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Assessing electric mobility and renewable energy synergy in a small New Caledonia island community

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Abstract : In this paper, we evaluate the synergy between variable renewable energy (VRE), electric mobility, and Vehicle to Grid (V2G) deployment for a small community transitioning to a low-carbon economy. We propose an integrated deterministic modeling approach that accurately describes electric mobility activity within the electric grid in the ETEM-SG long-term capacity expansion model. This approach allowed us to keep the entire approach in the linear programming domain. We then perform a scenario analysis on the Isle of Pines case. The results show that V2G is essential for electric vehicles to make a positive contribution to the electric system by providing a supply-demand balance service. The deployment of electric vehicles allows reaching a VRE penetration rate of up to 94%, at no additional cost compared to a solution without electric vehicles, and even with a global-cost reduction of up to 5.3% thanks to a decrease of the capacity of stationary battery packs needed for storage.

Keywords : Energy transition, electric mobility, renewable energy, Vehicle-to-Grid, bottom-up approach

1 Introduction and literature review

A challenge associated with a massive introduction of variable renewable energy (VRE) in an electricity system (with a low share of dispatchable sources) is maintaining the balance between supply and demand on the power system at all times, keeping sufficient reserve capacity to cope with contingencies and intermittency. Another challenge is to maintain a sufficient inertia to cope with unforeseen events since distributed energy resources interfaced by power electronics tend to reduce the inertia of the electric system. Electric Vehicle (EV) mobility and smart grid development permitting Vehicle-to-grid (V2G) activity will help to address these challenges while introducing new constraints to the electric system. In this paper one proposes an integrated assessment model designed to analyze the EV - renewable energy (RE) synergy to achieve a 100% renewable electricity mix in a non-interconnected area. The model is applied to a case study for Isle of Pins,[1] which is a small French island system southeast of Grande Terre in New Caledonia. The analysis concerns the deployment strategy for electric vehicles and associated infrastructures and an evaluation of technical, economic and environmental impacts (GHG emissions). This study is linked to an energy transition plan for the South Province (STEPS)[2] aiming to decarbonize the Isle of Pins[3] by 2025. Accessible by boat and by plane from Noumea, the island is one of the most touristic places in the New-Caledonia archipelago. The small size of the territory, which is not connected to other islands, has allowed a precise description of its electrical system and the mobility needs of the population and of the main tourism actors. The originality of the model development and application resides in the modeling of vehicle to grid (V2G) and electric mobility in ETEM-SG, a linear programming energy modeling tool that has proved effective to assess the transition to 100% renewables in non-interconnected[4] regions [3].

Recently there has been a flurry of papers on the integration of electric mobility into power distribution systems. Reference [21] is a review of research articles published before 2019 that deal with linking transportation network modeling and power system assessment. The focus is put on the location and usage of fast charging stations. The modeling approach mixes traffic equilibrium in congested network and power flow distribution models. Among more recent papers dealing with the coupling between power distribution networks and transportation networks, we may refer to [24] where a dynamic traffic model with point queues is proposed to describe the spatial and temporal evolution of traffic flows. In the power distribution network, the electricity prices are determined using a second-order conic program. In [16], a new nexus scenario is investigated, coupling electrified highway network (EHN) and power transmission network (PTN). The independent but interrelated operations of the two networks is analyzed. On the EHN side, a combined charging-driving navigation (CCDN) model, which considers EV travel speed and charge/discharge behaviors, is proposed and formulated as an irregular dynamic programming problem. A chronological search algorithm is designed to derive the optimal charging-driving decision sequences. The economic operation of the PTN is formulated as a direct current optimal power flow problem. Hourly location marginal prices (LMPs) and charge/discharge demands are exchanged between the two networks. The interaction leads to a Nash-type game, in which both networks aim to minimize their own operation costs. In [25], an EV fast charging model is proposed as an optimization coordination problem subject to the coupled feeder capacity constraints in the distribution network. The need of fast charging is expressed by the total charging time, and the relative tendency to fully charge within the desired time period. The objective of the optimization problem tradeoffs the EVs' battery degradation cost, the load regulation in the distribution network, the satisfaction of charging and the total charging time, which is non-separable among individual charging behaviors. A hierarchical algorithm is proposed. In [15], the coupling between traffic networks and power distribution networks is modeled with a multi-period optimal traffic and power flow models that consider time-varying electricity and traffic demands. In [17], a bi-level model is formulated to optimally determine EV's charging stations fees for guiding EV charging behaviors and minimizing the total social cost. The uncertainties in wind power output and origin-destination (O-D)

[1] Kunie in Kanak, Kwênyii

[2] Schéma de Transition Energetique de la Province Sud, 2017.

[3] The Isle of Pines, an elevated atoll, measures 14 by 18 kilometers.

[4] These are regions, like island or isolated territories that are not connected to a national transmission system.

traffic demands are considered in the proposed model and a deep reinforcement learning (DRL)-based solution framework is developed to decouple and approximately solve the stochastic bi-level problem. In [19], a coordinated solution for Unit Commitment (UC) and Traffic Assignment Problem (TAP) is proposed. A heuristic algorithm using Benders decomposition is proposed in which full use of existing software packages of TAP and stochastic UC is possible. In [18], an optimal dispatch of electric vehicles (EVs) aimed to minimize the system operation cost while satisfying the requirements for peak shaving, congestion management and voltage regulation is considered. A bilevel optimization model is formulated to enable participation of the EV aggregators in the day-ahead dispatch while ensuring various system operation constraints. In [20] the potential offered by EV aggregator's to provide a flexible energy source is evaluated for Japan using a stochastic programming approach. In [23] a distributed planning method for EV dynamic wireless charging system is proposed. The Nesterov's model with multiple traffic patterns is adopted in the traffic network to solve the traffic assignment problem and the traffic wave theory is used to analyze the distribution of road traffic density. In power distribution network , the effect of EV connection modes on the expansion cost of power lines is considered. A mixed-integer linear programming (MILP) is formulated. In [17] a bi-level model is formulated to optimally determine EV charging service fees for guiding EV charging behaviors and minimizing the total social cost. At the upper level, power distribution network with wind power generation is formulated as a second-order cone problem where CSF is determined. At the lower level a traffic assignment problem is formulated to capture the individual rationality of single EV owners in UTN. The uncertainties in wind power output and origin-destination traffic demands are considered in the proposed model and a deep reinforcement learning-based solution framework is developed to decouple and approximately solve the stochastic bi-level problem. Hedging policies to cope with the stochasticity of charging demand and the intermittency of renewable energy. are considered In [12], where an optimal EV charging strategy in a distribution network is proposed to maximize the profit of the distribution system operators while satisfying all the physical constraints. When dealing with the uncertainties from EVs, a Markov decision process model is built to characterize the time series of the uncertainties, and then the deep deterministic policy gradient based reinforcement learning technique is utilized to analyze the impact of uncertainties on the charging strategy; In [7] a mean-field game approach is used to model the uncertainty of traffic assignment in a coupling of EV's charging and power distribution network.

In the case study of Isle of Pins, it was possible to have a sufficiently precise description of the trips by type of vehicles at different timeslices. This has permitted us to keep the whole approach in the realm of linear programming. The model still belongs to the family of models that link a capacity expansion and distribution power model to an aggregate traffic model of several vehicle types. The power model is derived from ETEM-SG [6] a version of ETEM, an integrated open source energy model of the MARKAL/TIMES [14] family of models. The consideration of smart-grid developments, and henceforth the linking with electric mobility in TIMES was proposed in [11]. The flexibility offered by EV charging in a smart-grid was represented in OseMOSYS, an open-source energy model, permitting, as for ETEM, an easy modification of its equations [22]. The integration of smart-grid and distributed energy resources in ETEM was studied in a strand of papers [9, 2, 4, 1] in which all models are formulated as linear programs.

The rest of the paper is organized as follows: in Section 2 we show how power grid and EV-mobility can be modeled in ETEM-SG; in Section 3 the application to the energy transition plan of Isle of Pins is described; in Section 4 scenarios and simulation results are discussed and in Section 5 one concludes.

2 Modeling power grid and EV-mobility with ETEM-SG

To analyze the synergy between variable renewable energy penetration and electric mobility, we have adapted the ETEM-SG model, which is described and documented in [5, 6]. This model has already served to assess the transition to 100% renewables in non-interconnected regions [3]. The originality of this new application lies in the modeling of V2G and electric mobility. In the following, we briefly recall the structure of the ETEM-SG model and then describe its extension to the modeling of power flows and EV mobility.

2.1 ETEM-SG in a nutshell

ETEM (*Energy-Technology-Environment-Model*) is a multi-sector, multi-energy and technology-rich model specifically designed to analyze the energy transition at the regional or national level. ETEM is a linear programming model, related to the TIMES family of models [10, 13, 14].

In its standard version, the model is driven by exogenously defined useful energy demands (i.e. demand for energy services) and imported energy prices. All technologies are defined as resource transformers and are characterized by technical coefficients describing inputs and outputs, efficiency, capacity limits, date of availability (for new technologies), lifetime, etc. The economic parameters define the costs of energy use and the costs of energy supply. The economic parameters define the investment, operation and maintenance costs for each technology. The planning horizon is usually long enough to allow the energy system to have a complete technology mix turnover.

Typically ETEM proposes an optimal development path for an efficient regional energy system with a planning horizon of 10 to 50 years generally divided into periods $t \in T$ of 1 to 5 years (2 years in the simulations presented in this paper). In each period, a few typical days are considered (e.g., 36 days corresponding to the twelve months and three types of days – weekday, weekend and holiday). Each of these days is subdivided into hours or groups of hours to finally obtain a set of time slices $s \in S$ that will be used to represent load curves, demand distribution and resource availability in different seasons and at different times of the day. This temporal structure is particularly important to correctly represent the dynamics of demand and how its flexibility can be exploited (e.g. through demand response mechanisms). ETEM calculates an investment plan and a supply/demand balance at each time slice for a set of typical days. In order to adapt to possible variations in demand (in particular, peak demand) and to compensate for the intermittency of variable renewables (e.g. wind and solar), reserve requirements are then modeled in ETEM.

ETEM-SG, is an extension of ETEM, where distributed energy resources with Smart Grid are represented. Transmission and distribution constraints and options can be considered as well as possibility of using V2G and smart appliances to provide system services.

2.2 Modeling the power flows in ETEM-SG

Renewable capacities and charging stations will be spatially distributed throughout the territory leading to power transfers among the different nodes (or buses). Let us describe the modeling of these power flow constraints in ETEM-SG. For interested readers, the representation power flow constraints and nodal marginal prices in ETEM-SG is described in details in [8].

For a given point in time, the system operator dispatches the committed units so as to minimize the total operational cost. Consider a transmission network with N_b nodes (or buses) linked by L lines described by the following variables and parameters:

y_n: Net power injection at node $n = 1, \ldots, N_b$; $\mathbf{y}$ is the N_b vector with elements y_n.

z_ℓ: Flow along line $\ell = 1, \ldots, L$; $\mathbf{z}$ is the L vector with elements z_ℓ.

$\bar{A}$: Network incidence matrix $L \times N_b$, with $a_{\ell,n} = 1$ if line ℓ originates from n, $a_{\ell,n} = -1$ if line ℓ terminates on n, $a_{\ell,n} = 0$ otherwise. Note that the sum of the columns of A is always equal to the the null column.

A: An $L \times (N_b - 1)$ matrix obtained by removing a column corresponding to the *swing bus*[5] in the matrix $\bar{A}$.

[5] Usually the swing bus is numbered 1 for the load flow studies. This bus sets the angular reference for all the other buses. Since it is the angle difference between two voltage sources that dictates the real and reactive power flow between them, the particular angle of the swing bus is not important.

S: An $L \times L$ diagonal matrix, $\mathbf{S} = \mathrm{diag}(\mathbf{S}_1, \ldots, \mathbf{S}_L)$, where $\mathbf{S}_l$ is the susceptances[6] vector of line l.

For the sake of simplicity, we assume that the demand schedule from charging stations is fixed, and defined exogenously. In order to remain within a linear programming framework, it is typical to model power flows using linearized equations[7] can be written as

$$\mathbf{z} = \mathbf{S}A\theta, \tag{1}$$

where θ is the $(N_b - 1)$-vector of angles at the different nodes (buses). Since $\mathbf{y} = A^T\mathbf{z}$, and by introducing $A^T SA$, one gets:

$$\mathbf{z} = \mathbf{S}A(A^T\mathbf{S}A)^{-1}\mathbf{y}, \tag{2}$$

which can be rewritten

$$\mathbf{z} = \Psi\mathbf{y}, \tag{3}$$

where Ψ is now called the injection shift factor matrix.

The distribution of power in the different lines of the transmission network is given by Eq. (2) which we rewrite as follows

$$P_f = \Psi(P_{Gen} - P_{Load}), \tag{4}$$

where $P_f = \mathbf{z}$ is the vector of power flows on each line of the network and $P_{Gen} - P_{Load} = \mathbf{y}$ is the vector of net power injection (generation power P_{Gen} minus load P_{Load}) at each bus (node) of the network, which is defined endogenously by ETEM-SG. Notice that at each bus node n, $P_{Load}(n)$ is the sum of conventional (non-flexible) and flexible (in our case PV charging) loads.

The *transmission sensitivity matrix* $\Psi = \mathbf{S}A(A^T\mathbf{S}A)^{-1}$, also known as the *injection shift factor matrix*, gives the variations in flows due to changes in the nodal injections. The shift factor matrix is a function of the characteristics of the transmission elements and of the state of the transmission switches.

2.3 Modeling Electric Mobility and V2G

In this section, we describe the modeling of electric mobility within the power grid. We assume the system handles different vehicle types characterized by their mobility profile and their charging station infrastructure. In this paper, we consider buses, private cars, car fleets and renting cars. We denote $Vtype$ the set of vehicle types. For the sake of simpler notations and as the constraints are the same for all vehicle types we remove the index for periods and EV categories in the following.

The model will therefore define the share of each vehicle category to be electrified, denoted $Share$, and the location of charging and V2G infrastructures. For the electrified mobility part, the model will have then to determine at each time step the charging activity of the EV batteries and/or their V2G contribution to the power grid at the different nodes of the network according to the number of vehicles present at this node. The number of vehicles present at each node at each moment is an exogenous data determined by a preliminary study of the transportation sector. To avoid introducing integer variables to track the movements of each EV, we do not calculate the battery charge level at each node but only at the region level. This simplifying assumption of a single battery per vehicle category avoids numerical issues. The ETEM-SG objective function therefore incorporates the investment costs of electrifying the transportation sector as well as the operating costs of EV and remaining fuel cars.

The following constraints are introduced in ETEM-SG to model the EVs. For a given point in time, the state equations describe the evolution of the state of charge $X(s)$ of the batteries of the different

[6] In electrical engineering, susceptance ($\mathbf{B}$) is the imaginary part of admittance. The inverse of admittance is impedance and the real part of admittance is conductance. In SI units, susceptance is measured in siemens.

[7] This power flow model corresponds to the Approximate DC flow where Power flow obeys Kirchoff'sb voltage law, reactive power is ignored and phase angle differences are small and per unit voltages are set to 1.

EV categories during typical days. The dynamics are represented from one hour s to its successor $s+1$

$$X(s+1) = X(s) - \text{EVcons(s)} + \sum_{n \in N_b} P_{ev}(n,s) - \sum_{n \in N_b} P_{V2G}(n,s), \tag{5}$$

where EVcons(s) is the exogenously computed EV consumption at timeslice s, $P_{ev}(n,s)$ and $P_{V2G}(n,s)$ are the charging activity and V2G variables, respectively at node n and hour s.

The upper bound on state of charge is given by

$$X(s) \leq Share \cdot \text{Tv} \cdot \text{Cbat}, \tag{6}$$

in which the variable $Share$ is the share of electrified vehicles over a total of Tv vehicles. The parameter Cbat is the average EV battery storage capacity (200kWh for buses and 60kWh for cars).

At each node, the charging and V2G activity is limited by the number of EVs present $\bar{\text{EV}}(n,s)$ at hour s at that node n

$$P_{ev}(n,s) + P_{V2G}(n,s) \leq \bar{\text{EV}}(n,s), \tag{7}$$

and by installed capacity of charging stations $Cstation(n)$ at that node n

$$P_{ev}(n,s) + P_{V2G}(n,s) \leq Cstation(n). \tag{8}$$

Note that to disable the V2G option, the variable $P_{V2G}(n,s)$ are set to zero.

3 Implementation issues

In this section, the spatial and temporal structure of the modeling approach and the representation of the transport and energy networks that were selected for application to the Isle of Pines are presented.

3.1 Spatial and temporal decomposition

3.1.1 A simplified representation of energy and transport networks

We worked with a simplified representation of the electricity and transportation networks. A geographical analysis of the origins and destinations – cities and villages, airport, and hotels, as well as the main touristic areas lead to the following simplified grid model with 10 nodes: each node aggregates all identified consumers located within an area delimited around it, as shown by Figure 1.

3.1.2 Time decomposition

To account for the variation in demands at different time scales, the following temporal decomposition was established: (a) a 10-year horizon (2020–2030) is subdivided into 5 two-year periods; (b) in each month of a year, three typical days are distinguished: weekdays, weekends, and holidays; in each day, there is an hourly decomposition. This temporal decomposition is motivated by the island's tourist activity, which varies from month to month and significantly impacts electricity demand and mobility.

3.2 Transportation network details

Given the small size of the territory, the very specific usages on each geographical zone, and the small number of vehicles, it is possible to use a deterministic modelling approach instead of the stochastic one often referred to in the literature review. According to ISEE statistical data (2019), there are 420 vehicles on the island. We could specifically identify 112 vehicles through a survey showing, the type of user and type of vehicles in a database with the following specifications: Car owner; One-way or round trip; To each destination and from each origin; Weekday/weekend/holiday; Number of cars,

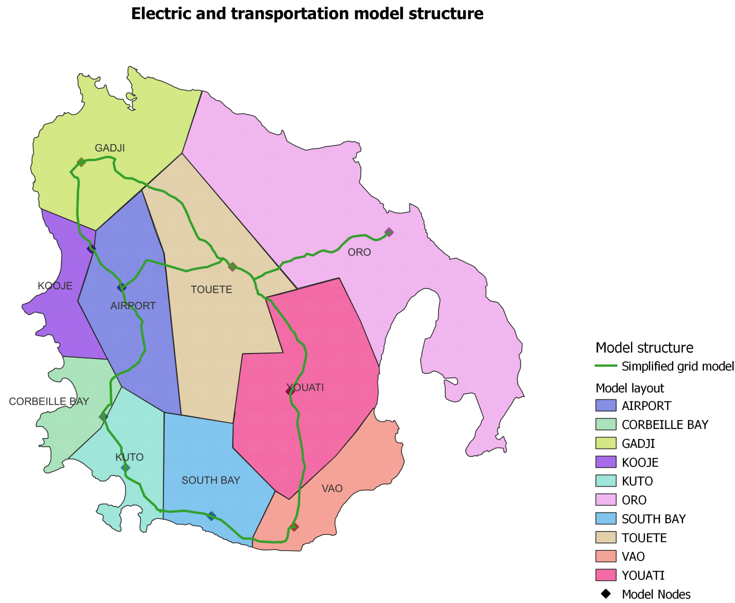

Figure 1: A simplified layout of the electricity and transportation networks

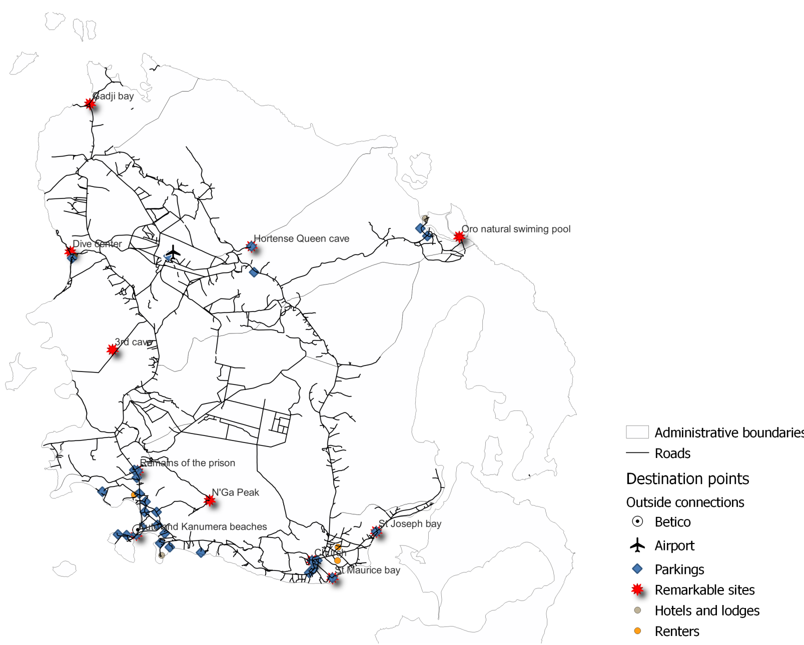

Figure 2: Transportation system and specific vehicles destination points

Travel distance; Electric or thermal vehicle; Type of vehicle (Company fleet/bus/rental car/private car).

In the transportation model one considers two categories of vehicles: tourist and non-tourist. Tourist vehicles are buses and rental cars with typical destinations, frequencies, and shares of vehicles used during the weekday, weekend, and holidays. Four types of trips are identified: (i) To and from the airport, synchronised with the airplanes time schedule; (ii) To and from the port, synchronized with the Betico time schedule; (iii) Daily trips to some specific touristic locations such as beaches, dive center, etc. (iv) Daily round trips through the whole island to visit touristic spots. For non-tourist vehicles: (i) each identified vehicle through the survey is associated to its corresponding area of the model; (ii) the vehicles that couldn't be identified are then spread through the island following the repartition of the urbanized and rural houses surface areas for their origin node, and urbanized, industrial and commercial for their destination node. Given the size of the island, all trips are done within an hour time.

Table 1 reports the number of vehicles per category and the total distance travelled per vehicle type and per typical day. These total distances are then distributed temporally on each hourly time step and spatially between each pair of nodes. These distances include intra nodal mobility.

Table 1: Summary of the transportation sector

	Number of vehicles	Total distance travelled in km		
		Weekday	Weekend	Holiday
Company fleet	37	220.0	0.0	55.9
Buses	18	24.5	103.1	259.5
Rental cars	29	0.0	26.8	84.6
Private cars	335	593.3	8.9	36.9

From this analysis, we know in detail the trips made by the different types of vehicles and the location of these vehicles on the island at hourly time steps. This information will be valuable for charging electric vehicles at the various nodes of the network.

3.3 Energy system

The electric grid of Isle of Pins is limited to high (15kV) and low voltage distribution system with 114 km of electric lines. The installed generation capacities include a 3.6 kW thermal power plant in Comagna, a 250 kW ground based photovoltaic system in MWire, and a 24.8 kW building integrated photovoltaic system on the airport. In addition, the current energy policy has already defined new PV projects for a total of 1.5 MW (in Gadji, Igesa, Grand Wharf and Maison de sante) and a 2.2 MW capacity of battery packs. It also plans to develop an additional 1 MW of PV capacity whose location has to be decided.

The projection of the yearly electricity demand excluding electric vehicles is assumed within the range of a low increase rate of +0.2%/year − assumption of the local investment plan − and a high increase rate of +0.8%/year − assumption of the local energy operator from 2019. The analysis of the hourly load curve is based on a set of measured data of the biggest consumers and total energy production. The hourly load curve has been reconstructed as illustrated in Figure 4. The energy demand of the biggest consumers is associated to the corresponding grid nodes. The rest of the demand, which is not associated to specific consumers is then allocated to each node in proportion of the associated urbanized areas.

Finally, a solar photovoltaic potential is introduced at the Airport, Touete, Youati, Baie Sud and Kuto nodes. The main constraint concerning solar development is the exclusion of the forest which covers a large share of the island's surface. It should be noted that there is no potential for other renewable energy sources on the island.

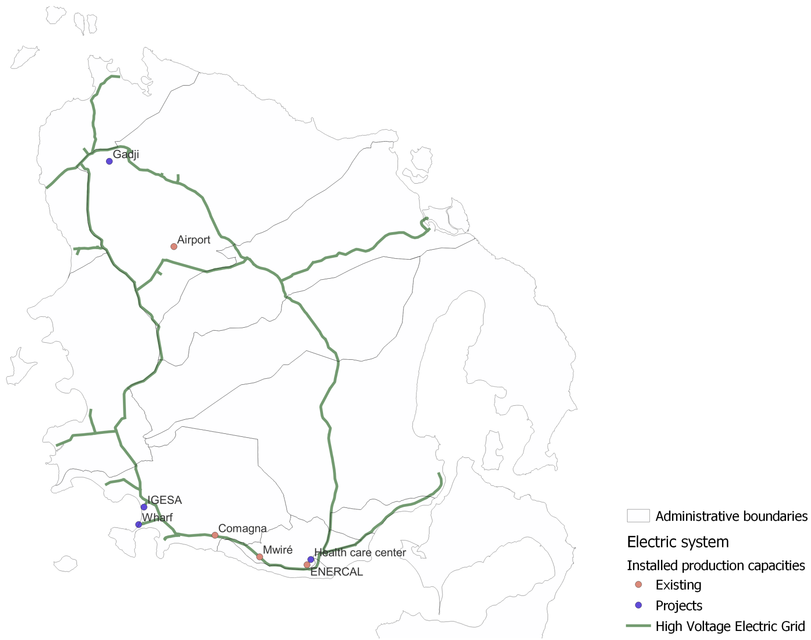

Figure 3: Existing electric system of the Isle of Pins

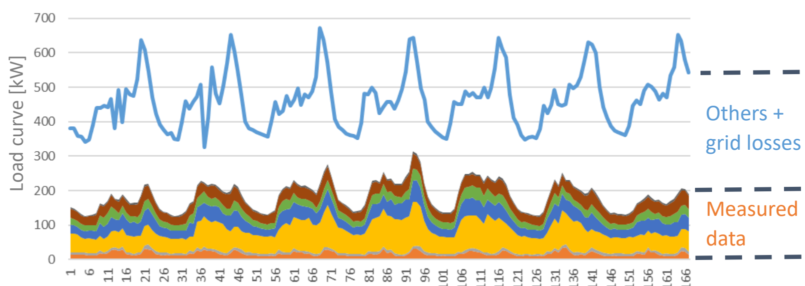

Figure 4: Load curve structure of the Isle of Pins

4 Scenarios and simulation results

4.1 Definition of scenarios

In this section, we describe the scenarios we considered in our analysis, as well as the results obtained in each case. Our goal is to assess the synergy between electric mobility and VRE generation, and in particular the role of controlled EV charging and V2G participation in a transition to a low-carbon economy. We propose the following four scenarios:

- A Reference scenario in which the evolution of the electricity (capacities of VRE and batteries) is fixed to the current energy policy as defined above. EV penetration is optimized by the model and V2G activity is limited to 50% of EVs. This scenario answers the following question: Is there an interest for a transition to electric mobility given the current energy policy?
- A pessimistic scenario that takes into account the current evolution of the transport sector: limited EV penetration (25% of the total number of vehicles corresponding to all rental cars, buses and corporate fleets), limited controlled charging for EVs and no possibility of V2G activity. In this scenario, the installed VRE and battery capacities are optimized with no upper limits. The question to be answered here is: Does the current trend in the transportation sector limit the deployment of VREs?

- Two optimistic scenarios (Optimistic and Optimistic 100%) in which the electric system and the transportation sector are optimized by the unconstrained model. EV charging can be optimized to 80% and V2G is fully deployed. In the Optimistic 100% scenario, a 100% renewable energy target for electricity generation is imposed in 2030.

Table 2 below provides a summary of the conditions imposed in the four scenarios.

Table 2: Scenario definition

	Reference	Pessimistic	Optimistic	Optimistic 100%
VRE objectif	Optimized	Optimized	Optimized	100% in 2030
VRE potential	Constrained	Free	Free	Free
Battery pack potential	Constrained	Free	Free	Free
EV penetration	Optimized	Fixed to 25% in 2030	Optimized	Optimized
EVs with controlled charging	80%	10%	80%	80%
V2G participation in 2030	50%	0%	100%	100%

4.2 Simulation results

4.2.1 Global overview

In Tables 3 and 4, we present a summary of the results in 2030 for the mobility and electricity sectors, respectively. We observe that under the current energy policy (Reference scenario), only 25% of private cars are electrified and associated with slow charging stations. The economic gain is limited to 0.4% of the total discounted cost compared to the cost of the same scenario without electric mobility. Renewable energy, under the current planned investments, reaches 78% of the total electricity production. The diesel plant produces the remaining 22%. The current policy does not seem to foster a strong development of electric mobility.

Table 3: Mobility results

Mobility		Reference	Pessimistic	Optimistic	Optimistic 100% VRE
EV Conversion	Private cars	25%	0%	50%	50%
	Rental cars	0%	100%	0%	0%
	Company fleet	0%	100%	0%	0%
	Bus	0%	100%	100%	100%
Charging stations	Total	330 kW	1116 kW	1172 kW	1628 kW
	Including fast charging	0	500 kW	600 kW	550 kW

Table 4: Energy system results

Energy system	Reference	Pessimistic	Optimistic	Optimistic 100% VRE
VRE penetration	78 %	93 %	94 %	100 %
Solar panel installation [MW]	2.8	4.8	5.2	7.9
Storage capacity [MW]	2.2	2.4	1	1
Impact on system cost*	-0.4 %	+2.3 %	-5.3 %	+3.5 %

(*) Difference wrt the reference scenario cost without electric mobility.

Under pessimistic assumptions, we find that mandating electrification of rental cars, buses, and corporate fleets is not a cost-optimal solution. It leads to a cost increase of 2.3%, with much higher investments in VRE capacity and batteries, without the possibility of operating EV and V2G charging systems. The share of renewables increases to 93%, as VRE capacity is no longer limited. In the optimistic scenario, buses and half of the private cars are electrified and VRE capacities increase to 5.2 MW, but battery pack investments are reduced to 1 MW (instead of 2.2 MW in the current energy policy). As controlled charging and V2G are enabled, battery packs are less crucial for the supply/demand balance. This results in a cost reduction of 5.3% compared to the Reference scenario without electric mobility. It seems promising to optimize the energy system at the same time as the electrification of transport, which shows a strong synergy between the two systems. As far as the share of renewable energy is concerned, the impact is limited (94%) compared to the pessimistic scenario. In the last scenario, a 100% renewable target is imposed. We observe higher investments in solar panels and in slow charging stations. The model fully exploits the flexibility offered by controlled charging and V2G at different locations and times of day. Unfortunately, this results in an additional total cost of 3.5%. In the last three scenarios, fast charging is used exclusively for buses.

In the following sections, we discuss in more details the evolution of the transportation sector and the energy system for the four scenarios.

4.2.2 Evolution of the energy system

Figures 5 and 6 show the evolution of installed capacity and generation by scenario. We observe the highest share of VRE generation in the Optimistic scenarios, although in the Reference and Pessimistic scenarios, batteries are used to compensate for intermittent renewable generation. As defined, the Optimistic 100% scenario achieves 100% PV generation.

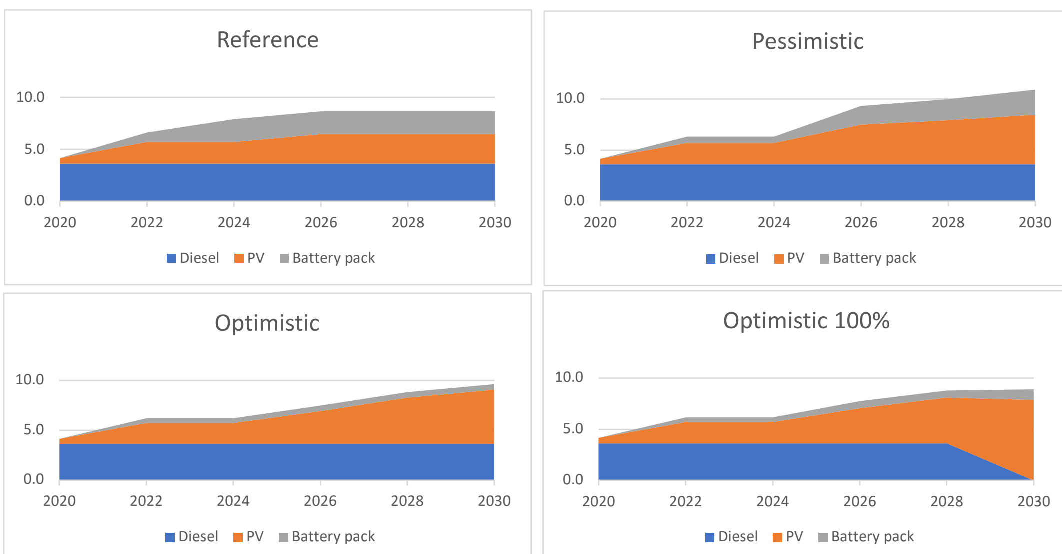

Figure 5: Evolution of installed capacities (in MW)

Figure 7 displays representative load curves in 2030 (i.e, weekday, weekend and holiday in February). They highlight the role of battery packs and V2G between 6pm and 7am while PV panels produce almost all electricity during the day on the four scenarios. Extra PV generation during the day is either used to charge battery packs or to charge EV batteries as shown later. Diesel production is still needed in the Reference scenario to meet the demand. It shows that the current energy policy is not ambitious enough to attain a 100% renewable scenario. We notice in the Pessimistic scenario a high discharging activity of battery packs in the evening due to the demand for EV charging of location and rental vehicles.

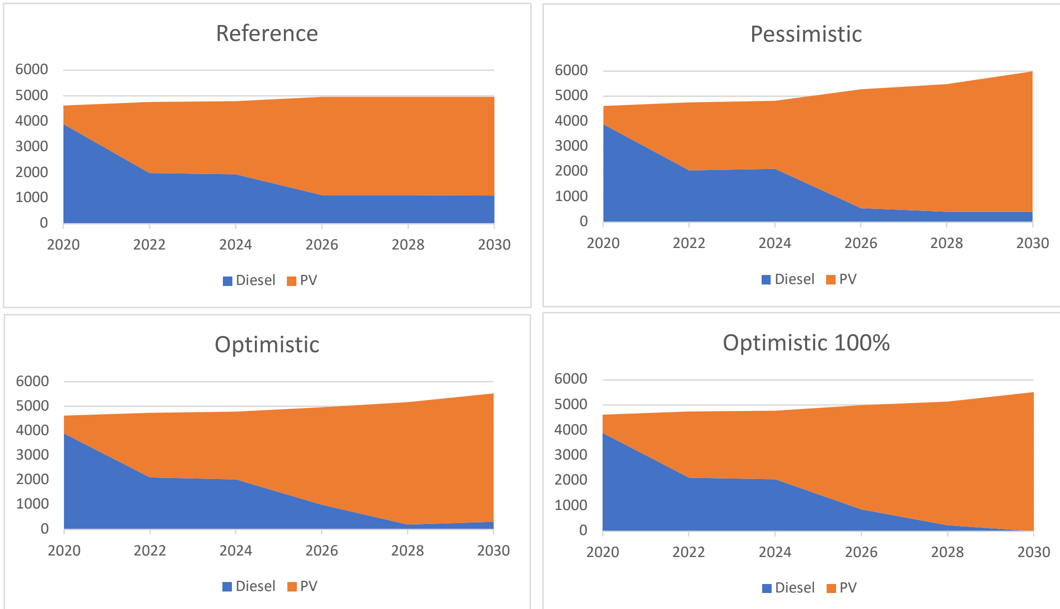

Figure 6: Evolution of electricity generation (in MWh)

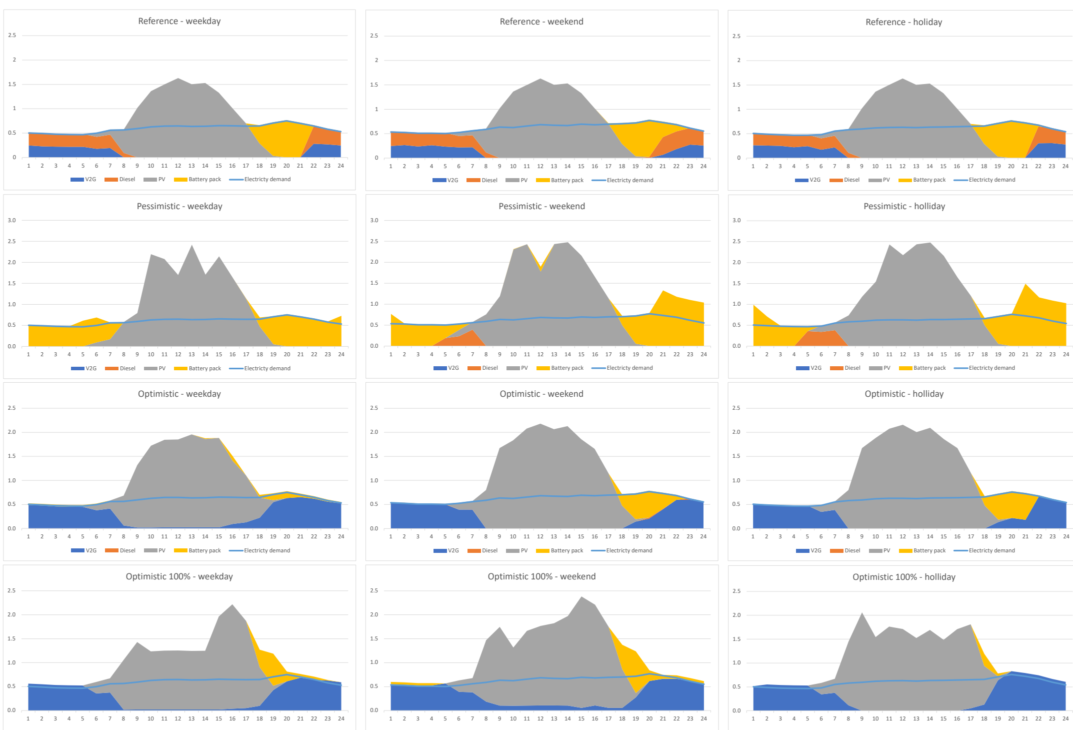

Figure 7: Load curves (in MW) – February 2030

4.2.3 Evolution of the transportation system

Figure 8 shows the evolution of the EV share by vehicle category, while Figure 9 shows the spatial distribution of charging stations (fast charging stations for buses). The charging stations are mainly installed at workplaces to facilitate charging during the day when solar energy is abundant and at home to allow electricity to be fed back into the grid at night.

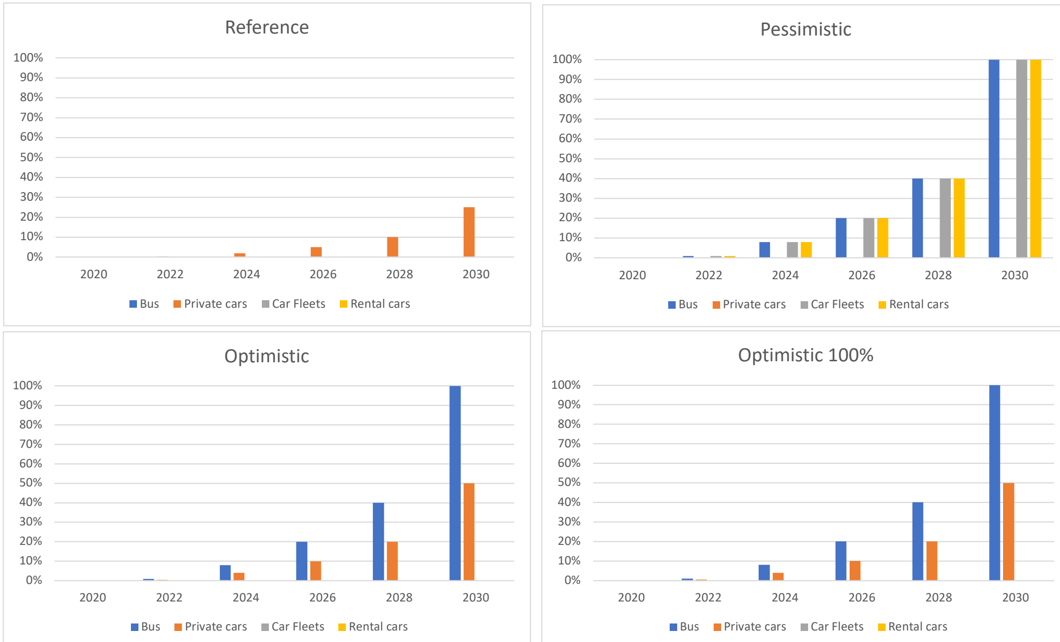

Figure 8: EV penetration by vehicle category (in %)

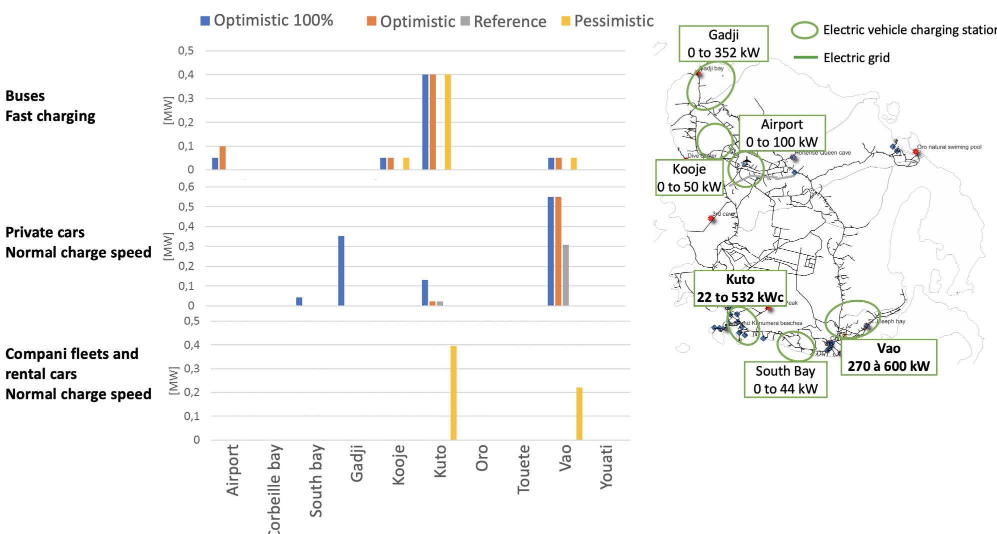

Figure 9: Location and capacity of charging stations by vehicle category in 2030

4.2.4 EV charging and V2G activities

In the appendix four figures summarize the hourly charge level of EV batteries and their charging and V2G activities by vehicle type for the "Reference" scenario (Figure 10 for private cars), the "Pessimistic" scenario (Figure 11 for buses, fleet and rental cars), the "Optimistic scenario" (Figure 12 for buses and private cars) and the "Optimistic 100%" scenario (Figure 13 for buses and private cars).

These figures illustrate the synergy that exists between PV generation and V2G activity. When V2G is enabled in the reference scenario and the two optimistic scenarios (Figures 10, 12 and 13), the vehicles charge their batteries during the day and feed energy back into the grid at night. The situation is completely different for the pessimistic scenario in which V2G is not allowed (see Figure 11). Charging activity is observed mainly at night, when electricity demand is lower. The differences in charge level, charging and V2G activity that can be seen between weekdays, weekends and hollidays can be explained by the different mobility profiles and therefore different availability of the vehicles.

5 Conclusion and policy implications

Grid-injection of electricity from the electric vehicle (V2G) is essential for electric vehicles to make a positive contribution to the electrical system. This requires that charging stations be positioned so that vehicles can connect to them during the day and at night. Electric vehicles primarily provide a supply-demand balance service: They absorb surplus generation during the day and release it at night. This implies that the charging stations can be controlled. This strategy is particularly effective on a territory such as the Isle of Pins because of its small size: the trips are short (in duration), which allows a high availability of the vehicle, the storage capacity of electric vehicles is very high compared to daily needs, which allows a significant part of the battery to be allocated to network services.

In this study it has been shown that the deployment of electric vehicles can achieve a VRE penetration rate of up to 94%, without any additional cost compared to a solution without EVs, and even with a reduction of up to -5.3% (in the unconstrained Optimistic scenario) thanks to a reduction in the necessary battery packs for storage. To achieve this result, the conversion to electric vehicles must be aimed primarily at private vehicles, up to 50% of the fleet, and target diesel vehicles on Vao and Kuto Buses, up to 100% of the fleet. The introduction of electric vehicles must be accompanied by a doubling of the photovoltaic fleet: 2.8 MW to 5.2 MW. Increasing the rate of renewable energy beyond 94% by means of PV + storage + electric vehicles alone requires: (i) a significant increase of the PV park: +2.7 MW; (ii) a 40% increase of capacity for the electric vehicle charging stations so that there can always be a sufficient number of electric vehicles connected to the network; (iii) setting up a strong incentive for electric vehicle owners to have their vehicles plugged in when they are idle.

Because of the small size of the island and the main local activity, i.e. tourism, it was possible to develop a deterministic model in the realm of linear programming. If the analysis were to be developed in a larger region with more vehicle types and usage patterns, the loads calculated for each node in the transportation network would be too uncertain to remain in a deterministic framework. It might then be considered to introduce robustness into the energy sector optimization model to account for variability in demand and timing of charging and battery use for different vehicle types. Some guidance on how to implement such an approach is given in Refs. [7] and [2].

Appendix

A Charging and V2G activities

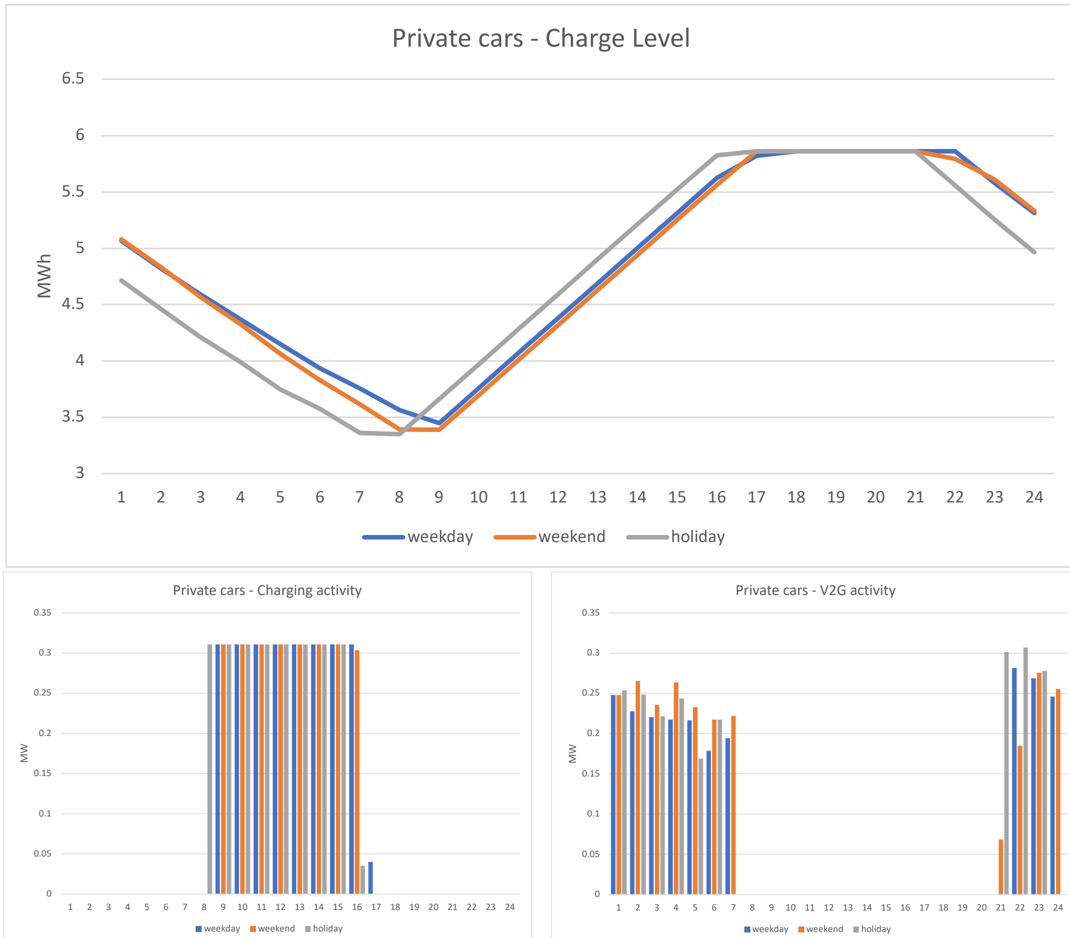

Figure 10: EV charging and V2G activity for private cars in the Reference scenario – February 2030

Figure 11: EV charging for buses, fleet and rental cars in the Pessimistic scenario – February 2030. Remind that V2G is not activated in this scenario

Figure 12: EV charging and V2G activity for private cars and buses in the Optimistic scenario – February 2030

Figure 13: EV charging and V2G activity for private cars and buses in the Optimistic 100% scenario – February 2030

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