POLITECNICO
MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

E-mobility charging time-series evaluation in support to future scenarios assessment

TESI DI LAUREA MAGISTRALE IN
ENERGY ENGINEERING
INGEGNERIA ENERGETICA

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Academic Year: 2021-22

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Abstract

In order to achieve the IPCC's goals of keeping the global temperature increase compared to pre-industrial values below 1.5°C, so as to avert the catastrophic consequences of climate change, decisive and profound action is needed by key policy makers to reduce climate-altering gas emissions in the sectors most responsible for them. In this direction, the road transport sector will be strongly influenced by a profound electrification process in the years to come, as it is responsible for 11.9 % of greenhouse gas emissions worldwide. Guided by the uncertainties in the literature regarding the assessment of the consequences of such an electrification process within the energy sector, this thesis aims to define an assessment of the increase in demand for electricity as a result of the electrification of the private transport sector, public buses and light and heavy transport within future scenarios. At the same time, a methodology is also presented for the implementation of smart charge and vehicle-to-grid strategies, which can ensure a more effective coupling between the transport and energy production sectors, especially in scenarios heavily dependent on renewable energy sources, by providing additional energy storage capacity and improved peak demand management.

Keywords: e-mobility, energy modelling, smart charge, vehicle-to-grid

Abstract in lingua italiana

Per poter raggiungere gli obbiettivi posti dall'IPCC di contenimento dell'aumento della temperatura rispetto al periodo pre-industriale al di sotto dei 1.5 °C, in modo da scongiurare le catastrofiche conseguenze relative al cambiamento climatico, è necessario un deciso e profondo intervento da parte dei principali policy maker per ridurre le emissioni di gas clima alteranti nei settori che ne sono maggiormente responsabili. In tale direzione, il settore del trasporto su strada sarà negli anni futuri, fortemente influenzato da un profondo processo di elettrificazione, in quanto a livello mondiale è responsabile dell'11.9% delle emissioni di gas serra. Guidato dalle incertezze presenti in letteratura, in merito alla valutazione delle conseguenze di un tale processo di elettrificazione all'interno del settore dell'energia, questa tesi si pone l'obbiettivo di definire una valutazione dell'aumento di richiesta di energia elettrica a seguito dell'elettrificazione del settore del trasporto privato, degli autobus pubblici e del trasporto leggero e pesante all'interno di scenari futuri. Al tempo stesso, viene anche presentata una metodologia per l'implementazione di strategie di smart charge e di vehicle-to-grid, le quali possono garantire un più efficace accoppiamento fra il settore dei trasporti e quello della produzione di energia, specialmente in scenari fortemente dipendenti da fonti di energia rinnovabili, fornendo una capacità aggiuntiva di immagazzinamento dell'energia e una migliore gestione delle domande di picco.

Parole chiave: mobilità elettrica, energy modelling, ricarica intelligente, vehicle-to-grid

1 Introduction

According to the International Panel on Climate Change (IPCC), road transport represents 11.9% of the anthropogenic greenhouse gas emissions globally and the introduction of electric vehicles (EVs) is seen as a viable path for reducing emissions in the sector [1]. Yet, the extent to which such integration would represent a burden for the power system (both in term of grid stability and variation of peak demand) is still an unanswered question.

Energy system modelling is one of the tools that must be used to analyse how electric mobility affects the energy system. For this kind of method, the best time resolution used is hourly [2]. It is therefore necessary to study the impact of e-mobility at an hourly level and then to build hourly charging profiles for different types of vehicles and for different charging strategies.

This thesis aims to evaluate the hourly impact of electric mobility on the electricity system. In order to achieve this, different vehicles categories and charging strategies will be considered and their impact studied for a regional case study: the South Tyrol region.

State-of-the-art methods for simulating electric vehicle mobility behaviour and charging profiles are largely based on stochastic modelling techniques, which can be divided into two main sub-categories: methods based on Markov chains and methods based on other stochastic techniques.

Markov chain approaches consider user behavior as a series of sub-sequent “states”, and the passage from a starting state to a given destination is associated with a specific probability. Muratori et al. [3] proposed a Markov chain model to simulate uncontrolled vehicle charging, but required extremely specific habits data for the US, making it difficult to applicate the same methods in other contexts.

Gruosso and Gajani [4] have also proposed the Markov chain process. In order to calibrate their model of charging profiles at a 15-min resolution, they used field data from 800 electric cars used in an Italian car sharing project. This severely restricts the model's ability to be adjusted to different contexts and to the mobility patterns of privately owned cars, moreover the charging profiles are created using a standard charging cycle, making it impossible to simulate various charging strategies.

The approaches based on stochastic methods, instead, generally aim at reproducing the randomness of user behavior without assuming a consequential relationship between subsequent events. These techniques lead to less detailed output in terms of reciprocal influence of the sequence of events, but with a significant reduction of input data. In this direction, O'Mahony et al. [5] proposed a Monte Carlo approach to simulate mobility and charging patterns, even if this approach is simpler if compared to Markov chain, the model only works for 2 weeks, not capturing seasonal effect.

Table 1.1 - Literature review regarding the electric vehicles modelling

Author	Ref	Vehicles Considered	Spatial Configuration	Method Used
Muratori et al.	[3]	Passenger Cars	District	Markov Chain
Gruosso et al.	[4]	Passenger Cars	Municipality	Markov Chain
O'Mahony et al.	[5]	Passenger Cars	Regional	Monte Carlo
Dallapiccola et al.	[6]	Passenger Cars	District	Ramp-Mobility
Lubello et al.	[7]	Passenger Cars	District	Ramp-Mobility
Corinaldesi et al.	[8]	Passenger Cars	District	Emobpy
Joglekar et al.	[9]	Passenger Cars	District	Emobpy
Approach proposed by this thesis		Passenger Cars, Public Bus, Commercial Vans, Heavy Truck	Regional	Emobpy

In order to explicitly characterize users' chain of activities over the course of a day, highly resolved and abundant mobility data are required, making Markov chains and other data-intensive approaches a viable option. However, large-scale models may have limitations in the absence of such specific data. In contrast, when only straightforward data, like time-of-use surveys, are available, other stochastic algorithms are used. Such systems are more adaptive to varied contexts and suited for the modelling of long-term or extreme scenarios due to their reliance on simpler and smaller sets of parameters, but at the expense of less exact data in terms of spatial or temporal disaggregation.

Due to the limitations of these two types of approaches, two open-source tools for the definition of the electricity consumption of the vehicles have been published, with the aim of providing a more flexible and user-friendly approach for the definition of EVs electricity demand: RAMP-mobility [10] and emobpy [11]. The former is based on the definition of chain of events (similarly to the Markov chain approach) but is grounded on probability distribution of mobility patterns, the latter is instead based on a stochastic approach to define the mobility pattern and the charging availability.

However, like most of the other studies in the literature, also the studies developed using these tools focus almost exclusively on the passenger car sector, as it is responsible for 43% of emissions within the transport sector and is also the most utilized passenger transport mode [10].

Dallapiccola et al. [6] and Lubello et al. [7] utilized RAMP-mobility to calculate electric passenger cars consumptions in small residential areas, similar studies were developed by Corinaldesi et al. [8] and Joklekar et al. [9], using the emobpy tool instead. Although these studies represent a fundamental first step in assessing future scenarios, in order to achieve the targets set by the European Union of a 90% reduction in emissions in the transport sector [12], the electrification process cannot be limited exclusively to passenger cars and will necessarily include other vehicle types. In this direction, policies at national or European level have begun to extend the subjects of their directives to include buses and light and heavy transport (i.e. the "Fit for 55" package, which regulates the electrification of passenger cars and light-duty vehicles in the EU [13]).

Hence, this thesis aims to evaluate the increase in electricity demand on the grid as a result of the electrification of all these categories of vehicles, highlighting the different recharging methodology, both in terms of power and the strategy used, in order to study the potential impact on the electricity grid in terms of increased daily electricity demand.

Another shortcoming of previous studies is the limited understanding of how to sustainably integrate EVs with current renewable energy generation technologies. To reduce the emissions of greenhouse gas and fulfil the 1.5 °C objective proposed by the IPCC, the power generation sector will be increasingly dependent on renewable energy sources, intermittent or not. It is therefore necessary to verify that the increase in energy demand can always be met, thus ensuring balance in the power grid. In this regard, EVs (and especially passenger cars) can provide key flexibility for the power system, thanks to the implementation of smart charging strategies that make also possible the bi-directional exchange of energy between vehicle batteries and the electricity grid as a function of renewable generation patterns (defined as "vehicle-to-grid technologies"). The use of a smart strategy could make it possible to make greater use of moments of overproduction of renewable energies, while the further implementation of vehicle-to-grid technology would allow the car fleet to act as a battery, supplying energy to the grid whenever a reduction in production from renewable energy sources occurs. Most of the studies for the implementation of smart strategies utilizes a "separated" approach, in which, starting from a timeseries of the electricity demand, the production of the power sector and the EV demand, the model provides an optimal charging solution. Richardson et al. [14] analyzed the implementation of smart charge for a small fleet of vehicles, but the simulation is limited to only 24 hours and with the only aim of maximizing the power provided to the EVs within a randomized number of hours available. Ioakimis et al. [15] starting from data of EV consumption, PV power generation and dwell time in a parking lot, modelled a smart charge behaviour to reduce the demand of a nearby building, but without considering the V2G technology. Ivanova et al. [16] proposed an optimization problem to minimizing the operational cost of a PV rooftop plant, comparing the revenues from selling the electricity to the grid or providing it to the EVs load, the seasonality effect is considered but only on the PV production side and not also in the variation of EV consumption. Moreover, this analysis doesn't include another demand that needs to be fulfilled, causing no need to implement a V2G technology.

Table 1.2 - Literature review regarding the modelling of Smart Charges and Vehicle-to-grid for electric passenger cars charging

Author	Ref	Optimization method	Spatial Configuration	Tools used	Strategies considered
Richardson et al.	[14]	Separated	Municipality	MATLAB, digsilent	DUMB, SC
Ioakimidis et al.	[15]	Separated	District	MATLAB	DUMB, SC
Ivanova et al.	[16]	Separated	Municipality	MATLAB, IBM ILOG CPLEX	DUMB, SC
Wu et al.	[17]	Separated	District	CVX MATLAB	DUMB, V2H
Cai et al.	[18]	Integrated	District	unknown	DUMB, SC
O'Neill et al.	[19]	Integrated	District	unknown	DUMB, V2G
Approach proposed by this thesis		Integrated	Regional	cbc	DUMB, SMART, V2G

Wu et al. [17]analysed instead the possibility for the EVs to give back the energy absorbed during charging sessions, but even if the results show an actual reduction of the charging cost, the study is applied only for one EV (linked with a single-family house) to reduce the domestic electricity demand without the possibility to provide electricity to the grid. Cai et al. [18]proposed an optimization problem considering a wider range of energy mix (i.e. wind, PV, and gas turbines) in a microgrid, in which however the EVs charging is the only load, and so the V2G is never exploited. O'Neill et al. [17] instead proposed an "integrated" approach using the microgrid modelling software openCEM. A residential area in Australia is considered, linked with its electricity demand, its power production sector (composed by wind, PV, and diesel plants) and also coupled with the electricity demand of EVs. This study provides an important step towards the evaluation of the benefits of V2G technology within a more effective coupling between the transport sector and the power production, allowing an higher flexibility for the system behaviour. However, this analysis is still applied to a small-size single-node case study due to the limitation of the tool utilized. In order to better assess the consequences of future EV penetration scenarios it is necessary to define multi-node systems, at least at regional level, like the one considered in this study.

The novelty and unique contributions of this thesis are listed below:

- Extend the categories of vehicles considered inside the future electrification of the road transport sector (i.e. buses, commercial vans and heavy trucks) in order to evaluate their impact on grid demand in future scenarios.
- Investigate the impact of smart charge and V2G, gradually being adopted by owners of electric passenger cars, as methods of providing flexibility to the electricity grid in scenarios of high dependency on renewable energy sources.

The thesis is structured as follows. Chapter 2 describes the tools used and the methodology applied for the modelling of the e-mobility sector and the energy system. Section 3 presents the case study considered for the assessment of future scenarios regarding e-mobility. Section 4 enlist the results and discussions for the simulations considered and Section 5 presents concluding remarks.

2 Materials & Methods

2.1. Emobpy

Emobpy is an open-source, python-based tool developed in 2020 by Gaete-Morales et al. for the German Institute for Economic Research [11]. The tool uses a sampling approach to create profiles of BEVs based on customizable assumptions, physical properties of vehicles and on empirical mobility statistics, relying on data provided by German institutions [20]. A BEV profile is composed by four consequential time series as reported in **Errore. L'origine riferimento non è stata trovata.**:

- Vehicle mobility: contains the location of the vehicle at each time step and the time steps during which the vehicle is driving with information of the distance traveled.
- Driving electricity consumption: specifies how much electricity the vehicle consumes for driving in each time step.
- BEV grid availability: provides information whether and with which power a BEV is connected to the electricity grid for each timestep.
- BEV grid electricity demand: provides information on how much electricity a vehicle demands from the electricity grid in a time step, according to the chosen charging strategy.

Each time series is based on the one previously obtained, with the addition of further input data, which are partially set by emobpy and partially customizable by the user.

As final output, for each vehicle and for each time step (by default set to 15 minutes), the tool provides the grid electricity demand, along with its location and the type of charging station. The results can be later aggregated to evaluate the consumption of the whole car fleet simulated.

For each of the four time series, it will be analyzed the list of input data requested by the tool, presenting the default values implemented by the developers.

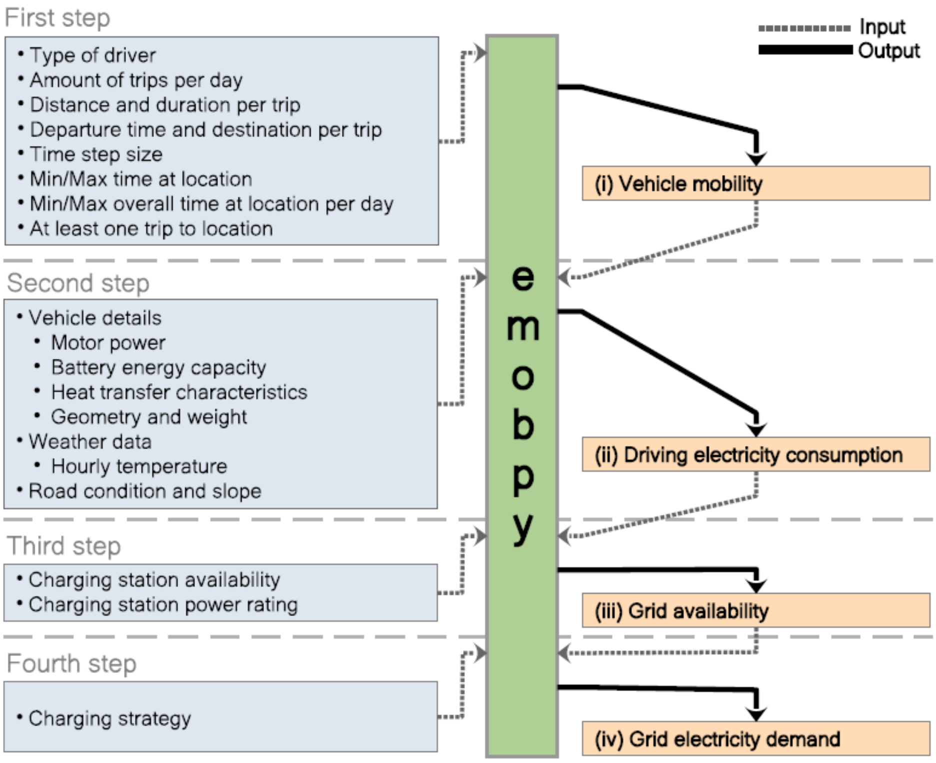


Figure 2.1 - Inputs and outputs of emobpy and sequence of generating four types of time series. The boxes on the left-hand side show customizable input assumptions, the boxes on the right-hand side indicate the four types of time series.

2.1.1. Vehicle mobility

Emobpy differentiates the population between three different categories, following the same partition done inside the MiD survey [20]:

- Full-time Commuters: people going to work by car, employed in a full-time job.
- Part-time Commuters: people going to work by car, employed in a part-time job.
- Non commuters: people not going to work by car but still using the vehicle for other destinations.

For the definition of the mobility patterns, Emobpy is based on three probability distributions, which are created by the tool as .csv files, to make more accessible the customization by the user, the meaning of each file is now explained.

2.1.1.1. DepartureDestinationTrip

This file is the only one to have a different version for commuters (both full-time and part-time) and non-commuters. It contains all the probability distribution for the trip generation inside the time series.
The default differentiation is between Saturday, Sunday and weekdays. The data are taken from the Mobilitat in Deutchland (MiD) survey [20] and represent the probability of driving towards a particular destination in each hour of the day. The default differentiation of trip destination is between workplace, shopping, errands, escort, leisure, and home, aggregating the categories proposed in the MiD survey. An example for errands is a visit to the doctor or to the authorities. In the case of escort destinations, the driver transports other persons.

If the timestep is changed, the probability must be changed accordingly, moreover the sum of all the probability in the day must always be equal to 1. The user can also change the number and name of the trip categories according to data availability; however, the category home must be always present.

2.1.1.2. DistanceDurationTrip

This file contains the probability of driving for a certain distance (rows) in a certain amount of time (columns), allowing the evaluation of the average velocity for each trip.

Table 2.1 - Joint probability distributions (given in %) for the distance travelled by trip and trip duration.

Distance	Trip duration (minutes)						
	10	10-15	15-20	20-30	30-45	45-60	60-185
1 km	2.9	0.3	0	0	0	0	0
1-2 km	3.5	4.8	0.8	0	0	0	0
2-5 km	8.4	10.2	5.7	0	1.2	0.4	0
5-10 km	1.3	12.2	14.4	0	2.4	0.6	0.7
10-20 km	0	0.9	6.3	0	4.7	1.3	0.5
20-50 km	0	0	0	0	8.6	2.1	1.6
50-100 km	0	0	0	0	0	0.6	2.1
100-400 km	0	0	0	0	0	0	1.5

The default data are taken from Mobilität in Tabellen (MiT 2017), which is an extrapolation of the results obtained from the study Mobilität in Deutschland (MiD 2017 [20]). The table has null values on the corner due to the necessity of removing inconsistent velocities (e.g. it is improbable to make shorter distances in more than 60 minutes or large distances in a shorter time. Also, it was assumed '60 min and more' as 185 minutes and '100 km and more' as 400 km, considering a maximum average velocity of 130 km/h)

2.1.1.3. TripsPerDay

This file includes the probability of doing a specific amount of trip for each day, differentiated between working day (from Monday to Friday) and weekend (Saturday and Sunday). The probability of doing only one trip in a day is set equal to zero, since the tool always imposes that for each day the first trip starts from home and the last trip is towards home.

Table 2.2 - Probability distributions for the amount of trips per day by days of the week.

Number of trips	Working day	weekend
0	35.41%	50.7%
1	0%	0%
2	29.9%	27.5%
3	8.3%	4.4%
4	12.5%	10.2%
5	13.9%	7.2%

The maximum number of trips that a vehicle can do in a day is initially set to five. If more data are available, this upper limit can be increased with the only caution of reducing also the time-step in order to allocate more precisely a higher number of trips per day.
Even if this procedure can lead to more accurate results, the computational time required will increase, since the modelling of the daily trips is usually the more time-demanding part of the tool.

2.1.1.4. Rules

Another input required for the creation of the mobility time-series is the list of rules, which defines some constrain about the behaviour of drivers.

The full list of the rules that can be set by the user is reported below, all of them can be distinguished for working day and weekend and for full-time commuters, part-time commuters and non-commuters:

- “max_same_trip_times”: defines the maximum amount of trip to a certain location
- “last_trip_to”: sets the destination of the last trip for all the days
- “first_trip_to”: sets the destination of the first trip for all the days
- “not_last_trip_to”: prohibits one or more destinations to be the las one of the day

- "at_least_one_trip": defines one trip destination that must always be present for each day
- "overall_min_time_at": defines the minimum time that a person should spend in a place during the day
- "overall_max_time_at": defines the maximum time that a person should spend in a place during the day
- "min_state_duration": defines the minimum time that a person should spend in a place before the next trip
- "max_state_duration": defines the maximum time that a person should spend in a place before the next trip

For all the rules related to time duration (e.g. overall_max_time_at or min_state_duration), the values inserted must always be a multiple of the time-step set at the beginning, otherwise the program wouldn't be able to generate the trip destination time series.

The rules set by default are reported in Table 2.3**Errore. L'origine riferimento non è stata trovata.**, this method allows for example to better differentiate the trip towards work for the different shares of the population. For example, the full-time workers are forced to spend seven hours per day at the workplace during working days, for part-time workers this limit is equal to three and half hours, while for non-commuters there are no upper or lower limits, allowing the simulation of occasional trips towards the workplace.

Table 2.3 – Rules implemented by default in emobpy to select consistent day trips.

Rule		Non-commuter		Full-time commuter		Part-time commuter	
		Working Day	Weekend	Working Day	Weekend	Working Day	Weekend
Minimum time at	Home	0.5 h	0.5 h	0.5 h	0.5 h	0.5 h	0.5 h
	Workplace	-	-	3.5 h	3.0 h	3.5 h	3.0 h
	Other destinations	0.5 h	0.5 h	0.5 h	0.5 h	0.5 h	0.5 h
Minimum time per day at	Home	9 h	6 h	9 h	6 h	9 h	6 h
	Workplace	-	-	7 h	3 h	3.5 h	3 h
	Other destinations	-	-	-	-	-	-
Maximum time at	Home	-	-	-	-	-	-
	Workplace	-	-	8 h	4 h	4 h	4 h
	Other destinations	-	-	-	-	-	-
At least one trip to	Home	Yes	Yes	Yes	Yes	Yes	Yes
	Workplace	-	-	Yes	No	Yes	No

2.1.2. Driving Electricity Consumption

In the second step of emobpy, each of the mobility time-series previously obtained is associated with a car model among the tool database, to evaluate the corresponding battery consumption after each trip.

To evaluate the energy consumption for each time step in which the vehicle is in the "driving" state, the tool evaluates a power balance across the battery as stated in Equation 2.1. The positive power outputs included are the auxiliary power (P_{aux}), the electrical power for heating/cooling device (P_{device}) and the power provided to the motor ($P_{m,in}$), while the negative power input is provided by the generator in case of regenerative braking ($P_{G,out}$):

$$P_{all} = P_{m,in} - P_{G,out} + P_{aux} + P_{device} \tag{2.1}$$

Each of the terms of the Equation are also represented in the schematic description of the vehicle in **Errore. L'origine riferimento non è stata trovata.**.

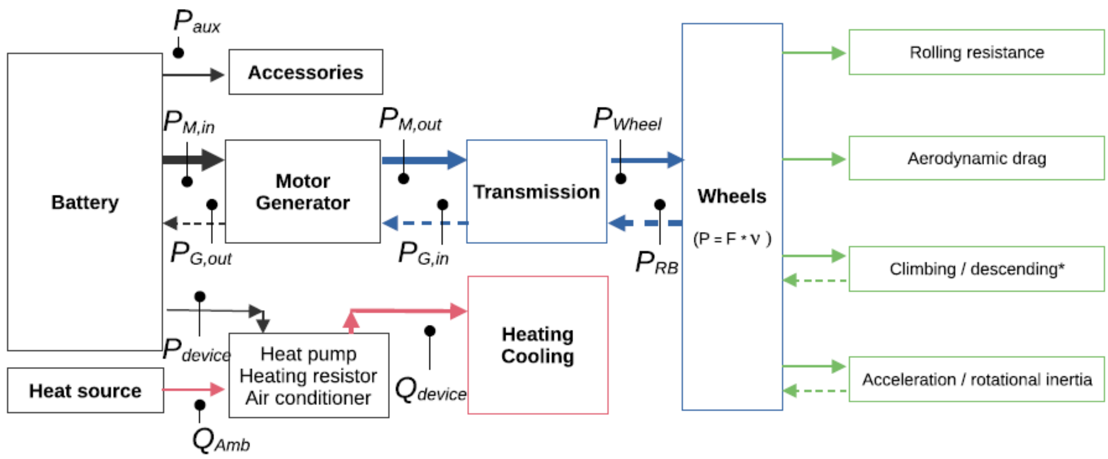


Figure 2.2 - Block diagram of the power flows at the components of the electric vehicle while driving. Black lines: electrical power, blue: mechanical power, red: heat transfer rate, green: acting forces. Dashed lines represent flows related to regenerative braking. Line thickness indicates typical flow magnitudes

As showed in Equation 2.1, if the sum of all the powers P_{all} is positive, then the battery is providing energy to the vehicle as it discharges and the discharging efficiency $\eta_{discharge}$ is used. If P_{all} is negative, then the battery is charged via regenerative braking. In that case, the battery load $P_{battery}$ is negative, hence the charging efficiency η_{charge} is utilized.

$$P_{battery} = \begin{cases} \dfrac{P_{all}}{\eta_{discharge}}, & if\ P_{all} > 0 \\ P_{all} * \eta_{charge}, & otherwise \end{cases} \tag{2.2}$$

The total energy consumption per trip $\boldsymbol{E_{total}}$ is defined in Equation 2.3, where battery load is aggregated through the duration of the trip at every second t.

$$E_{total} = \sum_{t=1}^{\tau} P_{battery,t} \tag{2.3}$$

2.1.3. Grid Availability

The grid availability time series are then created by emobpy by having as inputs the time series of driving electricity consumption as well as locations and distances from the mobility time series. Further, emobpy requires the probability distributions of charging stations, defined as the probability of finding an available charging station for each location. including their respective power rating. These values can be easily modified by the user, based either on assumptions or on actual data of the scenario to be simulated.

2.1.4. Grid Electricity Demand

Once evaluated for each timestep if a vehicle is able to find a free charging station, emobpy differentiates between four principal control strategy:

- Immediate – full capacity (named "Immediate"): BEVs charge their batteries at full power rating as soon as a charging station is available. Charging stops when the battery is full or when the next trip starts. This behaviour mimics a condition in which there are no incentives nor technical possibilities to charge the battery of the vehicle in a more balanced way.
- Immediate – balanced (named "Balanced"): BEVs start charging their batteries as soon as they arrive at a charging station but with a constant power rating (which is usually below the power rating of the charging station), such that a 100% SOC is reached just before starting the next trip, assuming perfect foresight of the next departure time. Even if this approximate a smoother charging behaviour, its implementation is possible only thanks to the tool structure, in which the location of the vehicle in each time-step is already

defined in the previous step (i.e. Step 1 in **Errore. L'origine riferimento non è stata trovata.**).

- At home – balanced (named "Home"): this strategy is similar to the previous one, but BEV only charge when at home, even if other charging options are available at other locations. This reflects a personal preference or an economic incentive for home charging instead of using a public charging station.
- Night time-balanced (named "Night"): similar to the "Balanced" charging strategy, but with charging time restricted to the time window between 23:00 and 8:00. This mimics the effect of potential tariff incentives for night-time charging. Even if this behaviour includes charging when the electricity demand is lower, it is crucial to consider future scenarios for the development of RES, in which also during the night-time the production of energy is reduced and so this strategy may become a counter-effect of the previous one, since a possible peak of demand during the night-time may not be fulfilled.

All of the charging strategies proposed will be taken into account for the tool comparison, due to the high variety of both spatial and temporal differentiation available with these methods

2.2. RAMP-Mobility

The RAMP-Mobility programme is an open-source, Python-based model that simulates electric vehicle mobility and charging time series at high temporal resolution (1 min), purely based on freely available and simple to collect data given by Eurostat [21]. The model is based on the previously developed RAMP engine, already used for stochastic user behavior simulation [22], expanding it with mobility-specific features. The model was validated against actual charging transactions measured in the Netherlands using the NelaadNL dataset, and the developers used it to replicate the charging behaviour of 28 different European countries (including Italy).

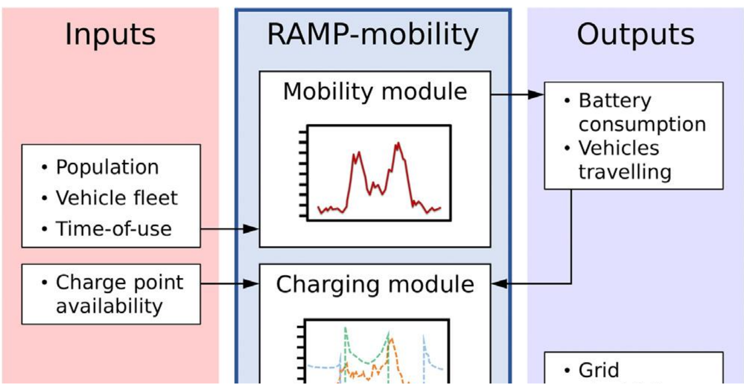


Figure 2.3 - Conceptual scheme of the RAMP-mobility structure, featuring one model for the simulation of mobility patterns and one for the charging strategy

2.2.1. Mobility Module

The first step of RAMP-mobility tool is the definition of the country population. In this case the subdivision is between three macro-categories: *workers, students and inactive.*

Each individual user is then associated with one of three possible BEVs classes, namely *small, medium* and *large.* Battery capacities for the three classes of vehicles considered are taken from representative commercial vehicles in current market, summarized in Table 2.4.

Table 2.4 – Default Car Class definition in RAMP-mobility

Car Class	Representative commercial model	Battery capacity (kWh)
Small	Volksvagen e-Up!	37
Medium	Opel Ampera-e	60
Large	Tesla Model X Long Range	100

RAMP-mobility, in contrast to emobpy, doesn't include any other additional data (e.g. vehicle dimensions, acceleration, drag coefficient) due to the more simplified calculation of the vehicle consumption, which will be presented in Paragraph 2.2.2.

To model the user behavior, instead of defining a chain of events based on probability distributions like emobpy, the idea behind RAMP's mobility module is based on *functioning windows,* time frames in which mobility events can randomly occur.

The definition of such time frames grounds on the Harmonised European Time Use Surveys (HETUS) [21], which provide time-explicit information about the participation rate of different categories of citizens to a number of activities, including mobility, at the EU level.

For each category of users, the model distinguishes between *main functioning windows*, in which the main daily travels (e.g. commuting to work/study place) occur and *free-time functioning windows*, which account for additional occasional trips.

For the case of *students* and *workers*, two main functioning windows are considered, which match the commuting-related morning and evening mobility peaks recorded in the majority of time-of-use surveys across Europe [21]. They are complemented by free-time windows, in which non-work and non-study related trips may occur.

Inactive users are characterized by only one main functioning window, encompassing the whole range of hours in which a person is typically awake and active in a day, and by two free-time windows for trips that occur in the early morning or during the night.

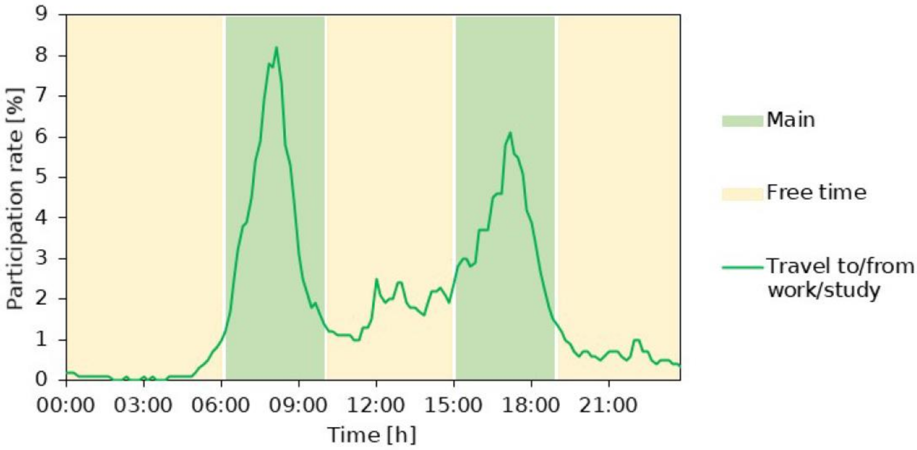


Figure 2.4 Example of functioning time frames calculation for workers in the Netherlands. The main time frames are highlighted in green, the rest of the day is considered as free time, and highlighted in yellow.

In the next step, mobility patterns are differentiated according to the day type: *weekday*, *Saturday and Sunday* (or festivity), in agreement with real-world mobility patterns, with *workers* and *students* behaving similarly to *inactive* users during *Saturdays* and *Sundays or festivities* [23].

Alongside the definition of functioning windows, the model computes the total distance travelled each day ($dtot$) as well as the fraction of main versus free-time mobility activities from the JRC mobility survey [21]. As a final step, single travels are randomly simulated until reaching an amount of travelled kilometers which equals the mobility demand of the day.

The determination of an average trip velocity enables the conversion of the daily travel requirements from spatial to temporal units. The latter is calculated as the ratio of two parameters, the average trip distance and the average journey length, which are again acquired for each user class, day-type, and nation from the JRC survey [19].

2.2.2. Battery Consumption

During the simulation of each travel, the model randomizes the average trip velocity around the velocity previously obtained (±30%). Hence, since the battery power consumption is computed as a quadratic function of such car velocity as shown in Equation 2.4, also the battery consumption is randomized. The coefficients a, b and c are specific for small, medium and large car power functions, based on the work of Pasaoglu et al [24].

$$\boldsymbol{P_{ev}} = \frac{\boldsymbol{1}}{\boldsymbol{12}} * (\boldsymbol{a} * \boldsymbol{v_{rand}^2} + \boldsymbol{b} * \boldsymbol{v_{rand}} + \boldsymbol{c}) \tag{2.4}$$

The approach followed in this step is necessary due to the lack of data regarding the vehicle characteristic, especially if compared with the in-depth approached followed by emobpy. Nevertheless, also for RAMP-mobility the weather's effect on consumptions is considered: outdoor temperature effects are included in the form of a multiplication coefficient, which accounts for heat and cooling systems' consumption. The coefficient is computed as per the formulation proposed by Fischer et al. [25] and displayed below:

$$\frac{\boldsymbol{P_{EV}(T_{amb})}}{\boldsymbol{P_{ev}}} = \begin{cases} \boldsymbol{1.12 - 0.01 * T_{amb}} & \boldsymbol{if\ T_{amb} < 15°C} \\ \boldsymbol{1} & \boldsymbol{if\ 15°C \leq T_{amb} \leq 20°C} \\ \boldsymbol{0.63 + 0.02 * T_{amb}} & \boldsymbol{if\ T_{amb} > 20°C} \end{cases} \tag{2.5}$$

2.2.3. Charging Infrastructure

RAMP-mobility doesn't provide a spatial definition of the movement of each vehicle (which was instead possible with emobpy), hence for each time step the vehicle is simply "driving" or "parked", but without knowing in which location (e.g. *home, workplace, shopping, leisure).* Since it is impossible to define a value of charging station availability according to the location, the probability of finding a free charging point simply depends on the power rating but not on the position, both types of values can be defined by the user.

2.2.4. Charging Strategy

The RAMP-mobility tool allows to include four different charging strategies, which can be selected by the user:

- **Uncontrolled charging:** This strategy presupposes complete remote control of vehicles by aggregators, who, thanks to "perfect foresight," only manage to supply next-trip energy to plugged-in vehicles in the last useful minutes of their parking time, allowing the vehicle to be freely charged and/or discharged according to power system requirements without compromising user comfort.
- ***Perfect Foresight*:** This strategy assumes full remote control of vehicles by aggregators, which - thanks to a 'perfect foresight' - manage to provide next-trip energy to plugged vehicles only in the last useful minutes of their parking time, in such a way to ensure that they can freely charge and/or discharge the

vehicle in all the preceding minutes, as a function of power system needs, without affecting user comfort.

- ***Night Charging***: Users are incentivized to charge vehicles during night hours (i.e. between 21:00 and 6:00), in such a way to avoid overloading the power system during the already critical morning and evening hours. Furthermore, the charge does not occur at full power, but at the minimum power that allows to completely charge the battery during night hours.
- ***V-RES Charging***: When there is an excess of renewable generation in the area, users are encouraged to charge. The charging methodology is substantially the same as for charging at night, with the exception that the time windows during which charging is permitted are now those in which solar and wind generation surpasses the amount of electricity needed by a certain country's power system. To compute the difference between electricity load demand and renewable generation (i.e. the *"residual load curve")*, it is assumed that: electricity demand is that known for 2016 and provided by ENTSO-E [26]; renewable capacity factors are those made available through the platform Renewables.ninja [27], [28]; and installed PV and Wind capacities are those assumed by the PRO-Res JRC-EU-TIMES scenario [21].

The first strategy is identical to the *immediate* strategy available in emobpy, while the timeframe of the night strategy is slightly shifted backwards but is still based on the same assumption of the equivalent version in emobpy. The two major differences are the absence of a *home* strategy, since the tool doesn't know when the vehicle is actually at home and also the lack of a *balanced* strategy, which was the first step for the definition of a "smart-charging" behavior to reduce the grid impact of the BEVs development.

Instead, the *V-RES Charging* strategy is introduced, showing a first glance of the possibility of coupling a tool for BEV grid consumption with the energy production sector. However, this strategy is not considered for the purpose of this analysis, in which instead the electricity demand evaluated is later combined with the production sector, modelled with the Oemof software with higher precision.

RAMP-mobility also allows to include a logistic function that correlates the plug-in probability to the state-of-charge of the battery when the car is parked, similar to other approaches present in literature [29], [30], with the objective of including in the charging patterns also the social behavior of the drivers.

$$\boldsymbol{CP_{prob,(SOC)} = 1 - \frac{1}{1 + e^{-k(SOC - \%SOC)}}} \tag{2.6}$$

In the Equation 2.6, k is the gradient of the curve at the SOC defined by %SOC. Constant k is set to 15 and %SOC to 50%, in such a way to obtain a symmetric curve. However, the function, adapted from the work by Fischer et al. [25], is not used (as suggested by the RAMP-mobility developers [10]) due to the high uncertainty and subjectivity surrounding this behavioral phenomenon.

For all the charging strategies available, the tool defines a minimum and maximum allowable value for the SOC (respectively equal to 20% and 85%), in order to prevent the degradation of the vehicle battery [30].

2.3. Tool Comparison

In order to define which is the best tool for modelling the mobility patterns and the charging demand for public buses and light and heavy freight vehicles, the emobpy and RAMP-mobility tools are compared when modelling the same fleet of passenger cars, thus assessing the characteristics of the outputs obtained and the flexibility of use.

For both tools the year considered is 2016 and the number of vehicles simulated is 460, this value represents a thousandth of the total amount of vehicles circulating in South Tyrol in that year [31], with the objective of evaluating the consequences of a complete shift from traditional cars to battery electric vehicles in terms of grid electricity demand.

On one side the parameters considered are taken from real data related to the territory of South Tyrol, situated in the North of Italy (e.g. the percentage share of the population between *commuters* or *non-commuters* in emobpy or between *workers, students* and *inactive* in RAMP-mobility), on the other some parameters are necessarily referred to Germany due to structural limitations of the tools (e.g. mobility patterns of emobpy are based on behavioral analysis and surveys effectuated in Germany) and consequently also in RAMP-mobility the mobility patterns chosen are the German ones, even if also other nations are available.

2.3.1. Input data requested

2.3.1.1. Population definition

For the application of emobpy to this comparison, the type of drivers are defined starting from the data available for the South Tyrol. The population is initially split between *commuters* (47.1% of the population) and *non-commuters* (52.9% of the population) starting from the data provided by ISTAT for the Alto Adige [32]. Later, the *commuter* share is furtherly split between *full-time workers* (76.2% of the total) and *part-time workers* (23.8% of the total) [9]. As a result, the population is eventually split between the three categories as requested by the tool.

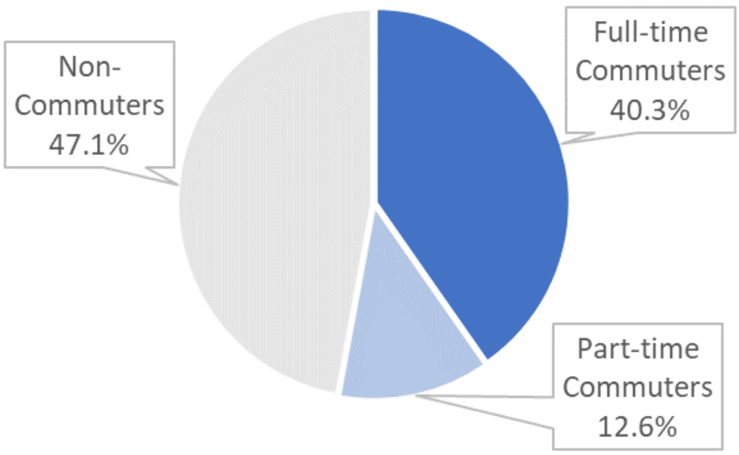


Figure 2.5 – South Tyrol population, split between the emobpy categories, 2016

For the RAMP-mobility tool, in which the subdivision is between *workers*, *students* and *inactive*, the share of each category is obtained from the ASTAT database [32]

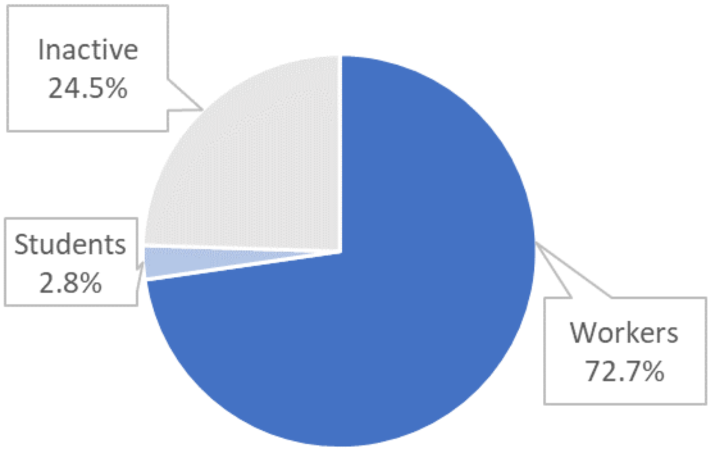


Figure 2.6 – South Tyrol population, split between the RAMP-mobility categories, 2016 (population in the 15-64 age is considered)

2.3.1.2. Vehicle fleet definition

The *emobpy* tool includes almost 25 different BEV models, including different information about dimensions and performance (i.e. acceleration or battery capacity), necessary to evaluate the energy consumption. The vehicle fleet for 2016 is defined starting from the BEV model sold in Germany in the previously two years [33] and then translated in a probability value. For example, 12.1% of BEV sold in 2015 and 2016 are Renault Zoe, so 12.1% of cars circulating in Germany in 2016 are Renault Zoe). If a car model is not included in emobpy, it is substituted with the most similar model in term of size, power and battery capacity.

Table 2.5 - Fleet definition for Germany in 2016, inside the emobpy tool

Car Model	Simplified Market Share [%]
e-GOLF SE	21.6
e-tron 55 quattro	12.3
Renault Zoe Q90	12.1
Hyundai IONIQ Electric	12.1
Nissan Leaf S	11.8
BMW i3	10.4
Tesla Model S 60D	9.4
Nissan Leaf SV	5.4
Kia Soul	4.8

Regarding instead the RAMP-mobility tool, the vehicle fleet share is defined starting from the BEV models used for emobpy, so as to ensure an effective comparison between the two tools. each of the models enlisted in Table 2.5 is grouped into one of the three classes, whose battery capacity is recalculated as a weighted average of the battery sizes of the vehicles included in each class. The fleet share is the sum of the market share of all the car models included in each class. The final fleet composition is described in .

Table 2.6 - Fleet definition for Germany in 2016, inside the RAMP-mobility tool

<table>
<tr><th>Models Included</th><th>Battery Capacity [kWh]</th><th>Equivalent Car Class</th><th>Fleet Share</th></tr>
<tr><td>BMW i3</td><td>22</td><td rowspan="6">Small (25.7 kWh)</td><td rowspan="6">66.8%</td></tr>
<tr><td>e-GOLF</td><td>24.2</td></tr>
<tr><td>Nissan Leaf S</td><td>26</td></tr>
<tr><td>Hyundai IONIQ Electric</td><td>28</td></tr>
<tr><td>Nissan Leaf SV</td><td>30</td></tr>
<tr><td>Kia Soul</td><td>30.5</td></tr>
<tr><td>Renault Zoe</td><td>45.6</td><td>Medium (45.6 kWh)</td><td>12.1%</td></tr>
<tr><td>Tesla Model S 60D</td><td>60</td><td>Large (86.3 kWh)</td><td>21.7%</td></tr>
</table>

2.3.1.3. Charging infrastructure definition

For this comparison, the power ratings of the charging stations inside emobpy, are set according to the charging infrastructure in South Tyrol [34] and reported in Table 2.7.

Table 2.7 – Nominal capacity of the charging stations within the South Tyrol charging infrastructure

Charging Station Category	Power Rating [kW]
Home	3.7
Public	22
Workplace	22
FastCharge 100	100
FastCharge 150	150

The availability of charging station at home is set to 80%, keeping the default value set by the developers of the tool. For all other locations, the probability of finding an available charging station depends on different factor such as hour of the day or traffic congestion, which cannot be considered in this tool. To consider this level of uncertainty, it was developed a sensitivity analysis with a public charging station availability varied from 50% to 80%, including the lower availability of fast-charge station due to the lower presence on the territory. The availability at the workplace is increased accordingly to achieve the same total availability. All the scenarios evaluated are reported below, named according to their public station availability. The locations are placed in the rows while the charging station categories are placed in the columns, with the term “none” indicating the probability of not funding any station available.

Table 2.8 – Charging station availability - EMOBPY50 Scenario

	Home	Public	Workplace	Fast100	Fast150	None
Home	80%	-	-	-	-	20%
Workplace	-	7.5%	42.5%	-		50%
Other locations	-	40%	-	5%	5%	50%

Table 2.9 - Charging station availability - EMOBPY60 Scenario

	Home	Public	Workplace	Fast100	Fast150	None
Home	80%	-	-	-	-	20%
Workplace	-	10%	50%	-		40%
Other locations	-	45%	-	7.5%	7.5%	40%

Table 2.10 - Charging station availability - EMOBPY70 Scenario

	Home	Public	Workplace	Fast100	Fast150	None
Home	80%	-	-	-	-	20%
Workplace	-	12.5%	57.5%	-		30%
Other locations	-	50%	-	10%	10%	30%

Table 2.11 - Charging station availability - EMOBPY80 Scenario

	Home	Public	Workplace	Fast100	Fast150	None
Home	80%	-	-	-	-	20%
Workplace	-	15%	65%	-		20%
Other locations	-	55%	-	12.5%	12.5%	20%

For the South Tyrol case study, the power ratings are the same expressed in Table 2.7, while the charging availability is reported in the Table 2.12, where the term *"not charging"* indicates the probability of not finding a station available

Table 2.12 – Charging infrastructure probability distribution, as defined within the RAMP-mobility tool

Power rating	Charging Stations Availability
not charging	20%
3.7 kW	48%
22 kW	28%
100 kW	2%
150 kW	2%

The charging availability assumed is similar to the scenarios EMOBPY50 (Table 2.8) and EMOBPY60 (Table 2.9).

RAMP-mobility also allows to consider a piece-wise probability function, as proposed by Harris et al. [35]. Even if this possibility could partially limit the absence of a location-related charging availability, it is not considered in the comparison due to its absence in emobpy and most of all the uncertainties related to this kind of approach.

2.3.2. Output provided

To evaluate the possible consequences of a complete shift of the passenger transport sector from traditional vehicles (e.g. Oil or diesel) to electric cars, the grid electricity demand obtained in each simulation is multiplied by a factor equal to 1000. In this way the 460 vehicles simulated can more correctly model the total number of cars in South Tyrol, almost equal to 459378 cars [31]

For the analyses reported in this paragraph, one week (from Monday to Sunday) is sufficient to correctly observe the different daily driving behaviour. Since both the probability distributions and the rules set in Paragraph 2.1.1.4 are differentiated only in terms of day of the week and not in term of "period of the year", the share between *home, workplace* or *public* stations utilized is not sufficiently influenced by the seasonality. The effect of seasonality is instead analysed in the comparison between emobpy and RAMP in terms of total electricity demand, in which the effect of ambient temperature is more relevant.

An aspect that needs to be highlighted is that, due to the consequential structure of emobpy, all the following scenarios (from 50% to 80% of public stations availability) are obtained from the same vehicle consumption time-series.

2.3.2.1. Charging Location

The first graph analysed is related to the charging location share, since emobpy provides the position and the type of station each time the vehicle is charged, it is possible to analyse the trends during the day, reported in Figure 2.7.

On working days, the charging location has a recurring pattern that corresponds to the pattern of vehicle location. The highest share of BEVs connected to the grid is reached during the evening, when the cars are back home and the charging stations are more available. In the other hours of the day the share of vehicles charging is reduced due to the lower availability of "public" and "workplace" stations. During the weekend, the set of rules doesn't bind a minimum time at work and so almost no vehicles charge in the workplace, its share is replaced especially by "home" stations but also with "public" ones due to the higher amount of trips related to leisure or shopping in the weekend, as reported in the MID database which is used to create the mobility pattern.

When the availability of public charging points is increased, the peaks during the day are reduced and the total share of BEV connected oscillates around 80% during the whole day.

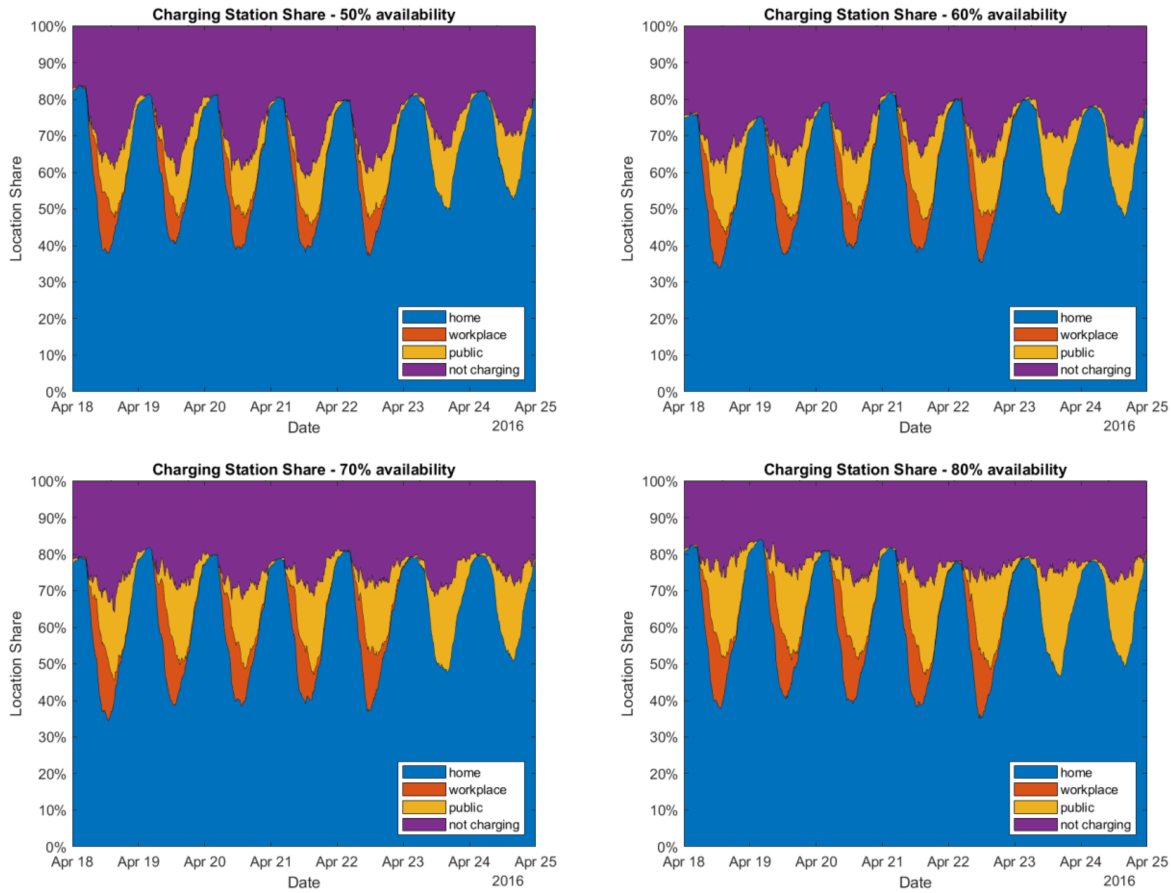


Figure 2.7 – Charging Location Share for each of the scenarios considered. A spring week is considered, from Monday to Sunday.

2.3.2.2. Charging Strategy Influence

In this section it will be analysed the effect of the different charging strategy to the grid power demand in emobpy, with also the possibility to include an additional disaggregation related to the type of charging station used in each moment of the day (for the purposes of this analysis, if a car is connected to a *FastCharge* station, the demand will be included in the *public* share.

The *immediate* strategy (Figure 2.8 – Top Left**Errore. L'origine riferimento non è stata trovata.**) leads to the most unstable behaviour through the days, with huge peaks close to midday, when most of the population is connected to *workplace* and especially *public* stations, using them at their maximum power. The share of *workplace* stations is centred only in the first hours of the morning, when most of the workers reach their workplace. That is because emobpy evaluates the probability of finding an available charging station only when the vehicle reaches the new location, hence the model is simulating a case in which all the vehicles try to find a charging station at work when they arrive and do not leave it to other people even after the vehicle is fully charged. During the afternoon, when the drivers progressively return at their home, the electricity demand is progressively substituted by *home* stations. Nevertheless, the total load curve reduces due to their lower power rating (3.7 kW compared to the 22 kW of *public* and *workplace*). During the night, the vehicles progressively reach the maximum SOC and so the grid demand reduces, reaching the minimum value in the early morning (between 6.00 and 8.00).

The *balanced* strategy leads to a smoother behaviour if compared to the previous one, following more precisely the movement of the drivers during the day and the stations availability as described in the Figure 2.8 (Top Right). The *workplace* share in this case is almost constant, since the charging process is distributed along the parking time at work. The *home* share is strongly influenced by the non-commuters' behaviour, the much higher time spent at home during the day leads to a charging process that is spread along a high amount of hours, leading to a more constant electricity demand compared to the *immediate* strategy. In this strategy, the *public* stations contribute widely to the electricity demand, due to the high share of public stations utilized during the day, as showed in Figure 2.7. As a result of all this effects, the grid demand is still affected by fluctuations during the day, but the overall value never get closer to zero, in contrast with the *immediate* strategy. The minimum is reached around midnight, with the only contribution of home charging stations.

The *home* strategy has the same pattern of the *home* share in the *balanced* strategy, with peak values centred in the evening hour, when the commuters come back at home. However, the peak values are increased due to the higher amount of vehicles that need to be charged, especially by commuters, since the charging was not "allowed" during the parking time at work or in any destination.

The *night* strategy shows the highest value of change in demand, leading to possible stress to the grid. The peaks are concentrated after the 23.00 and mostly fulfilled by home stations, with the only exception of night-workers and people that in the late night are away for leisure or for shopping. The presence of an electricity demand also during the morning hours is related to a problem of the tool, not correctly ending the charging process at 8.00.

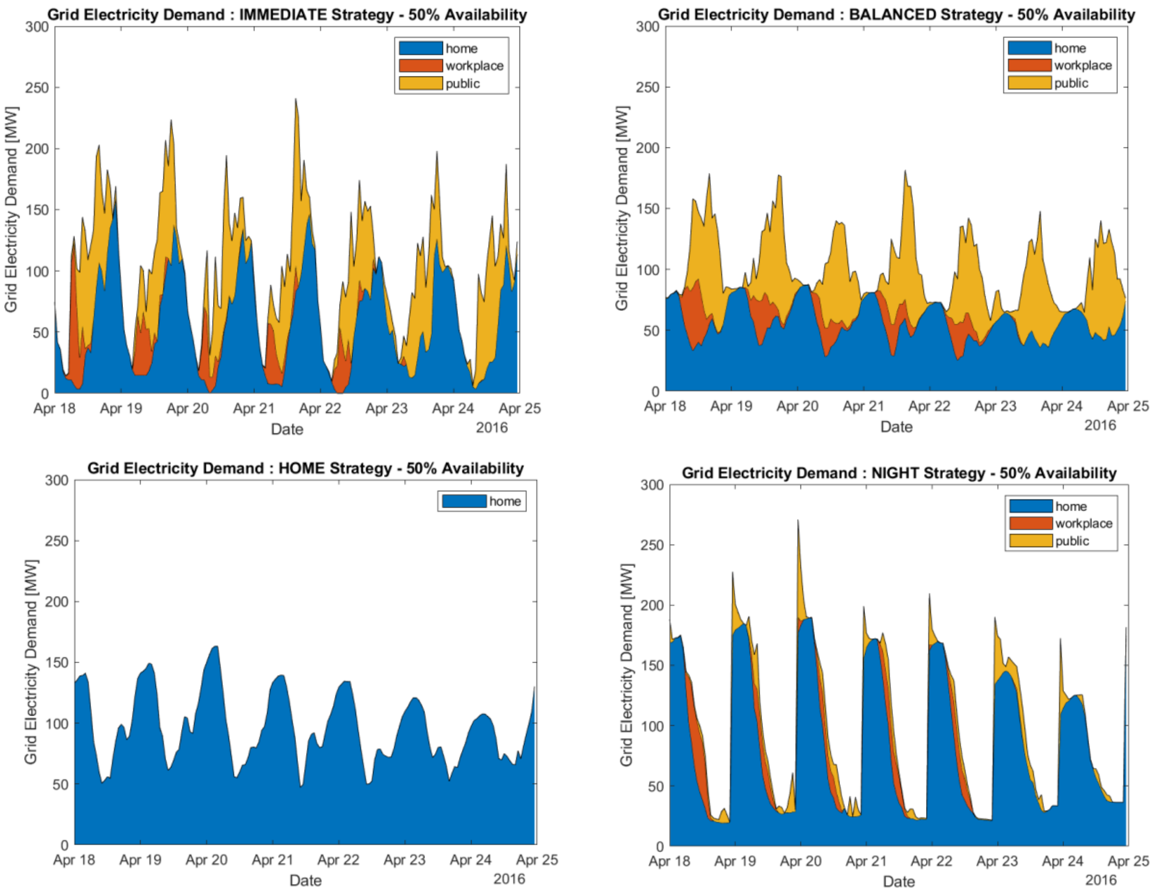


Figure 2.8 – Effect on the grid electricity demand of the adoption of the different charging strategies implemented in emobpy. Immediate (Top Left), Balanced (Top Right), Home (Bottom Left), Night (Bottom Right)

As represented in Figure 2.9, the trend of the different charging strategies is not strongly influenced by a change of public charging stations availability (with the only exception of the *balanced* strategy, in which an increased amount of public charging availability, leads to an higher amount of share of this type of stations, leading consequently to a slightly increased value of grid electricity demand during the day.

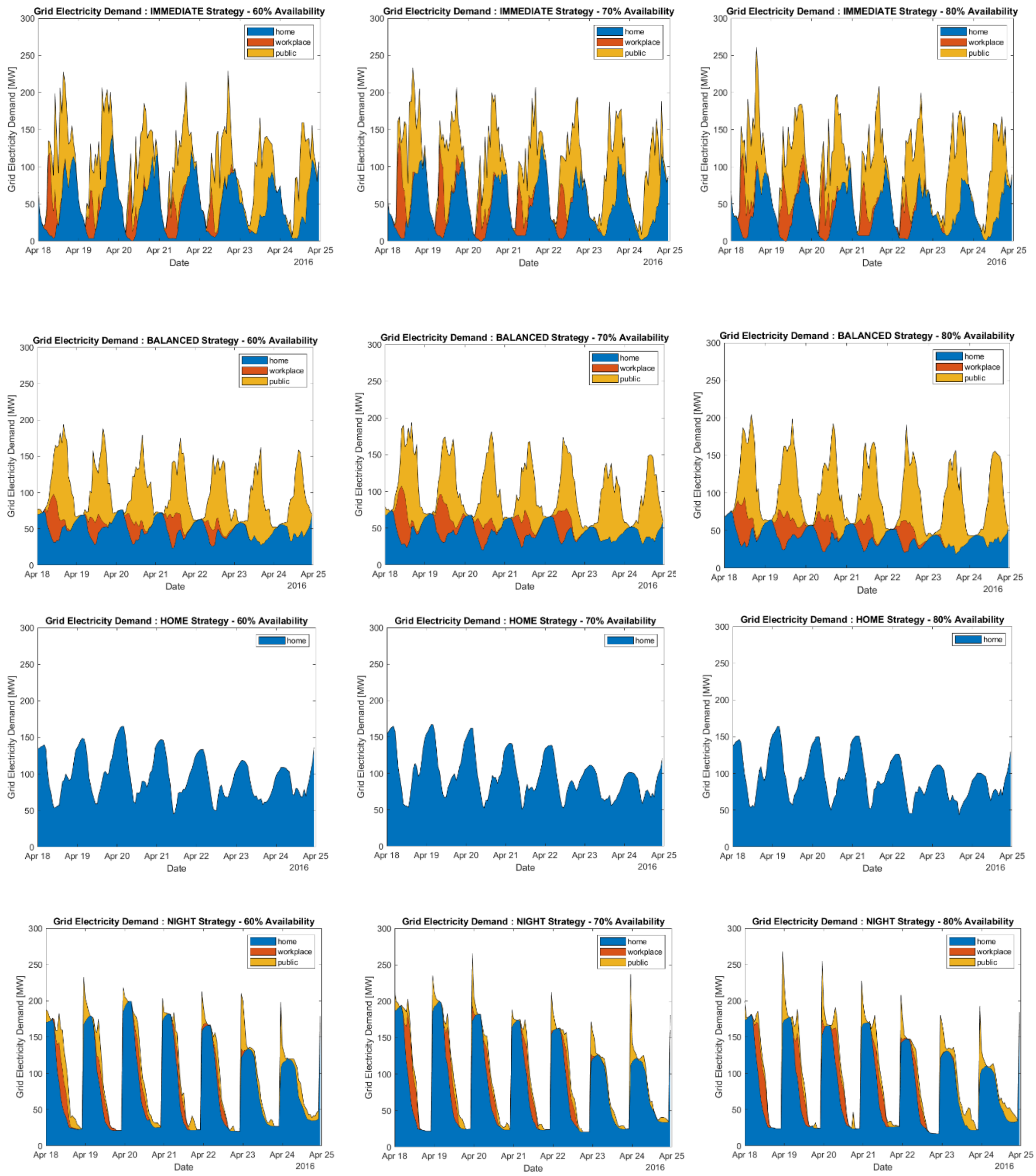


Figure 2.9 – Grid electricity demand, according to charging strategy and scenario considered

2.3.2.3. Seasonality effect

In this paragraph, the results obtained for RAMP-mobility and emobpy (with the EMOBPY50 and EMOBPY60 scenarios) are compared, in order to assess how both tools modelled the same passenger cars' fleet. The final grid electricity demands are confronted an *immediate* charging strategy since it is the only one available for both tools that is not strongly constrained to a precise time window (like the *night* strategy). The graphs are related to four different weeks (one for each season) in order to also evaluate the effect of seasonality, especially related to the change of ambient temperature.

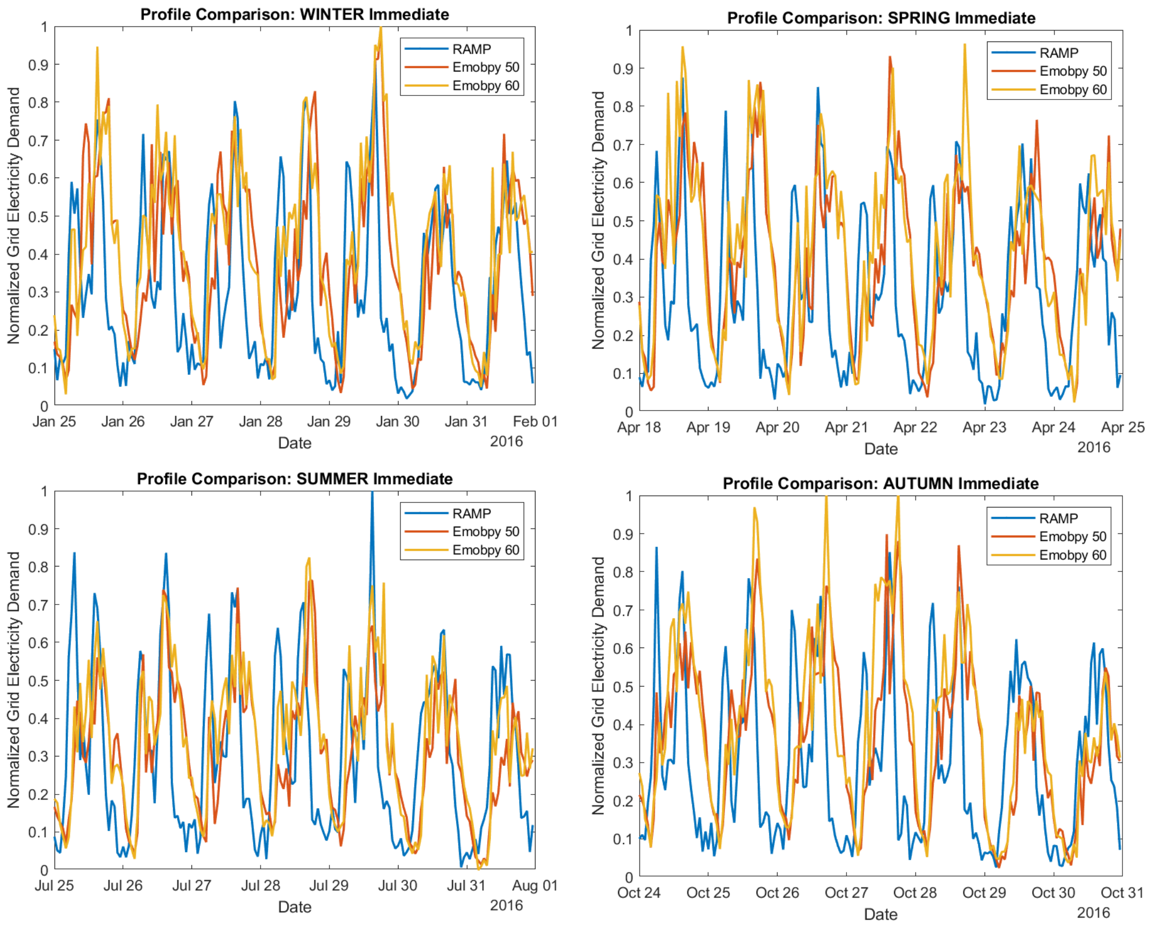


Figure 2.10 – Tool profile comparison for each season. The profiles are normalized with respect to the maximum reached by each profile during the year

The first difference of the two tools is a direct consequence of the two procedures used to create the mobility patterns. For RAMP-mobility, the definition of the two main *functioning windows* lead to an electricity demand where the two major peaks are more visible, concentrated in the first hours of the morning and in the evening. Emobpy instead is based on a more detailed "chain of events", providing a more precise description of the movement during the day, especially in term of "free-time destinations" (e.g. *leisure, shopping* or *errands*). For this reason, the evening peak (when the commuters turn back home and charge their vehicle) is correctively described by both tools, while the energy requested in the morning in more concentrated in few hours in RAMP-mobility and more spread during the whole morning in emobpy.

In terms of seasonality of the results, there is not a strong influence of the ambient temperature on the electricity demand, with the only exception of the summer season, in which the specific consumptions of the vehicles reach the minimum [32] and therefore also the grid electricity demand is reduced.

2.3.2.4. Additional Energy Demand

Another key aspect is the additional yearly energy requested to the grid if the new electricity demand related to the BEV charging infrastructure is added. For all the simulations the energy is evaluated as the summation of the power requested in each time-step of one hour. It is also included a percentage increase with respect to a reference value of 3012 GWh, which is the yearly electricity demand of Alto Adige in 2016 [36].

Table 2.13 – Yearly grid electricity demand related to BEVs charging

Charging Strategy	Scenario	Grid Electricity Demand [GWh/y]	Percentage increase
Immediate	RAMP	787.91	26.16%
	Emobpy 50	821.49	27.27%
	Emobpy 60	824.04	27.36%
Balanced	Emobpy 50	828.19	27.50%
	Emobpy 60	828.87	27.52%
Home	Emobpy 50	807.77	26.82%
	Emobpy 60	813.45	27.01%
Night	RAMP	789.31	26.21%
	Emobpy 50	820.52	27.24%
	Emobpy 70	820.96	27.26%

According to the results obtained, a complete electrification of the cars in Alto Adige, would lead to an increase of the electricity demand close to 27%, with small variations according to the charging strategy followed. The *home* strategy should lead to the lower electricity demand, even if the reduction is not significant. Regarding the comparison between the tools, the results of RAMP-mobility tend to be slightly lower than the same charging strategy modelled with emobpy.

Even if this analysis can provide a first effective description of the consequences of the electrification of the transport sector, it could conceal the major differentiation among the charging strategies, which is related to the different demand curve during the day and how it adds up over the already existing daily demand curve.

2.3.2.5. Additional Power Demand

In this paragraph, each of the grid electricity demand is added to the load demand of Alto Adige. The load demand is obtained starting from the load demand of the North region (which includes Valle d’Aosta, Veneto, Piemonte, Lombardia, Liguria, Friuli Venezia Giulia, Emilia Romagna and Trentino-Alto Adige) provided by the TERNA database [37], the load is then normalized to the maximum value during 2016 and then re-scaled to consider only the South Tyrol territory, by knowing its yearly electricity demand. In this way it is possible to evaluate which charging strategy provides more instability to the grid and which could instead be able to reduce the day/night oscillations already visible in the load demand curve.

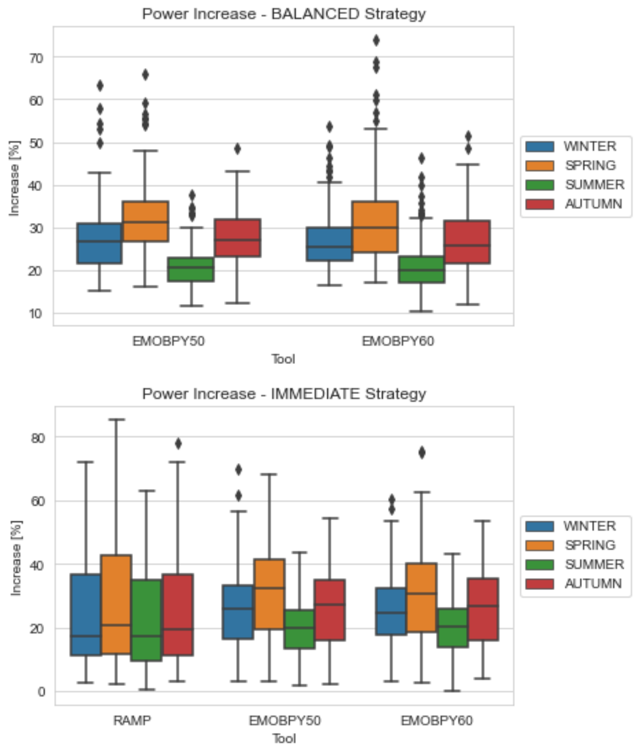


Figure 2.11 – Percentual power increase for the immediate and balanced charging strategies

The graph in Figure 2.11 shows the percentage increase of power demand for each charging strategy and for each period of the year.

For both graphs the summer season is the one with the lower power increase due to the lower electricity demand for charging, as already stated in Paragraph 2.3.2.3. The percentual power increase for the *immediate* strategy during the year simulated is tendentially higher than with a *balanced* strategy, both in terms of median value and especially considering the increased value of 75th percentile. Moreover, even if the RAMP-mobility tool models a slightly lower energy demand, the power increase includes a wider range of value between the 25th and 75th percentile, but the median value is lower if compared to emobpy.

In the graphs below is instead represented the daily load demand curve (labeled "Basic Demand"), with the inclusion of the additional electricity demand related to the BEVs obtained with both tools, grouped by charging strategy.

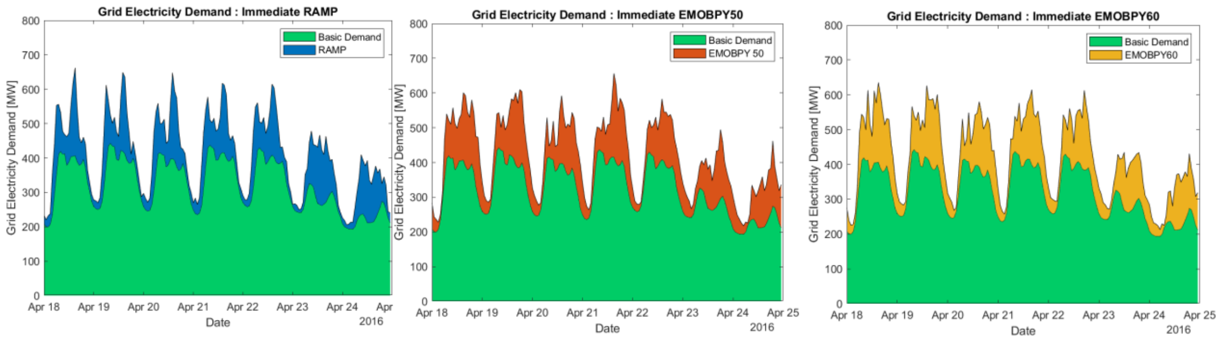


Figure 2.14 – Additional Grid Electricity demand following an *immediate* strategy

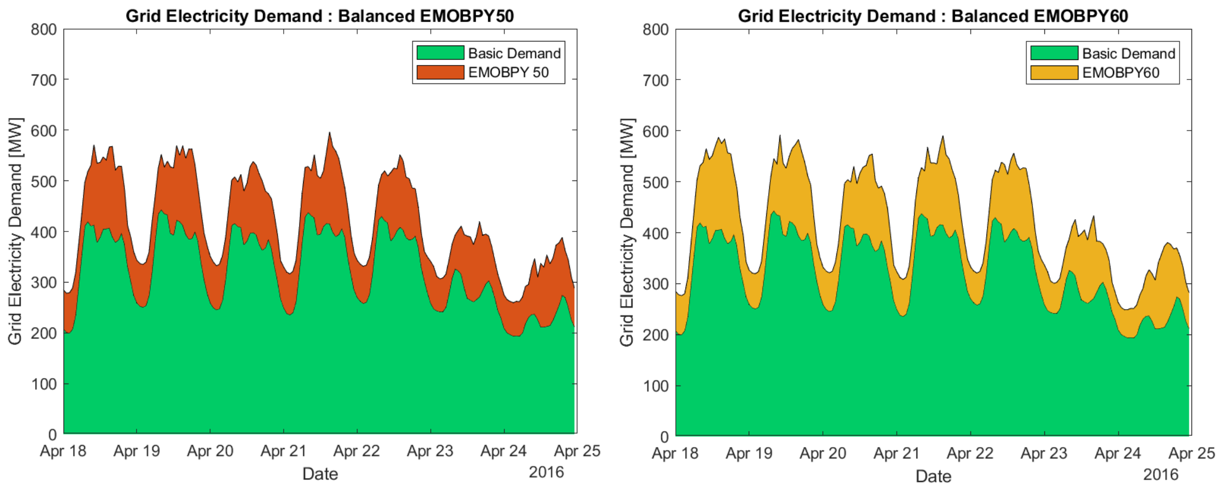


Figure 2.13 – Additional Grid Electricity demand following a *balanced* strategy

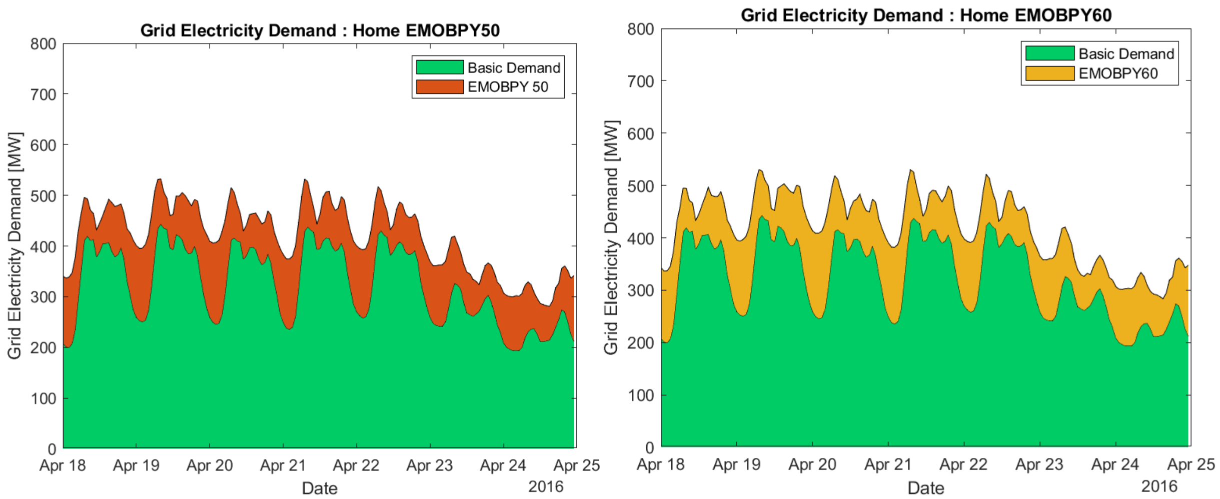


Figure 2.12 – Additional Grid Electricity demand following a *home* strategy

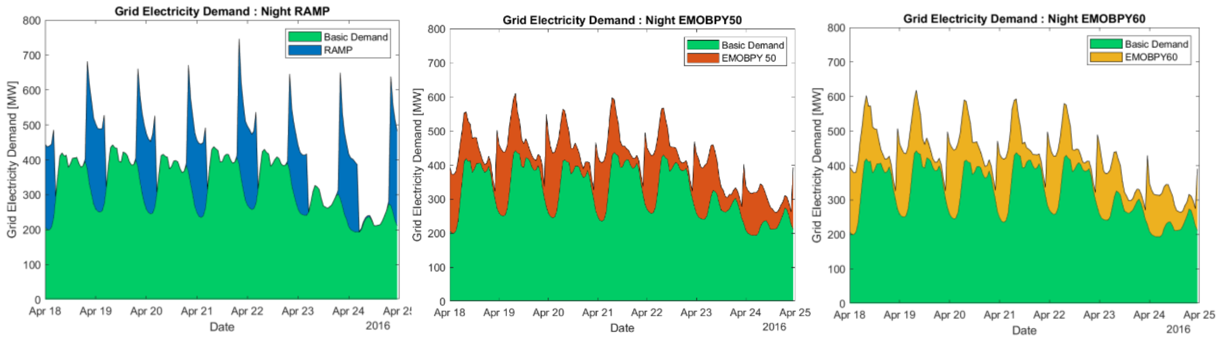


Figure 2.15– Additional Grid Electricity demand following a *night* strategy

The *immediate* (Figure 2.14) and *balanced* (Figure 2.13) charging strategies lead to an increase of the already visible peak value during the day, even though for the *balanced* strategy the increase is lower, with the load also partially distributed when the "Basic Demand" is at the minimum during the night.

For the *home* strategy (Figure 2.12) this aspect is even more accentuated, leading to a new load demand with reduced differences between day and night. But even if this represents a more constant energy request to the grid, it doesn't necessary imply a lower stress to the grid. In possible future scenarios with an elevate share of energy produced by renewable sources (especially in the case of photovoltaic technologies), a significant energy demand during the night could not be satisfied by the grid.

The *night* scenario (Figure 2.15) represents an extreme case in this direction, concentrating all the demand when the load would otherwise be lower, will lead to a severe stress to the grid extreme peak values. This effect is less visible in *emobpy*, but this is related to the incorrect modelling of this strategy, as already stated in **Errore. L'origine riferimento non è stata trovata.**.

2.3.3. Public Transport & Freight Vehicles inclusion

In the light of what has been analysed so far, to move on to the next step of this thesis, concerning the evaluation of the increase in electricity demand due to the electrification of public transport buses and light and heavy vehicles, the tool used will be emobpy. This decision derives mainly from the use of a greater spatial characterisation of vehicle movements, which also makes it possible to define the recharging infrastructure in the area in greater detail, thanks to the ability to define a 'recharging availability' depending on the location of the vehicle. The possibility of modelling vehicle movements also through the use of rules chosen by the user makes a more accurate definition of vehicle movements possible, as will be shown in the next chapter.

In order to include vehicles different from passenger car inside the *emobpy* tool, few simplifications have been made, starting from the mobility pattern. The possible locations are restricted between «headquarters» (corresponding to the bus terminal and the main distribution center for light and heavy freight) and «*delivery point*» (aggregating all the possible destination of the trips), assuming a continuous "back and forth" during the day, aggregating all the intermediated stops of the bus lines or the multiple deliveries done especially for the light freight sector.

For the public transport, the possible locations are the "Headquarters" (corresponding to the bus terminal) and the generic "End of the ride", aggregating all the intermediate stops of the bus lines. For light and heavy freight, the locations are restricted to the "Headquarters" (corresponding to the main distribution center) and a generic "delivery point", aggregating all the possible destinations of a trip). In both cases, a continuous "back and forth" is assumed, aggregating all the intermediated stops of the bus lines or the multiple deliveries done especially for the light freight sector. For this reason, the trips modelled by *emobpy* will be lower and longer if compared with reality.

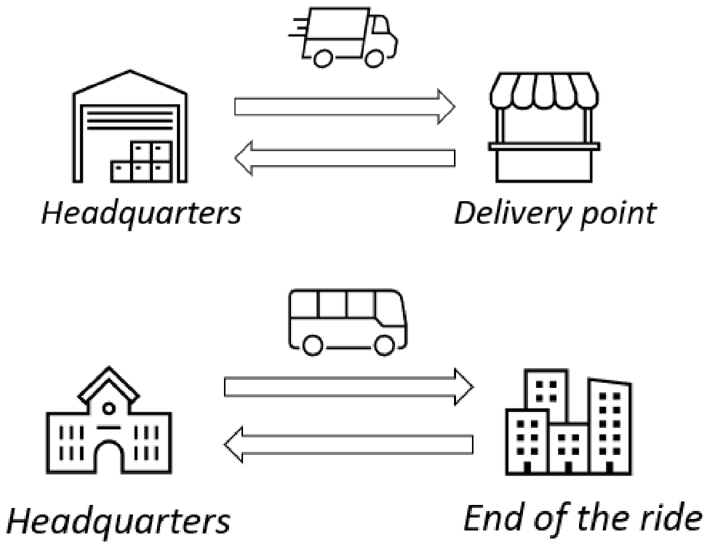


Figure 2.16 – Schematic representation of the mobility pattern for light/heavy freight (above) and buses (bottom)

2.4. Oemof

For this study, the energy system framework has been chosen using the Oemof framework [38]. Oemof is a collection of Python-coded modelling tools for various aspects of energy supply systems that are distributed under an open-source licence. Thus, bottom-up energy dispatch/operational and investment models with any desired level of spatial and temporal resolution can be produced using the toolbox "solph" like LP or MILP. Additionally, it enables integration of the three primary energy system sectors—electricity, heat, and transportation—and is thus particularly well adapted to handle complicated sector coupling issues.

To model future scenarios, a generic dispatch/operational optimization problem is considered, which aims at finding the optimal use of resources to satisfy the demand at least costs. Equation 2.6 expresses the objective function and the total cost of generation as the sum of the variable costs $\boldsymbol{vcn,u,t}$ [€/MWh] of generation unit u, node n at time t and its electricity generation value, $\boldsymbol{En,u,t}$. Variable costs take into account O&M costs and fuel costs.

$$\min\left[\sum_{n}^{N}\sum_{u}^{U}\sum_{t}^{T} E_{n,u,t} * vc_{n,u,t}\right] \tag{2.6}$$

Several distinct kinds of limitations apply to the aforementioned objective function. The first type is represented by Equation 2.7, which represents the hourly power balance in each node. Here, **En,u,tdischarge** is the power given by storage units through discharging of the storage, **En,u,tcharge** is the electricity required for charging of the storage, and **En,tgridloss** is the electricity lost in grid transmission. **Dn,t** is the electricity demand of node n at time t. If the generation at any time exceeds the demand, the surplus power production is taken into account by the appropriate decision variable.

$$\sum(E_{n,u,t} + E_{nu,t}^{discharge} + E_{n,u,t}^{charge} - E_{n,t}^{gridloss} \geq D_{n,t} \tag{2.7}$$

The maximum power of each generator unit is also a limitation. Each fossil fuel generator's power output, **Pu,t**, must be positive and less than or equal to its nominal output, **Pnom,u** (see Equation 2.8). Each renewable energy source's nominal capacity and a normalized profile of resource availability are used to calculate the amount of power it produces.

$$0 \leq \mathrm{P_{u,t}} \leq P_{nom,u} \tag{2.8}$$

The production of power from fossil fuels and all other types of dispatchable power Pu,t depend on the amount of fuel that is available at time t, Qt. Equation 2.9 explains how the amount of power generated is dependent on the fuel supply and plant-specific efficiency. Another non-fossil example of a dispatchable unit is a hydroelectric power station, which uses reservoir water as its fuel. Consequently, η,u represents the generation unit's efficiency.

$$\frac{\mathrm{P_{u,t}}}{\eta,\mathrm{u}} \leq Q_t \tag{2.9}$$

The storage balance, which takes into account the charging, discharging, and self-discharging of the storage units, is another limitation. This constraint is illustrated by Equation 2.10, where Pu,tcharge denotes the power charging the storage unit u at time t, Pu,tdischarge denotes the power discharging the storage unit u at time t, u,charge and u,discharge denote, respectively, the efficiency of the charging and discharging processes of the storage unit u, Su,t denotes the state of the storage unit u at time t, and u,self denotes the At each time-step t in T, the following restriction is imposed to each storage unit u in U.

$$\left(\mathrm{P}_{\mathrm{u,t}}^{\mathrm{charge}} * \eta_u^{charge} - \frac{P_t^{discharge}}{\eta_u^{discharge}}\right) * \Delta t - \left(S_{u,t} - S_{u,t-1}\right) * \eta_u^{self} = S_{u,t} - S_{(u,t-1)} \qquad (2.10)$$

Moreover, the storage level $\boldsymbol{S_{u,t}}$ is limited by the nominal storage capacity NS_u (Equation 2.11) of storage unit u.

$$\mathrm{S}_{\mathrm{u,t}} \leq NS_u \qquad (2.11)$$

The electrical grid's transmission wires are a further restriction. The nominal transmission value NPuflow, as shown in Equation 2.12, limits the power flow relative to the powerline u linking two nodes, Pu,tflow at time t. The value of transmission losses is considered to be 3% and is taken into consideration. This indicates that between two nodes, 3% of the power being transferred is lost.

$$\mathrm{P}_{\mathrm{u,t}}^{\mathrm{flow}} \leq NP_u^{flow} \qquad (2.12)$$

2.4.1. Smart Charge & Vehicle-to-grid Implementation

For this thesis, the implementation of Smart Charge and V2G is done with the definition of an optimisation model within the Oemof tool. Since the introduction of these strategies depends primarily on energy-related reasoning, considering the power balances of the various nodes, and not merely economic considerations related to the cost of energy, the optimisation model does not include some economic parameters, such as the cost of energy that would favour specific charging time windows or a precise cost for the electricity imported from abroad, which would require ad-hoc information that cannot be easily determined or assumed and are not in the scope of this thesis.

A cost is nevertheless associated with each energy source and the model is developed in such a way that the system prefers the cheaper recharging of vehicles at times of overproduction of renewable energy, rather than the more expensive import of energy from abroad. This assumption stems from the goals set for the introduction of the smart charge, not just a reduction in energy production costs, but also an evaluation of the possibility of making the South Tyrolean electricity grid more self-sufficient.

The first step for the implementation of the smart charge is the introduction of a dummy region, named "R_BEV" linked with the original region R simulated.

Considering "dumb" charging, the grid electricity demand values were only allocated to the “real” region R. Switching instead to a completely "smart" approach, the vehicle recharging process takes place within the fictitious region "R_BEV", whose input data are not the time series related to the final grid electricity demand (aggregating all vehicle fleets), but rather the time series of vehicle consumption, which are provided among the outputs of the emobpy software.

Within each of the fictitious R_BEV nodes, an 'electrical storage' (named R_BEV, storage) is also connected, which represents the sum of all electric vehicle batteries associated to that node, considering the real capacities of the vehicle models considered for this case study (Table 2.5).

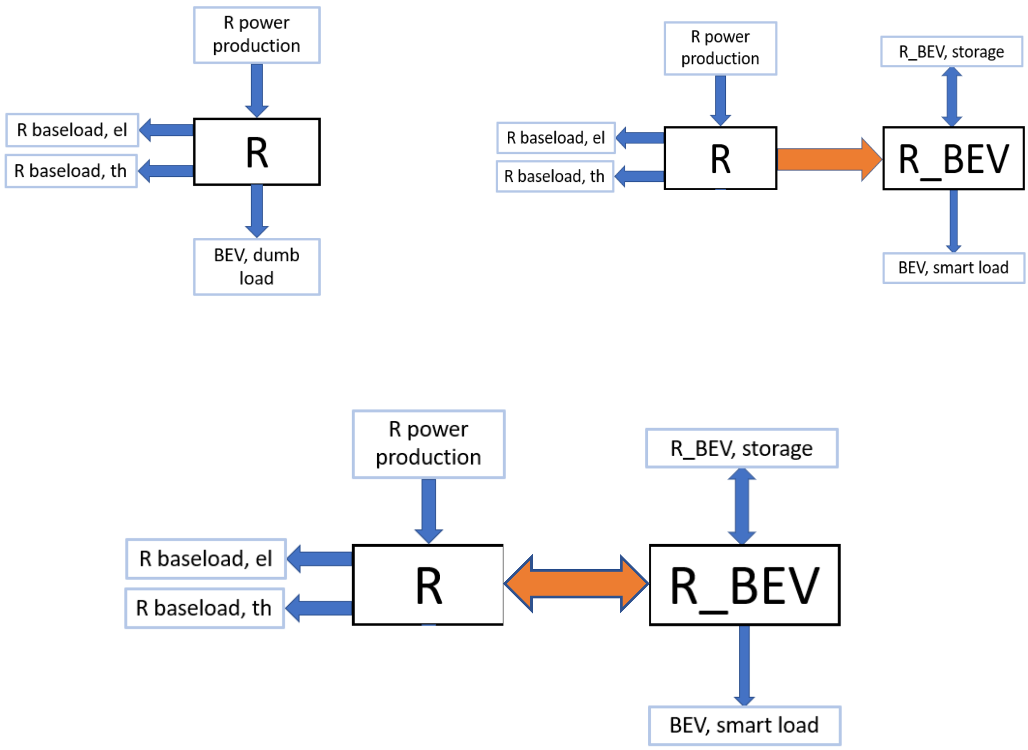


Figure 2.17 – schematic representation of the charging strategies implemented in this study. “Dumb” strategy on the top left, “Smart strategy” on the top right and V2G on the bottom. The bidirectional arrow for the V2G case indicates the possibility for the EVs to provide energy back to the grid

To better clarify the concept behind this implementation, the R_BEV region is comparable to a single electric vehicle, in which both the battery capacity of all electric vehicles present in that specific node, both the consumption of electricity due to all the trips, modelled through the use of the emobpy tool have been aggregated.

The nominal capacity of the powerline connecting each node R with the corresponding node R_BEV has been calculated, this value is equal to the number of vehicles, multiplied by an assumed value of 3 kW. Moreover, in order to ensure the proper functioning of V2G technology and smart charge, this nominal value is then multiplied by the percentage amount of electric passenger cars that are connected to the electricity grid in the timestep t, expressed by the percentage value $\%\boldsymbol{vc_t}$. In this way it was finally calculated, for each hour, the maximum power exchangeable between each node R and its fictitious node R_BEV.

$$\boldsymbol{P_{(R_{BEV}\ to\ R),max,t} = \#vehicles * 3kW * \%vc_t} \tag{2.13}$$

By setting each node as described (i.e. as a pair of real node R and dummy node R_BEV for vehicle charging only), for each timestep the energy consumption of the vehicles can be satisfied in two ways:

1. By supplying energy through the dummy battery "R_BEV,storage" present in the fictitious node. This process can be assimilated (thinking of the case of the single aggregated vehicle) to the discharge of the battery of the vehicle during a travel.
2. By providing electricity from the R region, this process is comparable (thinking of the case of the individual vehicle) to the charging of vehicles after a journey, once a charging station is found available.

Having allocated to the R region a higher cost to the import of electricity than to the production on site, especially with regard to the production of renewable energy sources, the R node will prefer to give energy to the R_BEV region (thus going to recharge vehicles) at times when the production of electricity exceeds the electricity demand. At times when the demand for electricity is high, instead, the fictitious demand BEV,smart load will be satisfied through the discharge of the fictitious battery.

Therefore, considering the implementation of SC and V2G in this way, the value of the electricity demand grid required for vehicle charging will be equal to the amount of energy that is exchanged from the R region to the R_BEV region in the simulated time frame. In addition, to avoid unrealistic behaviour of the fake storage "R_BEV, storage", it has been set that the value of the SOC at the beginning and at the end of the simulation will have to coincide, so as to prevent that the storage is completely discharged at the beginning, and then never recharged.

The possibility to include also a more gradual spread of the smart charge and the V2G across the EV users is considered. This stems from some social and psychological considerations, although it has been found that these two technologies could implement numerous advantages within the electricity grid, it is also worth considering the potential disadvantages for users, such as battery deterioration. For this reason, instead of considering switching to a "full smart" or "full v2g" recharge, four different “soft switch” scenarios have been considered:

- 20% demand switch from “dumb” to “smart charge”
- 50% demand switch from “dumb” to “smart charge”
- 20% demand switch from “dumb” to “v2g charge”
- 50% demand switch from “dumb” to “v2g charge”

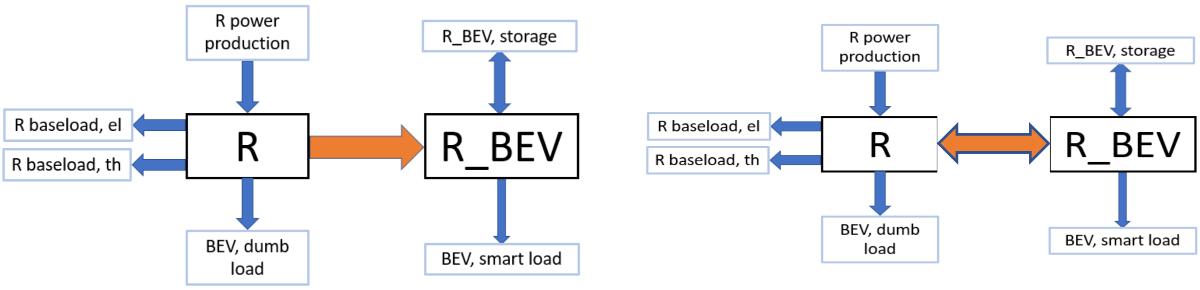


Figure 2.18 – Schematic representation of the gradual implementation of smart charge (left figure) and V2G (right figure) within the Oemof tool

In order to be able to split the load between dumb and smart/v2g charge, the following steps were taken (the procedures were then repeated for each of the original six nodes):

1. the profile of energy consumed by the passenger cars was divided between dumb load and smart load, depending on the percentage of "switch" considered (20% or 50%)
2. smart load values were placed within the “BEV, smart load” within the dummy region R_BEV
3. Starting from the dumb charge values obtained, the normalised grid electricity demand profiles (obtained through emobpy) were used to obtain the nominal capacity of the grid electricity demand so that the total energy supplied by the grid via dumb charge in the year was equal to the sum of the energy consumed by the vehicles during the year (also taking into account the efficiency of charging electric vehicles).
4. The values thus obtained were then entered into the R-region, corresponding to the “BEV, dumb load”, added to the electricity demand of buses and light/heavy freight vehicles

Through this procedure, it is possible to distinguish between a "fixed" recharging share, corresponding to the “BEV,dumb load”, and a "flexible" recharging share, i.e. the amount of energy that each region R gives up to its own fictitious region R_BEV, in order to be able to satisfy the consumption of vehicles that need to be recharged in a "smart" manner.

Consequently, the new amount of energy required from the grid to recharge vehicles will be equal to the sum of the two contributions, as expressed by the Equation 2.14:

$$\boldsymbol{P_{ev,t} = P_{BEV,dumb,t} + P_{R\ to\ R_{BEV},t}} \tag{2.14}$$

3 Case study

3.1. South Tyrol transport sector electrification

As can be seen in the Figure 3.1, elaborated from data of the "PianoClima 2022" [39] and relative to the South Tyrol region, although passenger cars are the largest contributor to emissions in the transport sector, in order to achieve the European objectives of gradually reducing and eventually zeroing emissions from this sector, the impact of other vehicle types must also be considered, which will therefore necessarily have to undergo a process of partial or total electrification. For this reason, also in light of the recent policies proposed by the European Union that are beginning to place constraints also on new sales or on emissions of buses and light and heavy transport[13], it was considered crucial to also include these types of vehicles in this analysis, so as to assess their recharging in terms of the increase in energy demand and their impact on the electricity grid.

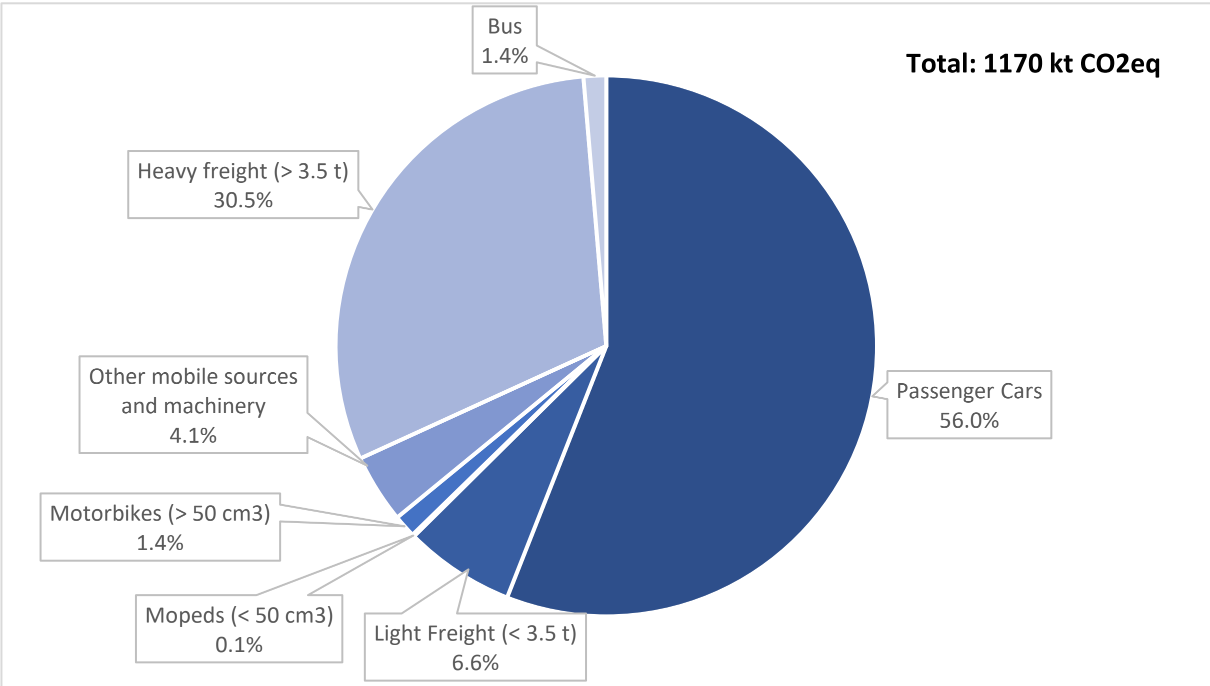


Figure 3.1 - Breakdown of emissions from fossil fuels inside the transport sector in South Tyrol, 2019. With the inclusion of Bus and light/heavy freight, it is possible to represent the electrification of vehicles collectively responsible for 81.6% of the emissions in the transport sector

For this reason, although the number of four-wheeled vehicles in South Tyrol is mainly composed by passenger cars, as can be seen in the Table 3.1, all the major four-wheeled vehicles were included in *emobpy*, calculating the input values for the tool accordingly [31]. Two-wheeled vehicles (e.g. mopeds and motorbikes), despite their impact in the emissions of the transport sector, were not taken into account because, although *emobpy* can be extended more easily to other four-wheeled vehicles, this process cannot be carried out correctly for two-wheeled vehicles as well.

Table 3.1 – Number of vehicles circulating in Alto Adige in 2019, belonging to the categories implemented in emobpy for future scenarios evaluation

Type of vehicle	Total number
Passenger Cars	450 000
Light Freight (Vans)	10 000
Heavy Freight (Heavy truck)	1 600
Bus	750

In the following pages, in addition to the presentation of the data chosen for passenger cars, which are in line with the steps presented in the previous chapter, the methodologies required for modelling these additional vehicle types within *emobpy* will then be presented in detail, listing and justifying the simplifications that have been imposed and the assumptions that have been made, as well as the input values that have been chosen for describing the vehicles.

3.1.1. Passenger Cars

3.1.1.1. Rules

The rules are the same presented in Table 2.3, assuming that the values can be considered constant also in this case.

3.1.1.2. Population & Vehicle Models

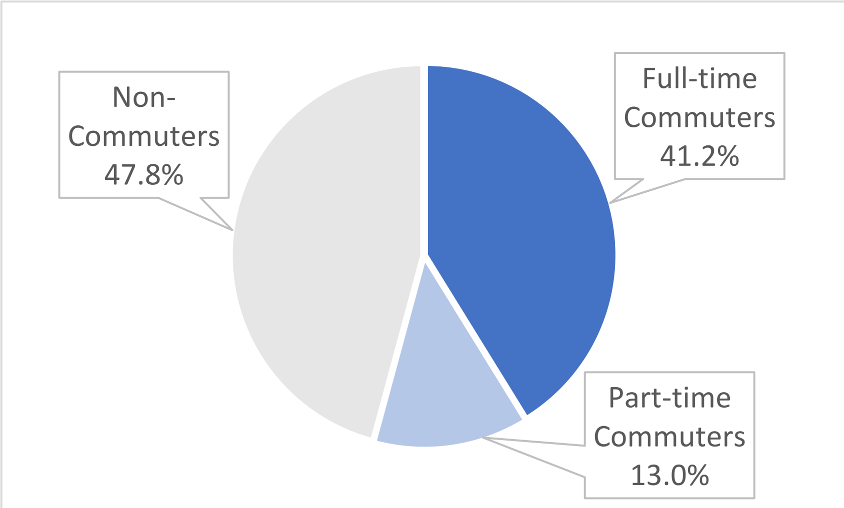


Figure 3.2 - Alto Adige population, split between the emobpy categories, 2019

The population is defined following the same criteria presented in Paragraph 2.3.1.1. The values of the share between *full-time commuters*, *part-time commuters* and *non-commuters* are updated considering the values for 2019 and reported in Figure 3.2[40].

Each mobility time series is then associated to a car model. In order to consider the best technology available for the study of future scenarios, the BEV models are chosen starting from the sales in Italy from January 2021 to August 2022 and then translated in a probability value [33], [41]. If a car model was not included in *emobpy*, it is substituted with the most similar cars in term of size, power and battery capacity.

Table 3.2 – Passenger Cars model definition for Italy

from January 2021 to August 2022

Car Model	Simplified Market Share [%]
FIAT 500-e	45.3
Renault Zoe Q90	21.1
Volkswagen ID3	18.3
Tesla Model 3	8.2
Tesla Model Y	7.1

3.1.1.3. Grid Availability

Regarding the nominal capacity of the charging stations, the values are set accordingly to the real charging infrastructure of Alto Adige, as reported in Table 2.7.

The probability of finding an available charging station for each location is then chosen considering the results of the sensible analysis carried in the previous paragraph. The scenario considered is the "EMOBPY 60", reported in Table 2.9, which considered a 60% probability of finding a public station when the vehicle is parked in all locations except *home*, where the probability is set to 80%.

This assumption is based on the small differences of the results for the four scenarios previously considered, both in terms of hourly power demand and yearly electricity consumption. Therefore, this scenario was chosen considering both the increased availability of charging columns that can be achieved in future scenarios, while still maintaining a cautious approach, as the probability of finding a charging column cannot reach extremely high values (80% or higher) in any case, as it does not depend solely on the number of installed columns (which tends to increase in the coming years [42]), but also on aspects related to traffic or time of day.

3.1.1.4. Charging Strategy

Among the four charging strategy proposed by *emobpy*, only the *immediate* strategy is chosen, with BEVs charging their batteries at full power rating as soon as they find a charging station available. This assumption derives from considerations in terms of reliability and effective representation of real charging behaviour, which led to discarding the other possible choices: the *balanced* strategy, even with its potential of describing a behaviour close to the "smart-charging", couldn't correctly be referred to all the possible location of a vehicle, considering that the BEV user doesn't always has a perfect foresight of when the next trip will occur. The *night* strategy, despite its potential to level out the demand curve throughout the day, and partially in line with the actual behaviour of certain drivers, is not correctly modelled inside the *emobpy* tool, with a share of vehicle charging also during the day, as showed in Figure 2.14. The *home* strategy was not considering due to the lack of certain information regarding the number of drivers who only recharge at home.

3.1.2. Light Freight

3.1.2.1. Departure Time & Destination

The departure time and destination has been evaluated starting from a study regarding the province of Singapore, using the software *SimMobility* to model the trips of a fleet of e-commerce delivery vehicles. The study provides the distribution of the number of trips during the day, distinguishing between outward trips, aggregating both trips for delivery and for pickup (i.e. when a request for the return of a product is made) and return trips to base.[43]

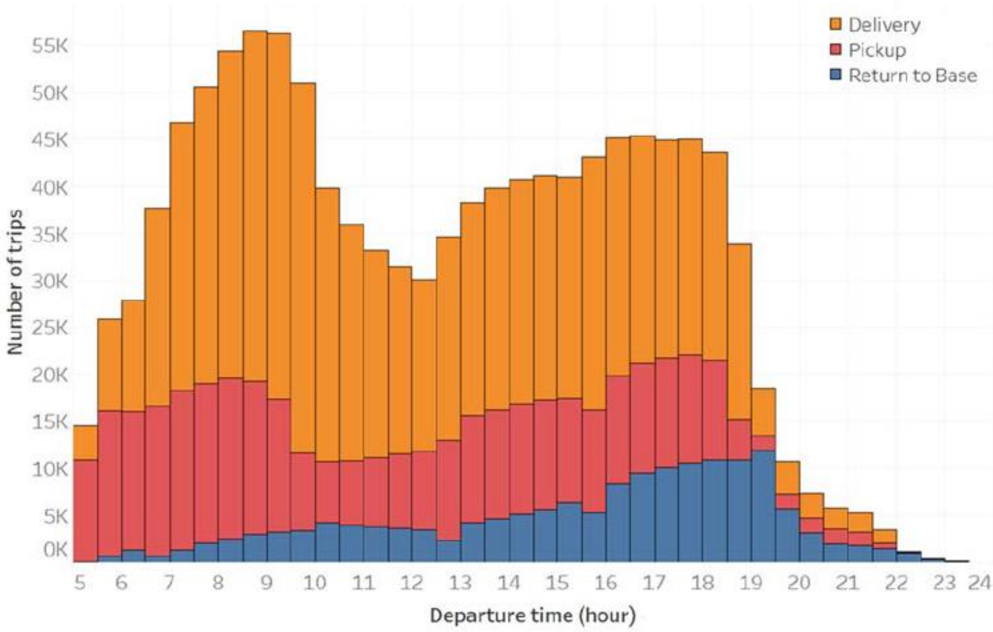


Figure 3.3 – Freight vehicle trips by purpose

These data are then converted in a probability of departure time and destination, as requested by emobpy.

3.1.2.2. Rules

To obtain a more realistic mobility behavior, without excessively increasing the computational time requested by the tool, the only rules imposed to the system are:

- ***The last trip must always be towards headquarters:*** in this way the tool simulates a situation in which each vehicle must be at the main distribution centre during the night.
- ***At least one trip has to be done during workdays*** (from Monday to Friday).
- ***Minimum amount of time spent in each shipping destination set to 30 minutes:*** in this way the number of stops required by law are aggregated at the end of each travel.

3.1.2.3. Number of trips

The probability distribution of the number of trips per day is defined considering the simplifications done. Since the trips are defined as a continuous "back and forth" and the last trip must always be towards the headquarters, only even numbers of trips per day are allowed.

Table 3.3 - Probability distributions for the amount of trips per day by days of the week, related to the light freight vehicles

Number of trips	Working day	weekend
0	12%	30%
1	0%	0%
2	52.5%	45%
3	0%	0%
4	35.5%	25%

3.1.2.4. Trip distance and duration

The probability distributions of the distance and duration of each trip are gradually modified starting from the default values of *emobpy*.

Table 3.4 – Trip duration probability distribution for light freight vehicles

Distance	Trip duration (minutes)			
	20	**30**	**40**	**60**
20 km	12.5	27.2	0	0
20-30 km	0	27.9	10.2	0
30-40 km	0	0	20.9	1.3

To check the validity of the mobility patterns obtained, two parameters are compared with real data: the first one is the average speed, which was in line with the results of the same study, slightly below 50 km/h, considering that most of the trips are in urban areas. The second parameter considered is the average km/vehicle in a year, which was instead compared to real data provided by the U.S. Department of Energy [44].

Table 3.5 – Comparison of the values obtained from the mobility simulation and real data related to light freight vehicles

Parameter	Value Obtained	Reference Value
Average speed	45.6 km/h	48 km/h
Average km/vehicle in a year	19338 km	20000 km

3.1.2.5. Vehicle Models

For the definition of the vehicle fleet intended for light transport, the three best-selling commercial vans in Italy from 2010 to 2019 were considered. The same percentage of sales was then maintained after switching to the electrified version of the three vehicles.

Table 3.6 – Light freight fleet definition

BEV Model	Simplified Market Share [%]
FIAT E-Ducato	40.2
Fiat E-Doblò	35.1
Iveco E-Daily	24.7

All the vehicle information in terms of dimensions, driving performance and electrical components are obtained from the datasheets provided by the manufacturers, inserted inside the emobpy database and used for the simulation of the whole fleet of light freight, the precise values are reported in the appendix A.

3.1.2.6. Grid Availability

Regarding the charging infrastructure, it is assumed that all the private companies have their personal charging stations for their own fleet, which is modelled according to the technology of the vehicles. For this reason, it is assumed that the commercial vehicles can be charged only when they are at the main distribution center. At the headquarters, the vehicle can always find one of the two possible charging stations, according to the technology of the commercial vehicles considered and the maximum charging power they can receive.

Table 3.7 – Charging infrastructure definition for the light freight vehicles

Charging Station Category	Nominal Capacity [kW]	Availability
Slow	22	70%
Fast	70	30%

3.1.3. Heavy Freight

3.1.3.1. Departure Time & Destination

The departure time is evaluated starting from a study of the GPS data of almost 3 million heavy truck trips in the province of Alberta [45], including both local and long-distance operating vehicles . The study provides the distribution of the number of trips during the day, which is then converted in a probability of departure time, as requested by emobpy.

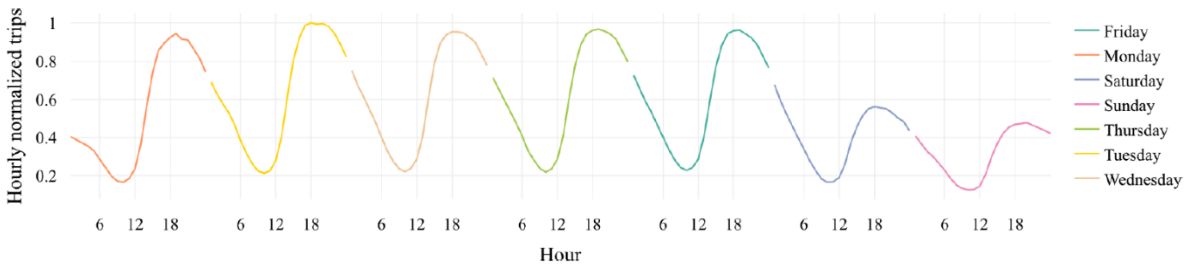


Figure 3.4 – Week-long hourly variation of normalized truck trips

Figure 3.4 shows that truck traffic is concentrated during weekdays (with a regular pattern from Monday to Friday) with only about 19% of truck travels happening on the weekends. At the same time, most of truck trips are concentrated in afternoon and during the evening, this may be caused by the request of the establishers to receive the delivery before the first hours of the morning (before most businesses open) or to deliver goods in turn to the light transport sector, which in fact has the first peak of travel in the early hours of the day, as showed in Figure 3.3. Considering the application to an Italian region, the ban for heavy truck travels from 8.00 to 22.00 on Sunday is also included [46].

Due to the absence of specific data, the heavy truck trips are then split between travels towards «Delivery destination» and travels towards «Headquarters» following the same repartition used for the definition of light freight vehicle's mobility patterns in Figure 3.3.

3.1.3.2. Rules

For this vehicle's category, the rules imposed to the system are:

- ***The last trip must always be towards headquarters:*** in this way the tool simulates a situation in which each vehicle must be at the main distribution centre during the night.
- ***At least one trip has to be done during workdays*** (from Monday to Friday).
- ***Maximum amount of time spent in each shipping destination set to 2 hours:*** in this way the number of stops required by law are aggregated at the end of each travel (equal to 45 minutes after 4.5 hours of travelling), including also the time required for loading and unloading the goods.

- ***Minimum amount of time spent at the headquarters set to 6 hours:*** in this way it was possible to avoid unlikely situations in which the truck would return to base at late night and start again in the early morning of the following day, assuming a more correct charging procedure between each trip.

3.1.3.3. Number of trips

For the heavy freight sector, considering the longer distance of the trips compared to the other vehicles, it is assumed that for each day, the number of trips can be at maximum equal to two (one outward journey and one return journey).

Table 3.8 - Probability distributions for the amount of trips per day by days of the week, related to the Heavy freight vehicles

Number of trips	Working day	weekend
0	12%	30%
1	0%	0%
2	80%	70%

3.1.3.4. Trip distance and duration

The probability distributions of the distance and duration of each trip are gradually modified starting from the default values of *emobpy*.

Table 3.9 - Trip duration probability distribution for heavy freight vehicles

Distance	Trip duration (minutes)				
	163	**170**	**180**	**200**	**230**
150 km	1.8	5.7	0.8	0	0
150-160 km	0	23.7	3.8	0.7	0
160-170 km	0	0	9.8	32.2	15.2
170-180 km	0	0	0	3.1	3.2

To check the validity of the mobility patterns obtained, two parameters are compared with real data: the first one is the average speed, which was in line with the results of the same study, considering both the stretches of road traveled at low speed before entering the highway and the speed limitations of 80 km/h once reached. The second parameter considered is the average km/vehicle in a year, which was instead compared to real data provided by the U.S. Department of Energy [44].

Table 3.10 - Comparison of the values obtained from the mobility simulation and real data related to heavy freight vehicles

Parameter	Value Obtained	Reference Value
Average speed	53.4 km/h	55 km/h
Average km/vehicle in a year	95205 km	100000 km

3.1.3.5. Vehicle Models

The chosen elecric model used to simulate the behaviour of heavy freight vehicles is the Mercedes-Benz E-Actros, developed in 2021 and one of the first electric truck to reach a large-scale distribution.

All the vehicle's information in terms of dimensions, driving performance and electrical components (reported in the Appendix A) are then manually inserted inside the emobpy database and used for the simulation of the whole fleet of electric trucks.

3.1.3.6. Grid Availability

Also in this case, it is assumed that all the private companies have their personal charging stations for their own fleet, leading to a 100% probability of finding an available charging station. The charging capacity is set starting from the technology of the vehicles (e.g. the maximum charging power that can be borne by the battery) and considering a tecno-economical trade-off, selecting the lowest (and so most economical) solution for the company, that could guarantee a correct charging strategy for the whole fleet.

Table 3.11 - Charging infrastructure definition for the heavy freight vehicles

Charging Station Category	Nominal Capacity [kW]	Availability
Headquarters	80	100%

3.1.4. Buses

3.1.4.1. Departure Time & Destination

The mobility pattern of BEBs in Alto Adige is defined assuming the probability distribution of departure time and destination to be constant during the week. This probability is instead null from 21.00 to 6.00, assuming the absence of overnight buses in the urban area. Even if this assumption doesn't perfectly resemble the reality, due the absence of precise data in the way needed by *emobpy*. This assumption was necessary given the impossibility of translating the lower presence of night buses in the fleet sufficiently accurately in terms of the probability of a trip taking place during the night rather than during the day. Considering the lower number of vehicles in Alto Adige if compared to all the other categories also that the amount of routes covered by the night bus service and also the frequency of trips in such circumstances is significantly lower than daytime traffic, this assumption does not strongly influence the results obtained. However, as seen in **Errore. L'origine riferimento non è stata trovata.**, considering, a possible error has a low influence on the final electrical demand of the whole transport sector.

3.1.4.2. Number of trips

For the urban bus sector, considering the shorter and more frequent trips compared to the other vehicles, it is assumed that for each day, the number of trips can be at least equal to two. The upper limit is set to six trips per day, to avoid an excessive increase of the computational time required by the tool.

Table 3.12 - Probability distributions for the amount of trips per day by days of the week, related to the public buses

Number of trips	Working day	weekend
0	0%	0%
1	0%	0%
2	10%	30%
3	0%	0%
4	40%	40%
5	0%	0%
6	50%	30%

3.1.4.3. Rules

For this vehicle's category, the rules imposed to the system are:

- ***The last trip must always be towards headquarters:*** in this way the tool simulates a situation in which each vehicle must be at the main distribution centre during the night.
- ***At least one trip has to be done during workdays*** (from Monday to Friday).
- ***Minimum amount of time spent in each destination set to 30 minutes:*** in this way the number of stops required by law (both at the headquarters and at the end of the line) are aggregated at the end of each travel.

3.1.4.4. Trip distance and duration

The probability distributions of the distance and duration of each trip are gradually modified starting from the default values of *emobpy*.

Table 3.13 - Trip duration probability distribution for the public buses

Distance	Trip duration (minutes)							
	65	75	100	120	140	160	180	200
38 km	2.27	17	8	0	0	0	0	0
38-42 km	0	0	2.18	10	6	0	0	0
42-48 km	0	0	2.18	10	6	0	0	0
48-53 km	0	0	0	2.18	10	6	0	0
53-58 km	0	0	0	0	0	0.09	7	2
58-62 km	0	0	0	0	0	0.09	7	2

To check the validity of the mobility patterns obtained, two parameters are compared with real data: the first one is the average speed, which was in line with a study made for public transport sector in the Italian regions [47], considering that most of the trips are in urban areas and the frequent stops for passengers to get on and off the vehicle. The second parameter considered is the average km/vehicle in a year, which was instead compared to real data provided by the U.S. Department of Energy [44].

Table 3.14 - Comparison of the values obtained from the mobility simulation and real data related to public buses

Parameter	Value Obtained	Reference Value
Average speed	23.4 km/h	20 km/h
Average km/vehicle in a year	70658 km	70000 km

3.1.4.5. Vehicle Models

The chosen electric model used to simulate the behaviour of battery electric Bus is the Solaris Urbino 12 Electric. This vehicle was developed in 2020 and is one of the first electric bus to reach a large-scale distribution in Italy.

All the vehicle information in terms of dimensions, driving performance and electrical components are then manually inserted inside the emobpy database and used for the simulation of the whole fleet of electric buses.

3.1.4.6. Grid Availability

Also in this case, it is assumed that the public transport companies have their personal charging stations, which is correctly dimensioned for their own fleet, leading to a 100% probability of finding an available charging station when the vehicle is at the headquarters. The availability and capacity of the charging stations is set starting from the data related to the BEBs of Alto Adige [48], [49].

Table 3.15 - Charging infrastructure definition for the public buses

Charging Station Category	Nominal Capacity [kW]	Availability
Slow	80	95%
Fast (Pantograph)	300	5%

3.1.5. Charging Strategy

For public buses, commercial vans and heavy truck, among the charging strategy available with *emobpy*, the “Balanced” strategy is used. Hence, the electric vehicles start charging their batteries as soon as they arrive at charging stations, however with constant power rating (usually below the power rating of the charging station), such that a 100% state of charge is reached just before starting the next trip.

This decision derives from considerations in terms of reliability and effective representation of real charging behaviour, assuming that the public transport or delivery companies knows in advance the daily vehicle movement. Hence, when a vehicle starts recharging, a lower (and more economical) charging power can be chosen, since it is known when the next trip will begin [50].

3.2. Oemof Implementation Model

The modelling of the South Tyrol case study within the Oemof tool is based on previous analyses that have been carried out to represent the energy sector in this region. The main reference study is the one presented within the LifeAlps programme, entitled "Zero Emission Services for a Decarbonised Alpine Economy” [51]. Using the Voronoi method, the South-Tyrol is initially subdivided into six macro-regions and then the electricity and thermal energy consumption and the nominal power of the generation sources of electricity system is associated to each region through the use of Equation 3.1.

$$P_i \leq P_{tot} * \frac{A_i}{A_{tot}} \tag{3.1}$$

More specifically, the installed capacity of the source under consideration is divided into the various subpolygons when a polygon is divided by a Voronoi subdivision, assuming that the installed capacity is distributed equally throughout the municipality area. Ai is the area of subpolygon i while Pi is the installed power of subpolygon i. $Ptot$ is the total installed power of the considered polygon (which correspond to a municipality) and $Atot$ is its total area. This multi-node approach is relevant as variable renewable energy sources (VRES) modelling is largely affected by the underlying spatial resolution and it is also possible to include the major transmission lines between nodes.

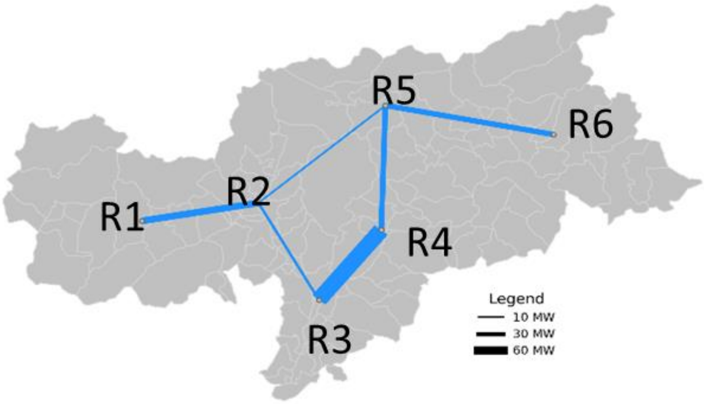
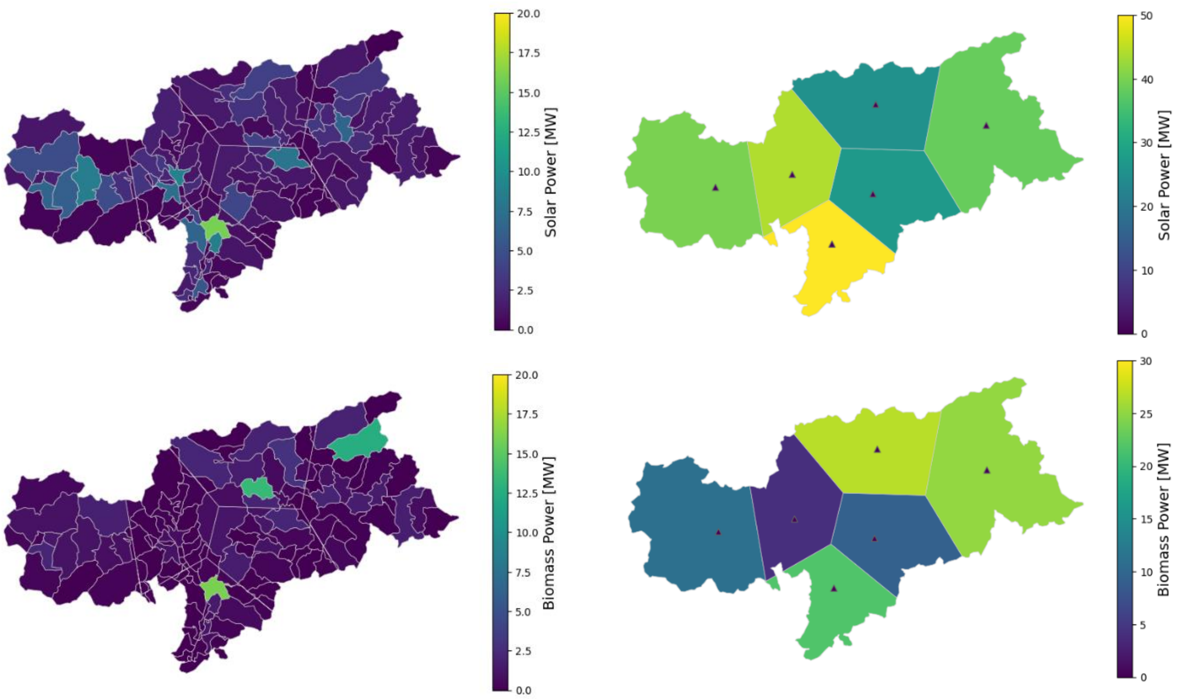


Figure 3.5 - Multi-node representation of the South-Tyrol region, as defined inside the Oemof tool

In the Figure 3.6, is reported the installed power of the different sources for each municipality (on the left), with also the aggregation into the six macro-regions on the right.



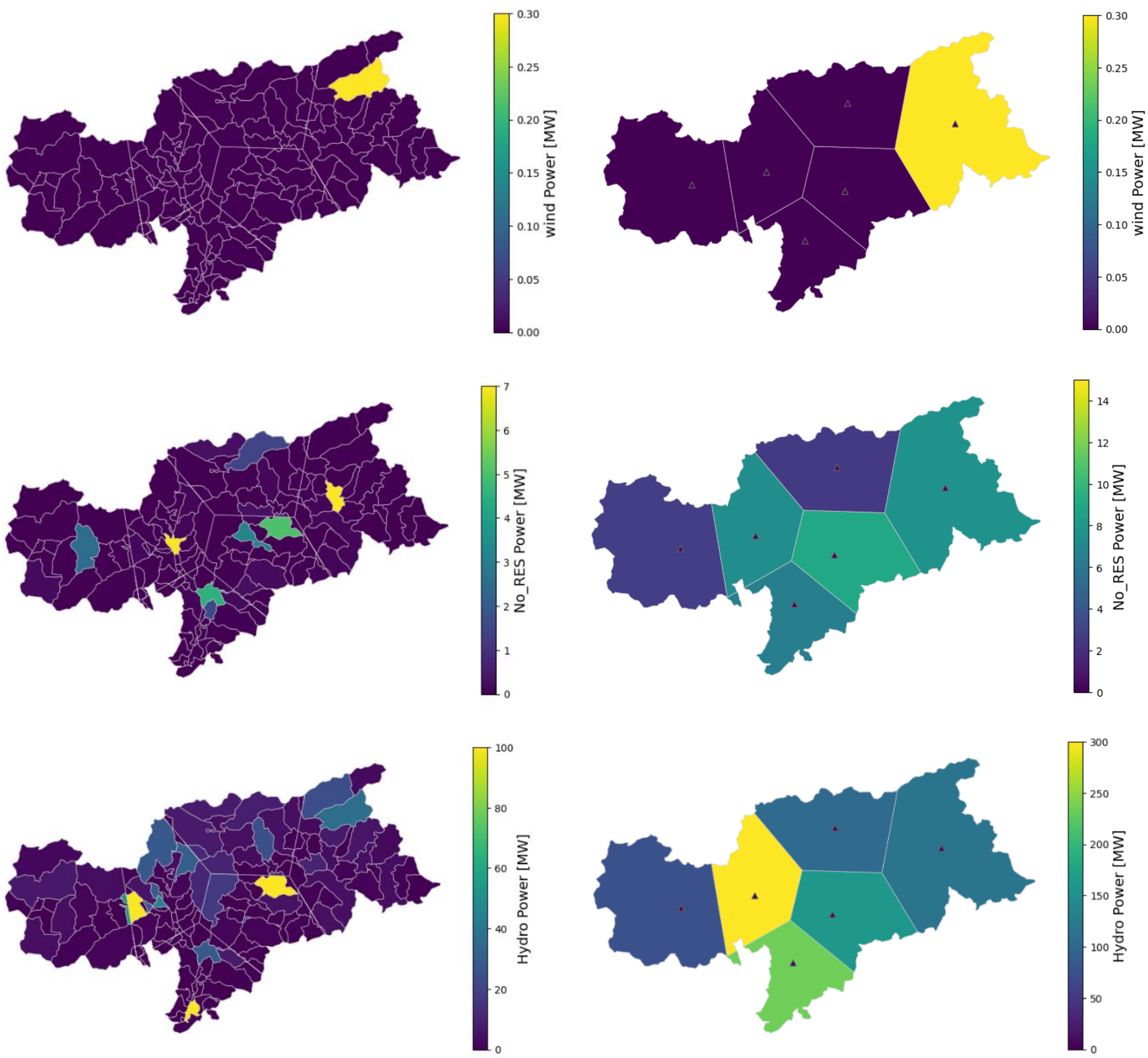


Figure 3.6 - Subdivision of installed power of generation sources (solar, biomass, hydro, No_RES, wind) in the six different nodes

Also the analysis of the Smart charge and Vehicle-to-grid technology is extended to a multi-node representation of the case study of South Tyrol. Only in this way it is possible to take into account the peculiarities of each node, evaluating whether the implementation of these technologies could provide a benefit to the grid.

The implementation of the fictitious region R_BEV was then included within the multi-nodal representation of the region. Each of the six nodes present (i.e. R1, R2, R3, R4, R5, R6) was then associated with a fictitious node (i.e. R1_BEV, R2_BEV, R3_BEV, R4_BEV, R5_BEV, R6_BEV).

The capacity of the storage in each node was derived from the amount of electric vehicles present in each node, obtained by dividing the amount of total electric vehicles according to the population present in each node.

Once the number of vehicles present was obtained, the capacity of the total storage was then calculated by adding up the real capacity of the vehicles considered for the simulation.

For these cases, four different scenarios are considered (two for each strategy implemented), assuming a more gradual spread of the smart charge and the V2G across the EV users. Following the structure presented within the Paragraph 3.1, each of the six nodes was associated with the thermal and electrical energy production sector (including the nominal capacity of the plants and their normalised production profiles) and the various loads, both thermal and electrical, which includes also the charging demand of the vehicles for which the "controlled" charging strategies are not considered (i.e. buses, commercial vans and heavy trucks).

4 Results

This section will present the results of the case study presented, both in terms of the charging profiles of the vehicles considered, and the subsequent implementation of this demand within the South Tyrolean energy system, evaluating different future scenarios and considering the potential benefits of implementing smart charge and vehicle-to-grid technologies.

4.1. Vehicle Location

In this section, the daily trends of the mobility patterns of the four main types of vehicles are presented. As far as passenger cars are concerned, the different types of travel destinations during the day can be seen in Figure 4.1. Most drivers leave their homes in the morning for their workplace, followed by all other destinations, whether for necessity (like escort or shopping) or for leisure. During the evening, following the probability distribution provided and especially considering the imposed rules system, all vehicles return to their homes. During the weekend, due to the different type of rules imposed (especially a reduction of the hours spent at work for commuters), a general reduction in the number of vehicles leaving their homes can be observed. On these two days there is also a significant increase in leisure trips, especially on Sundays.

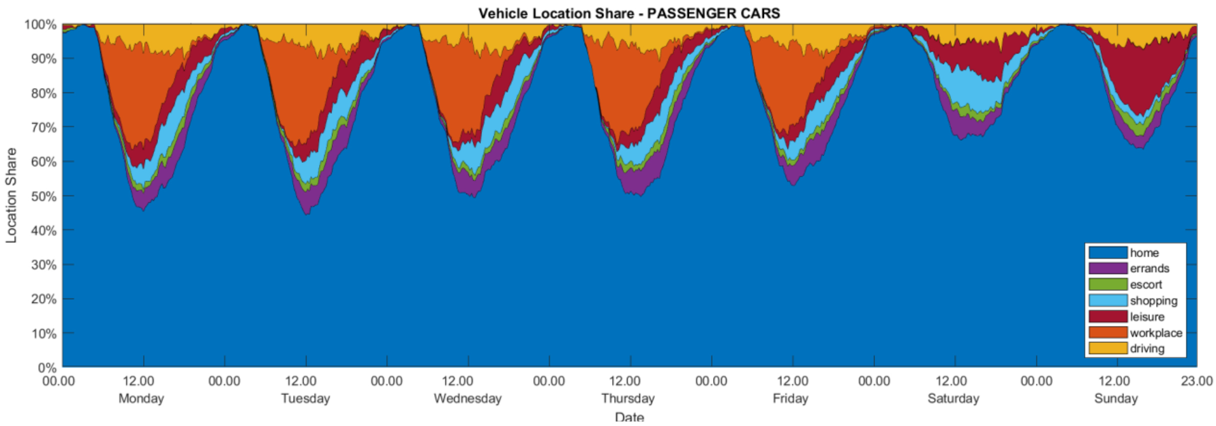


Figure 4.1 – Simulated time series of passenger cars locations

For other vehicles, as a result of the assumptions made to define the types of travel, a lesser variety of possible destinations is represented. In addition, for buses and heavy freight vehicles, the greater number of kilometres travelled per day leads to a substantial increase in the share of vehicles in the driving category during the day.

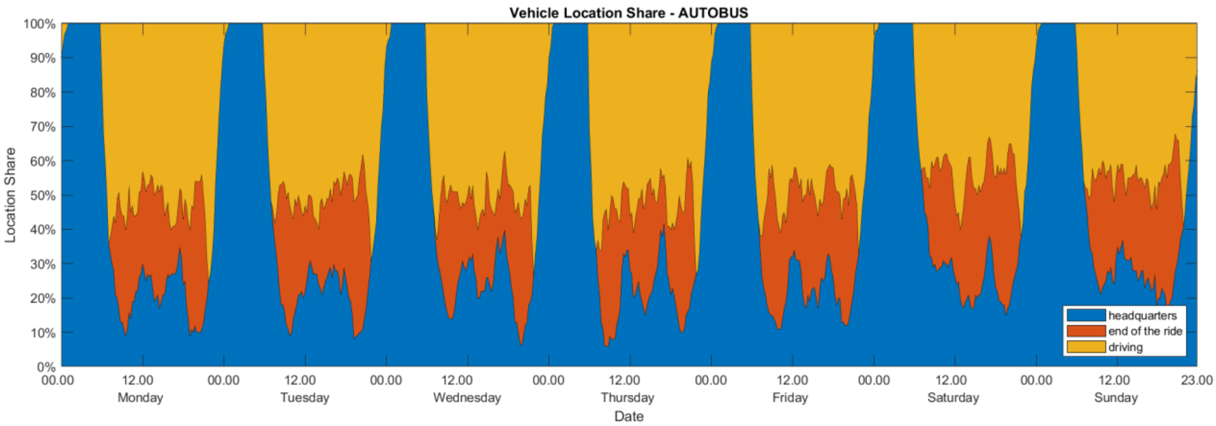


Figure 4.4 - Simulated time series of bus locations

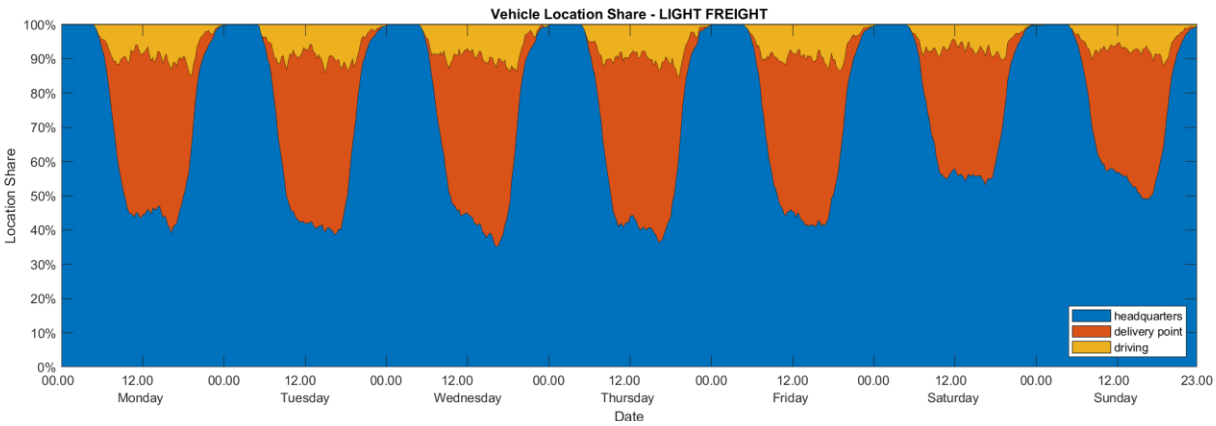


Figure 4.2 - Simulated time series of commercial vans locations

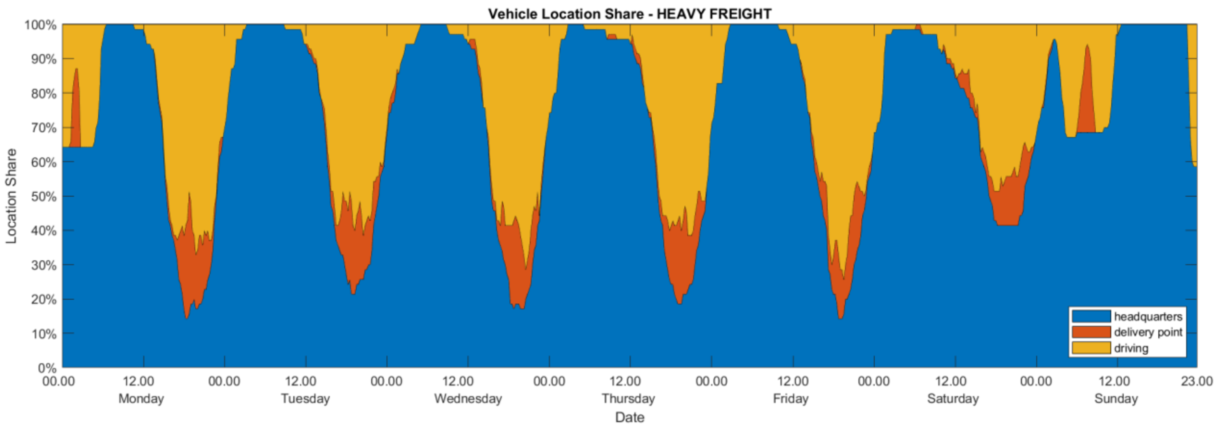


Figure 4.3 - Simulated time series of heavy trucks locations

As far as heavy trucks are concerned, the large number of vehicles in the headquarter on Sundays stems from the legally imposed travel ban.

4.2. Normalized Electricity demand

In this paragraph, the normalized grid electricity demand for the four type of vehicles considered are reported. It can thus be emphasised that each vehicle is indeed characterised by its own demand curve, which depends on the mobility pattern and the type of strategy considered.

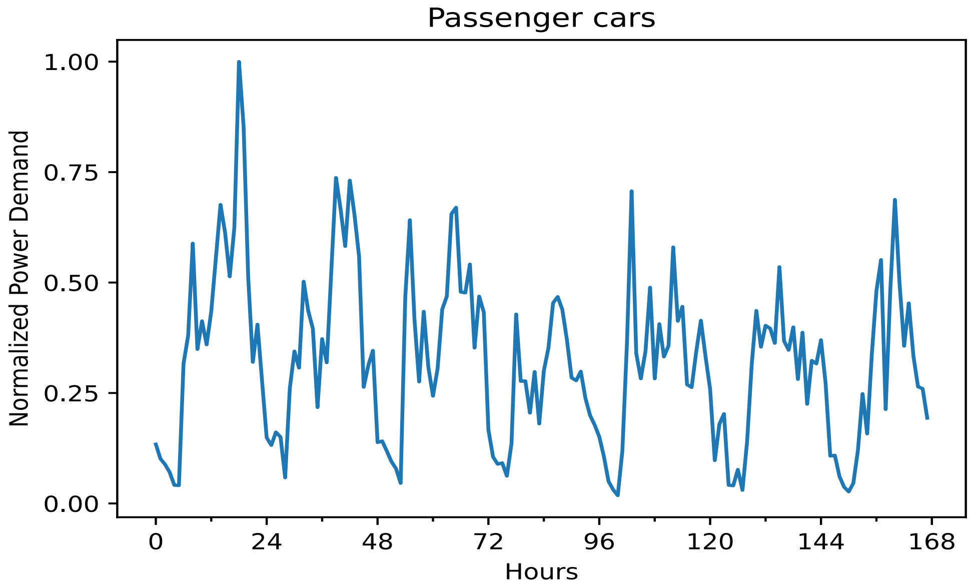


Figure 4.5 – Normalized grid power demand for the passenger cars sector for a spring week

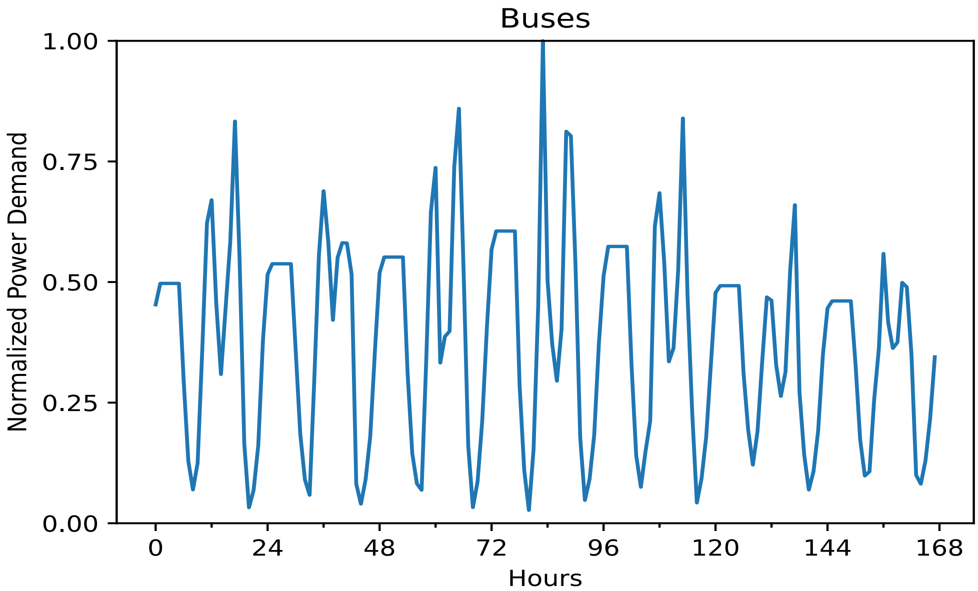


Figure 4.6 - Normalized grid power demand for the public buses sector for a spring week

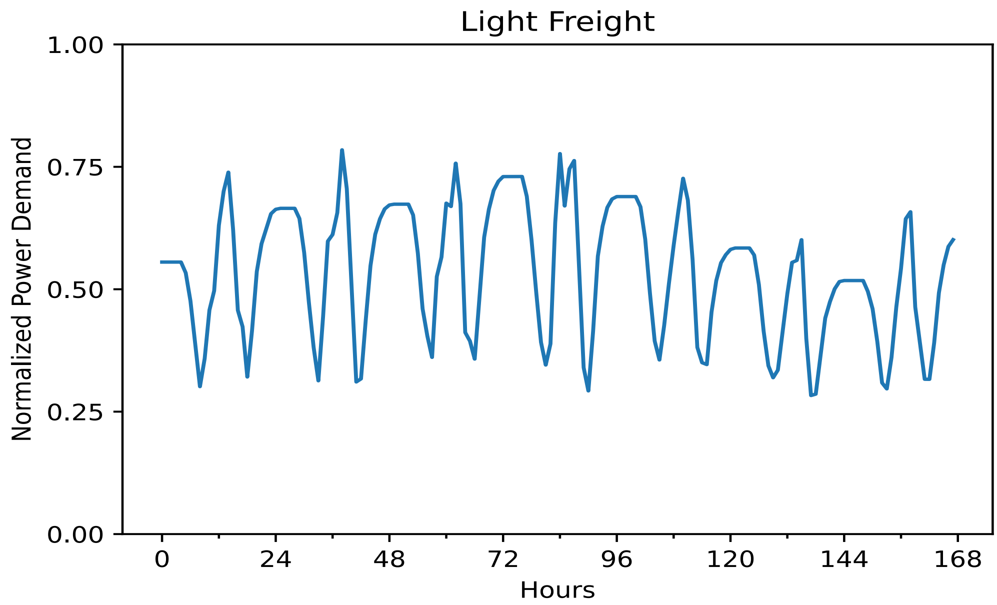


Figure 4.7 - Normalized grid power demand for light freight sector for a spring week

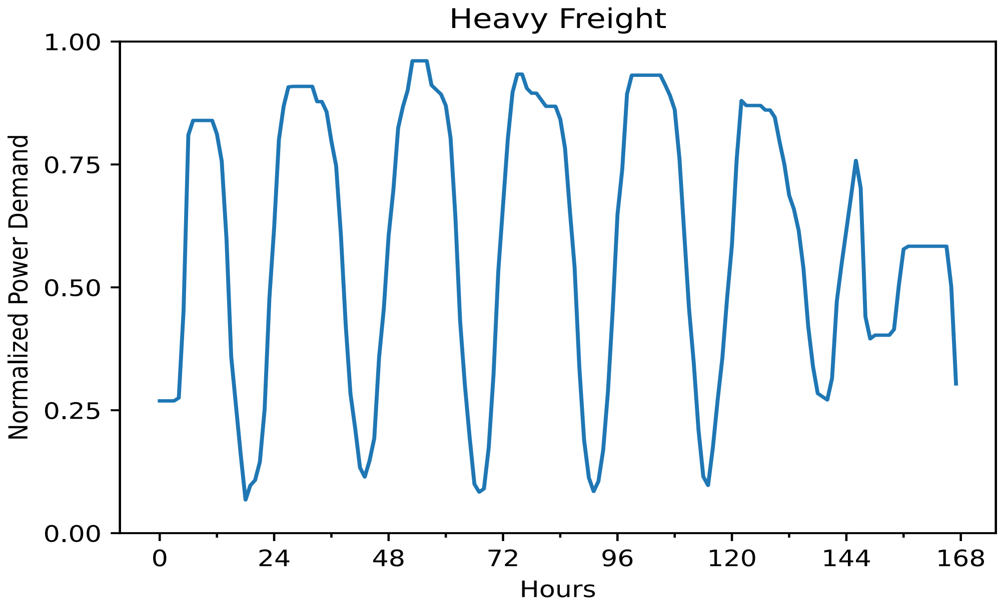


Figure 4.6 - Normalized grid power demand for the heavy freight sector for a spring week

The pattern related to passengers cars (Figure 4.5) is marked by two main aspects: on one hand the reduction of electricity demand at night-time, when vehicles that are charging at home use a lower rated capacity than public columns. During the day, on the other hand, the profiles show a greater irregularity, resulting from the use of an "immediate" strategy, in which BEVs recharge as soon as possible and at the maximum possible power.

For the bus category (Figure 4.6), there is a clear distinction between night-time recharges, which through the use of a balanced strategy can take place at a reduced power and spread out over a greater number of hours, and recharges that take place during short breaks in the day, where although the rated power is the same, the smaller amount of time available causes peaks in energy demand.

With regard to light transport (Figure 4.7), the same pattern as described for buses can be seen, with a visible distinction between night and day charges. However, as a result of the lower amount of kilometres driven, and with the consequent higher percentage of vehicles being in "headquarters" during the day, the difference in terms of power is less sharp.

For the heavy freight sector (Figure 4.8), the pattern is the most regular. Since the maximum number of trips is two, the trucks will recharge during the morning, once they return to base after completing their expedition during the night. On Sundays, when the traffic ban is imposed on this type of vehicle, and therefore most of them will remain at the main base, recharging will take place over an even longer period of time, allowing the power required from the grid to be reduced.

It is also reported the grid electricity demand, aggregating one workday and one day of the weekend, for the four vehicles, considering two different seasons of the year.

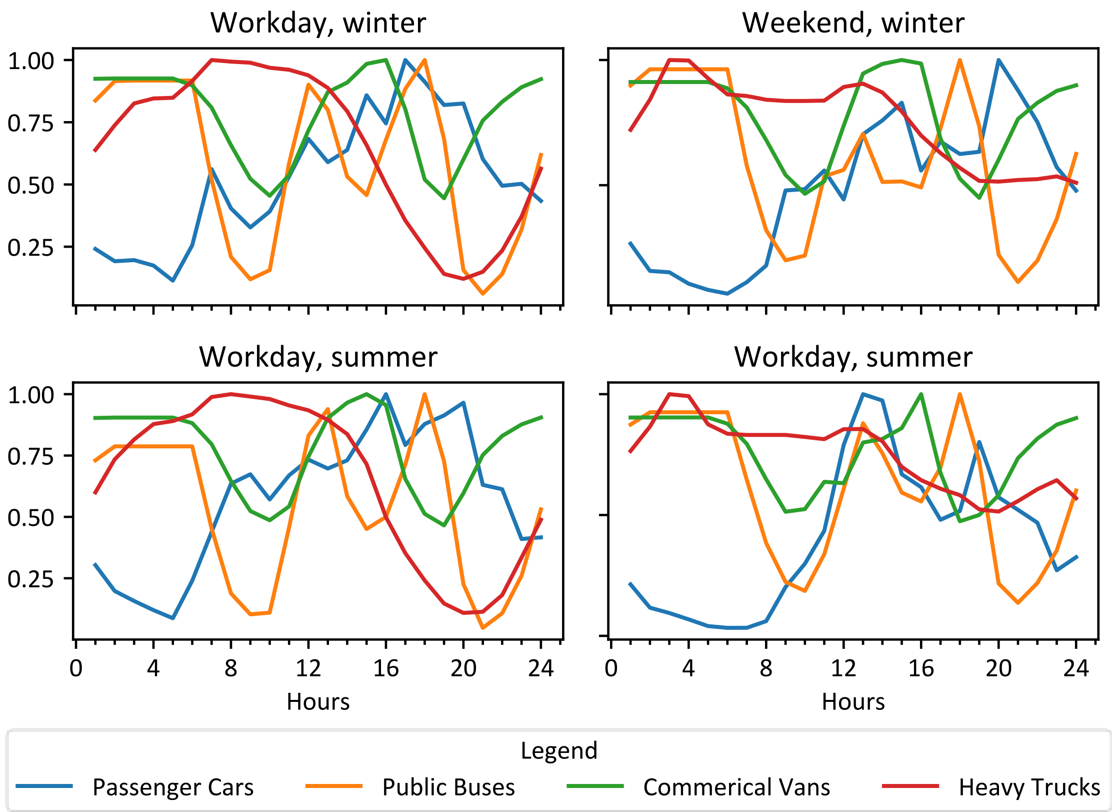


Figure 4.7 – Normalized electricity demand for an average winter and summer day, distinguished between workday and weekend

4.3. EV Penetration Scenarios

For the evaluation of the impact of the electrification of the transport sector, three different scenarios are considered: two mid-term scenarios (both having 2030 as the reference year) and one long-term scenario (which is instead referred to 2050).

The definition of two different types of scenarios derives from considerations of the form of European policies proposed for the reduction of emissions of the transport sector. In almost all cases, the binding directives refer to limits on new sales and not to blocks on existing cars. Hence, in order to analyse the effects of these policies, it is also necessary to consider a longer timeframe, to correctly represent the gradual transformation of the car fleet towards a zero-emission objective.

The reference study used for the definition of the medium-term scenarios is the "PianoClima 2022" [39], an analysis developed by Eurac Research, in which certain measures applicable within South Tyrol in various sectors (including transport) are shown, with the aim of achieving climate neutrality, in line with the most recent forecasts developed by the Intergovernmental Panel on Climate Change (IPCC). The long-term scenario is instead defined as an "extension" of the mid-term scenarios, with the inclusion of long-term European directives as well as objectives set by vehicle's manufacturers.

Following the same assumptions done for the "PianoClima 2022", a linear change of the new car fleet over the years is considered, with a partial effect on the overall present car fleet. It was also assumed that the overall car fleet remains unchanged (neither increasing nor decreasing) and that the average age of vehicles in South Tyrol does not change (e.g. equal to 10 years for cars, 12 years for public transport bus, 10 years for commercial vans and 8 years for heavy-truck) [39].

For the definition of future scenarios, it was also assumed that the value of the "basic demand" (defined as the electricity demand of South Tyrol without including the additional demand of the electrification of the transport sector) would remain constant and equal to the values for 2019. This decision stems from the absence of a regular trend in electricity consumption in South Tyrol over the last 20 years, which does not allow for a sufficiently accurate forecast of possible medium and long-term values [52]. Furthermore, in this way, any increase in electricity demand is due to the gradual electrification of the transport sector, allowing a clearer analysis of the results sought with this thesis.

4.3.1. ACTUAL Scenario

The two scenarios considered for the 2030 are those presented in the PianoClima 2022, developed by Eurac Research for Alto Adige:

- **ACTUAL scenario**: scenario in which current trends, local directives and European directives are considered, in terms of reduction of emissions in the transport sector. The most relevant measures implemented in this scenario are:
    - Ban on endothermic engines by 2035 for cars.
    - The number of zero-emission buses in public service by 2030 rises to 200 (equal to almost 25% of the total fleet).
    - Ban on endothermic engines by 2040 for light commercial vehicles.
    - 30% reduction in emissions by 2030 for heavy commercial vehicles.
- **IPCC scenario**: scenario that includes further measures to reach the 1.5 °C objective proposed by the IPCC (agreed at COP26 in Glasgow) which calls for a 45% reduction in emissions by 2030, compared to 2010 data. The main measures implemented in this scenario are:
    - For the car fleet, 80% of new vehicles sold are assumed to be zero-emission on-site in 2030.

- For public transport, this scenario assumes a complete conversion to zero-emission buses in 2030, i.e. 750 buses making up the total public service fleet.
- For light transport, 65% of new vehicles sold in 2030 are assumed to be zero-emission.
- For heavy transport, it is assumed that 45% of new vehicles will be zero-emission in 2030.

4.3.2. Long-term Scenario

For the definition of the long-term "ZEV scenario", the medium and long-term policies proposed by the EU are considered, in order to represent a condition in which a higher percentage of electrification of the transport sector is achieved with respect to the 2030 scenario, especially in the new sectors included inside *emobpy* (e.g. bus and light/heavy freight).

For each vehicle, the guidelines considered will be reported, also showing the trend of "new sales" and the change in the total fleet over the years until 2050, when almost all sectors will be electrified or at least composed only of zero-emission vehicles.

4.3.2.1. Passenger cars

For the electrification of the passenger cars, the European directive "Fit for 55%" is considered [13], which defines a minimum share of zero-emission vehicles (ZEV) among the new releases, this value is set to 15% in 2025, then it is set to 55% in 2030, while from 2035 onwards, only ZEVs can be sold. Even if the definition of ZEV includes also other technologies like fuel-cell vehicles, for this category it is assumed that in future scenario the BEV will be the only technology chosen by the users, like suggested by Abid et al. [53]

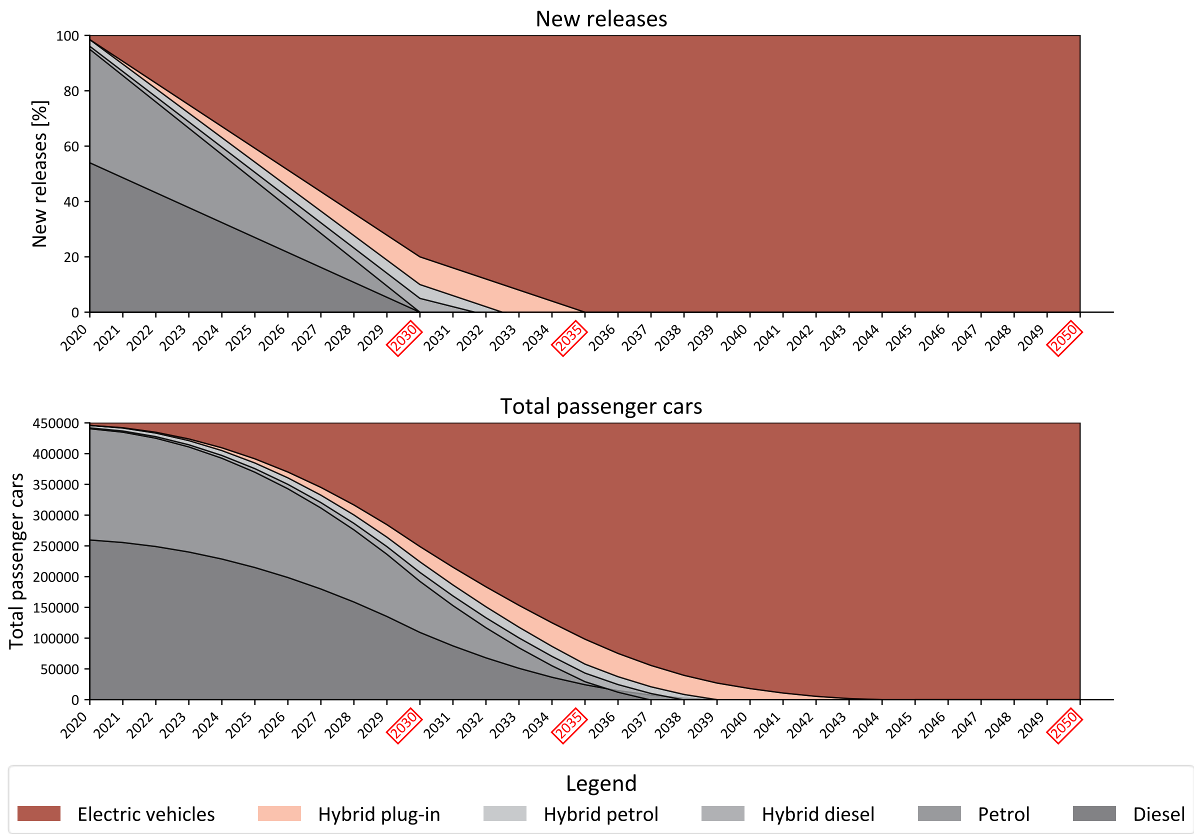


Figure 4.8 – Development of the passenger cars sector, in terms of new releases (Top) and total fleet composition (Bottom) in South Tyrol 2020-2050

Extending the scenario to 2050, following the medium-term directives imposed by the European Union, a complete electrification of the car fleet can be achieved in the long term. More specifically, as far as passenger cars are concerned, this goal is already reached around 2044.

4.3.2.2. Bus

For this kind of vehicle, the shares of new releases reached in the IPCC mid-term scenario are kept constant, assuming also a slight reduction of the share of Fuel Cell Bus until 2050.

Also in this case, the effect of the policies assumed leads to a public transport sector completely composed by ZEVs in 2041. After that year the share is almost constant, with just a gradual substitution of Fuel Cell bus with BEBs.

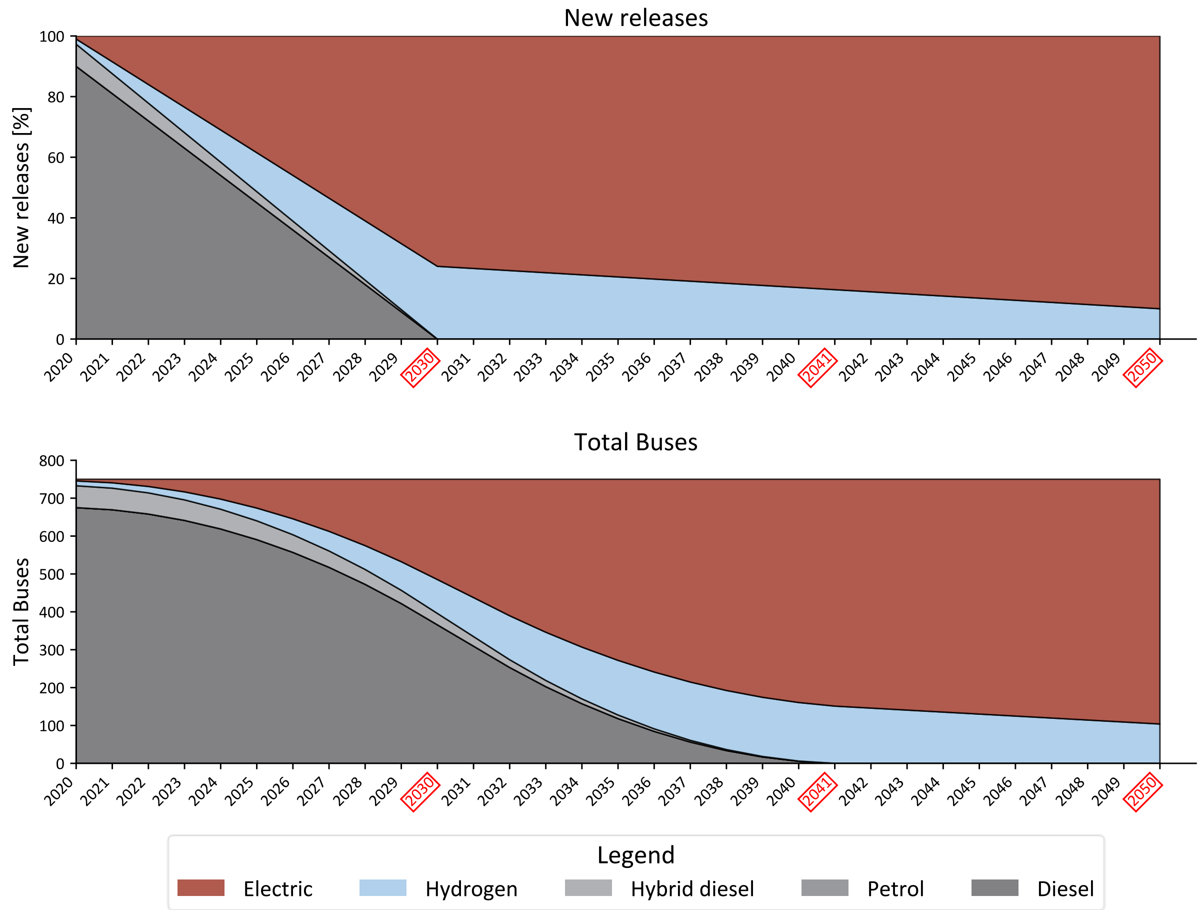


Figure 4.9 – Development of the public buses sector, in terms of new releases (Top) and total fleet composition (Bottom) in South Tyrol 2020-2050

4.3.2.3. Commercial vans

As for the passenger cars, the directive "Fitfor55%" also includes boundaries for the sales of light freight commercial vehicles. In this case the share of ZEVs among the new releases is set to 15% in 2025, then it is increased to 50% for 2030, while from 2035 onwards only ZEVs can be sold.

Due to the similar policies implemented with respect to the passenger cars, the trend of the vehicle fleet is similar to the one showed in Figure 4.8, with a complete electrification reached around 2024.

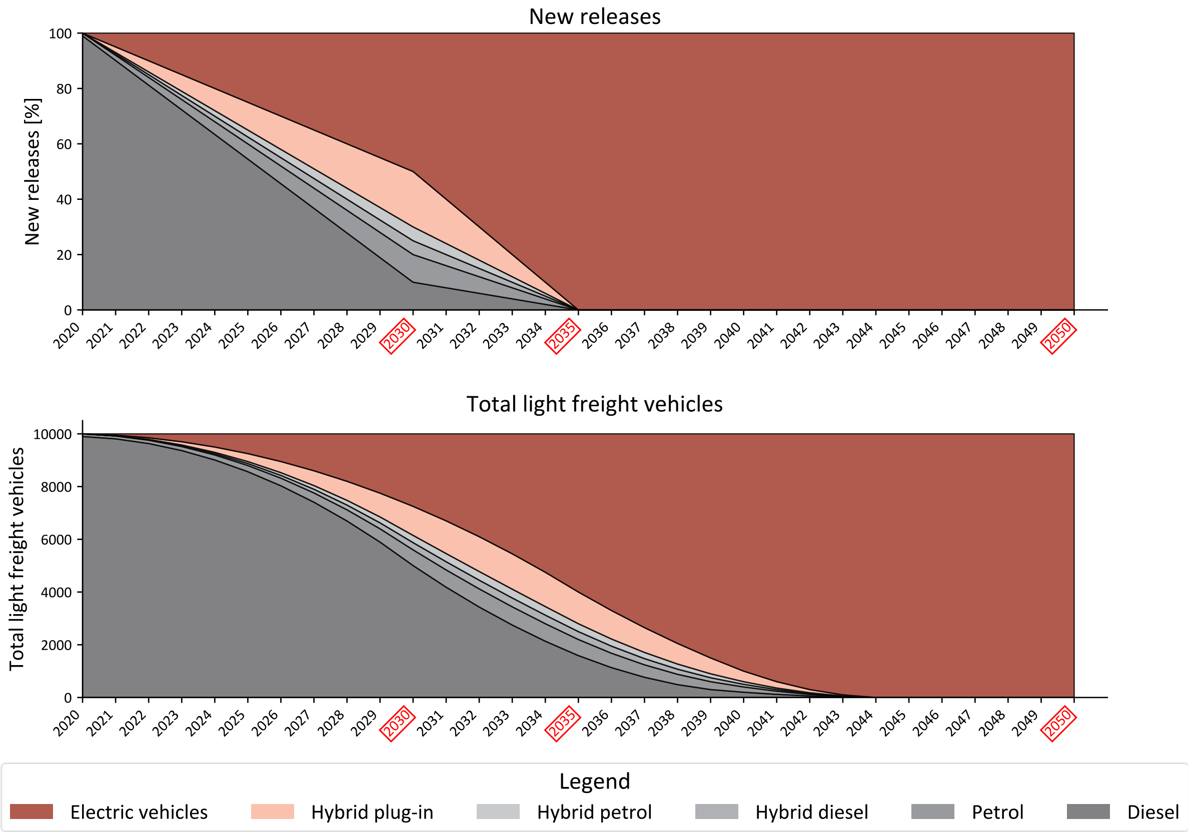


Figure 4.10 – Development of the light freight sector, in terms of new releases (Top) and total commercial vans fleet composition (Bottom) in South Tyrol 2020-2050

4.3.2.4. Heavy truck

To evaluate the trend of the new releases, due to the absence of local or European binding directives regarding the heavy freight sector, it is instead considered the selling objective of the heavy-duty truck manufacturers, in terms of share of ZEV among the models sold, as reported in Table 4.1.

Table 4.1 – Zero-emission vehicle fleet target, as proposed by the major manufacturers in the heavy-truck sector. LH: Long-Haul; RD: Regional Delivery

	Manufacturer	**2025**	**2030**	**2039**	**2040**	**Market Share in 2020**
Zero-emission vehicle fleet target	DAF	-	-	100%	100%	18%
	Iveco	-	-	-	100%	6%
	MAN	-	40% LH 60% RD	-	100%	15%
	Daimer Trucks	-	60%	100%	100%	18%
	Renault Trucks	10%	35%	-	100%	9%
	Scania	10%	50%	-	100%	18%
	Volvo Trucks	7%	50%	-	100%	16%

The trend of the heavy freight vehicles is then reported in Figure 4.11.

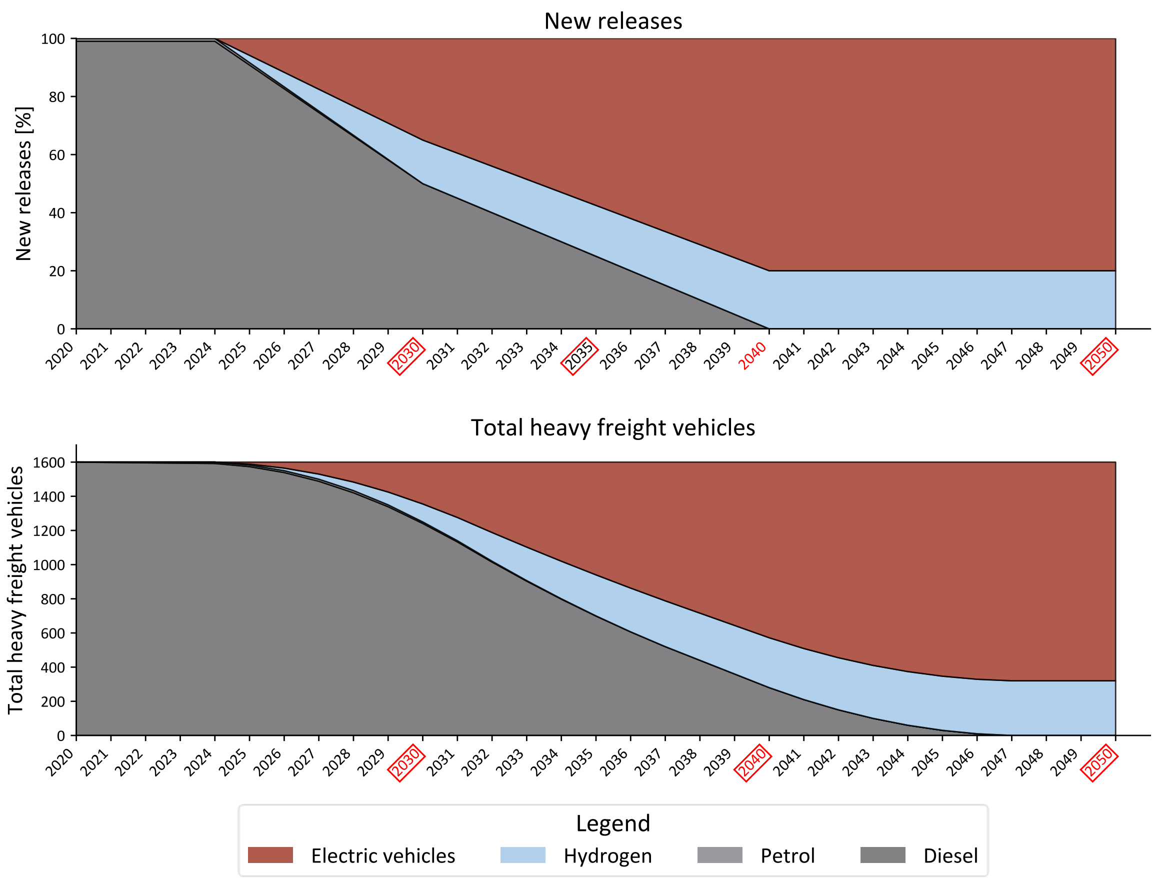


Figure 4.11 - Development of the heavy freight sector, in terms of new releases (Top) and total heavy truck fleet composition (Bottom) in South Tyrol 2020-2050

Of all the vehicles considered, heavy trucks are the ones that take the longest to achieve complete decarbonisation, due to the more gradual constrains on new sales, it is only in 2047 that a complete transition to zero-emission vehicles is achieved. This is also related to the fact that this sector is also the only one that has not yet seen strong sales of hydrogen and electric models on a large scale, due to the more complex transition from conventional petrol or diesel models, as a result of the large amount of kilometres travelled per trip that required a greater engineering effort from manufacturers.

4.4. EVs effect on the South Tyrol electricity demand

In this section the results obtained will be analysed, comparing the electricity demand for recharging vehicles, in addition to the "Standard Demand" energy consumption of South Tyrol, considering medium-term and long-term scenarios.

With regard to the ACTUAL 2030 scenario, the partial electrification of the vehicle fleet leads to a slight increase in energy demand. This demand is almost solely due to passenger cars, as this is the only sector that will achieve a substantial percentage of electric vehicles by 2030, with the exception of commercial vans, whose total number of vehicles on the road is, however, significantly lower than passenger cars, as shown in the Figure 3.1.

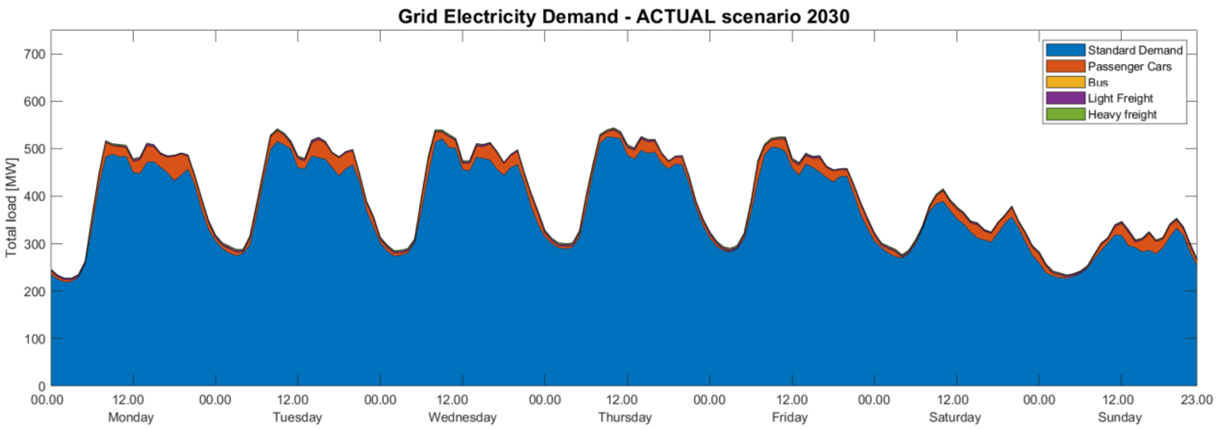


Figure 4.12 – Grid electricity demand – ACTUAL Scenario

As far as the IPCC 2030 scenario is concerned a visible increase in additional energy demand is present, which is, however, again mainly due to passenger cars. Despite the adoption of stricter measures concerning the proportion of zero-emission vehicles among the 'new releases' (which are mainly referred to 2030 or 2035), the car fleet does not see sufficient replacement by 2030, as no restrictions on the already existing vehicles are considered.

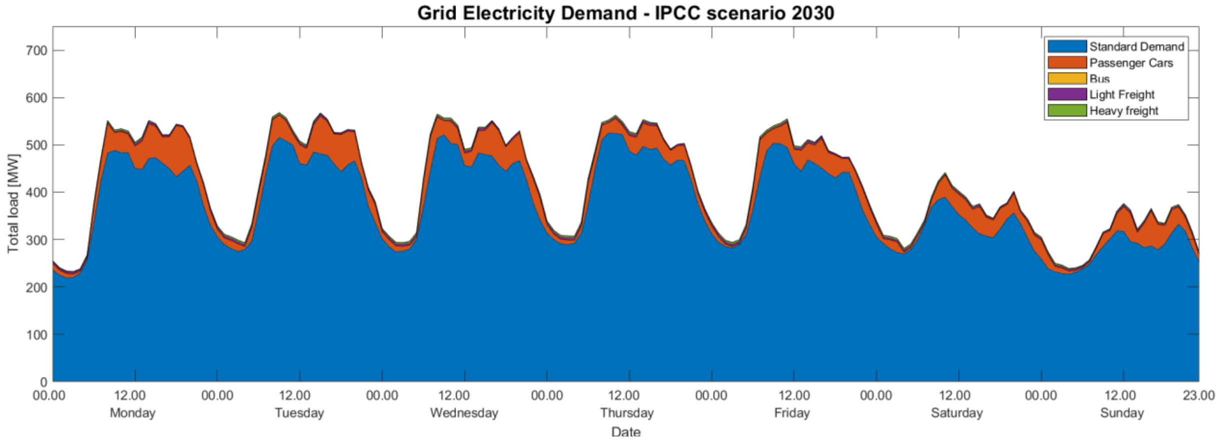


Figure 4.13 - Grid electricity demand – IPCC Scenario

In the ZEV 2050 scenario, on the other hand, two different aspects can be noted, mainly related to the transition to a long-term scenario.

Firstly, a further increase in the electricity required for recharging passenger cars, in line with the trend seen in the two previous scenarios. As can be seen in the Figure 4.16, by 2050 the results of the imposition of medium-term measures are beginning to be seen, as a result of which the passenger car sector in 2050 is completely made up of electric vehicles, leading to a net increase in the number of electric vehicles on the road and thus in the energy required for the grid.

From the second point of view, considering a long-term scenario set in 2050, the policies and regulations imposed for other types of vehicles also take effect, and as seen in the Figure, almost all four-wheeled vehicles on the road are electric vehicles (with the exception of the bus sector, with a share of zero-emission vehicles made up of hydrogen-powered buses). Hence, there is a more substantial demand for electricity to recharge commercial vehicles (which represent the second largest vehicle type) and trucks, which, despite the even smaller number of vehicles on the road, require a significant amount of electricity to recharge their large on-board batteries.

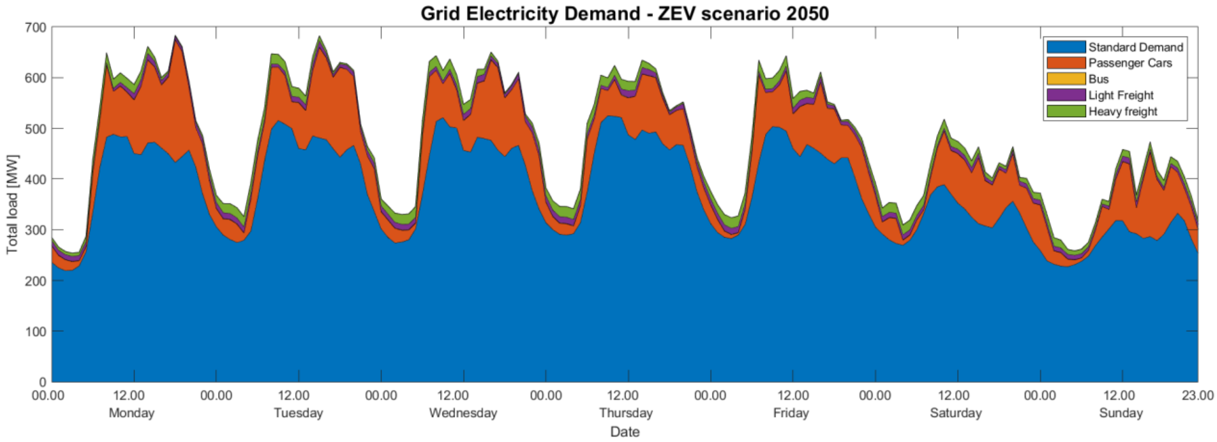


Figure 4.14 - Grid electricity demand – ZEV Scenario

In all three scenarios considered, there is little 'stressful' recharging on the network for electric buses, which are the least numerous vehicle type in South Tyrol.

An important consideration must also be made with regard to the charging strategy chosen for the various vehicles, and the consequences for the South Tyrol energy system. As far as passenger cars are concerned, the use of an immediate strategy implies a greater number of peaks throughout the day, and also a demand for electricity concentrated in the daytime hours, when the vehicles start moving from home and begin recharging at the highest possible power as soon as they reach their destination and find an available charging station. In this context, the majority of charging stations are public charging stations, which have a significantly higher nominal capacity than domestic charging stations. As far as the other types of vehicles are concerned, the choice of a balanced strategy makes it possible to have a more evenly distributed recharging. Consequently, although for this type of vehicle the charging stations used have a significantly higher nominal capacity than the charging stations for passenger cars (with the exception of fastchargers, which are, however, much less present on the territory), for buses and light and heavy transport, the impact on the electricity grid is more uniform. For this reason, at night, the energy required mainly by trucks and commercial vehicles (which are recharging before the start of the new working day) exceeds the energy required by passenger cars, which, on the other hand, have recharged mainly during the day if they have had the opportunity, or are at most recharging at home at low power.

4.5. South Tyrol energy system in future scenarios

For the implementation of BEV inside the energy system of the case study considered, the values obtained in the previous chapter are taken into account, relative to the electric vehicles energy demand. For each scenario, it will be reported a yearly analysis and an hourly analysis, in order to investigate the capability of the grid to continuously fulfil the demand

4.5.1. ACTUAL scenario

The Figure 4.15 shows the increase of the yearly electricity demand due to the partial electrification of the transport sector in the ACTUAL scenario, and how the different regions are affected. All the regions are just lightly affected by the increased electricity demand, without showing any evident critical issue.

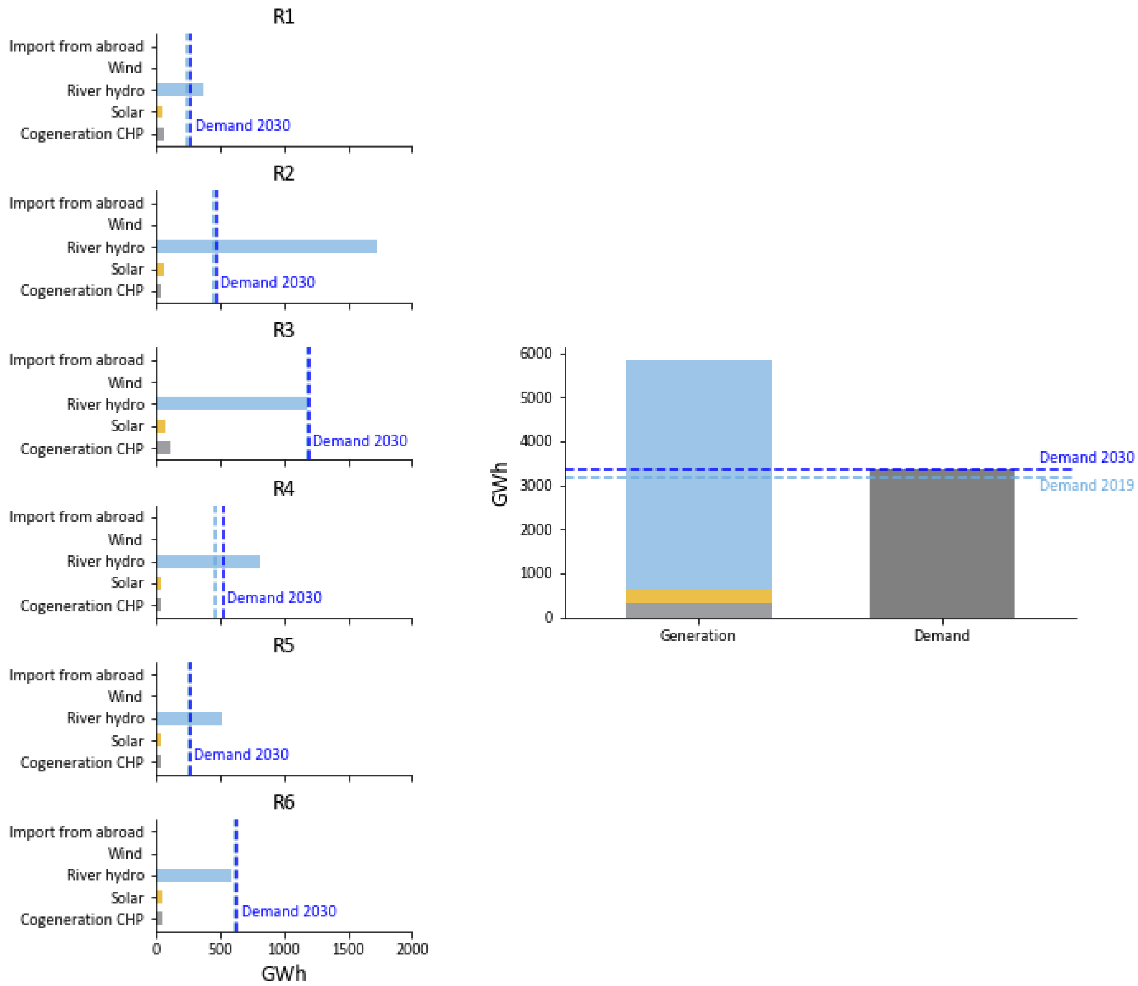


Figure 4.15 – Yearly electricity generation and demand of the different nodes (on the left) and the overall values (on the right) – ACTUAL Scenario

In the Figure 4.16, are instead represented the profiles of the hourly generation and consumption of electricity, also to illustrate the effect of seasonality on the behaviour of the energy system of each macro-area. At the same time, on an hourly basis a mismatch between hydro generation and electricity demand could occur, in those cases the system balanced by exchanges of electricity between the different nodes of the grid. In some regions the export of electricity to other nodes is more frequent, especially those where the hydropower production, which can provide a very constant supply of renewable energy, is largely higher than the demand.

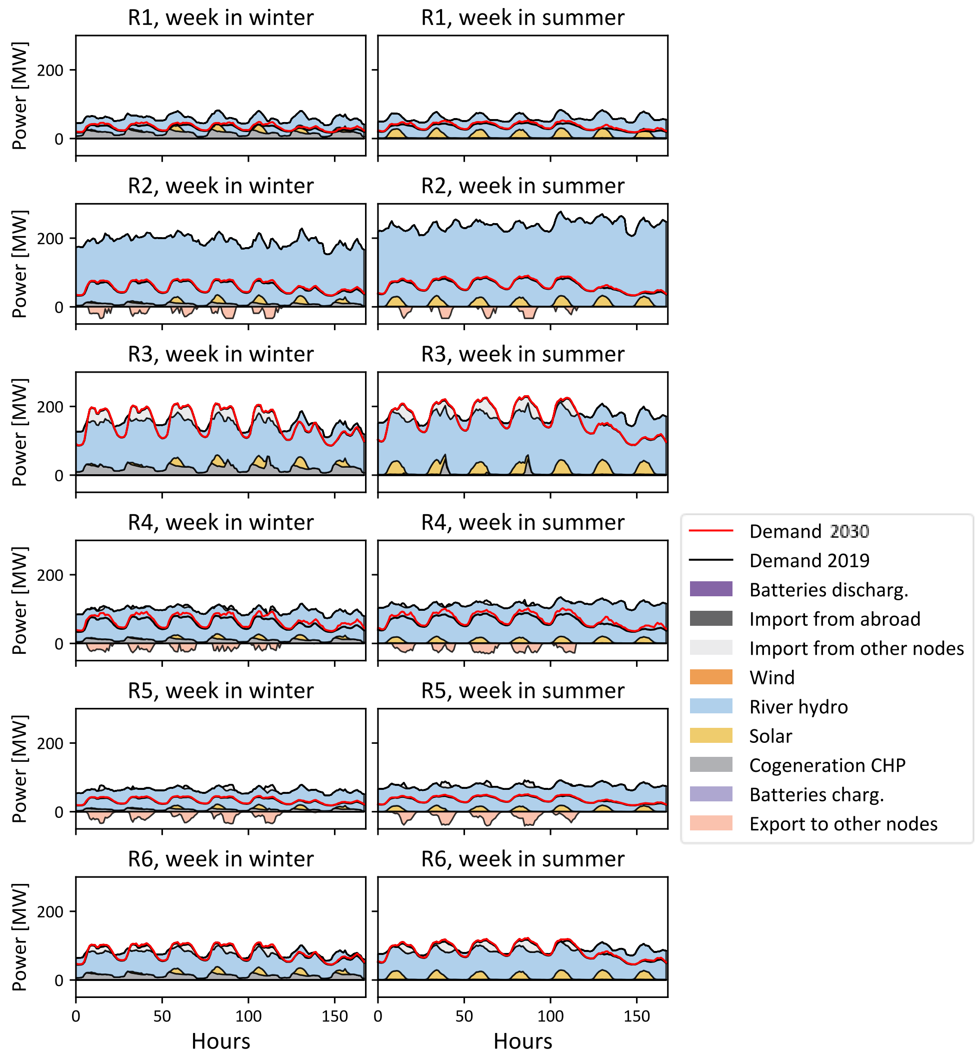


Figure 4.16 - Electricity generation and demand of the different nodes for a week in winter (on the left) and a week in summer (on the right) – ACTUAL Scenario

Figure 4.17 highlights instead the connections between the nodes and their bottlenecks. It shows how many hours of the year the bottlenecks are saturated and congestion problems might arise.

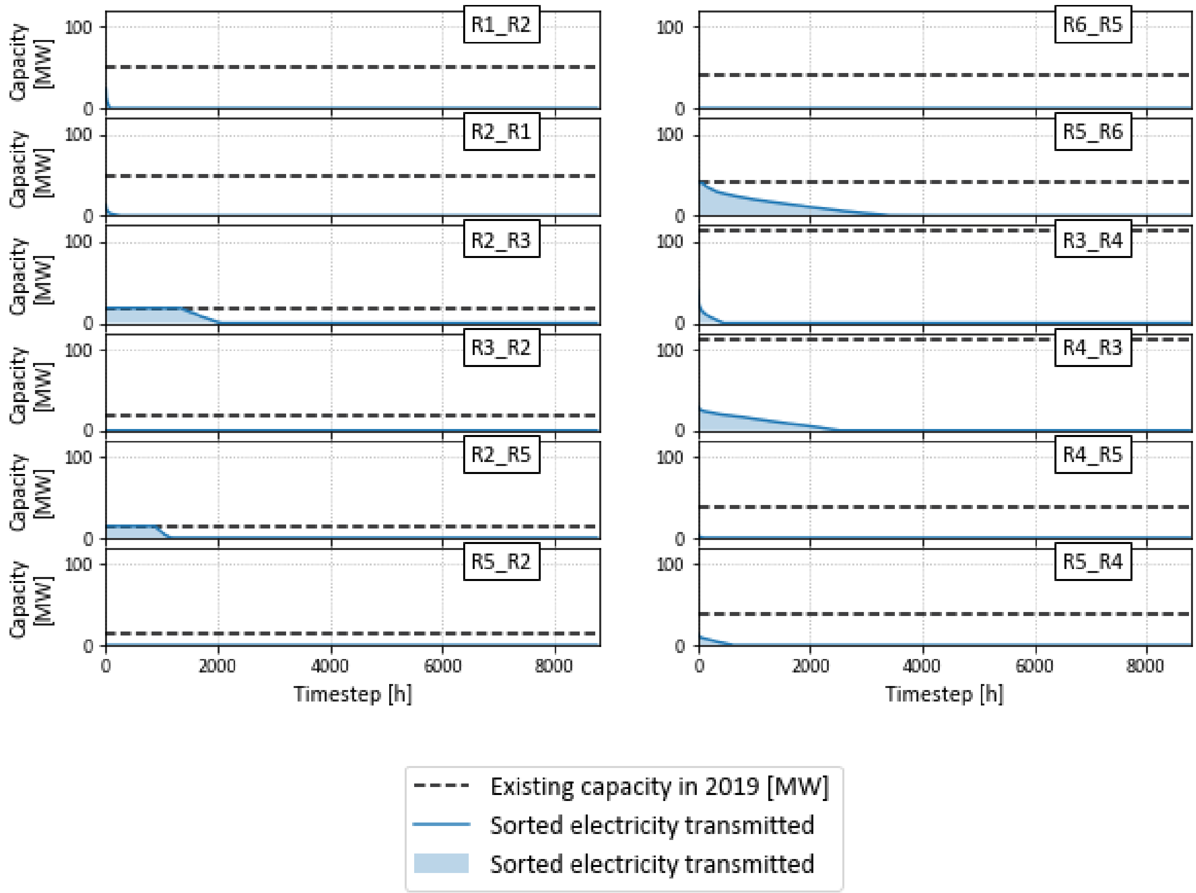


Figure 4.17 - Saturation of the connections between nodes – ACTUAL scenario

4.5.2. IPCC Scenario

In the IPCC the amount of electric vehicles is increased, so a corresponding increase of the electricity demand is expected.

The Figure 4.18 shows the increase of electricity demand due to the partial electrification of the transport sector in the IPCC scenario, and how the different regions behave. It's evident that even in this case, the stability of the system is not particularly affected. Each region is able to meet its own electricity demand, either through on-site production, or through the inport of electricity from other nodes.

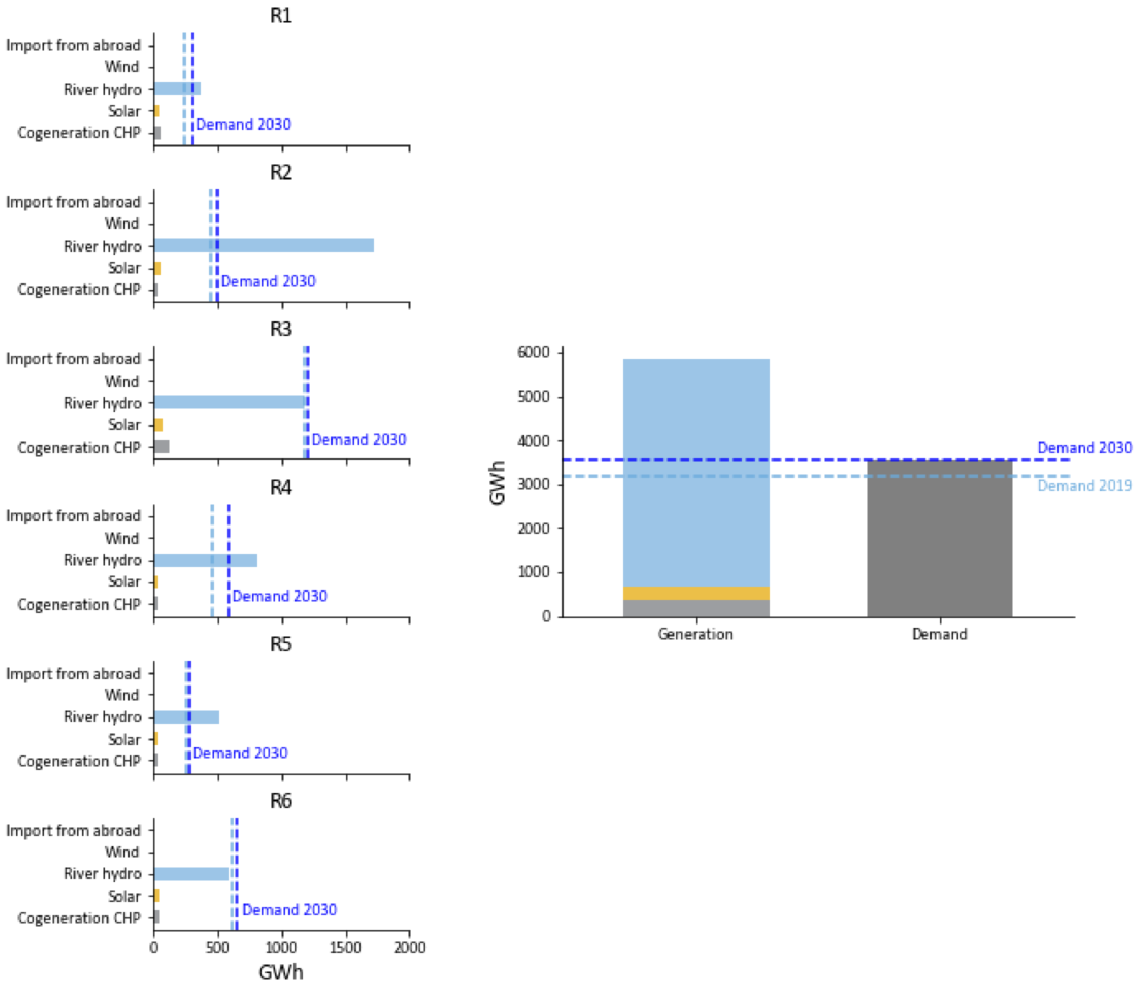


Figure 4.18 - Yearly electricity generation and demand of the different nodes (on the left) and the overall values (on the right) – IPCC Scenario

In the Figure 4.19, are instead represented the profiles of the hourly generation and consumption of electricity, also to illustrate the effect of seasonality on the behaviour of the energy system of each macro-area. In some regions the export of electricity to other nodes is more frequent, especially those where the hydropower production, which can provide a very constant supply of renewable energy, is largely higher than the demand.

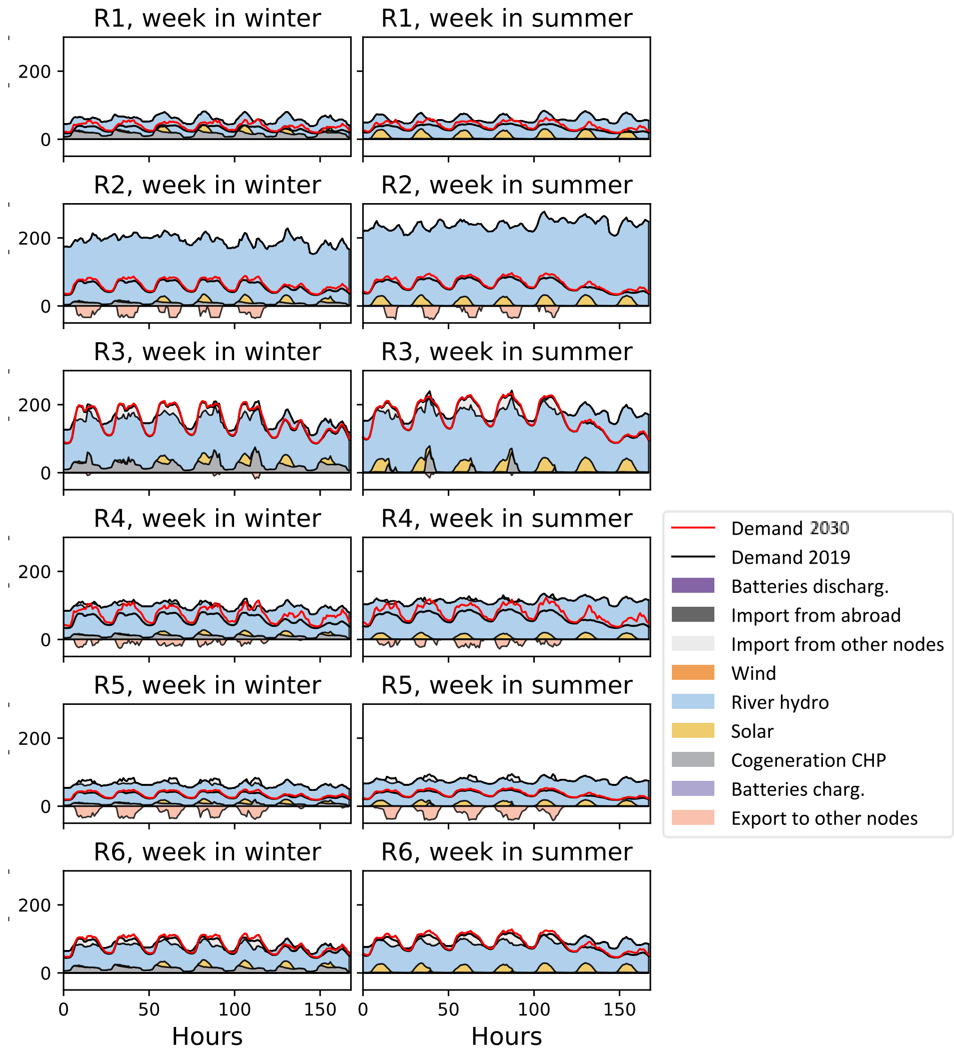


Figure 4.19 - Electricity generation and demand of the different nodes for a week in winter (on the left) and a week in summer (on the right) – IPCC Scenario

Figure 4.20 highlights instead the connections between the nodes and their bottlenecks. It shows how many hours of the year the bottlenecks are saturated and congestion problems might arise. In the scenario IPCC the saturation level of the grid bottlenecks does not visibly change with respect to the ACTUAL scenario.

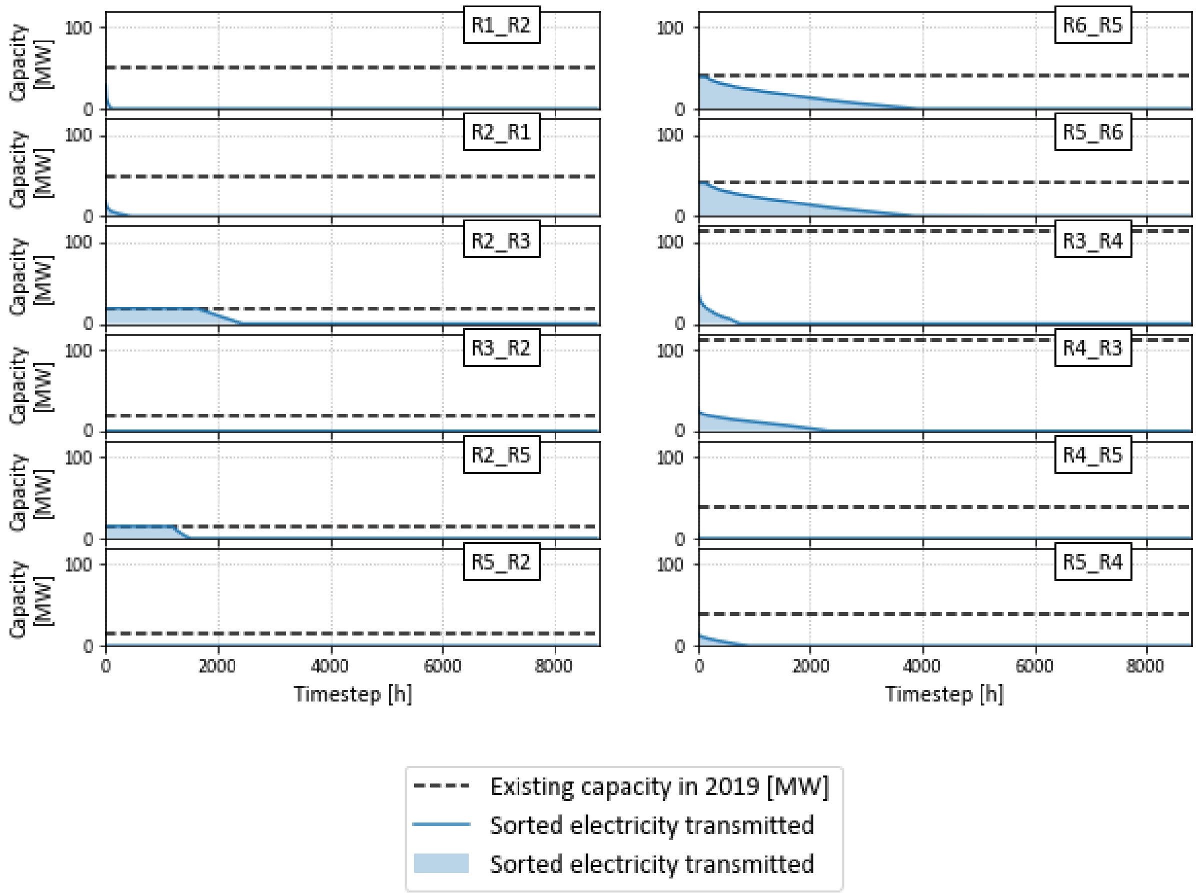


Figure 4.20 - Saturation of the connections between nodes – IPCC scenario

4.5.3. ZEV scenario

In this case, the switch to a long-term scenario causes a huge increase of the amount of electric vehicles circulating, in this case the impact on the system is extremely more relevant. Considering the Figure 4.21, the increase of the electricity demand causes some critical imbalances in the regions where the hydroelectrical power is less abundant, only the regions R2 and R5 could apparently support this stress to the grid, keeping on fulfilling the demand on a yearly basis with on-site Hydroelectric power plants.

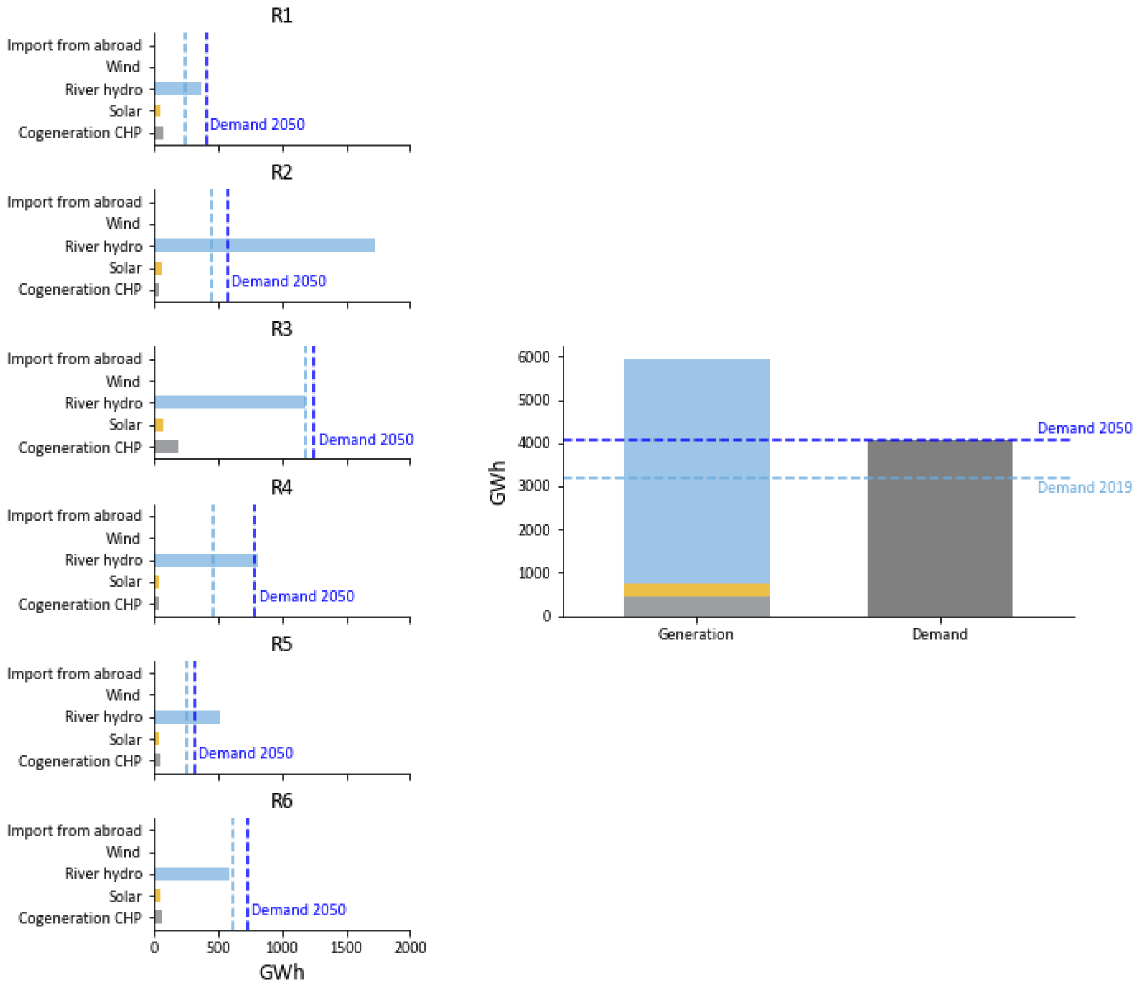


Figure 4.21 - Yearly electricity generation and demand of the different nodes (on the left) and the overall values (on the right) – ZEV Scenario

But if an hourly dispatch is considered, like in Figure 4.22, the major criticalities are shown. In some regions, during the middle hours of the day, the production of hydroelectric, solar, chp and import from other nodes are not enough to meet the increased demand for electricity, and so those regions are forced to import energy from abroad, generally leading to possible congestion problems. This phenomenon occurs both on summer and on winter periods.

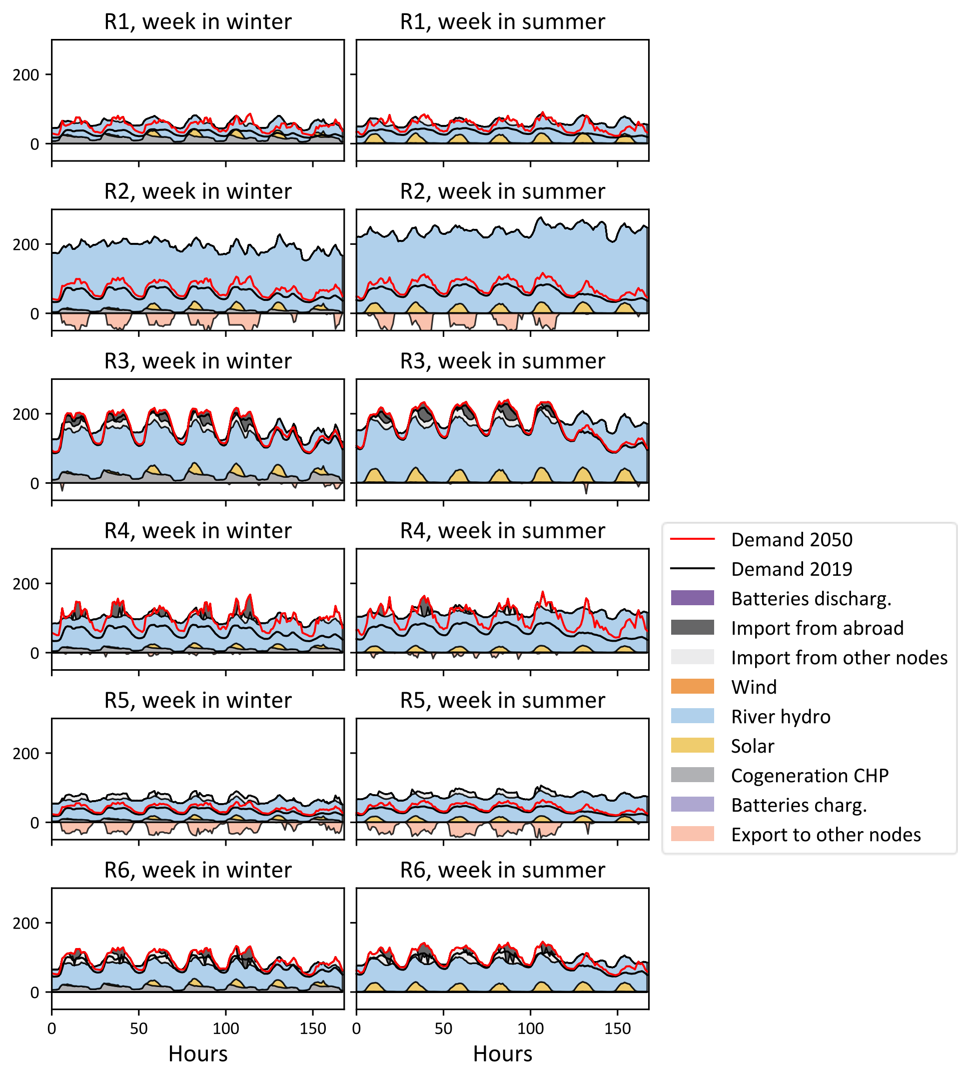


Figure 4.22 - Electricity generation and demand of the different nodes for a week in winter (on the left) and a week in summer (on the right) – ZEV Scenario

In Figure 4.23 the trasmission grid behaviour is reported, showing that the need of energy from abroad couldn't be completely overcome by a simple increase of the power that can be trasmitted between each node.

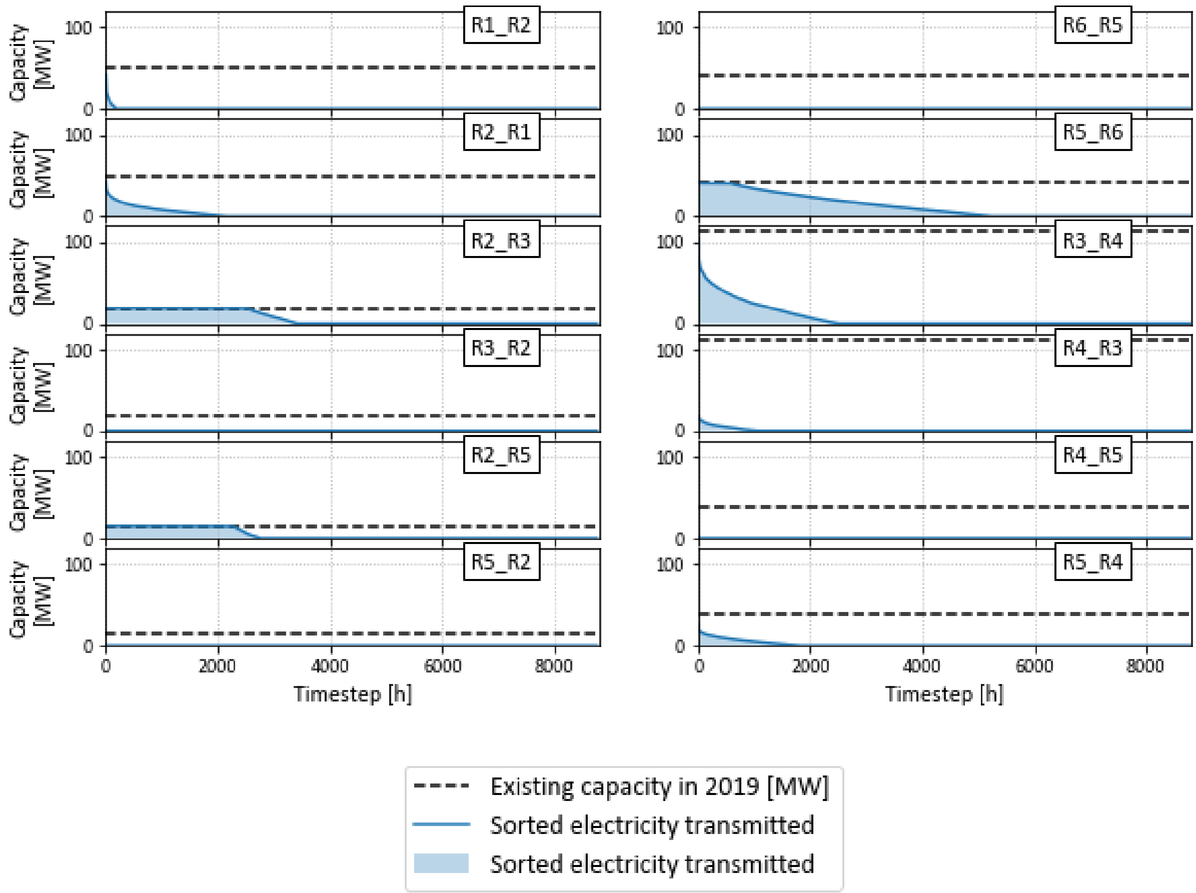


Figure 4.23 - Saturation of the connections between nodes – ZEV scenario

4.6. Controlled Strategies implementation

In the light of the results shown in the previous paragraph, it can be seen that even in South Tyrol, an area in which the production of energy through renewables is currently double the demand, if a long-term scenario is taken into consideration, in which the goal of complete replacement of fossil-fueled cars in favour of electric cars and hydrogen vehicles is achieved, the increase in demand for electricity will become such that it will be necessary to increase the import of energy from abroad, with possible congestion problems.

In order to evaluate the effectiveness of the possible implementation of the "controlled" charging strategies (hence including both smart charge and V2G), an "aggregate" (i.e. single-node) representation of the South Tyrol region is initially taken into account, including all the power generation and thermal and electricity demand into only one "real" node R, which is connected to the corresponding "fictitious" node R_BEV, evaluating the correct behavior of the system through a sensitive analysis, thus varying the energy mix of the region considered (only one spring week is reported, extracted from the yearly simulation). The technologies taken into consideration for such analyses will be only those more present inside the South Tyrol, that is photovoltaic and hydroelectric. Cogeneration plants are not initially taken into account because, for the initial assessment of the effectiveness of the assumptions applied, the thermal load of the region R was not included, but only the electrical load.

Among the three future scenarios considered, the one that was taken as the reference for the subsequent implementation of smart charge and vehicle-to-grid technologies is the long-term one called ZEV 2050. This is because it represents the scenario in which the greatest increase in the electricity demand occurs, leading to possible stress on the grid, and so there is the greatest possible benefit of using these technologies.

4.6.1. Smart charge

4.6.1.1. Full PV scenario

Within this scenario, the R region is only powered by photovoltaic systems. In the lower part of the Figure 4.24, the graph of consumption of electric vehicles (black line) is reported. In the moments when in the real region R the production through photovoltaic exceeds the demand for electricity, the excess energy is sent to the R_BEV region for the recharging of the vehicles. Within the R_BEV region, this energy is used to meet the electricity demand of the vehicles, and the excess is sent inside the fictitious R_BEV, storage.

In this way, it can be seen that, from the point of view of the R region, the vehicles are actually recharged exploiting the moments of production through renewable. Another aspect that is correctly carried out within the R region is that, when PV production is not sufficient to meet demand, the system uses the import of energy from abroad, the imported energy is only used for this purpose, In fact, the electrical energy required for the charging of vehicles is through the discharge of the storage.

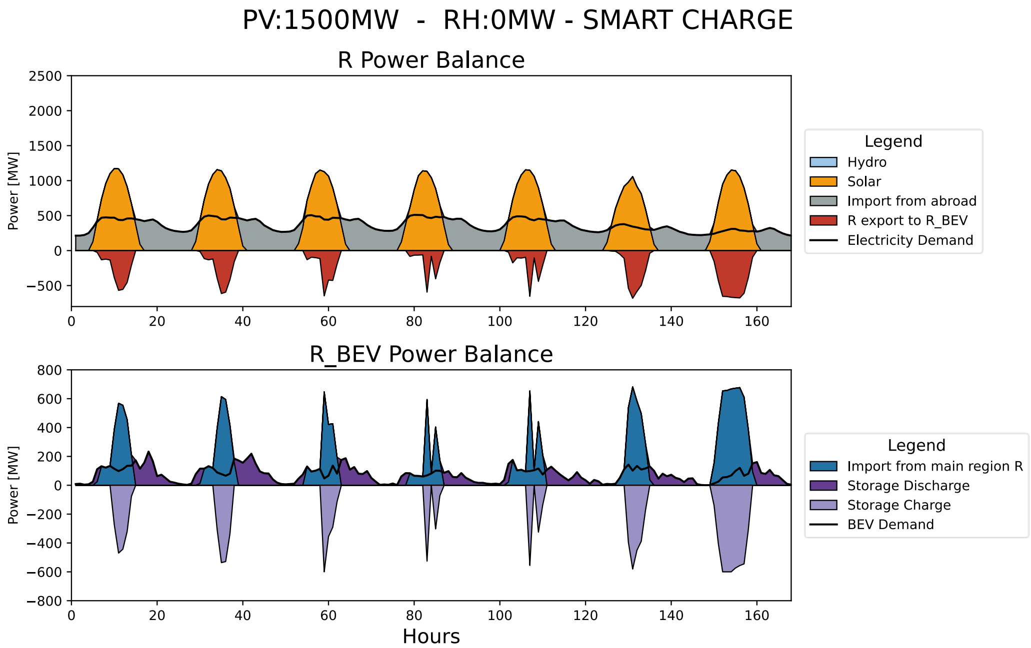


Figure 4.24 – Power balance of the main region R (top) and its fictitious node R_BEV (bottom), considering a "full-PV" energy production sector, when a smart charge strategy is introduced

Gradually increasing the nominal capacity of the photovoltaic systems installed, the behavior is the same, with the correct charging of the vehicles in the moments of overproduction by photovoltaic, is however evident as only through the use of photovoltaic systems and a smart charge strategy, the system still needs to resort to the import of energy from abroad.

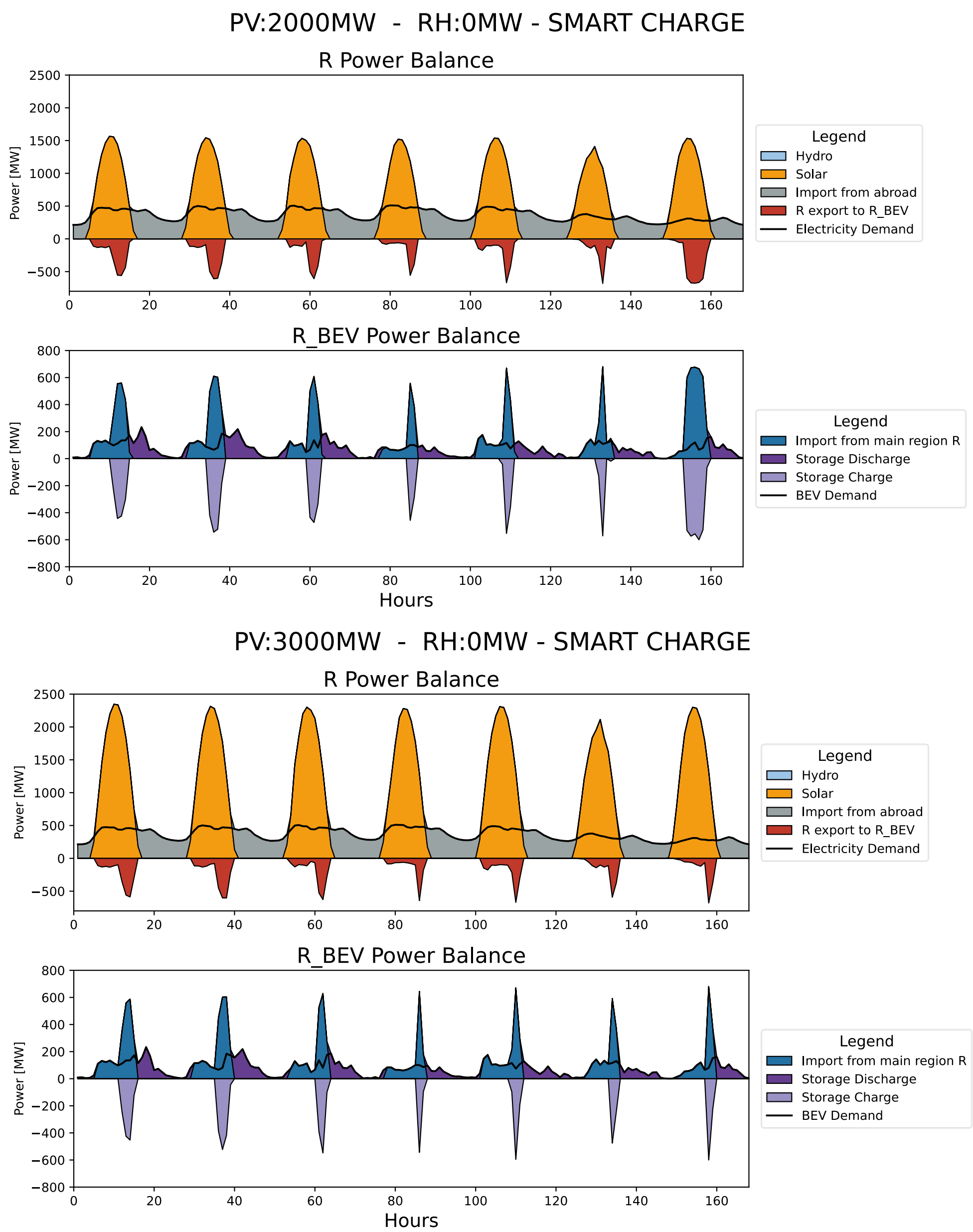


Figure 4.25 - Power balance of the main region R and its fictitious node R_BEV, considering a gradual increase of the PV capacity installed, when a smart charge strategy is introduced

4.6.1.2. PV + Hydro

In this case hydroelectric plants are also taken into account, in this way the consequences of the introduction of a more constant renewable energy source (compared to only photovoltaic) are assessed.

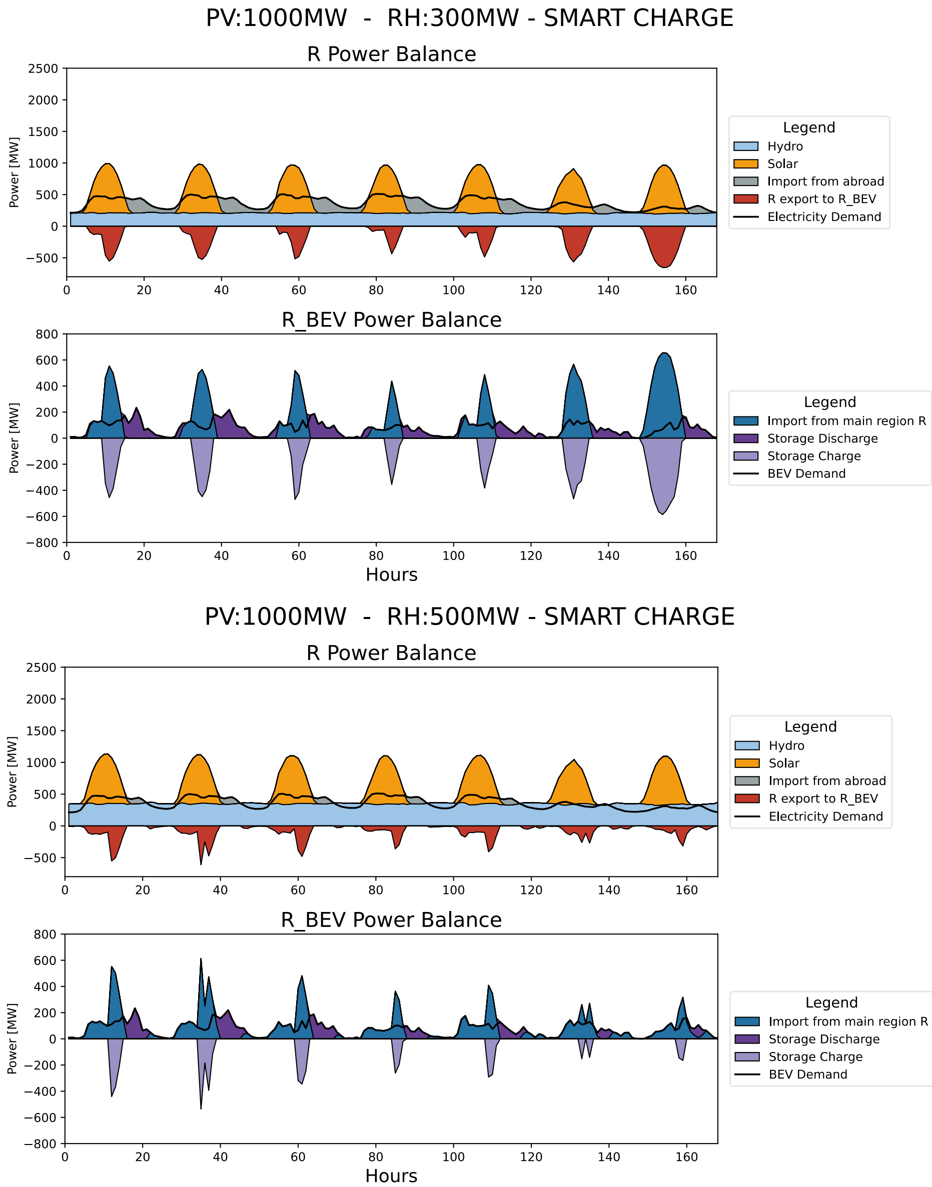


Figure 4.26 - Power balance of the main region R and its fictitious node R_BEV, considering a gradual increase of the RH capacity installed, when a smart charge strategy is introduced

As a result of the inclusion of hydroelectric technology, there is no substantial difference in the energy profile that is transferred from Region R to Region R_BEV (thus equivalent to the transfer of energy by the grid for vehicle recharging). The only noteworthy aspect is the correct reduction of the amount of energy that must be imported from abroad, thanks to the hydroelectric energy that allows to cover the electricity demand, especially at night.

4.6.1.3. Actual Energy Mix

In this case, instead, the nominal capacity of the power plants currently installed within the region of South Tyrol has been considered. It can be noted, unlike the cases previously considered, the much larger amount of hydroelectric installed.

Considering the capacity currently installed in South Tyrol, it can be noted that, given that the energy production far exceeds the demand, the region R fulfils «instantaneously» the demand for charging electric vehicles in the R_BEV region, without ever using storage. In these cases, since the system does not benefit from recharging the vehicles at certain times (as opposed to what happened previously with the transfer of energy only in the middle of the day), the "smart charge" profile coincides with the profile "dumb".

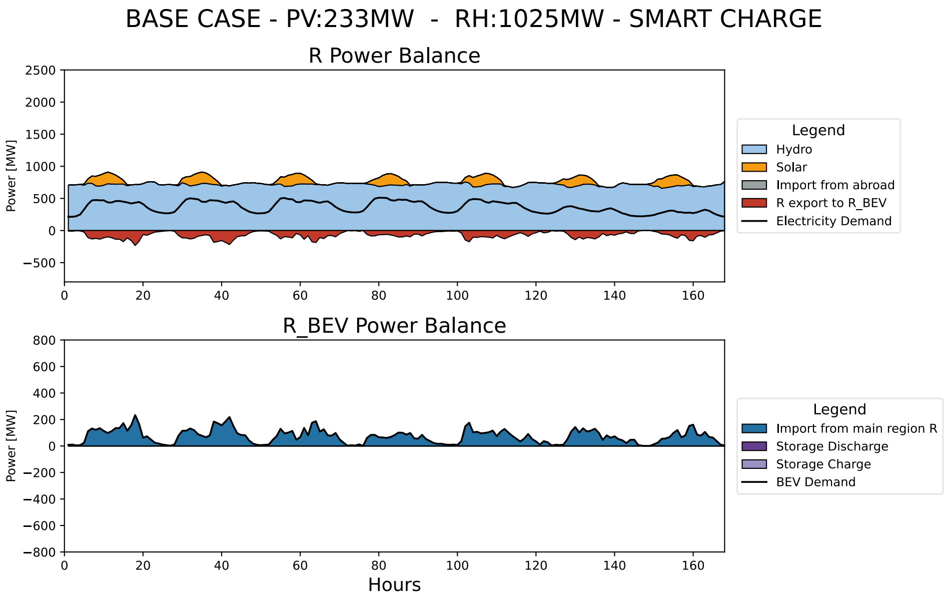


Figure 4.27 - Power balance of the main region R (top) and its fictitious node R_BEV (bottom), considering the actual capacity of PV and RH power plants in South Tyrol, when a smart charge strategy is introduced

4.6.2. Vehicle-to-grid

Considering the above paragraph, it is clear that the implementation of a V2G technology is crucial to reduce the need to import energy from abroad, and at the same time to ensure greater autonomy of the electricity grid, allowing electric vehicles to behave like a "storage system", capable of supplying electricity to the R region if necessary.

As expressed in Figure 2.17 the implementation of V2G technology within oemof does not differ significantly from the assumptions used for the definition of the smart charge, the only substantial difference is that the link between the R region and the R_BEV region is bidirectional, in order to allow the exchange of energy from the

R_BEV region to the R region (which represents the possibility for the EVs to provide electricity to the grid).

4.6.2.1. Full PV scenario

In this case, as seen in the case of smart charge, are only considered photovoltaic systems, so as to evaluate the behavior outside the central hours of the day.

As a result of the introduction of V2G technology, the R region prefers to import energy from the battery of R_BEV vehicles rather than resort to import from abroad (correctly behaving after introducing a V2G technology). When this behaviour can be exploited, the battery in the R_BEV region provides more power than the demand for electric vehicles alone, the excess part is sent to the R region, to meet its electricity demand without resorting to import from abroad.

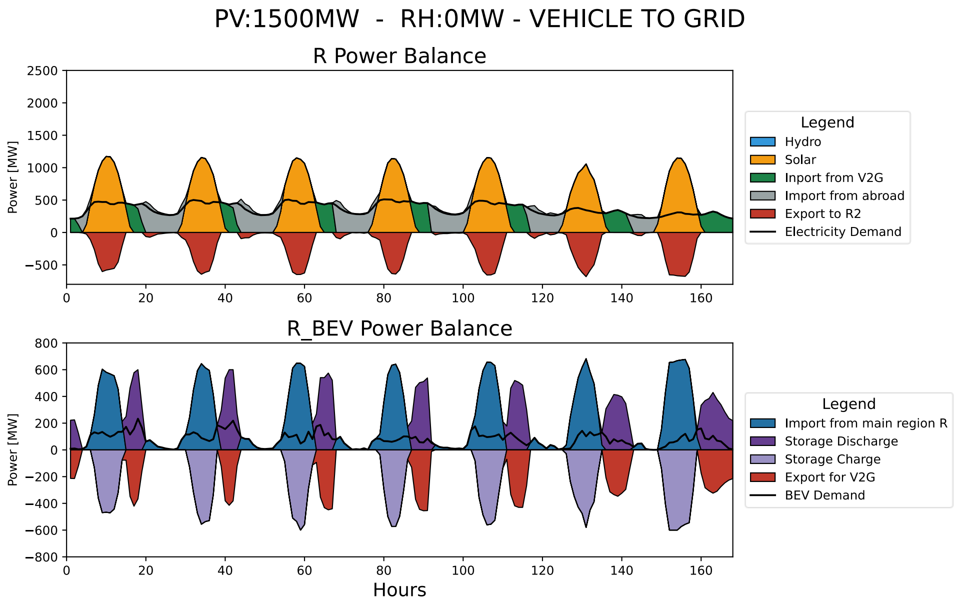


Figure 4.28 - Power balance of the main region R (top) and its fictitious node R_BEV (bottom), considering a "full-PV" energy production sector, when a vehicle-to-grid technology is introduced

The share of installed photovoltaic systems is now gradually increased in order to assess their impact both in the R region and in the fictitious R_BEV region.

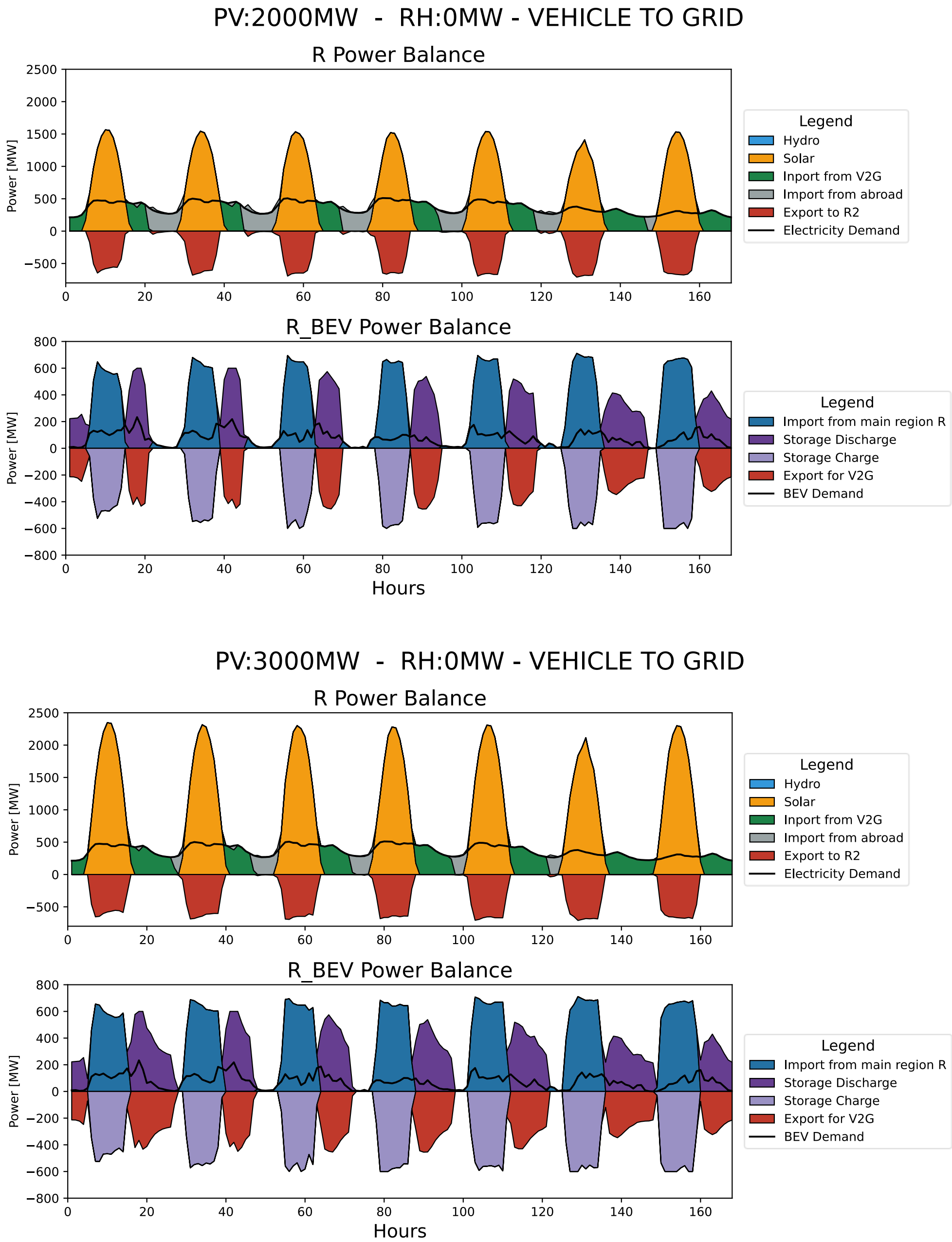


Figure 4.29 - Power balance of the main region R and its fictitious node R_BEV, considering a gradual increase of the PV capacity installed, when a vehicle-to-grid technology is introduced

By expanding the capacity of the photovoltaic systems installed, a reduction in the amount of energy that must be imported from abroad is clearly visible, this phenomenon occurs because in the hours of strong production through photovoltaic (usually in the middle of the day), the system decides to yield as much energy as possible (considering the limitations based on the amount of vehicles connected) to the R_BEV region, so that this energy can be "obtained back" later.

Despite the high amount of photovoltaic installed, it is still not possible to obtain a case in which the R region becomes completely "self-sufficient", for this reason the implementation of hydroelectric plants is now being evaluated, so as to affect the electricity demand at night.

4.6.2.2. PV + Hydro

Following the introduction of hydroelectric technology, it is not immediately possible to obtain a scenario of energy self-sufficiency, in determinate hours of the week (typically in the evening) the amount of hydropower only partially covers the Electricity demand, at the same time the amount of electricity extracted from R_BEV, storage is not enough, as it has not been charged enough by the energy of photovoltaic during the day, that is why it is still necessary to import energy.

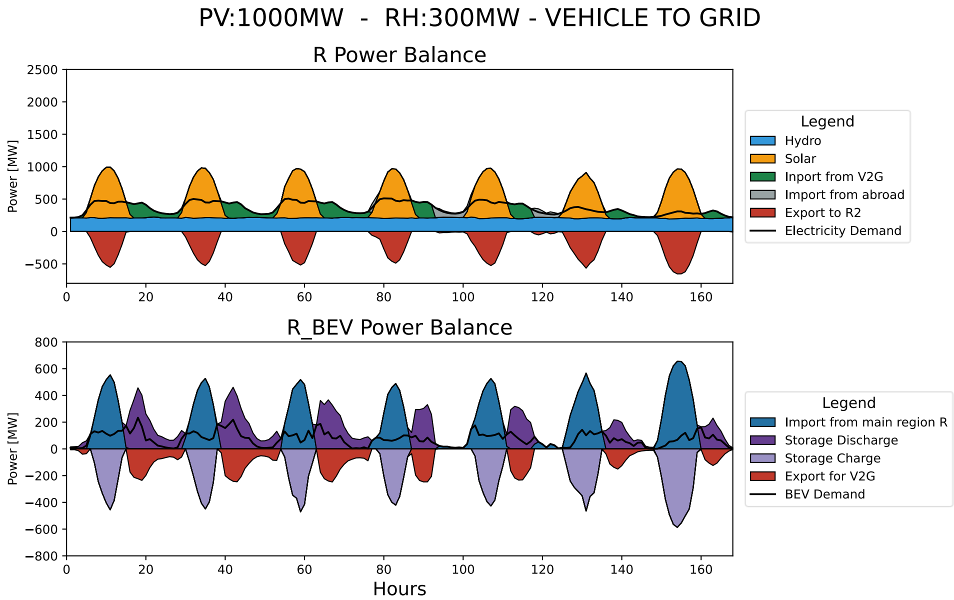


Figure 4.30 - Power balance of the main region R (top) and its fictitious node R_BEV (bottom), including both RH and PV, when a vehicle-to-grid technology is introduced

The situation changes considering a further increase in installed hydropower, in these cases the energy produced on site within the R region during the night, combined with the amount of energy coming through V2G, is enough to cover the electricity demand.

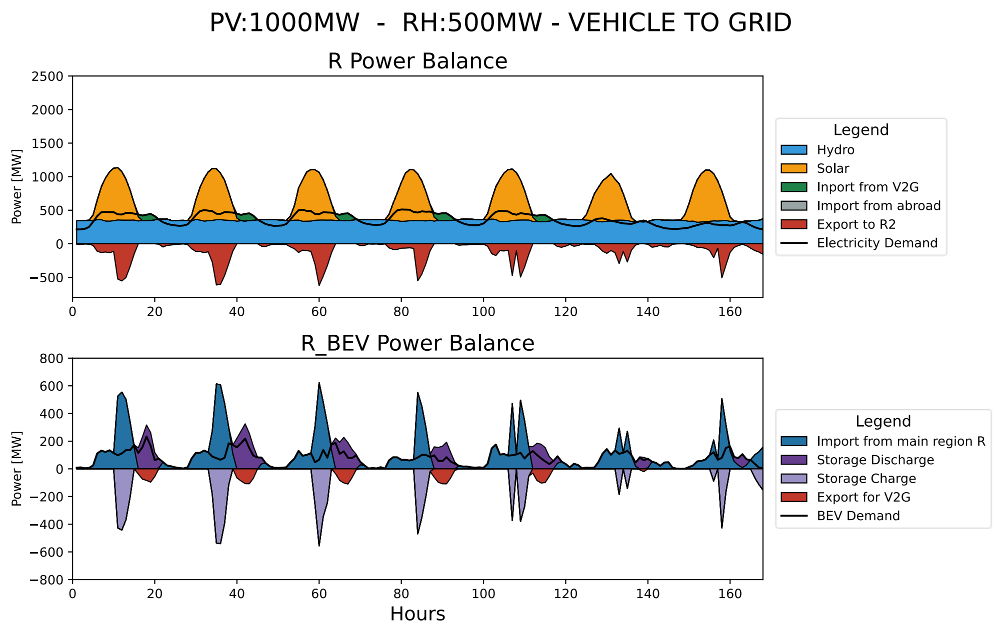


Figure 4.31 - Power balance of the main region R (top) and its fictitious node R_BEV (bottom), including a further increase of the RH capacity installed, when a vehicle-to-grid technology is introduced

4.6.2.3. Actual Energy Mix

Also in this case, as seen for the simple implementation of the smart charge, the installed hydroelectric capacity is sufficient to cover at all times the Electricity demand of the R, For this reason it does not need to import on any occasion from R_BEV, for this reason, the energy requirements of electric vehicles are met instantly, and once again the charging profile of these vehicles coincides with the "dumb" profile.

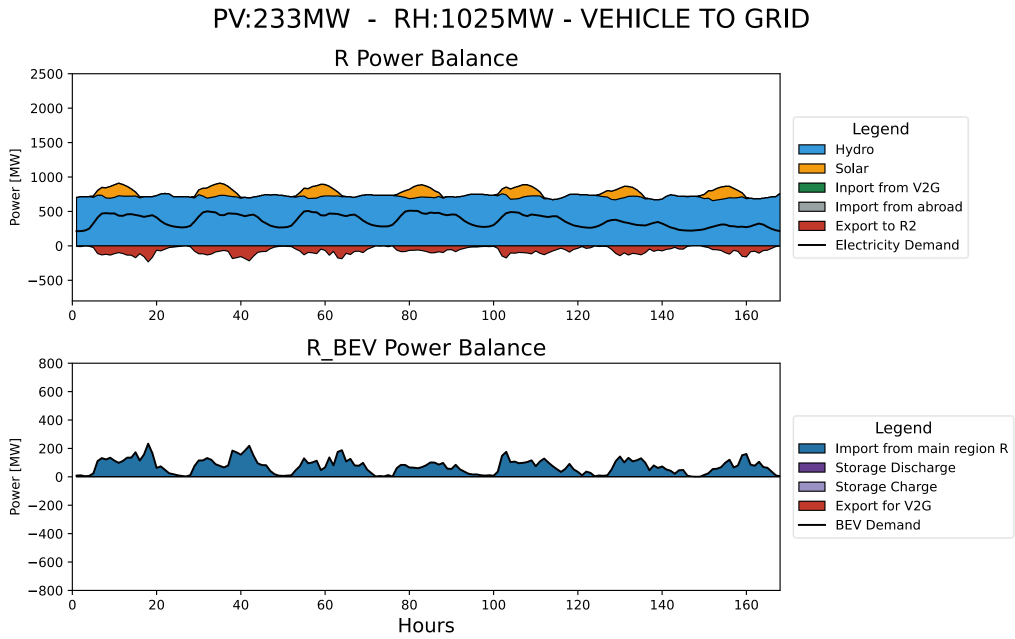


Figure 4.32 - Power balance of the main region R (top) and its fictitious node R_BEV (bottom), considering the actual capacity of PV and RH power plants in South Tyrol, when a smart charge strategy is introduced

After having verified the correct functioning of the smart charge and the V2G in the "single-node" framework, having shown the cases in which they can better allow a correct coupling between electric vehicles demand and the power production sector, it is necessary to extend the analysis to the multi-node representation of the case study of South Tyrol, highlighting the different behaviour for each of the nodes considered, depending on various aspects, such as the abundance or not of renewable energy production and the consequent relationship with the electricity demand, divided into dumb charge and controlled charge.

4.6.3. Multi-node Smart charge implementation

The first results to be analysed are those related to a gradual implementation of smart charge technology; for each R node in the graph, the corresponding fictitious region R_BEV is also shown. The Figure 4.33 shows the power balance of the nodes with a smart charge implementation of 20% of the total number of electric vehicles fleet.

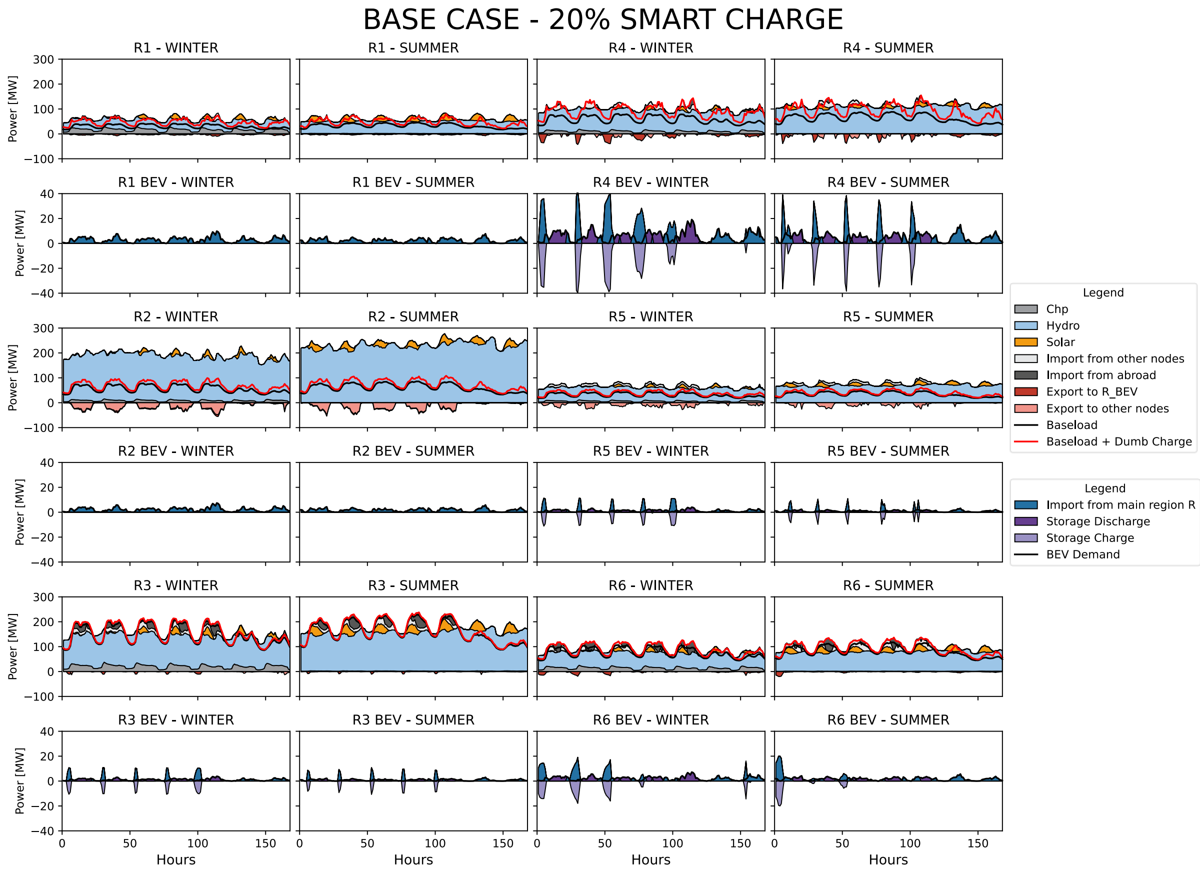


Figure 4.33 – Power balance of each pair (region R on top and region R_BEV on the bottom) representing the six node of the South Tyrol case study, considering a summer and winter week, after the implementation of 20% of EV demand fulfilled with smart charge

Following the same behavior seen within the sensitivity analysis of the energy mix, in regions where production is always greater than demand, smart behavior coincides with dumb behavior. This happens for example in the nodes R1 and R2, both in summer and during winter, in which analyzing the graph relative to the corresponding fictitious regions, the demand of the electric vehicles is punctually satisfied through the import of energies from the main regions.

Within the other regions, except R6, the usage pattern of the smart charge is the same. In workdays, during the night hours when the production of hydroelectric power exceeds the electricity demand (including the dumb charge), the energy is sent to the fictitious region for charging the vehicles, and the excess is sent to recharge the R_BEV, storage. During the weekend, when demand is reduced and is therefore always lower than energy production, the system prefers to instantly recharge the vehicles, thus following a "dumb" strategy.

Despite this, in the R3 and R6 regions, at peak demand during the day, the internal production of energy and the exchange of electricity from other nodes are not enough and it is therefore necessary to import energy from abroad.

Even by increasing the percentage of vehicles recharged by smart charge, there is no marked improvement in the criticalities identified within the regions, highlighting again the need to implement a V2G strategy in order to achieve a deeper change in the power balance profiles of nodes, in line with the results obtained within the previous sensitivity analysis.

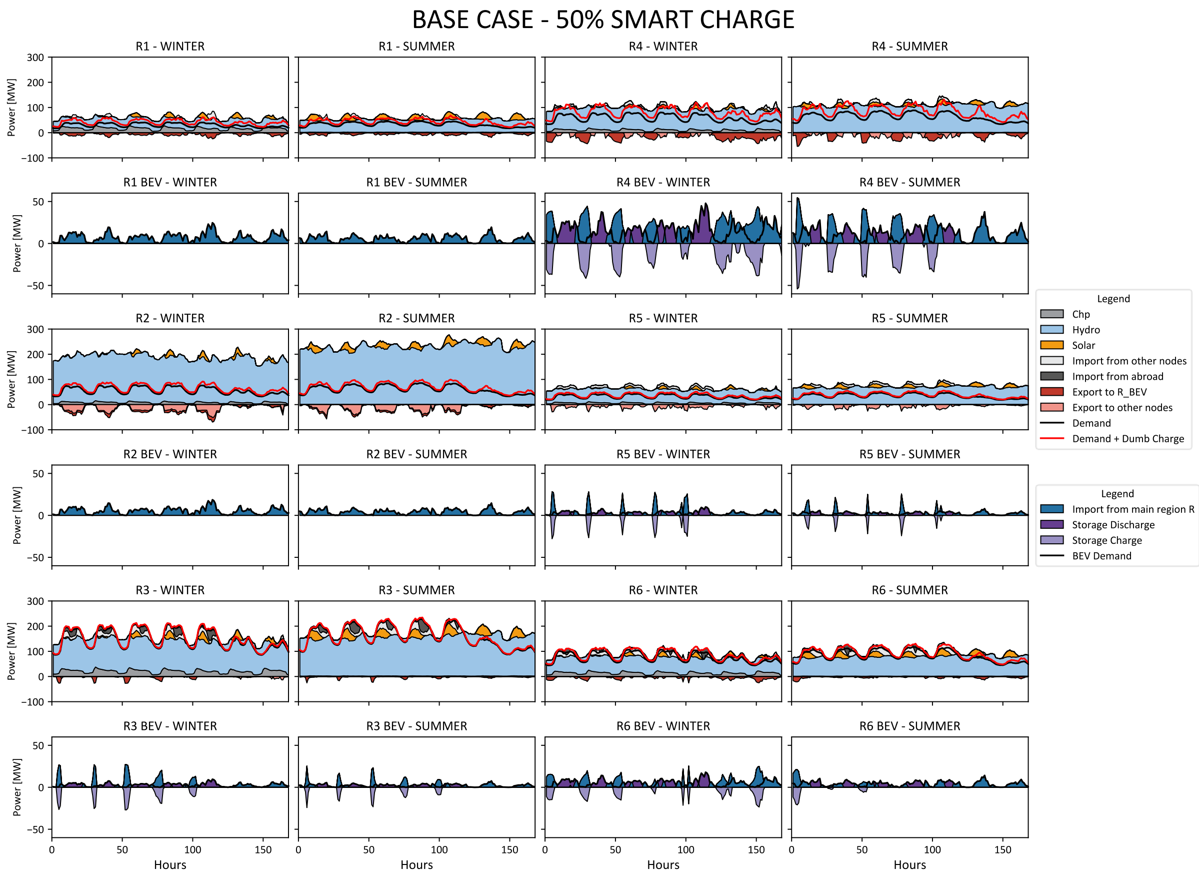


Figure 4.34 - Power balance of each pair (region R on top and region R_BEV on the bottom) representing the six node of the South Tyrol case study, considering a summer and winter week, after the implementation of 50% of EV demand fulfilled with smart charge

4.6.4. Multi-node Vehicle-to-grid implementation

The results of the implementation of vehicle to grid technology are now presented, starting with the scenario comprising 20% of vehicles charged in this way

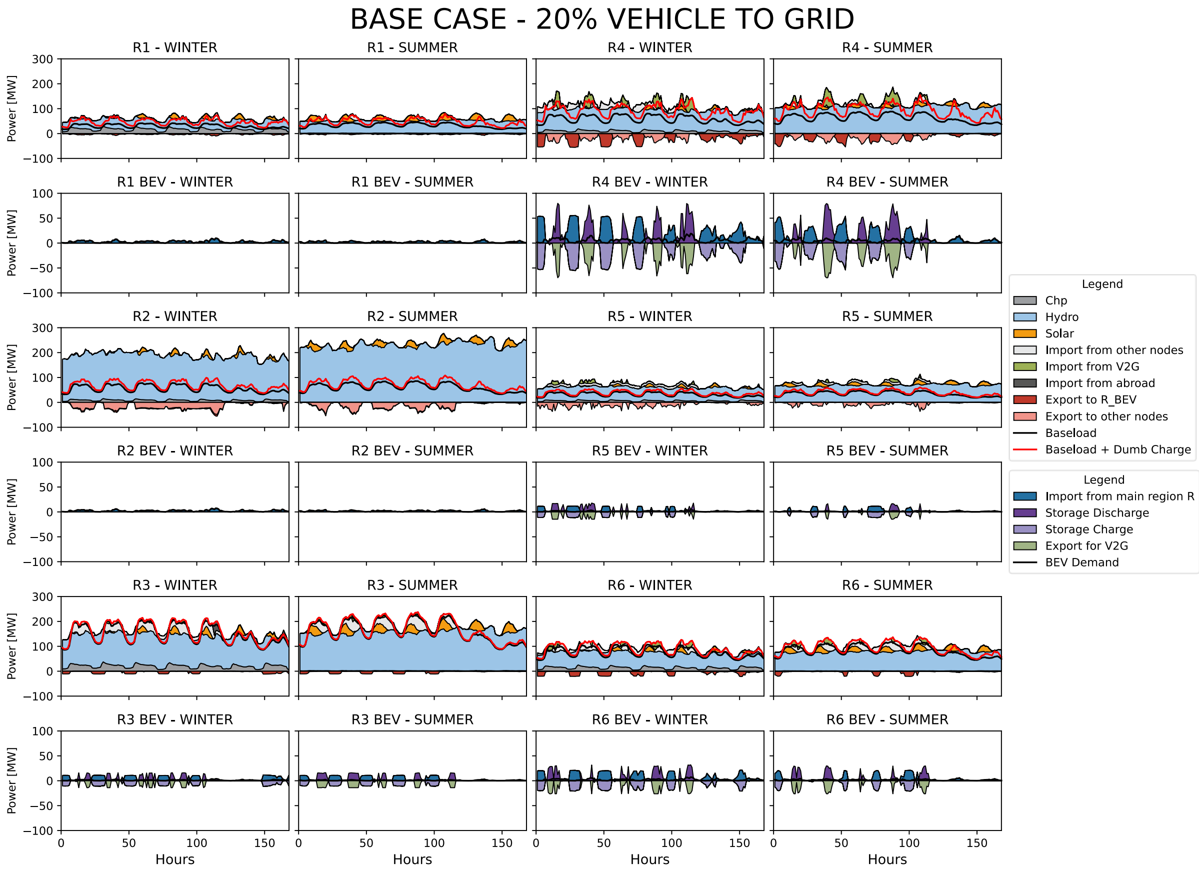


Figure 4.35 - Power balance of each pair (region R on top and region R_BEV on the bottom) representing the six node of the South Tyrol case study, considering a summer and winter week, after the implementation of 20% of EVs using a vehicle-to-grid technology

Even for such a small percentage of vehicles considered, there can be a sharp change in the profiles of the various nodes. The R1 and R2 regions also in this case continue to charge the vehicles instantly, not needing the new technologies implemented. In all other regions the possibility of using vehicle batteries as a source of energy is used correctly. This process, in line with what has been seen for the implementation of the smart charge, however, takes place only on working days, in this case the daily peaks are partially satisfied by the energy from the fictitious region R_BEV.

In this way, the times when it is necessary to import energy from abroad, especially in the R4 and R6 regions, are drastically reduced. it is also important to note that the implementation of V2G technology, properly follows the principle of charging at times of overproduction and discharge at times of demand, However, the times at which this happens are different from those present in most studies that have dealt with this topic [54]. V2G technology in most cases has been analyzed in conjunction with photovoltaic systems, which are characterized by a precise pattern throughout the day, in that case the vehicles were recharged mainly by day to give up energy during the night. Within the case study of South Tyrol, where production with renewable energy sources is mainly through the contribution of hydroelectric power, the vehicles are mainly recharged at night, where the electricity demand is lower, and then they provide power to the grid during the day, when the production of electricity remained constant, but the electricity demand is strongly increased.

Nevertheless, the amount of energy that can be transferred from vehicles to the grid is still not sufficient to allow complete autonomy of the electricity network, both for the R4 region and for the R6 region, in some hours of the weeks considered, the import of energy from abroad is still necessary. For this reason, the possibility of increasing the percentage of vehicles available to use a V2G technology has been investigated, increasing to 50% of total passenger cars.

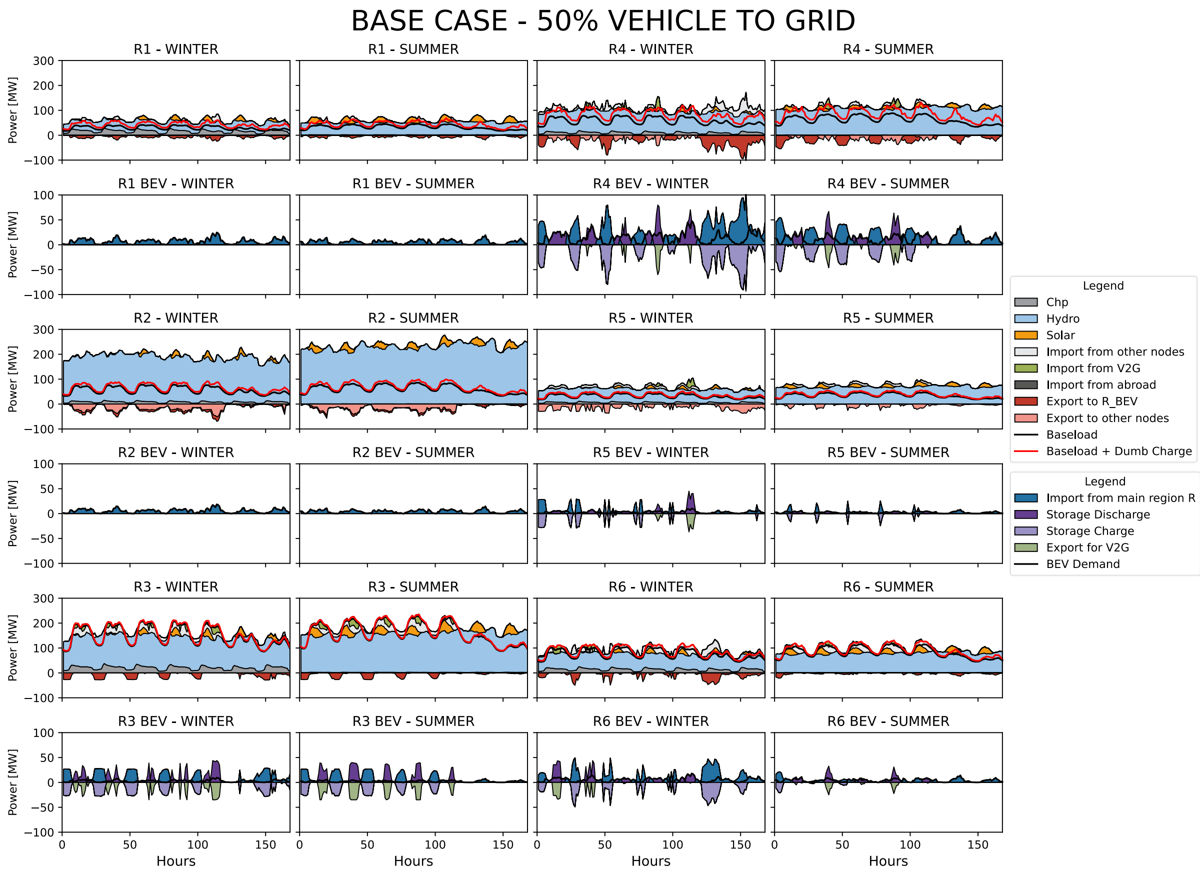


Figure 4.36 - Power balance of each pair (region R on top and region R_BEV on the bottom) representing the six node of the South Tyrol case study, considering a summer and winter week, after the implementation of 50% of EVs using a vehicle-to-grid technology

By increasing the availability of vehicles to transfer energy to the grid, the energy imported from the R_BEV region to the R region increases further. Although the energy passages between a node and its fictitious node follow the same pattern as the previous case. The amount of power exchanged on each occasion increases further, ensuring a further reduction in the amount of energy imported from abroad in the periods represented in the figure.

To consider the year-round results simulated in this case study, the Table 4.2 shows the change in the total amount of energy imported from abroad in a year, divided according to the region and the scenario considered.

Table 4.2 – Yearly electricity imported from abroad [MWh] for each region (rows), for each of the scenarios considered (columns)

	DUMB	20% SMART	50% SMART	20% V2G	50% V2G
R1	1577	350	194	0	0
R2	17	3	0	0	0
R3	54181	58670	49192	37340	31993
R4	39280	16296	8413	10988	7857
R5	182	630	391	10	47
R6	41439	40512	26132	20401	16483
TOTAL	136676	116461	84322	68739	56380
% REDUCTION	-	14.8%	38.3%	49.7%	58.7%

It can be seen how the strategies implemented can effectively reduce the amount of energy imported from abroad, ensuring a better coupling between the field of electricity production on site and the electricity transport sector, this occurs both by reducing the amount of vehicles that are recharged through a "dumb" behavior, and especially through the use of vehicle-to-grid technology, in which vehicles can operate as batteries for the system. The cases in which the amount of electricity imported from abroad increases, such as within the R5 region, are linked to the connection between the various nodes, where, for example, the R5 node imports energy from abroad in order to be able to then yield energy to the surrounding nodes (both R6 and R4 have the greatest distance between production and demand, and therefore use as much as possible also import from other nodes).

4.6.5. Normalized grid electricity demand

It is now represented the normalized profiles of the energy required to the grid for the recharge of vehicles, this value, as expressed in the Equation 2.14, is obtained by summing for each timestep, the energy that is supplied inside the R node to the vehicles that are recharged in a dumb way to the energy that is sent from the R region to the R_BEV region for the recharge of the vehicles through "controlled strategy" (therefore valid for both the case of smart strategy and for the vehicle-to-grid). The profiles in Figure 4.37 are obtained, taking into account an average working day and an average day during the weekend. In the graphs the regions are then divided, considering both a summer week and a winter week.

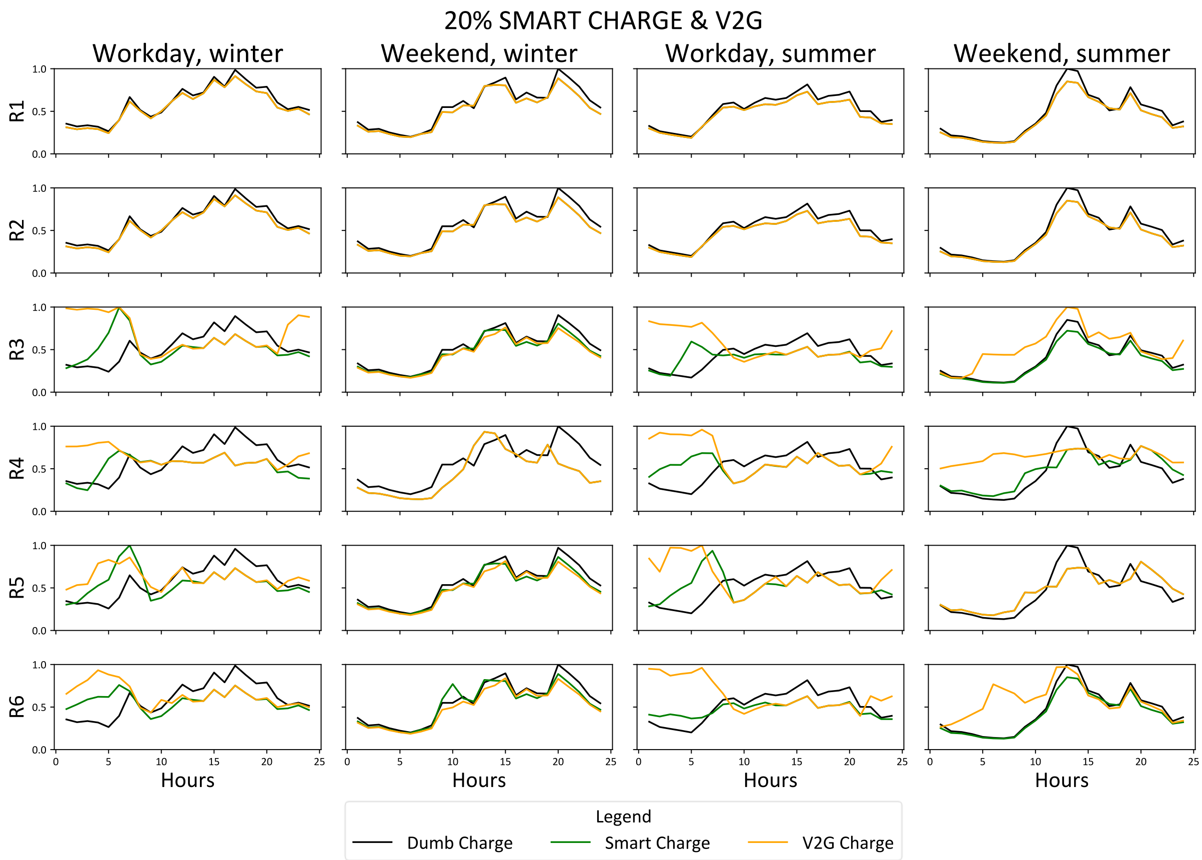


Figure 4.37 – Normalized grid electricity demand for each of the six nodes (rows) for an average day during workday and during weekends, considering a summer and winter week (columns), considering a 20% of EV charge fulfilled with a “controlled” strategy”

This graph, closely connected with the previous graph depicting the power profiles, allows to analyze more correctly another advantage related to the implementation of these different types of charging. The smart charge and the V2G allow not only to reduce the amount of energy imported from abroad (which is however a relevant aspect within the case study considered) but more generally allow to reshape the curve of charging vehicles. Apart from in the R1 and R2 regions, where as previously mentioned, the Smart charge and V2G strategy are not considered, in the other regions using a "smart" strategy, the load at night is greater than there would be with a "dumb" strategy and at the same time peaks are reduced during daylight hours. Considering a strategy using V2G, this phenomenon is further exacerbated, this increase in consumption at night is actually due to the fact that an even greater amount of energy is imported in R_BEV, which is then released during the day. In these hours the smart profiles and V2g coincide, but because in this type of graph was not considered the transfer of energy from vehicles to the grid, because in certain hours of the day negative values would be obtained, that would have been little intuitive at the end of the demonstration of the validity of this technology This phenomenon is further exacerbated by further reducing the amount of vehicles recharged by a dumb strategy, in this case the peak charging at night is even more evident, showing an even more effective ability to match the electric vehicle sector, and their demand for electricity, with the energy production sector.

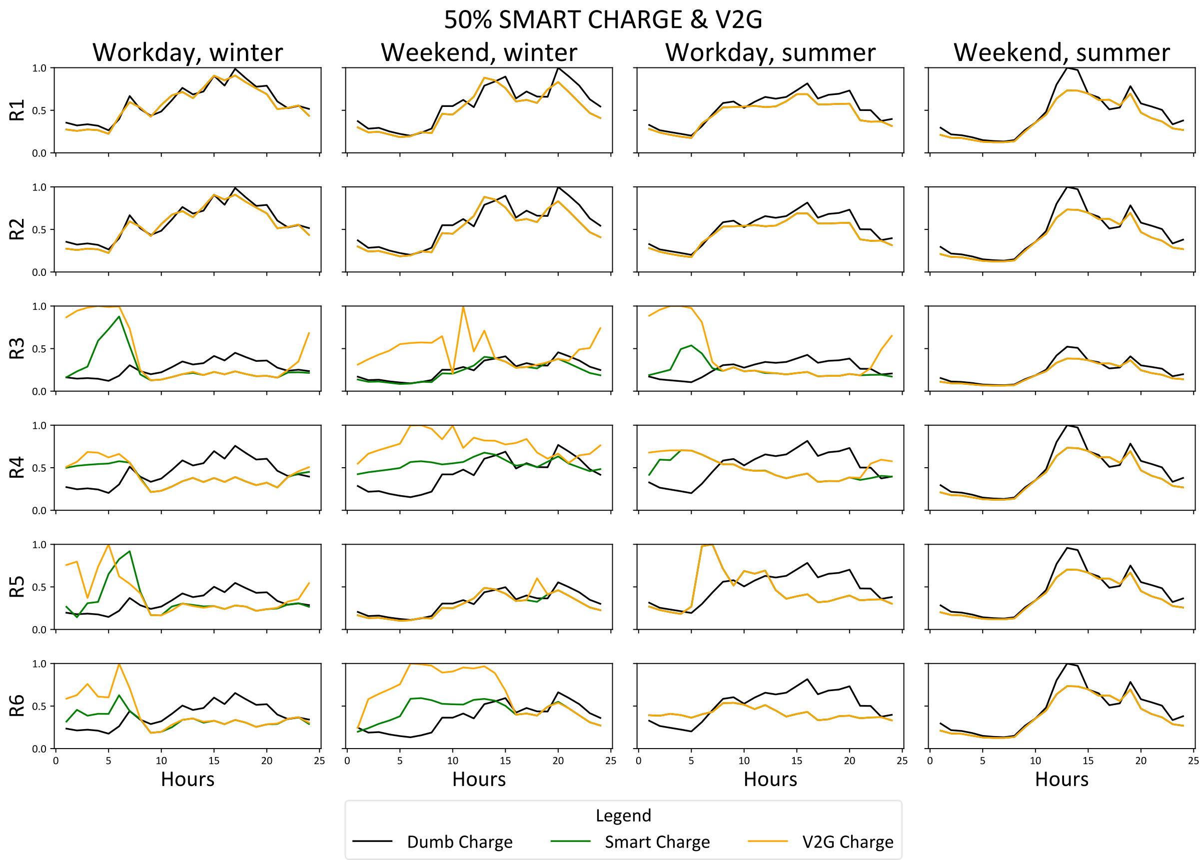


Figure 4.38 - Normalized grid electricity demand for each of the six nodes (rows) for an average day during workday and during weekends, considering a summer and winter week (columns), considering a 50% of EV charge fulfilled with a “controlled” strategy”

5 Conclusions

Policy decisions pertaining to the mass-scale deployment of electric vehicles for integration with the power system are currently slowed down by unanswered questions concerning the impact that such a deployment would have on electricity demand and the potential of smart charging mechanisms to mitigate it. To this end, this thesis provides a further step towards a better clarification of these uncertainties.

Firstly, the two most promising open-source tools for the simulation of electric vehicles consumption and charging time series are compared in terms of flexibility, input data and accuracy of the output provided. Then, after identifying *emobpy* as the most suitable tool for the purposes of this thesis, due to its more precise spatial description of the mobility patterns and the charging events of the vehicles during the day and the better definition of different charging strategies, a new approach is proposed to calculate the electricity demand of other types of vehicles which will be part of the electrification process of upcoming years (i.e. buses for public transport and vehicles for the light and heavy freight). This is achieved from studies regarding the mobility patterns of fossil-fuelled versions of those vehicles and real data on the charging infrastructure in the South Tyrol case study.

To evaluate the impact on the grid of an increasing electrification process due to local and European directives, two mid-term and one long-term scenarios have been introduced. The electricity demand of the transport sector thus calculated is later integrated with the other aspects of the energy supply system (i.e. power generation, heat and electricity demand) using the Oemof tool. Using this tool, through a multi-node representation of South Tyrol, it was possible to assess whether the current production sector could meet the new demand for electricity. The implementation of the long-term scenario set in 2050 has shown that, even in a region with high and constant electricity generation from renewable sources like South Tyrol (currently double the electricity demand), an almost complete electrification of the transport sector would significantly increase the energy import from abroad to meet the new energy demand, with risk of providing grid congestion problems.

To partially overcome this problem, as final part of this thesis, a methodology to implement “Smart Charge” and “Vehicle-to-grid” technology within the Oemof tool is proposed. Even considering just a partial adoption of those two strategies among the passenger cars' owners, the switch to a "controlled" charging strategy showed a potential benefit for the congestion problems, with vehicles being recharged mainly at times when there is overproduction from renewable energy sources. Furthermore, the implementation of V2G could effectively substitute the energy import from abroad, with energy provided by the EVs connected to the grid when the energy produced by on-site plants is not sufficient. Although the results presented in this thesis refer to a case-study with strong production by hydroelectric plants, a rather stable and constant source of renewable energy, the sensitive analysis applied to consider different energy mixes extends the effectiveness of the charging strategies introduced to other countries as well.

A Appendix A

A.1. Vehicles Datasheet

Model Name	Merced Benz e-Actros	Solaris Urbino 12 Electric	FIAT E-Ducato	FIAT E-Doblò	IVECO E-Daily
acceleration 0/100 [s]	38	35	19	11.2	20
axle ratio	3.55	3.73	3.6	3.6	3.6
battery cap [kWh]	336	240	79	50	110
curb weight [kg]	19000	18000	2680	1590	2100
drag Coeff	0.608	0.633	0.8	0.8	0.8
motor type	Asynchronous	Asynchronous	PMSG	PMSG	PMSG
height [m]	3.7	3.3	2.569	1.86	1.545
Length [m]	9.3	12	5.413	4.4	5.13
market	Europe	Europe	Europe	Europe	Europe
Power [kW]	330	300	90	100	140
Regenerative braking	no	no	yes	yes	yes
top speed [km/h]	89	75	100	130	138
Torque [Nm]	11000	21000	280	260	400
trunk volume	8000	1000	10000	775	7300
battery type	Li-Ion	Li-Ion	Li-Ion	Li-Ion	Li-Ion
weight [kg]	19000	18000	2680	1590	2100
Width [m]	2.5	2.55	2.05	1.84	1.8
Brand	Merced Benz	Solaris	FIAT	FIAT	IVECO
EV model	e-Actros	Urbino 12 Electric	E-Ducato	E-Doblò	E-Daily
Model year	2021	2017	2021	2022	2022
battery charging efficiency	0.9	0.9	0.9	0.9	0.9
battery discharging efficiency	0.95	0.95	0.95	0.95	0.95
transmission efficiency	0.95	0.95	0.95	0.95	0.95
auxiliary power	0.3	0.3	0.3	0.3	0.3
cabin volume	3.5	3.5	3.5	3.5	3.5
hvac cop heating	1	1	1	1	1
hvac cop cooling	2	2	2	2	2
fonte	[55]	[56], [57]	[58]	[59]	[60]

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Variable	Description	SI unit
E_{total}	Total energy consumption	J
F	Forces	N
P	Power	W
P_{aux}	Auxiliary power	W
$P_{battery}$	Battery power	W
P_{device}	Electrical power for heating/cooling	W
P_{ev}	Electric vehicle power	W
$P_{G,in}$	Generator input power	W
$P_{G,out}$	Generator output power	W
$P_{M,in}$	Motor input power	W
$P_{M,out}$	Motor output power	W
P_{RB}	Regenerative braking power	W
P_{Wheel}	Power at the wheel	W
$\dot{Q}_{Amb}$	Heat transfer from ambient by heat pump	W
$\dot{Q}_{device}$	Heat transfer rate for heating/cooling	W
T_{amb}	Ambient temperature	°C
v	Speed	m/s
v_{rand}	Randomized speed	m/s