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EXECUTIVE SUMMARY OF THE THESIS

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

TESI MAGISTRALE IN ENERGY ENGINEERING – INGEGNERIA ENERGETICA

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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 [21]. 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.

There is an abundance of studies and reviews on modelling the EV charging demand available in the literature. Muratori et al. [2] 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 et al. [3] used the same Markov chain approach to simulate a fleet of vehicles used for car sharing, limiting the possibility to extend this method to private passenger cars. O'Mahony et al. [4] proposed instead 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. 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: emobpy [6] and RAMP-mobility [5], the former is based on the definition of chain of events 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.

Table 1.1- Literature review regarding the electric vehicles modelling

Author	Ref	Vehicles Considered	Spatial Configuration	Method Used
Muratori et al.	[2]	Passenger Cars	District	Markov Chain
Gruosso et al.	[3]	Passenger Cars	Municipality	Markov Chain
O'Mahony et al.	[4]	Passenger Cars	Regional	Monte Carlo
Dallapiccola et al.	[7]	Passenger Cars	District	Ramp-Mobility
Lubello et al.	[8]	Passenger Cars	District	Ramp-Mobility
Corinaldesi et al.	[9]	Passenger Cars	District	Emobpy
Joglekar et al.	[10]	Passenger Cars	District	Emobpy
Approach proposed by this thesis		Passenger Cars, Public Bus, Commercial Vans, Heavy Truck	Regional	Emobpy

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.	[12]	Separated	Municipality	MATLAB, digsilent	DUMB, SC
Ioakimidis et al.	[13]	Separated	District	MATLAB	DUMB, SC
Ivanova et al.,	[14]	Separated	Municipality	MATLAB, IBM ILOG CPLEX	DUMB, SC
Wu et al.	[15]	Separated	District	CVX MATLAB	DUMB, V2H
Cai et al.	[16]	Integrated	District	unknown	DUMB, SC
O'Neill et al.	[17]	Integrated	District	unknown	DUMB, V2G
Approach proposed by this thesis		Integrated	Regional	cbc	DUMB, SMART, V2G

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 [5].
Dallapiccola et al. [7] and Lubello et al. [8] utilized RAMP-mobility to calculate electric passenger cars consumptions in small residential areas, similar studies were developed by Corinaldesi et al. [9] and Joklekar et al. [10], 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 [10], the electrification process 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 [11]). Hence, this thesis aims to evaluate the increase in electricity demand on the grid as a result of the electrification of 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 peak 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 fulfill 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 energy sources, 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 regarding 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. [12] 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. [13] 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. [14] 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. This analysis doesn't include another demand that needs to be fulfilled, causing no need to implement a V2G technology.

Wu et al. [15] analyzed instead the possibility for the EVs to give back the energy absorbed during charging sessions, but even if the results show a 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. [16] 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 thesis.

The novelty and unique contributions of this study 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 paper is structured as follows. Section 2 describes the methodology of this study. 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

For modelling the consumption of electric vehicles, and thus their electrical energy demand for recharging, two of the most promising recent tools

presented within the scientific literature were compared: RAMP-Mobility [5] and emobpy [6].
After comparing the two programs in terms of flexibility, input data and accuracy of the output provided, emobpy was identified as the most suitable tool for extending the analysis of the electrification of vehicles to buses, commercial vans and heavy trucks.

The main advantages of emobpy are:

- More precise description of the movement during the day from a spatial point of view, with the possibility to define location-specific probabilities for the charging infrastructure availability. In this way the distinction between the "home wallbox" and the public charging stations can be easily implemented.
- Greater amount of charging strategy available: immediate (charge at maximum power as soon as an available charging station is found), balanced (charge at a reduced power such that the battery is full when the next trip will begin), only at home or only during the night
- Possibility to implement an ad-hoc set of rules to model the vehicles' movements through the day, allowing a definition of the mobility patterns closer to real-data available.

Emobpy 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. A BEV profile is composed by four consequential time series:

- **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.

The integrations of vehicles different from passenger cars required a simplified definition of the daily mobility pattern: 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 the evaluation of the four time-series, the probability distribution of travel times is obtained from previous studies regarding mobility patterns of traditional fossil-fuelled models of commercial vans [18] and heavy truck [19], for public bus, those values are reasonably assumed. The vehicle consumptions are achieved starting from vehicle information in terms of dimensions, driving performance and electrical components, obtained from the datasheets provided by the manufacturers. The availability and nominal capacity of the charging infrastructure are defined starting from real data of the territory considered.

While for the passenger cars, a more conservative "immediate" strategy is chosen, for buses and light/heavy freight, a "balanced" strategy is considered, assuming that the public transport or delivery company knows in advance the daily vehicle movement. Hence, when a vehicle starts recharging, it is known when the next trip will begin.

Once the energy demand of the electric vehicle fleet has been assessed (aggregating all the grid electricity demands time-series provided by emobpy), the Oemof framework has been selected as the energy system framework for this analysis. Oemof is a set of tools to model different aspects of energy supply systems which are written in python programming language and published under an open-source license [20]. 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 1.1 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.

$$\min\left[\sum_{n}^{N}\sum_{u}^{U}\sum_{t}^{T}E_{n,u,t} * vc_{n,u,t}\right] \tag{1.1}$$

The smart charge and the vehicle to grid technology have been implemented within oemof through the definition of a fictitious region, called R_BEV. Inside the "main" region R, in addition to the corresponding energy production sectors, is assigned the load of electricity that will be satisfied through dumb charge. Within the fictitious region R_BEV, in addition to a fictitious storage representing the set of batteries of electric vehicles connected to the grid, is instead assigned the share of BEV electricity demand that can be satisfied

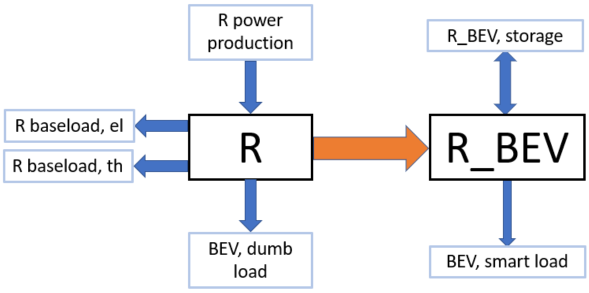

Figure 2.1 - Schematic representation of the fictitious region "R_BEV" definition in Oemof for the gradual implementation of Smart Charge and V2G

according to a strategy "smart charge".
In fact, if the "dumb" load present in the R region must be satisfied instantaneously through the production of electricity on site, the share of "smart" demand, within the fictitious region R_BEV, will be satisfied primarily at times when the R region has a period of overproduction or secondarily by discharging the R_BEV storage.

In this way, for each timestep the final value of the grid electricity demand related to electric vehicles, will be equal to the sum of the demand satisfied by dumb charge plus the part of electricity needed for smart charging, which corresponds to the amount of electricity that is transferred from Region R to Region R_BEV over the period considered.

$$\boldsymbol{P_{ev,t} = P_{BEV,dumb,t} + P_{R\ to\ R_{BEV},t}} \tag{1.2}$$

As for the further implementation of the V2G technology, the assumptions will be the same, except for the fictitious power line connecting the R and R_BEV regions, which in this case will be bi-directional. In this way, if the R region could not satisfy its demand, the electric vehicles (represented through the fictitious storage present in the R_BEV region), could give back their energy. However, the nominal capacity of the powerline connecting each node R with the corresponding node R_BEV is equal to the number of vehicles, multiplied by an assumed value of 3 kW, 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 $\%\boldsymbol{vc_t}$.

$$\boldsymbol{P_{(R_{BEV}\ to\ R),max,t} = \#vehicles * 3kW * \%vc_t} \tag{1.3}$$

3. Case Study

For the evaluation of the impact of the electrification of the transport sector, the South Tyrol region is considered, a region with a power generation sector almost entirely composed of renewable energy sources.
This region is split in six sub-areas, as exposed in Figure 3.1. 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

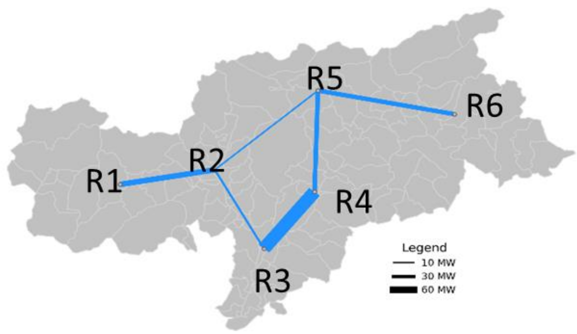

Figure 3.1 - Multi-node representation of the South-Tyrol region, as defined inside the Oemof tool

From a time perspective, 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).

ACTUAL scenario (2030): 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 (2030): 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 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.

ZEV scenario (2050): Since most of the directives considered are intended to regulate new sales and not vehicles on the road, it is crucial to consider a long-term scenario in order to more correctly assess the impact of these directives, with which a completely zero-emission vehicle fleet can be achieved only in 2050.

4. Results

The Figure 4.1 shows the values of the normalised electricity demand profiles for the four vehicle types considered. 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.

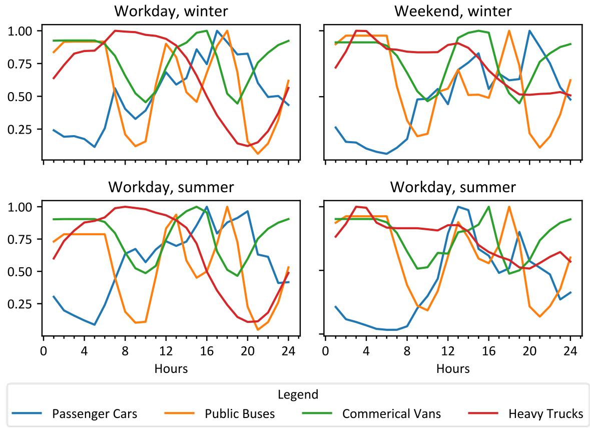

Figure 4.1 - Normalized electricity demand for an average winter and summer day, distinguished between workday and weekend

The pattern related to passengers cars 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, there is a clear distinction between day-time charges (at higher power during short breaks in the day) and night-time charges (at reduced power and spread over a greater number of hours). For the light transport sector, the higher amount spent at the headquarters between each delivery allows a smoother charge also during day-time. For the heavy transport sector, all the trucks will recharge during the morning, once they return to base after completing their expedition during the night.

Following the modelling of the three scenarios in the medium and long term, the one that has the greatest impact on the energy system of South Tyrol is the ZEV scenario, set in 2050. Although electricity production in South Tyrol currently exceeds more than double its demand, the total electrification of the vehicle fleet would lead to a sharp increase in electricity demand, not even the import of energy from other nodes would be sufficient, and it would therefore be necessary to import energy from neighbouring countries. This phenomenon is highlighted in Figure 4.2 (top graph), which analyses a winter week within the R3 region considering only dumb charge. In the middle of the day, the production of hydroelectric, solar, chp and import from other nodes are not

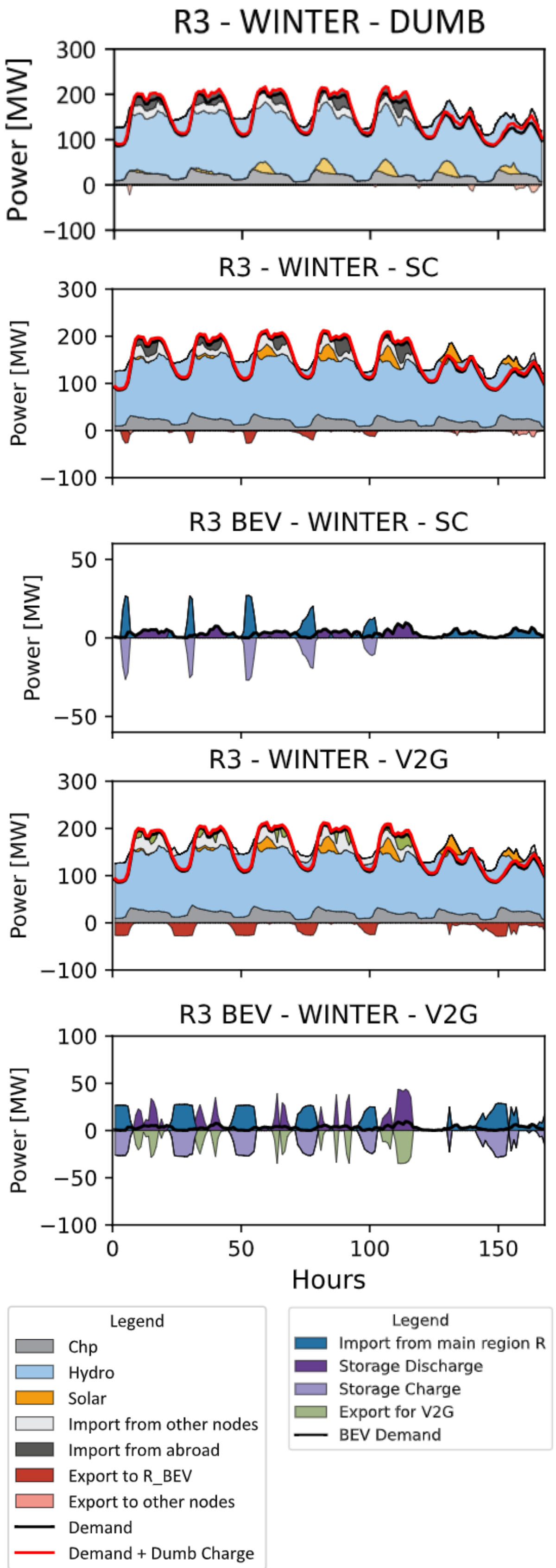

Figure 4.2 - Electricity generation and demand of the R3 node for a week in winter, considering Dumb charge (top), Smart Charge (two graphs in the middle) and V2G (two graphs in the bottom part).

enough to meet the increased demand for electricity.

In this case, the implementation of smart charge or vehicle to grid should provide a positive effect to the grid.

In Figure 4.2 (two graphs in the middle) is reported the same region in the same time frame, first including a 50% percentage of vehicles following a smart charge, and then a 50% percentage of vehicles that is willing to use vehicle to grid technology.

The implementation of a smart charge technology allows to partially reduce the dependence on import from abroad. The “smart” charging of vehicles takes place mainly at night, where there is an overproduction of electricity thanks to the hydroelectric systems present in the territory. However, electricity production is still not sufficient during the day and it is still necessary to import energy from abroad.

By implementing instead the V2G technology (Figure 4.2, two bottom graphs), this aspect can be solved. During the night the energy produced by hydroelectric is not wasted and even more directed to the charging of electric vehicles, which during the daytime hours, can instead give back part of the energy in their batteries to the grid. In this way it is no longer necessary to import from abroad during the day.

It is also reported the trend of the normalized grid electricity demand (aggregating the share of dumb and smart charge and referring it to the main region R, as presented in Equation 1.2.) for the region R3, to better highlight how the demand of the EVs changes according to the strategy considered. In Figure 4.3 four day-types are considered, considering an average day of the whole week previously showed.

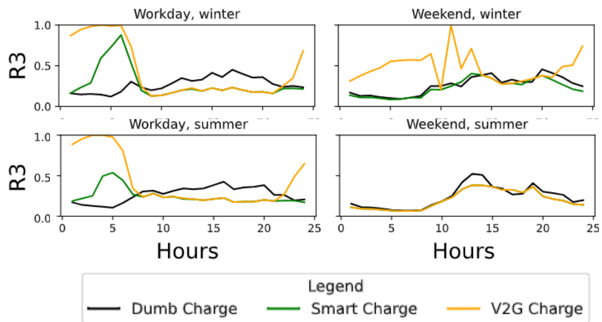

Figure 4.3 – Normalized grid electricity demand for the charging of passenger cars for the node R3 in winter (top) and summer (bottom), considering the different strategies and technologies implemented

It can be seen how, from the point of view of the electricity grid, the switch from a dumb strategy to a smart strategy allows the demand for electricity to be more correctly matched with the power generation sector. More specifically through a smart strategy, during working days the peak recharging of vehicles takes place during the night, when there is an overproduction of hydroelectricity, while at the same time being able to reduce the demand during daylight hours. This phenomenon does not occur at weekends, where, since demand can always be met, the region decides to recharge vehicles as soon as this is possible anyway (in that case, the smart and dumb profiles coincide).

When using vehicle-to-grid technology, the electricity demand tends to increase furtherly. This is due to the fact that in this case the battery can be discharged not only to recharge the vehicles in the R_BEV region, but also to provide energy to the R region, so the fictitious battery in the R_BEV region needs more energy to recharge itself, hence the increase in electricity demand during the night.

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.

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.

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