peak shaving and reduce the overall energy exchanged with the grid. Peak Shaving Function applies a penalty to grid power values that deviate significantly from the expected mean grid power, encouraging smoother and more stable power usage; Grid Selling Power Function penalizes energy sold to the grid to minimize total energy exchanges, aligning with the project's objectives to reduce impact on grid demand.

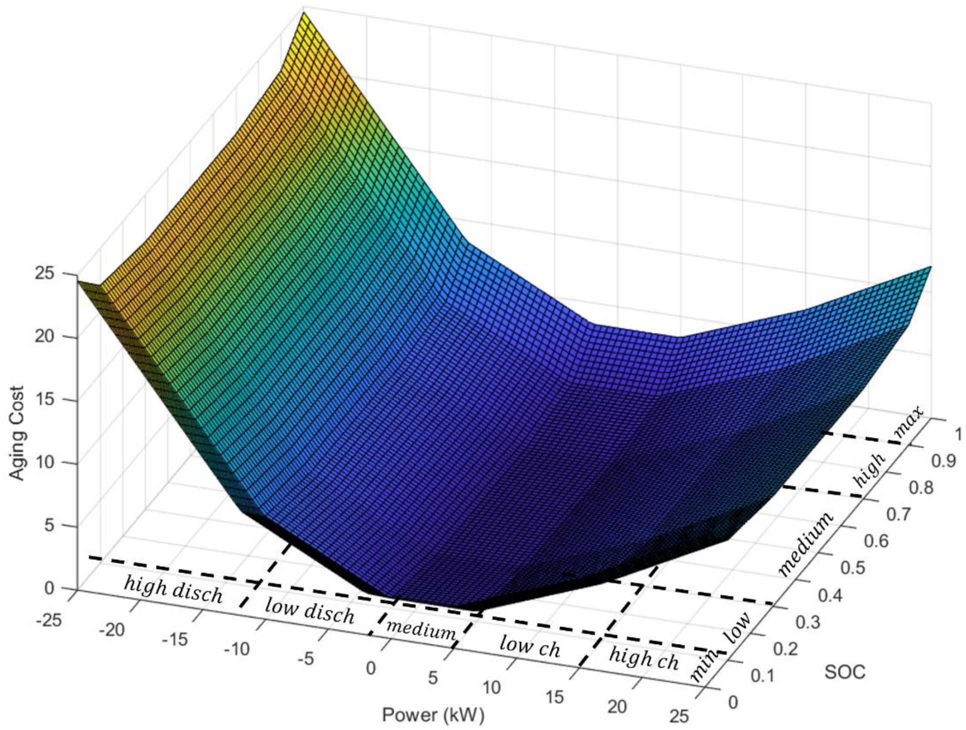


Figure 6: Custom piecewise-linear cost function for reducing battery aging. Boundary values for power are scaled with the capacity ($10\ kWh$ for this example).

An example of the possible results of intra-day optimization with mixed user constraints is shown in Figure 7: Priority users are granted maximum available power, while flexible users follow scheduled power flows aligned with peak PV production and low grid prices. Similarly, the BESS power flow is scheduled based on the same principles but with a broader optimization horizon and fewer constraints.

Cost Functions	**Equations**
Local	
Aging cost functions	$C_{cal\_aging} = K_{min}SOC_{min} + K_{low}SOC_{low} + K_{high}SOC_{high} + K_{max}SOC_{max}$
	$C_{cyc\_aging} = K_{high\_dis}P_{high\_dis} + K_{low\_dis}P_{low\_dis} + K_{low\_ch}P_{high\_ch} + K_{high\_ch}P_{high\_ch}$
Global	
Energy cost function	$C_{energy} = price \cdot P_{gl_{grid}}$
Peak shaving function	$C_{shaving} = K_{sh\_min}P_{gl\_min} + K_{sh\_low}P_{gl\_low} + K_{sh\_hig}P_{gl\_high} + K_{sh\_max}P_{gl\_max}$
Power selling penalty	$C_{sold} = K_{sold}P_{gl\_sold}$

Table 5: Cost Functions defined for the optimization problem.

Parameters		**Description;** Weighted applied to:	**Variable range**	**Param Value**
Energy price	$price$	Day-ahead energy prices	$[P_{grid\_min} \div P_{grid\_max}]$	$\sim(5 \div 30)$ $[eur/MWh]$
Aging cost parameters	K_{min}	Lowest SOC range	$[0 \div 0.1]$	9
	K_{low}	Mid-low SOC range	$[0.1 \div 0.3]$	3
	K_{high}	Mid-high SOC range	$[0.7 \div 0.9]$	3
	K_{max}	Highest SOC range	$[0.9 \div 1]$	9
	K_{high_dis}	High-discharging power range	$[P_{\max\ \_dis} \div -1.2 \cdot cap]$	$0.375 \cdot cap$
	K_{low_dis}	Low-discharging power range	$[-1.2 \div -0.2] \cdot cap$	$0.15 \cdot cap$
	K_{low_ch}	Low-charging power range	$[0.5 \div 1.5] \cdot cap$	$0.1 \cdot cap$
	K_{high_ch}	High-charging power range	$[1.5 \cdot cap \div P_{max\ \_ch}]$	$0.15 \cdot cap$
	K_{sh_min}	Lowest grid power range	$[P_{grid\_min} \div -3 \cdot P_{mean}]$	0.03
	K_{sh_low}	Mid-low grid power range	$[-3 \div -1] \cdot P_{mean}$	0.01

Peak shaving parameters	K_{sh_high}	Mid-high grid power range	$[1 \div 3] \cdot P_{mean}$	0.01
	K_{sh_max}	Highest grid power range	$[3 \cdot P_{mean} \div P_{grid\_max}]$	0.03
Power selling parameter	K_{sold}	Grid power globally sold	$[P_{grid\_min} \div 0]$	0.04

Table 6: Tuneable parameters for the optimization cost functions.

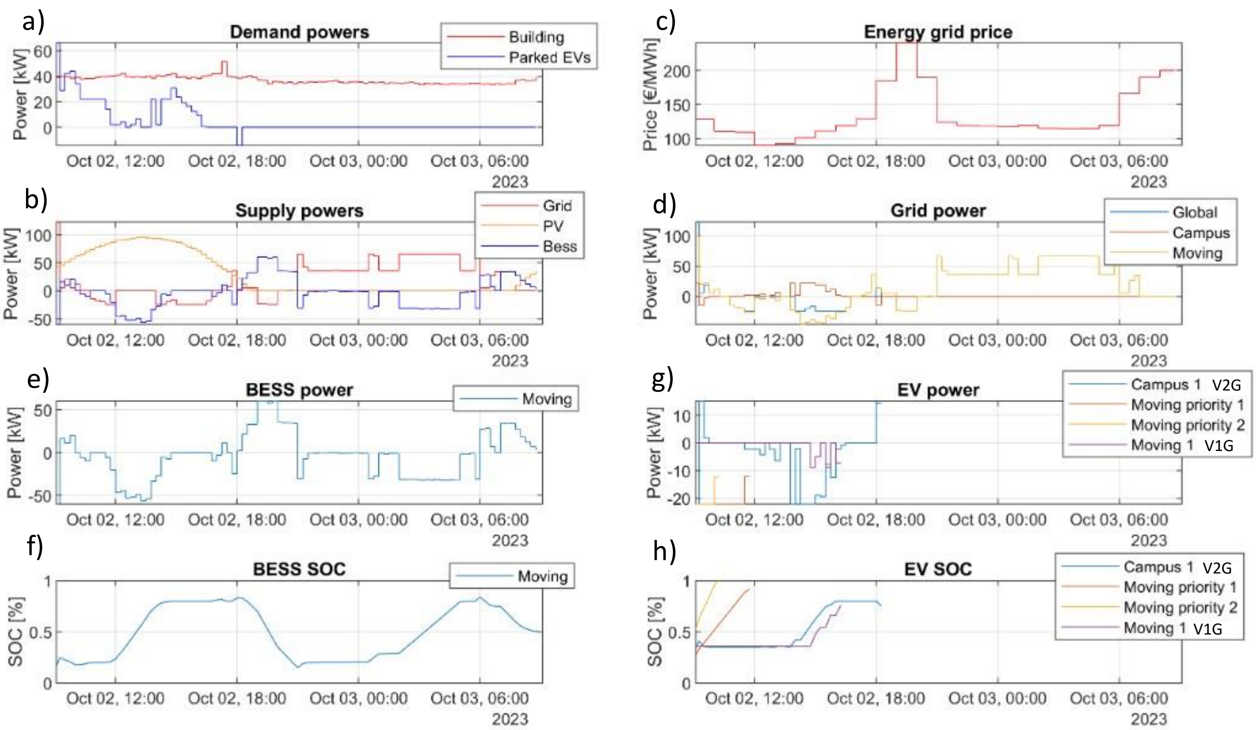


Figure 7: An example of intra-day optimization results: a-b) Comparison of demand and supply power, c) Energy price profile from ENTSO-e API, d) Grid power consumption profile from various sites, e-f) BESS power and SOC profile, g-h) EVs power and SOC profile with different user

2.3. Results

Virtual results are analysed to illustrate the model's behaviour. Considering a configuration example with two locations, the fixed parameters for the charging park are detailed in Table 7.

Location	Nominal power	Charger type	Current type	Land
Moving Lab	$[50;\ 22;\ 22]\ kW$	V2G; V2G; V1G	DC; DC; AC	Private Area
Design Campus	$[22;\ 22;\ 11]\ kW$	V2G; V2G; V1G	DC; DC; AC	Public Area

Table 7 Charging Park configurations for the examined case studies.

As outlined in paragraph 0, the pairing mechanism between user and charger operates based on the lowest level of flexibility. Then, whether a V2G user connects to the third V1G charger, the charging process will default to V1G mode.

For the simulations, four main scenarios are analysed to evaluate the impact of smart charging technologies on grid energy demand, RES share, and the service provided to vehicles:

- **V1G Scenario:** All users allow for smart charging flexibility.
- **V2G Scenario:** All users allow for bidirectional charging flexibility.
- **Priority 1 Scenario:** A hypothetical scenario where the same vehicles and load as in the first two scenarios are applied, but without any optimization. This serves as a baseline to assess the effectiveness of smart charging technologies.
- **Priority 2 Scenario:** All users are prioritized and always have access to a free charging point. This serves for assessing the reduction of number of vehicles served and the potential decrease in total energy consumption.

<u>Charging Park coupled with PV system:</u>

For this case study, the capability of smart charging technologies to reduce grid impact by aligning vehicle energy consumption with PV production is analysed. The peak power of the PV system is set to 30 kW. As shown in Figure 8, the optimization function significantly improves the alignment between vehicle consumption and photovoltaic production, leveraging the enhanced flexibility of V1G/V2G vehicles; Moreover, V2G enables energy to be fed back into the grid during periods of congestion and high energy prices. Some KPIs for the simulation are reported in Figure 9, highlighting a potential 9% increase in self-consumption of RES and a 10% increase in RES coverage of energy demand in the V2G scenario compared to the Priority 1 scenario. The total energy exchanged with the grid, which is formulated as:

$$EN_{grid} = \int_{t0}^{tf} |P_{grid}(t)|dt$$

is reduced by 45% compared to the Priority 2 scenario. However, due to the increased resting time per vehicle, the total number of completed charging sessions is reduced by 42%: This indicates that smart charging technologies are better suited for contexts with lower and more predictable demand, such as residential areas (for overnight events) and company parks (for daytime events). Conversely, for fast charging stations, it could lead to a significant reduction in service availability and potential revenue.

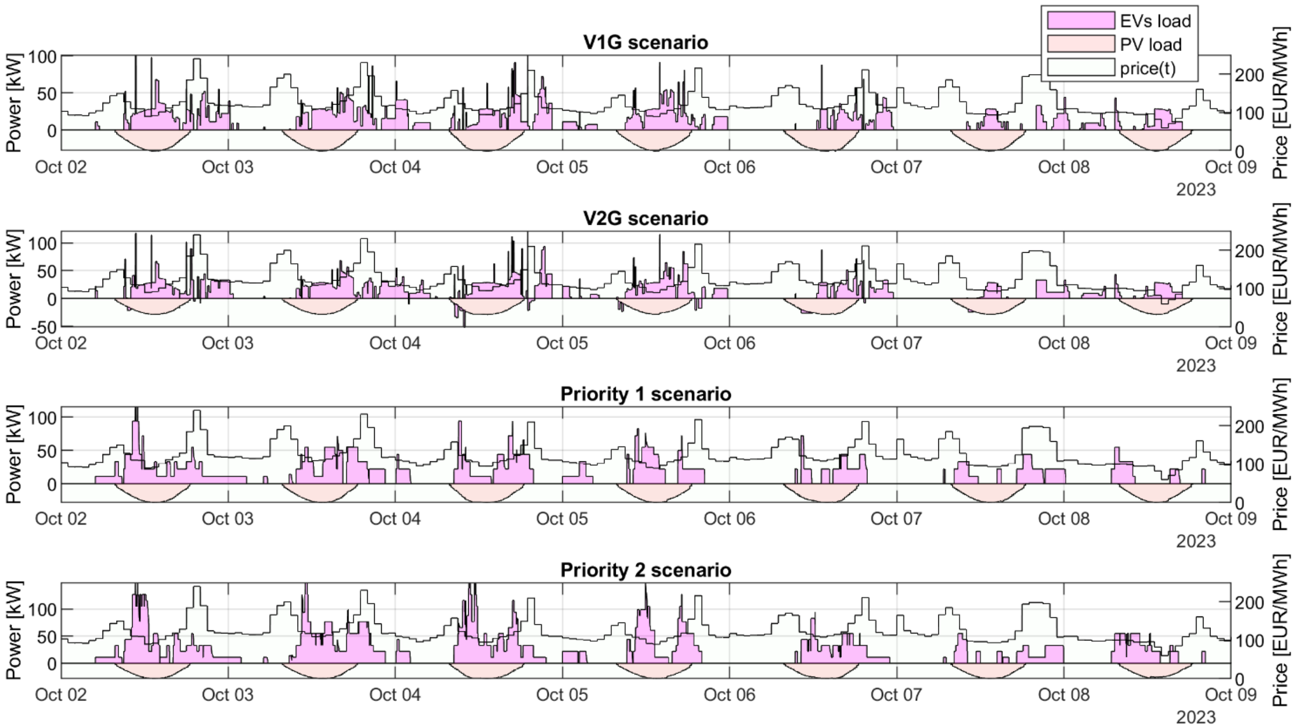


Figure 8: Simulated results for the PV coupling case study across four different scenarios: V1G, V2G, Priority 1, and Priority 2. The EVs' demand load is compared with PV production and the energy price profile throughout a week

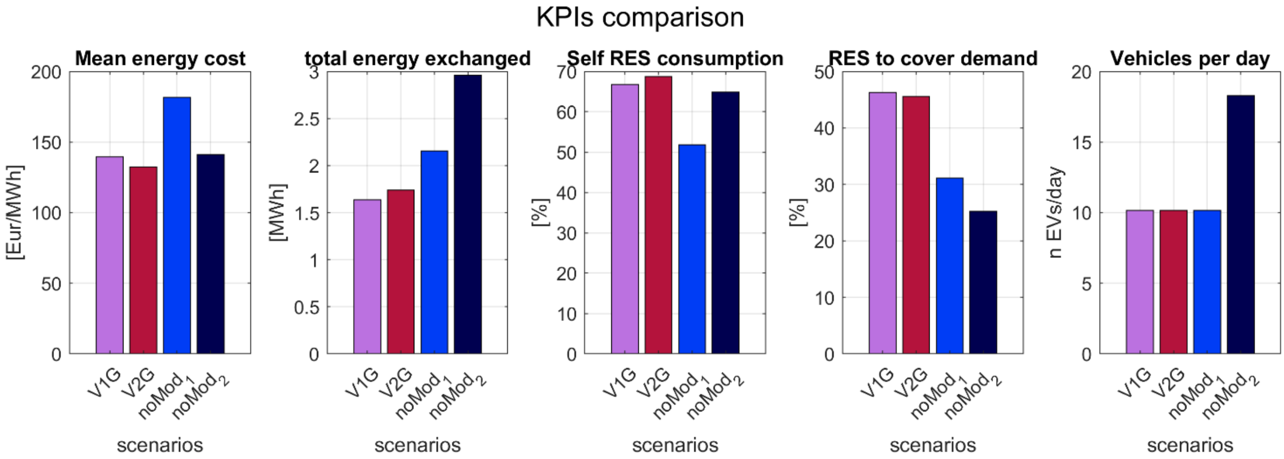


Figure 9: Comparison of KPIs for the different charging scenarios

<u>Charging Park Supporting Building Energy Demand:</u>

Capabilities of smart charging technologies to support building utilities are analysed, focusing on shaving overall grid power and reducing total energy costs. For this case study, the energy consumption of the Moving Lab building will be considered.

Simulated results indicate a marginal reduction in energy costs: 4% for V2G and 2.5% for V1G compared to the uncontrolled scenario, with the same amount of energy supplied. Using V1G, charging events are shifted to periods with lower energy prices, while V2G leverages discharging possibility to sell energy during high-price periods. This trend is clearly illustrated in Figure 10. Furthermore, these technologies can manage high power peaks demand from building by either pausing vehicle charging or providing V2B services.

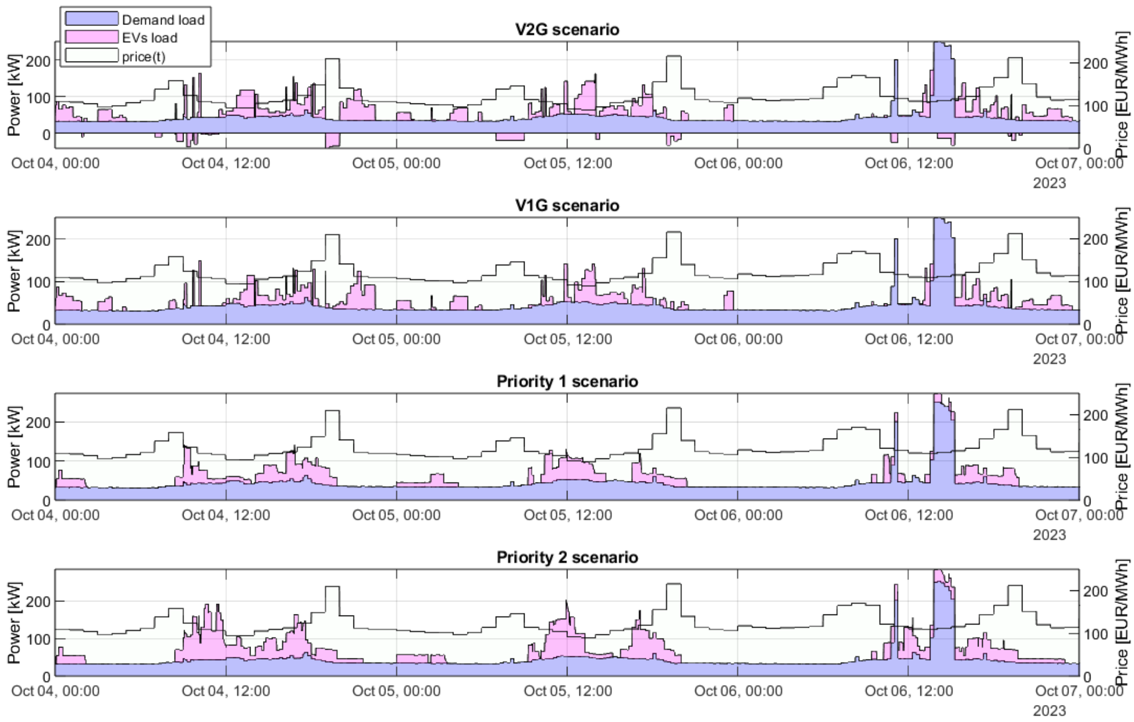


Figure 10: Simulated results over a 3-day time span, comparing building energy demand with EV power consumption across the four scenarios

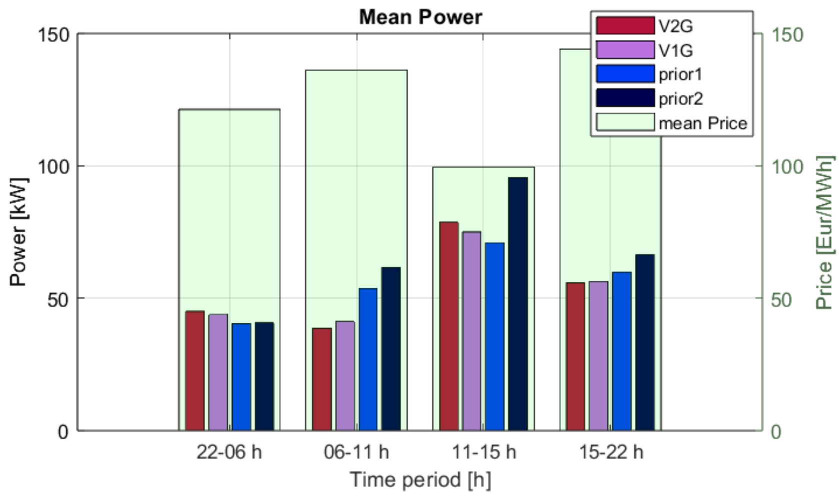


Figure 11: Comparison of average power consumption by time slot, relative to mean energy prices. V2G and V1G demonstrate flexibility to schedule charging during low-price periods

3. Neuman Aluminium Use Case

In this virtual use case, renewable energy sources in combination with storage possibilities including a vehicle-to-building concept are investigated. The overall goal is to analyse the energy consumption and the impacts of increasing renewable energy sources in terms of financial benefits. In general, the company Neuman Aluminium, located in Lower Austria, has a yearly energy demand of around 110,000 MWh because to their energy intensive production processes. The energy demand in the year 2022/23 can be divided in around 36% electricity demand and around 64% natural gas demand. According to this high energy demand, Neuman has employed two hydroelectric power plants with an overall size of 0.95 MWp and a photovoltaic (PV) system of size 100 kWp which was expanded to 1.1 MWp in June 2023. Currently, these power plants produce 4,100 MWh/year. The virtual use case contains two scenarios where the PV system is further increased up to 4 MWh (scenario 2) and two wind turbines with an overall size of 9 MWp (scenario 3) are included. An overview of the scenarios can be seen in Table 8.

	Status quo	Scenario 2	Scenario 3
Hydropower plant	0.95 MWp	0.95 MWp	0.95 MWp
PV system	1.1 MWp	4 MWp	4 MWp
Wind turbine	-	-	9 MWp

Table 8: Scenario Overview on the Virtual Use Case of Neuman Aluminium

The analysis contains four-steps, where the first two steps investigate the energy production and consumption data to determine the periods and amount of surplus of energy production. With these findings, a vehicle-to-building concept for a parking area for self-consumption optimization or peak shaving is conceptualised and investigated within the third step. When analysing this, it is also important to show under which conditions the employees would agree to (temporarily) discharge their vehicles. This is investigated by using survey data that were collected during the project. In the fourth and last step, a battery storage is simulated as an alternative storage solution. A schematic overview of the working steps in the Neuman use case can be seen in Figure 12.

Figure 12: Work steps in the Neuman Use Case

3.1. Methodology

One of the most important parts of this virtual use case are the real-world data provided by Neuman Aluminium. For the analysis consumption data in 15-minute resolution over

1 year of gas and electricity were used. The data show the energy consumption of three different facilities of the company. To represent the PV production of the different scenarios data of an already installed smaller PV (100kWp), where data of over one year are available, as well as data of a 1.1 MWp system which started to operate in June 2023 were used. For the hydropower plant, only monthly production data were available. The data was therefore distributed evenly over the month in order to obtain a data set of the same length. In order to include the wind turbine in the analysis, wind speed data from a nearby measuring station in Lilienfeld was used to make a model-based calculation of the expected production.

To calculate the electricity that can be produced by a wind turbine the equation below is applied. The power of the wind (P) is determined as:

$$P = 0.5 \cdot A \cdot \rho \cdot C_p(v) \cdot v^3$$

where the surface area of the blade (A) is defined by $A = \pi \cdot r^2$, where r is the radius of the rotors. In addition, ρ is the density of the air, C_p is the power coefficient that defines how much energy can be extracted by the wind turbine at a certain windspeed (v). For the analysis the power coefficient and other technical data of the Gamesa G128 – 4.5MW wind turbine were used (Wind Turbine Models, 2024).

The windspeed data are in 10-minute resolution from a monitoring station close to Neuman Aluminium. As the monitoring station measures windspeed in 10 m height the windspeed has to be adapted by applying the power law method which is defined by the following formula (Abbes et al., 2012):

$$v_2 = v_1 \cdot \left(\frac{h_2}{h_1}\right)^{\alpha}$$

where v_1 and v_2 are the windspeed at the height of the monitoring station (h_1) and the height of the wind turbine (h_2). The value of α is determined by the terrain type and generally is estimated to range from 0.1 to 0.4 in engineering application (Li et al., 2018).

Figure 13 gives an overview about the different data sources and how they are used for the scenario analysis. The green boxes represent the energy production while the blue boxes represent the three facilities at Neuman Aluminium that consume energy. In the middle of the scheme there are two grey boxes which represent the work steps in which the energy surplus/deficit is analysed and the energy management system which decides how the energy is used.

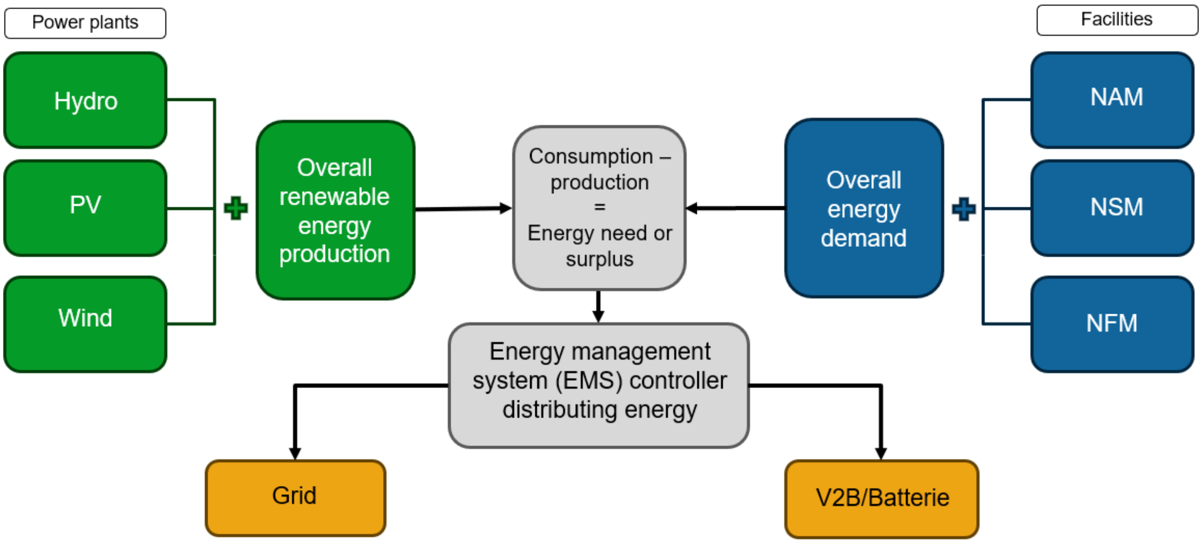


Figure 13: Data and Module Scheme of the Neuman Aluminium Use Case

The KPIs in Table 9 are used to evaluate the scenarios and the various configurations in financial and energy terms:

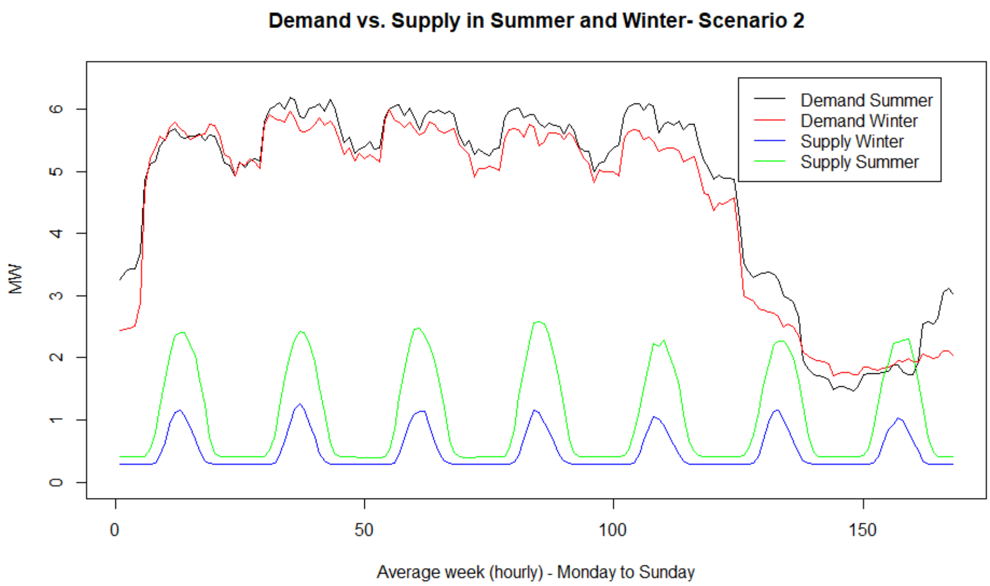
KPI	Formula
Self-sufficiency rate (SSR)	$\mathrm{SSR} = \frac{E_{used}}{D}$
Self-consumption rate (SCR)	$\mathrm{SCR} = \frac{E_{used}}{S}$
Net present value (NPV)	$NPV = \sum_{n=0}^{T} \frac{Cashflow_t}{(1+r)^t} - Investment$
Return on investment (ROI)	$ROI = \frac{net\ utility}{Investment} \cdot 100$
Pay-back period (PBP)	$PBP = \frac{Investment}{Cashflow}$

Table 9: KPIs used in the Neuman Aluminium Use Case

Where E_{used} is the amount of produced energy that is consumed, D is the energy demand and S is the energy production. The $net\ utility$ = ($Sav{\cdot}T$ − $annual\ costs{\cdot}T$) − $Investment$, where Sav are the yearly savings, T is 25 years. Finally, the annual cashflow is defined as $Cashflow$ = Sav − $annual\ costs$.

3.2. Results

To get insights about the potential energy surplus for the two scenarios, the average week was calculated and compared. As shown in Figure 14 there is only little room for surplus in scenario 2. During the week, the energy demand of Neuman Aluminium is still significantly higher than the energy production. When comparing scenario 2 with scenario 3 it can be seen that during the week, the energy demand is still higher than production but, on the weekend, there is potential for energy surplus that could be shifted to Monday when the energy demand of Neuman Aluminium increases again.



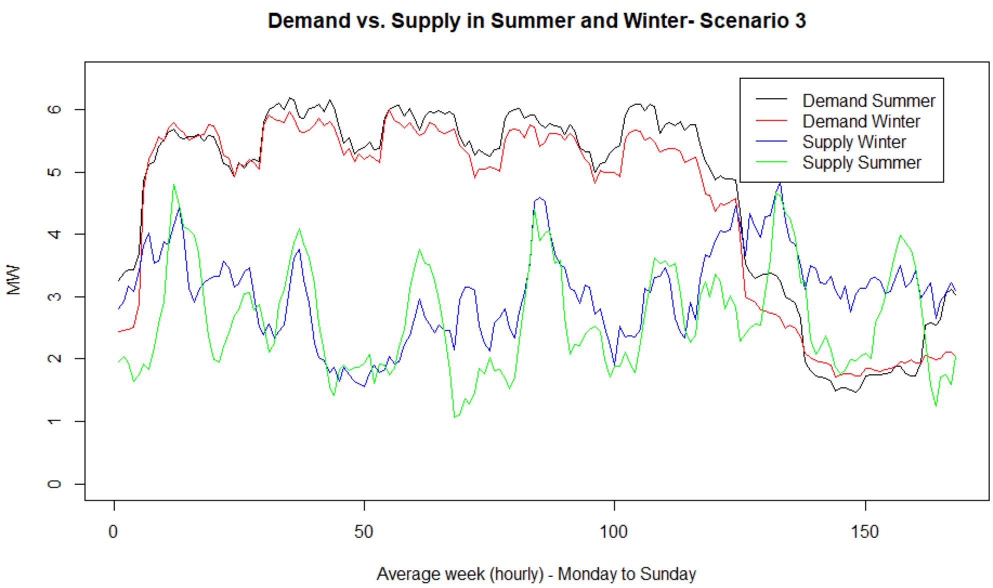


Figure 14: Average Week of Scenario 2 and 3

The next step was to take a closer look at the surplus per weekday. By cumulating the surplus energy per weekday, it could be seen that in scenario 2 mainly on Saturday and Sunday a surplus was generated. In comparison to that scenario 3 shows surplus energy over the whole week (see Figure 15). As in scenario 2 the biggest share of the surplus was generated on the weekend but overall, the surplus of over 6,600 MWh is significantly higher than the 170 MWh of surplus in scenario 2. Therefore, only scenario 3 was used to investigate the vehicle-to-building (V2B) use case and the local storage setup as only in this scenario the potential surplus is high enough.

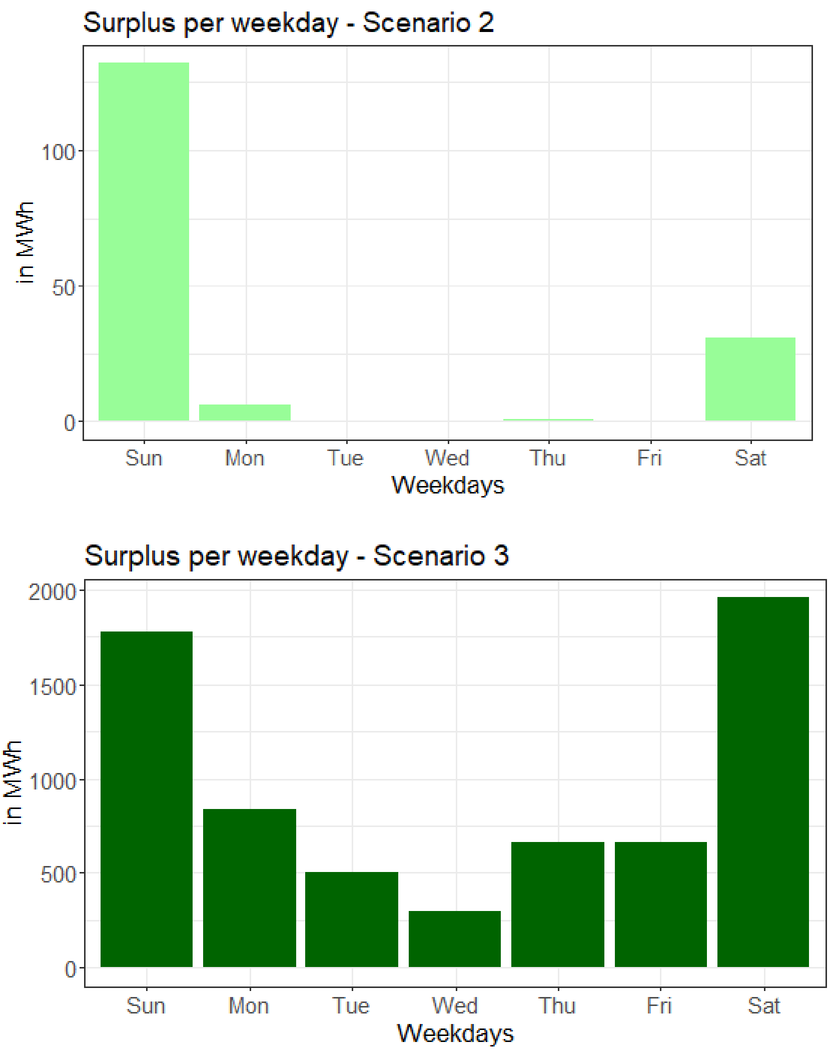


Figure 15: Surplus per Weekday in Scenario 2 and 3

Before the structure of the V2B and local storage is explained, the investment assumptions for the expansion of renewable energies for scenario 3 are presented. For the PV expansion, a price of EUR 700/MWp is assumed for the modules and installation, which corresponds to the conditions that Neuman Aluminium had for the PV expansion in June 2023, including governmental subsidies. An average value from several sources was used for the investment and installation costs of the wind turbine. Therefore, the assumed investment costs for the expansion of renewable energy in the scenario require investment costs of EUR 15.4 million. In addition, annual operating and maintenance costs of 1% of the investment costs are assumed (see Table 10).

Investment costs	EUR	EUR
PV	700,000 per	2.03 Mio.
Wind turbine	1.3 Mio. per	11.83 Mio.
Installation in EUR		
Wind turbine	1.57 Mio.	
Overall investment costs in	15.43 Mio.	
Yearly O&M costs	1% of investment costs	
Energy price		
Grid tariff	131.76	in
Feed-in tariff	86.97	In

Table 10: Investment and Price Information

For the V2B setup, the battery size of the vehicles is assumed to be 50 kWh, where 20 kWh are assumed as usable capacity per vehicle. The reason for this is that it is assumed that the SoC must not fall below 40% or above 80%. Depending on the number of EVs available, this results in a usable capacity of 2 to 8 MWh, when 100 to 400 EVs on the car park are assumed. According to information from Circontrol, the costs for the required charging stations are between EUR 730,000 and EUR 2,900,000 (see Table 11)

	Per charging
Max. power of bidirectional charging station	22 kW
Price for hardware for bidirectional charging stations	7,000 €
Software for bidirectional charging stations	150 €
Hardware for energy management platform and stationary	100 €
Energy management software	150 €

	Costs of the charging
100 EVs	732,500 EUR
200 EVs	1,465,000 EUR
300 EVs	2,197,500 EUR
400 EVs	2,930,000 EUR

Table 11: Investment Information on the bidirectional Charging Stations

One drawback of the V2B setup is, that the usable capacity is only available when employees are at work. Therefore, no capacity is available at the weekend. Figure 16 shows that during Saturday 05:00 a.m. and Monday 04:59 a.m. no useable capacity is available.

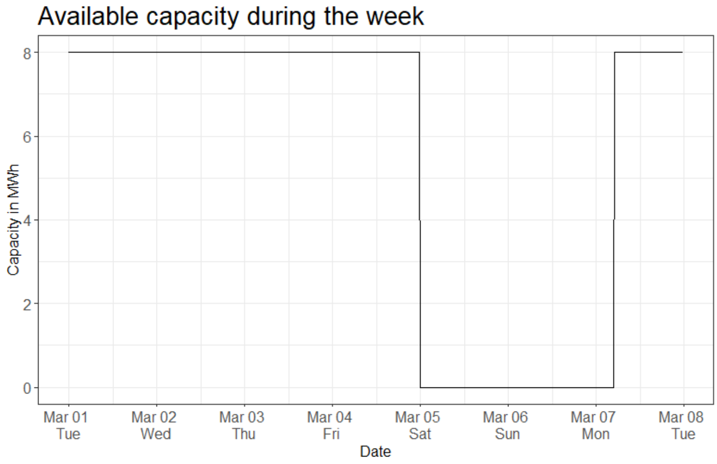


Figure 16: Available Capacity in the V2B Setup

When analysing this simplified setup of the V2B setup over a time horizon of 25 years, it can be shown that overall investment costs are between 16.2 to 18.5 Mio. EUR, depending on the number of charging stations assumed (see Table 12). Note that the costs for the renewable expansion are included as well. The analysis shows that with the V2B setup, savings of around 2.5 Mio. EUR per year can be reached. The net present value (NPV) is positive, and the payback period (PBP) lies between 6.6 and 7.4 years.

Vehicle-to-Building	100 EVs	200 EVs	300 EVs	400 EVs
Overall investment costs	16.19 Mio.	16.94 Mio.	17.70 Mio.	18.45 Mio.
O&M in EUR	146k	153k	161k	168k
Max Power / 15 min in	0.55	1.10	1.65	2.20
Savings in EUR	2.47 Mio.	2.48 Mio.	2.48 Mio.	2.49 Mio.
NPV	16.6 Mio.-	15.8 Mio.	15.0 Mio.	14.2 Mio.
ROI	211.2	198.1	185.8	174.4
PBP	6.6	6.8	7.1	7.4
SSR	46.5%	46.9%	47.3%	47.6%
SCR	74.8%	75.6%	76.2%	76.6%
Energy used in MWh	18.7k	18.9k	19.0k	19.1k

Table 12: Results of the V2B Setup

With the V2B setup the self-sufficiency rate (SSR) of Neuman Aluminium increases from around 10 % (status quo) up to 47.6% (when 400 EVs are available). The SCR in the V2B setup lies between 74.8% and 76.6% which refers to 18,670 to 19,115 MWh of used energy. Figure 17 shows the amount of energy bought, sold and used in this setup. The energy amount as well as the SCR, SSR and PBP change only slightly when increasing the number of EVs.

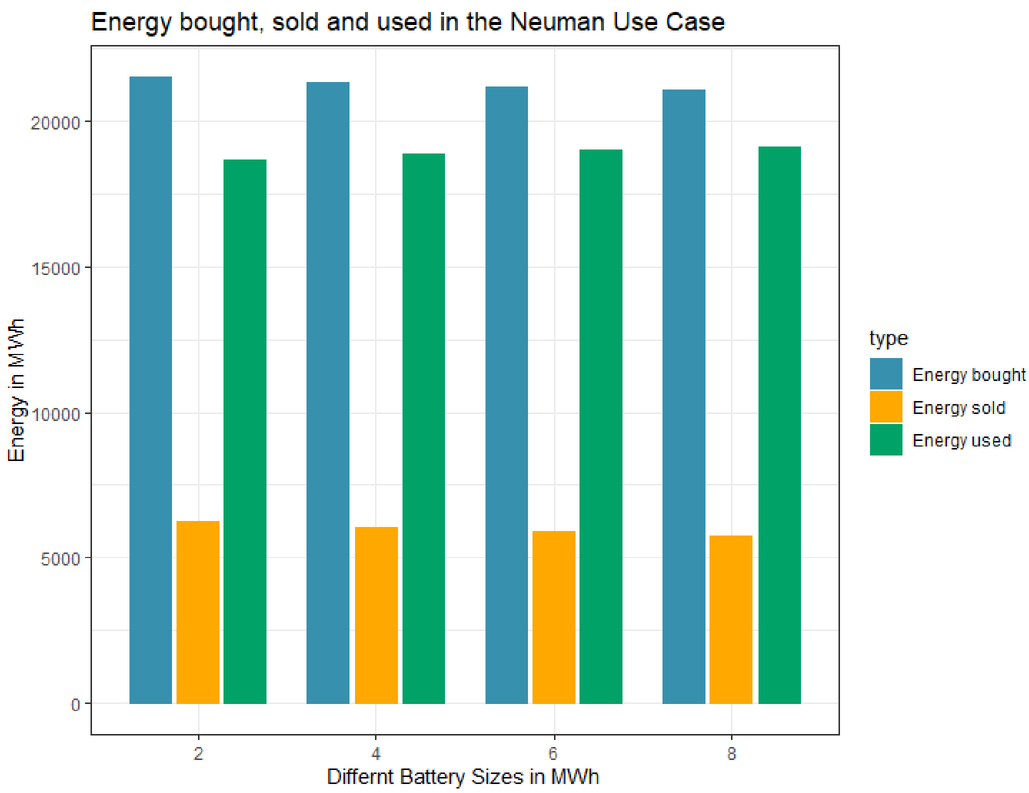


Figure 17: Energy bought, sold and used in the V2B Setup

Next, the V2B setup is compared to a setup where a local storage is used. Therefore, it is assumed that Neuman Aluminium uses a 2/4/6/8 MWh battery to store the surplus energy. The main advantage of the battery is, that it is always available in comparison to the EVs.

Table 13 shows the assumed investment costs. For the analysis we assume costs of 400,000 EUR/MWh for the battery as well as 3% of investment costs for installation and 1% of investment costs for the yearly operation and maintenance works. This leads to investment costs between 800,000 and 3,200,000 EUR depending on the used battery size. In addition, we assume that the battery must be changed after 3,000 cycles (European Commission, 2023).

Cost of local storage	
Costs per MWh	400,000
Installation	3% of investment costs
Yearly O&M	1% of investment costs
Cycles	3,000

	Costs of the local storage
2	800,000 EUR
4	1,600,000 EUR
6	2,400,000 EUR
8	3,200,000 EUR

Table 13: Investment Information on the Local Storage

Results show that in terms of investment the charging stations and the battery are quite similar (see Table 14). In general, the biggest part of the investment costs are the costs of the expansion of renewable energy in Neuman Aluminium which are around 15 Mio. EUR.

Battery storage	2 MWh	4 MWh	6 MWh	8 MWh
Overall investment costs	16.26 Mio.	17.08 Mio.	17.91 Mio.	18.73 Mio.
O&M in EUR	147k	155k	163k	171k
Max Power / 15 min in	1.0	2.0	3.0	4.0
Savings in EUR	2.48 Mio.	2.49 Mio.	2.50 Mio.	2.51 Mio.
NPV	13.3 Mio	10.0 Mio.	10.1 Mio.	7.6 Mio.
ROI	167.13	140.70	132.42	112.07
PBP	8.38	9.42	9.77	10.82
SSR	47.0%	47.7%	48.2%	48.6%
SCR	75.7%	76.8%	77.7%	78.3%
Energy used in MWh	18.9k	19.2k	19.4k	19.5k
Battery changes	4	3	2	2

Table 14: Results on the Local Storage Setup

Like the V2B setup, the yearly savings are around 2.5 Mio. EUR and the SSR and SCR increase up to 48.6% or 78.3%. But, in comparison to the V2B setup the NPV and the PBP are worse. The reason for that is that the battery must be changed 2 to 4 times within 25 years which impacts the overall economic feasibility of the setup. Comparing Figure 17 with Figure 18 a similar picture can be seen. The energy amounts, SSR and SCR are quite similar between the setups but the PBP for the battery setup increases.

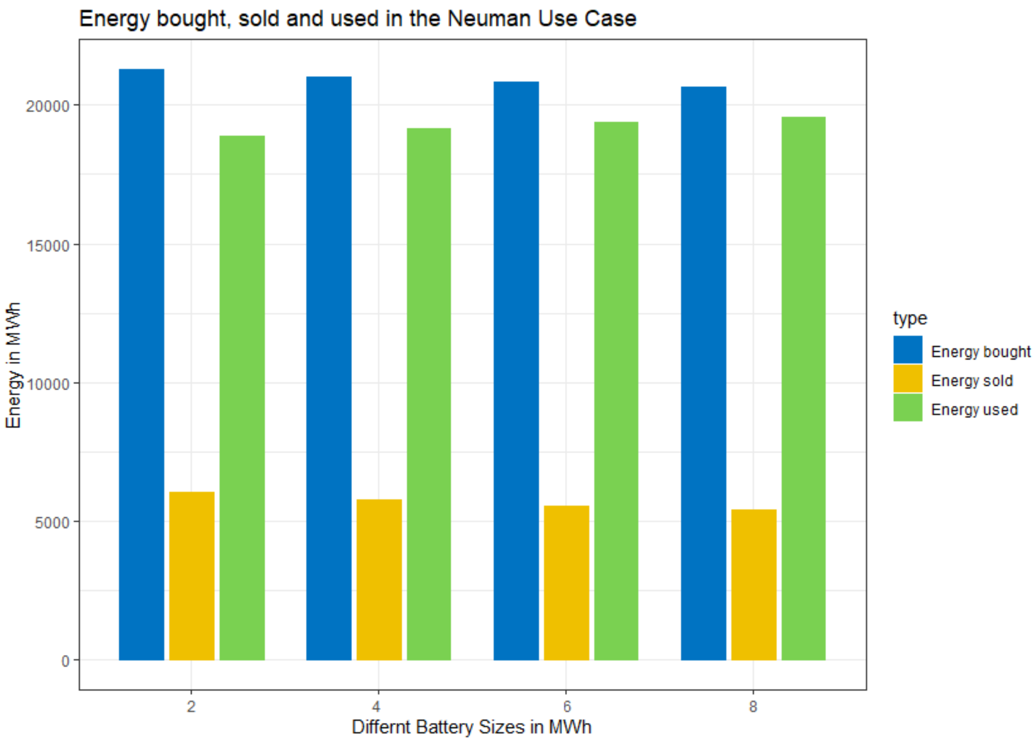


Figure 18: Energy bought, sold and used in the Local Storage Setup

When comparing these two setups it is shown that V2B can be an alternative for Neuman Aluminium in terms of investment (see Table 14). Nevertheless, there is one big drawback that must be considered, which is the willingness to participate of the employees as at the moment charging and discharging costs of zero are assumed. Therefore, the total costs over 25 years of usage were compared to find out how much room is available for incentives. When comparing the total costs of the charging stations and a local storage around 230 to 450 EUR/a can be given to the employees over 25 years.[2]

	100 EV / 2MWh	200 EV / 4MWh	300 EV / 6MWh	400 EV / 8MWh
Lifetime costs of the stationary	23.2 Mio.	25.9 Mio.	26.9 Mio.	29.6
Lifetime costs of V2B in EUR	19.8 Mio.	20.8 Mio.	21.7 Mio.	22.7
Difference in EUR	3.4 Mio.	5.1 Mio.	5.2 Mio.	6.9 Mio.
Difference per year in EUR	135,296	204,672	208,128	277,504
Possible incentives per EV per	451	341	231	231
Additional cycles per year through	70	52	43	37

Table 15: Comparison of the Lifetime Costs of the V2B and Local Storage Setup

To summarise, the total cost of the V2B concept (bidirectional charging stations and energy management system) is lower than that of a stationary battery system,

[2] Note: as there are three work shifts per day at Neuman Aluminium, the number of employees ranges from 300 to 1,200.

considering that employees use their private cars. This difference can be used to incentivise employees and motivate them to participate in V2B. Overall, it can be said that the V2B concept has lower costs and battery replacement is not required after a certain number of cycles are reached, but there is uncertainty about the usable capacity, which heavily depends on the SoCs of the EVs and whether employees are willing to participate. The advantage of local storage is that it is always available and there is no uncertainty regarding utilisation, resulting in a slightly higher SSR and SCR. However, local storage is associated with higher lifetime costs and the modules must be replaced after a certain number of cycles have been reached.

3.3. Further project activities

These first results show that V2B can be used as an alternative to local storages at an industrial environment. However, there are still uncertainties and open questions because of this first simplified analysis. Therefore, the model will be further developed to give more insights regarding the usage of V2B. Frist, the model will consider the different work shifts and variation in SoCs of the EVs. Second, we will include monetary user incentives and check if the V2B setup can still compete with the local storage. Therefore, we use insights from the survey on user behaviour and expert interviews which were undertaken in WP2. In these interviews and survey different types of incentives were explained and asked about. Therefore, these valuable insights will be used to enrich Neuman Aluminium's V2B model with an incentive system for EV users. In addition, further investigations regarding the use of the waste heat of the charging stations for heating will be done.

4. On-road parking in smart cities

In 2023, there were over one million electric vehicles in circulation in France, most of which were battery-electric.[1][1] According to the latest statistics, the total population of France is about 68 million, while the population of the Lyon metropolitan area is about 522,000 and the population of the entire Lyon metropolitan area is about 2,308,000 people. The population of the Lyon metropolitan area accounts for approximately 3.4% of the total population of France, while the urban area accounts for only 0.76% of the population. As shown in the following Figure 19 the number of BEVs in France is 595,795 and the number of plug-in hybrids (PHEVs) is 424,263 in 2023, that would put the overall number of rechargeable cars at more than 1 million. If we do a quick calculation, simply assume that the number of electric vehicles is linearly related to population, it is possible to roughly estimate the number of electric vehicles in the city of Lyon, which is about 34070 vehicles.

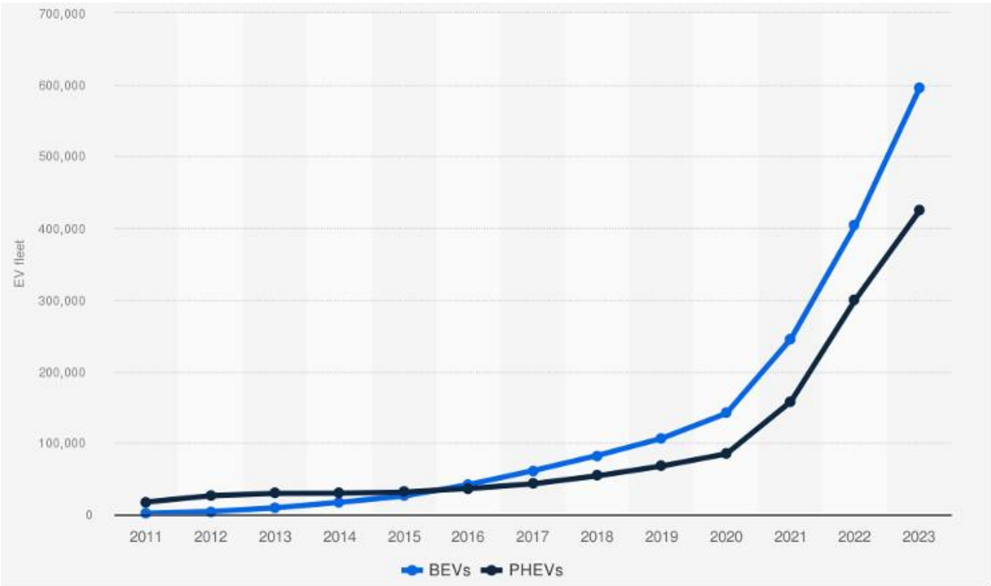


Figure 19: Electric vehicle fleet in France between 2011 and 2023, by propulsion type [2]

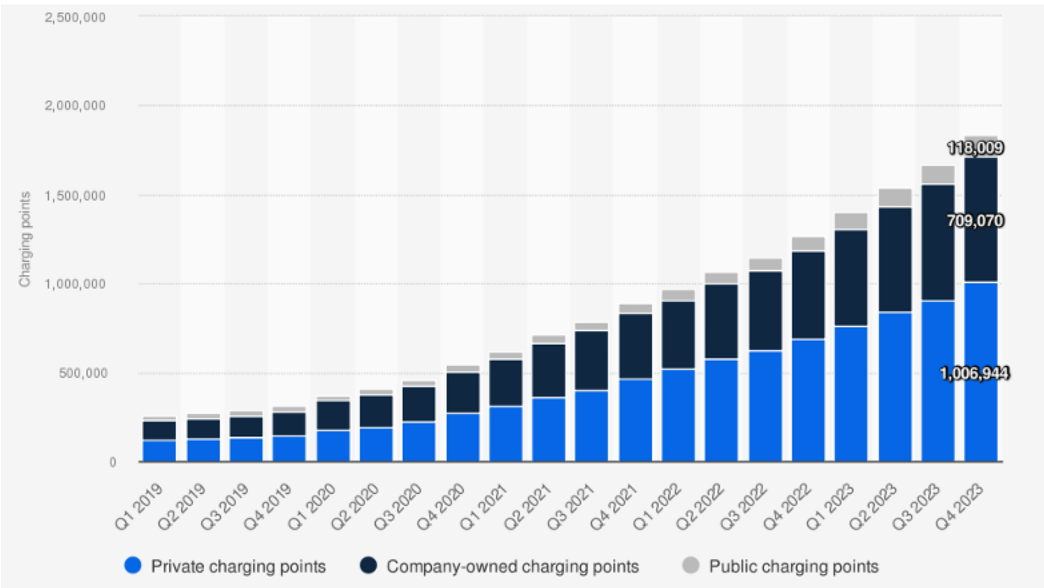


Figure 20: Quarterly electric vehicle charging points in France between the first quarter of 2019 and the fourth quarter of 2023, by type [3]

As shown in Figure 20, the number of public charging posts in France as of the fourth quarter of 2023 is 11,809 across the country, or about 4,012 if the number of public charging points of Lyon is also estimated based on the population share. It is easy to conclude that the ratio of public charging stations to the number of electric vehicles around the Lyon city is around 0.12. It can be imagined that during workday, most of the EV charging events can be handled at home or at company. Even though the number of private and company-owned charging points is relatively high compared to public charging points, and most drivers prefer to install a wall-box charger at home, the density of traffic in urban areas increases significantly on weekends, and there is a high probability that charging peaks and congestion will occur with the current share of public charging points.

In this virtual demonstration, efforts will be made to solve the problem of peak charging at urban area while taking into account as much as possible the charging behaviour of the users and minimizing their costs. This virtual demonstration is patterned based on Lyon, France, and generates charging events using public chargers based on the city's traffic and drivers' driving routes. Using these generated charging events, the benefits of applying smart charging and bi-directional charging technologies to public charging stations in the city is discussed. It also demonstrates the possibility of providing flexible energy storage for the grid while satisfying EV users' satisfaction.

4.1. Behaviour of electric vehicle drivers in Lyon

The IFPEN user model needs to predefine the user behaviour relative parameters to generate possible charging activities in Lyon. The model selects the appropriate charging station to park for charging between the starting point and the destination. The parking time is influenced by the time of the next activity defined by the users. Please refer to D4.2 and D4.3 [4][5] of this project for specific technical information on this user model.

- V2X: willing of the EV drivers to use the bi-directional charging technology like V2B or V2G. The percentage of users willing to use bi-directional charging technology was set to 0% 20% 40% 60% and 100% respectively.
- Range anxiety: It is a threshold to decide when the user will go for charging. The charging choice is triggered when SOC is below a given threshold minSOC (DoD), independently from future trip plans. As described in D2.2 of XL Connect [6], a min SOC value near 40-45% in average seems realistic, especially considering the incentives.
- Willingness to wait: The parking times of users are determined as the complement of the time spent on other activities. In the user model the next planned activities are predefined, so the users need to have their vehicle charged to the target energy so that they can go for the next activities E.g. go home, go to work, or shopping…
- EV penetration rate: By 2023, the world's share of electric vehicles is about 18%, with 21 % in the European Union [7]. If optimistically, this figure may increase slightly from the same level in the next two years. Therefore, we have chosen a 30% penetration rate as a scenario for the virtual presentation, and a 5% penetration rate for the comparison group.
- Vehicle battery capacity: Assume a normal distribution centered at 80kWh and truncated at 60/100 kWh.

- Battery health: The DoD of battery is limited to minSOC = 20% and targetSOC=80%.

4.2. Charging Activities

For the urban street parking scenario, the output details the actual charging activities of all EV users in the metropolitan area of Lyon who do not have the option to charge at home. Detailed information is provided about the charging station selected, the type of charger employed, as well as the quantity of charge. Their charging decisions are influenced by predefined parameters, such as range anxiety, the availability of charging points, the distance to these points, and pricing.
In each charging activities, the following parameters in the table are included:

Name	Description
scenarioName	generic name of the scenario
scenarioType	unique iD of the scenario
scenarioLocation	geographical area of the charging stations
scenarioCountry	iD of the country
scenarioTimeHours	temporal arc of the scenario
charActivities	list containing detailed information on users' charging relative activities
userId	iD of the user
stationId	iD of the charging station or building where the user stops
chargerId	iD of the specific charger used
type	charging type (same dictionary as scenarioName)
coordinates	coordinates of the station or building where the user stops
sequence	sequence of charging activities
initSOC	SOC at plugTime
requiredSOC	minimum SOC required to complete the driving activity
plugTime	time at which the user plugs his vehicle
unplugTime	time at which the user unplugs his vehicle
v2x	willing of the user to use the x technology

Table 16: Charging activities definition

*Refer to D4.2 for detailed reference values and examples.

Using the charging data generated by the user model for a full month of January 2024 in Lyon, it is possible to analyze and compare how EV penetration and user attitudes towards V2X technology have a concrete impact on charging activities.

The Figure 21 below compares the number of total charging activities in the Lyon metropolitan area for a full month at different EV penetration rates, 5% and 30%, when 100% of users agree to use V2X technology. It can be seen that when EV penetration reaches 30%, the number of charging events in the city increases dramatically, about 48 times as much as at 5% penetration. When EV penetration rate is determined, the percentage of users agreeing to V2X technology will not have any impact on the number of total charge activities.

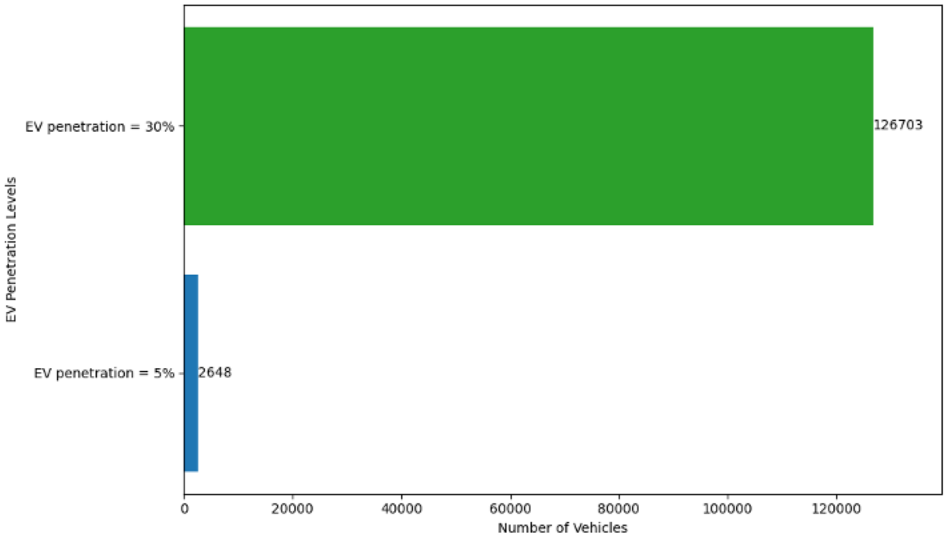


Figure 21: Comparison of charging activities number at different EV penetration, 30% and 5%, when 100% of the users agree to use V2X technology.

The charge incomplete rates calculated from the user model are 2.5% and 4.6% for different EV penetration rates of 5% and 30%, respectively. As shown in Figure 22 below, the average charging duration for EVs shrinks as EV penetration increases. As a result, there is a gradual increase in the number of occupied charging stations where users are not able to complete their charging event in the limited duration. With public charging facilities remaining unchanged, the flexibility to provide bi-directional charging per user decreases, but the number of EVs connected to the grid increases dramatically. This significantly increases the capacity of distributed energy storage and opens up the possibility of subsequent participation in the balancing market.

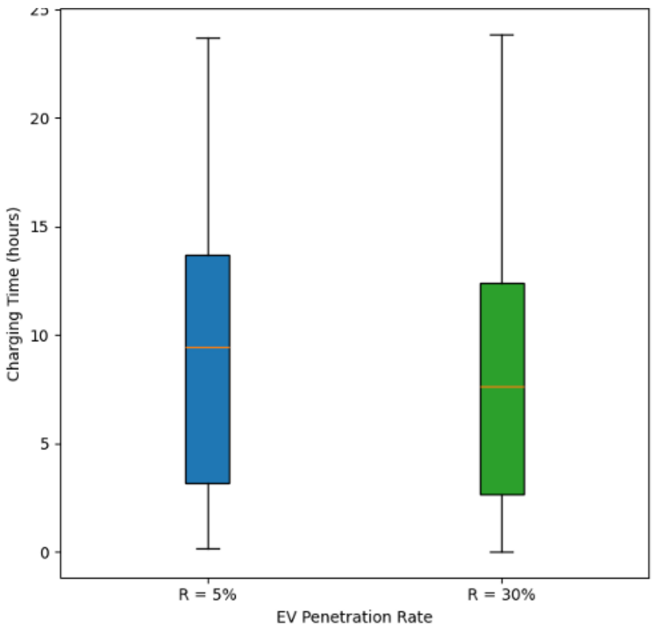


Figure 22: Comparison of connection time distribution at different EV penetration, 30% and 5%, when 100% of the users agree to use V2X technology

Figure 23 and Figure 24 below show how the number of EVs connected for charging varies over time The zoom in of the blue curve in Figure 23 is shown in Figure 24. throughout the month. Contrary to expectations, weekends are not necessarily the time when public chargers are most frequently used. It's hard to get a very clear pattern since people usually plan vacations in January as well, but peaks in the number of charging vehicles occur once every 5-7 days. During the day, the number of vehicles charging at public charging stations increases significantly from the afternoon onwards. When EV penetration is only 5%, there is little difference between the peaks and valleys of charging each day of the month, but when EV penetration reaches 30%, the cyclical occurrence of charging peaks is amplified.

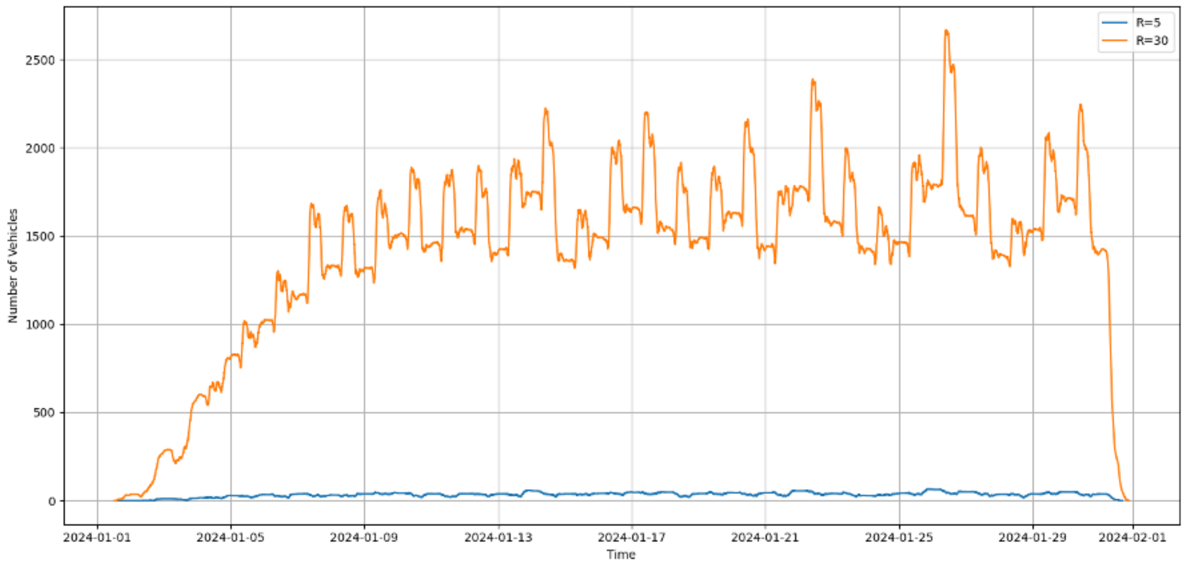


Figure 23: Comparison of plugged in vehicle number over time at different EV penetration, 30% and 5%, when 100% of the users agree to use V2X technology

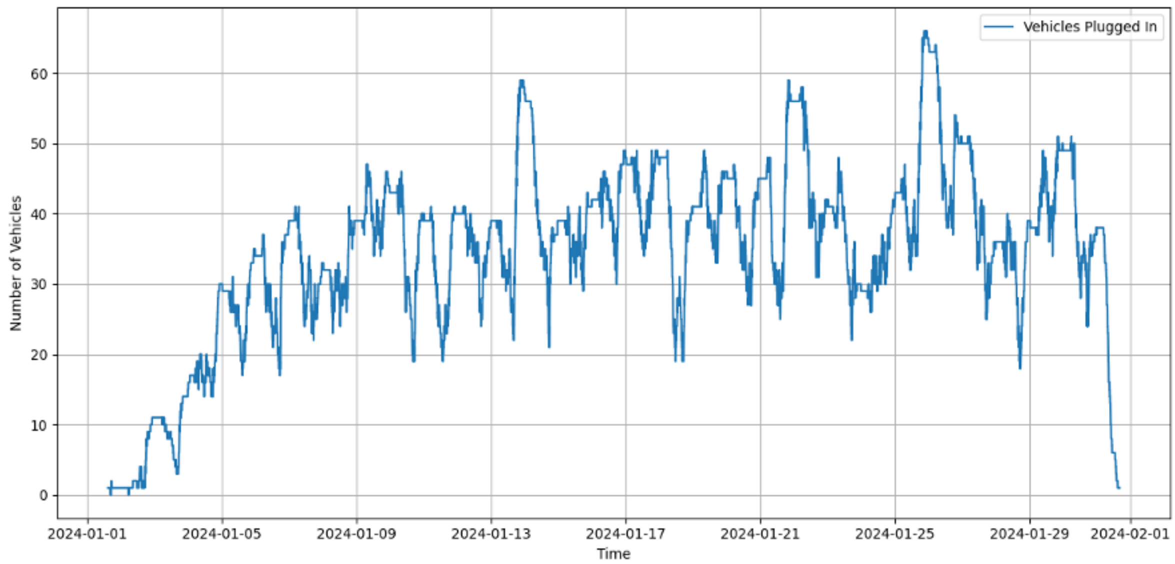


Figure 24: Zoomed in plugged in vehicle number over time at 5% EV penetration, when 100% of the users agree to use V2X technology.

4.3. Scenarios

The scenario for this virtual demonstration is based on the French city of Lyon. In this scenario, an EV aggregator is used to centrally control all the public charging stations scattered throughout Lyon. The aggregator is trained in reinforcement learning by using part of the charging activities mentioned above. The trained agent, also referred to as aggregator helps the charging station operators to set more reasonable dynamic retail prices based on the current market situation and charging demand. It also controls charging and discharging to meet the charging needs of as many users as possible.

The scenario is defined as follows:

- Simulation year: 2024
- Energy market price: France day-ahead market
- Retail price: The initial value of the retail price is obtained by multiplying the whole selling price by 3, where 3 is an experience value based on current market pricing.
- Number of vehicles: 10
- Location of charging stations: all the charging stations are located in Lyon, France
- Charging station max charging power: 50 kW, Since the maximum charging and discharging power of all charging posts in the user model is 22kW, under this condition all charging events use the maximum power to charge still 4.6% of the cars do not reach the target SoC in a limited time, here we will study the benefits of V2G for the user when the maximum charging and discharging power of the charging posts is extended to more than double.
- Charging station max discharging power: 50 kW
- Target energy: defined by user and next activities
- EV penetration rate: 30%
- V2G willing: 100%

4.4. Smart Public Charging in France

An EV aggregator will be used to realize the smart bi-directional charging the aggregator.

For an explanation of the detailed functions, please refer to D4.3 of XL Connect.

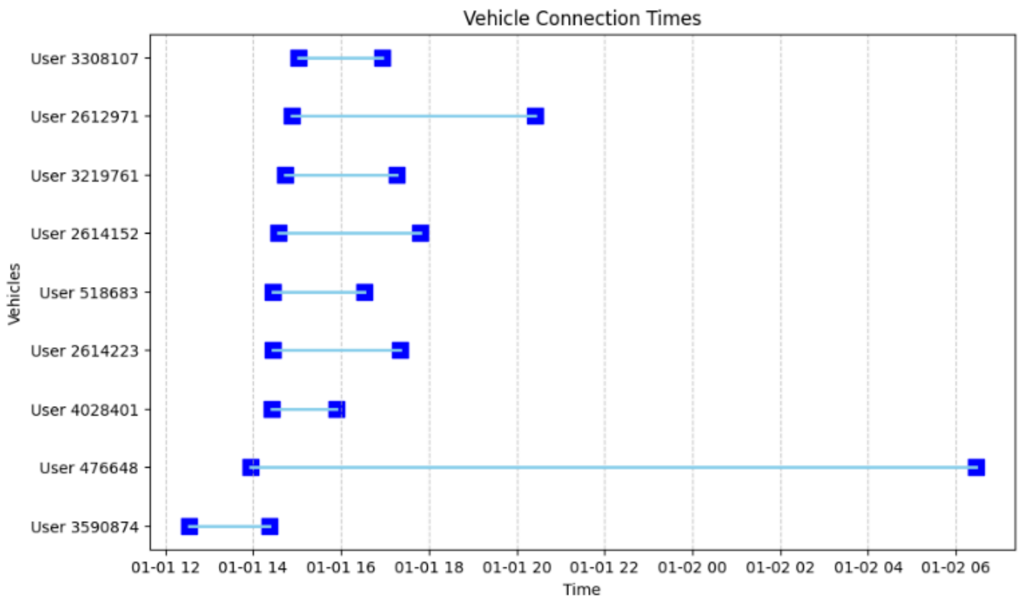


Figure 25: Vehicle Connection Times

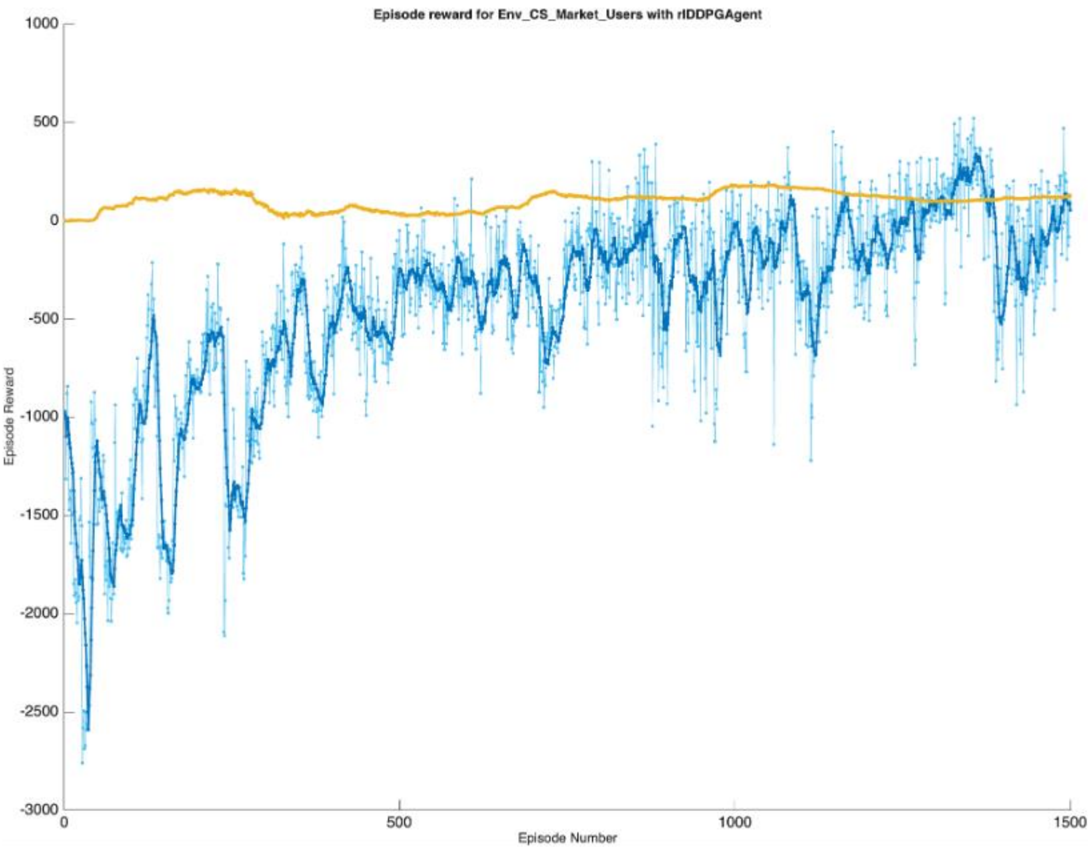


Figure 26: Episode reward for Env_CS_Market_Users with rlDDPGAgent

4.5. Outlook

For the current training and simulations, the number of vehicles used was set to a very limited number of 10 in order to explore the feasibility of the methodology and to save computational costs, but in the coming year, aggregators suitable for larger scenarios will be trained and the results will be presented in D4.3. Currently charging activities are only generated for the first month of the year, and since factors such as weather are not taken into account in the user model, the month does not have much effect on the public charging data generated for the user model. However, in the subsequent training of the aggregator, it is desired to include the ability to participate in the balancing market, so simulation for a full year is necessary due to the fact that the load profiles will be very different.

The virtual demonstration only focus on the France city due to lacking of public charging data from other countries, but we plan to include more real world charging data or simulated charging data in other European countries as the project progressed. And if it is possible to obtain real charging events of public charging stations in the coming year, it can also be used to validate the reference ability of the charging activities generated by the current user models.

5. Conclusion

The scalable model for Energy Communities with charging park areas investigates the potential to reduce energy costs as well as the exchanged energy with the grid by applying a simulation model in a MATLAB-Simulink environment for an V2G setup. In the analysis V1G and V2G scenarios with optimization algorithms are compared to uncontrolled reference scenarios at different daytimes. The simulated results show a slight reduction in energy costs. A reduction of 4 % for V2G and 2.5 % for V1G was recognised compared to the uncontrolled scenario, with the same amount of energy supplied. With V1G, charging processes are shifted to periods with lower energy prices, while with V2G the possibility of discharging is used to sell energy during periods of high prices.

The results of the Neuman use case show a comparison of V2B setup with a local storage set up. These results show that the V2B setups have the potential to become an alternative to an ordinary local storage, but there is a considerable uncertainty regarding the willingness to participate of the employees. Therefore, additional insights regarding willingness to use new charging technologies and user behaviour in general is needed to further develop the model. Therefore, the results of Task 2.1 are essential to further develop the model for the Neuman use case. In addition, the model is being further developed by including waste heat utilisation for heating purposes.

The virtual use case on bidirectional charging in smart cities shows first results. In this use case the charging activity is influenced by a designed user behaviour model of the EV users. Therefore, charging activities vary depending on the willingness to use V2X, the range anxiety of the user, the willingness to wait as well as the battery capacity and health. First the number of charging activities based on the EV penetration rate and the willingness to use V2G was investigated. It can be shown that charging activities increases 48 times when the EV penetration rate increases from 5 to 30%. Second, an aggregator that handles the charging sessions of 10 cars was trained by unsupervised learning algorithms. The results show charging sessions of 10 EVs at a 30% penetration rate assuming a 100% willingness to use V2G. The model will be further developed in increase the number of vehicles managed by the aggregator as well as to simulate scenarios other than for French cities.

References

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