Renewables self-consumption potential in districts with high penetration of electric vehicles

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Abstract

The need to act on the challenges brought by climate change calls for an increasing penetration of renewable energy sources (RES) in our society's energy supply, but such integration can be challenging. This study analyzes the impact of large numbers of smart electric vehicles (EVs) in a real urban district, using the Italian town Osimo as a case study, to determine the achievable degree of RES self-consumption and CO_2 emission reductions. Osimo features a multi-energy system with electricity, natural gas, district heating, and a 23% share of non-controllable RES capacity, mostly photovoltaics. The presence of EVs is evaluated in the present conditions and in scenarios with an increasing capacity of non-controllable RES. The case study is modeled in the deterministic hourly energy systems simulation model EnergyPLAN, which for these analyses is embedded within a framework aimed at enhancing its capabilities to consider the impact of uncertainties and obtain more robust results. The results show that a 10% EV penetration with vehicle-to-grid (V2G) capability can eliminate the need to export electricity surplus at the current PV capacity, lowering Osimo's CO_2 emissions by 3.5%. A 30% penetration achieves the same with twice the PV capacity, reducing the emissions of 17.6%.

Keywords: EV (Electric vehicles); Energy planning; Renewable energy sources; Multi-energy systems; EnergyPLAN

1. Introduction

There is a vast set of efforts by different stakeholders, from governments to industries, to lower the carbon footprint of our society, and more in general to move towards a more sustainable model of development [1]. The push towards decarbonization is transversal and impacts all the sectors in which energy is consumed, from electricity generation to heating, agriculture, and transports and is becoming increasingly urgent due to the effects of climate change [2].

An important strategy in this direction regards the use of an increasing share of renewable energy sources (RES) [3]. This is already happening both thanks to supportive policies that are being put in place and to technological development which is constantly decreasing the costs of exploiting RES. In fact, RES costs are already approaching grid parity in some countries [4].

However, decreasing costs of the major RES technologies notably photovoltaics (PV) and wind power [4] - is not the only important development. Costs of batteries and EVs are also decreasing due to a fast push from the automotive industry, especially for light-duty uses [5].

In its most basic form, a large fleet of EVs constitutes an additional electricity demand that weighs on the electric grid. Thus, given the EVs charging/usage patterns that have emerged so far, it is projected to potentially cause stress on local grids/feeders [6]. This is especially problematic in contexts that also have a high penetration of PV systems [7]. While the production of a PV system typically is not controlled, an EV can be considered as a battery that needs to be charged and potentially discharged while respecting specific constraints. For this reason, opportunities emerge with the ability to fully or partially control the EV charging process [6,8]. Smart charging provides the possibility of partially controlling the charging power over a given time span and vehicle to grid (V2G) also enables the inverse battery-to-grid flow. Hence, EV batteries can be used to feed electricity back into the grid and provide services including peak shaving and frequency regulation. Thus, the opportunities to decarbonize our societies brought by EVs are twofold: firstly, the phasing out of fossil fuel-based conventional cars, and secondly the opportunity to facilitate the integration of non-controllable RES in electric grids.

For these reasons, research in the interactions between EVs and non-controllable electricity-producing RES is intensifying. In particular, there is interest in the relationship with solar-based electricity generation technologies such as PV [9,10].

This is considered of interest also due to the relevant role that distributed generation is expected to play in the near future for several reasons such as having systems that are tailored to the local needs and increased involvement of consumers in reducing transmission losses [11,12].

In this context, the interactions between different energy networks and RES-generated electricity are particularly interesting within a distributed multi-energy systems [13]. Investigating the problem at a local scale allows to consider synergies that would not grant the same degree of benefits by considering a national/ regional scale problem. As a matter of fact, the research on the interactions between energy systems and vectors at a local scale is also intensifying [14]. In particular on the role of large capacities of RES in combination with district heating and cooling networks [15,16], with storage systems [17e19] and finally with EVs [20,21].

Thus, the case proposed in this study is of interest. It consists of the small town of Osimo (approximately 35,000 inhabitants), in central Italy. Here there is a single municipality-owned holding company that is in charge of managing, through its subsidies, different energy sectors in order to meet the demand of several commodities by the end-users. These are electricity, district heating, natural gas, and water. Moreover, the town can be considered a multi-energy microgrid since it has just one point of common coupling with the national transmission system and a significant amount of distributed electricity generation sources within its boundaries. Among the generation assets within the microgrid, that already has a high penetration of distributed energy resources and RES are a 1.2 MW_e CHP system connected to the district heating network, approximately 31 MWp of PV, 999 kW of biogas plant, about 400 kW of mini-hydro nominal power, 200 kW from bioenergy. The present PV capacity already causes excesses of production during weekends when the electricity demand is lower due to the closure of industrial activities, and especially in the summer when PV production is higher.

Similar research questions have already been faced in the literature. A study shows that the heavy presence of EVs is found to greatly help the adoption of large capacities of wind power with also a significant emissions reduction in a national context in Denmark [22]. A similar analysis has been performed in the national Italian and German contexts [23,24], finding that a complete electrification of the transport sector coupled with a significant increase in RES could lead to CO_2 emissions reduction ranging from 20 to 40%, furthermore proving the beneficial coexistence of the two technologies. A more recent study, also in Italy, confronts EVs with electrification of the heating sector as a means to address the surplus from high shares of RES [25], finding that EVs are more effective in welcoming higher shares of non-controllable RES.

The interactions between RES and EVs also gained interest while analyzing systems of smaller scales: from city/town scales to buildings. For example, in Ref. [26] the case of two Scandinavian cities is analyzed to find that PV yield can cover almost all of the EVs need in the summer, but otherwise, the temporal match could be improved. In Ref. [27] the interactions among physical islands having both high RES capacities and EV penetrations is analyzed, finding the cooperation among islands beneficial in welcoming higher shares of RES. Finally, in Ref. [28] a smart energy systems approach is compared with a traditional decoupled-sector approach for the city of Zagreb, finding the integrated approach much more effective in integrating RES.

Within this framework, this work presents a case study representative of a multi-energy microgrid characterized by a high penetration of non-controllable RES. Moreover, the case study can be fully characterized thanks to the amount of detailed data available.

This study performs an analysis of the potential beneficial impacts of a fleet of EVs on a local energy system with high RES penetration. More specifically the goal is to understand to which degree a fleet of EVs can plausibly help in self-consuming excesses of electricity production by non-controllable RES in a small-scale local energy system.

The study analyzes the effects of a large fleet of EVs on the local system by investigating the impacts of different EV penetration levels on the renewables self-consumption capabilities and the decarbonization of the microgrid. The analyses are performed simulating the current capacity and increasing the capacity of noncontrollable RES. This is considered of interest given that for the very same town the investment on an EV charging infrastructure is found to be profitable even without incentives [29].

This is achieved by simulating a set of scenarios by means of the EnergyPLAN model. The scenarios are used to analyze a progressive increase of three variables within the local energy system: the generation capacity of non-controllable RES (here PV plants), the number of electric vehicles, and their smart capabilities.

The EVs smart capabilities are considered on three different levels: from “passive” EVs (without any type of smart management capability) to “active” EVs with smart charging and finally vehicleto-grid (V2G) as follows:

i) Passive EVs refer to vehicles that weigh on the local grid as anadditional inflexible electricity demand defined with an hourly temporal resolution.
ii) Smart charging vehicles add to the passive EVs the capabilityof having the charging process (thus only grid-to-vehicle power flow) partially scheduled over time when needed.
iii) V2G vehicles add even more functionality by also allowingthe inverse power flow from the EVs to the grid, still if needed for balancing purposes by the local grid.

The three steps define an increasingly smart EVs fleet with an increasing capability to help in balancing the electricity generation from non-controllable RES.

With respect to the already available literature, a main contribution of this paper is that it considers the local dimension of both the RES and EV penetration more thoroughly with actual measured local data.

A second contribution lies in the introduction of a framework aimed at assessing the impact of uncertainties of different nature in energy systems simulation models such as EnergyPLAN in the specific work. This allows to perform simulations aimed at obtaining more robust insights [30]. Specifically, in this case, the uncertainties refer to the EVs electricity demand and the weather conditions, which impact both the yield of the PV systems and the demand of the local DHN. This is considered of importance within the study given the influence of both factors in determining the self-consumption capabilities of the local RES sources. As highlighted in Ref. [31,32] the consideration of uncertainty sources is necessary in energy systems modeling, in particular in light of the current challenges described in the introduction such as an ever increasing exploitation of non-controllable RES and the progressive electrification of many energy areas such as transport.

The article is structured as follows: In Section 2 the EnergyPLAN model is described and modeling of the case study is described, beginning with the measured data which was available to the modeling strategy for the considered uncertainty sources. In Section 3 the workings of the analysis framework are described, in Section 4 the results of the analysis are displayed and discussed, and finally in Section 5 the conclusions of the study are drawn.

2. Materials and methods

This section describes the methods used to model and analyze the proposed case study.

2.1. The EnergyPLAN model

As mentioned in Section 1, the analyses are performed by means of the EnergyPLAN model [33], which is a model that allows to perform the simulation of complex energy systems consisting in many energy carriers and energy conversion technologies, with hourly resolution over a yearly timespan. The energy system is modeled as a single point (thus without internal energy transfer capacity constraints) where production and demands across different energy sectors are balanced throughout the year.

The main reasons for choosing the EnergyPLAN model are related to the ability to represent several of the complex interactions across different energy sectors, and because of the fast computational capability which is required when running a large number of scenarios in a reasonable amount of time. EnergyPLAN is an energy system analysis model that takes as inputs the sizes and conversion efficiencies of the technologies within the energy system under study and simulates their workings in meeting a set of demands throughout a year.

The demands of several commodities can be defined both as yearly totals (as for example the demand of a given fuel in the transport sector) but also with hourly resolution, such as for the demands for electricity or district heating.

The energy system under analysis is also considered as connected to an external electricity supplier, which provides electricity if needed but also absorbs any excess of power generation.

EnergyPLAN is ideal to model the case study at hand, since the energy needs of Osimo are met by means of a wide set of energy conversion systems having just one point of common coupling with the Italian transmission system.

The output of the simulation allows to quantitively understand different relevant aspects of the energy system operation from the total CO_2 emissions, over the demands of different types of fuel to the need to import and export electricity across the system's boundaries. A general EnergyPLAN input-output structure is shown in Fig. 1.

In simulating the energy system EnergyPLAN uses a regulation strategy selected by the user. Among the options lies the possibility of either a technical regulation with a focus on just balancing the energy flows, like heating and/or electricity, or perform a simulation which strategy also considers economic parameters by optimizing the behavior against an external electricity market.

Given the goal of this study - evaluating the self-consumption capability of the district at hand - a technical regulation strategy balancing the electricity and heating flows is selected. This causes EnergyPLAN into trying to use in the best way possible the noncontrollable variable electricity production from the local RES sources, in the process also managing cross-sector technologies such as CHP systems. Also, the technical regulation strategies provide the technical possible operation which is interesting in this case.

EnergyPLAN has already been widely used to analyze complex energy systems for insights and policymaking at different levels but the main application of the model is the analysis of systems of large sizes such as national/regional [34]. Nonetheless, some analyses have been performed on systems of a smaller scale such as cities [35e38] and small towns [39,40] or small islands [41e43].

The software can handle the modeling of all the technologies and energy sectors of interest in this study by default. Particularly it can simulate the demands of the transport sector with both conventional fossil-fueled transport and electric mobility. For the latter, there is the capability of modeling both passive EVs, thus without any smart capability, and active EVs. These can have a different level of smart capabilities, from smart charging (meaning the possibility to partially schedule the charging process) to vehicle to grid (V2G, meaning the possibility of the fleet's batteries to be also discharged in order to help to balance the electricity system).

In EnergyPLAN the presence of non-smart EVs is simulated as an additional hourly electricity demand. The smart functionalities, both smart charging, and V2G, are introduced by means of a set of parameters defined for the whole fleet of vehicles within the system boundaries.

To simulate active smart EVs, the exogenously given demand distribution curve of passive EVs can be modulated in time by EnergyPLAN through a set of parameters that define the smart capabilities of the whole EVs fleet. A smart EV fleet is treated as a single rechargeable electricity storage system, with a different degree of availability throughout the day. Such battery can be charged and/or discharged (if V2G is introduced) in order to balance the electricity flows within the local grid according to its hour-by-hour availability. This availability is computed based on an hourly pattern, which is computed using the hourly distribution of the passive inflexible EV demand (which represents the behavior of the users), and two parameters expressing the share of vehicles that are driving at peak hours and their grid connection share. A more detailed description of the smart EV operation is available in Ref. [22] and EnergyPLAN's official documentation [44]. The needed parameters to model EVs are:

- Total demand for the transport sector in GWh/year
- Hourly distribution demand of the electric transport sector
- Electricity transfer capacity of the grid to battery connection in kW
- Efficiency of the grid-to-battery connection: both while charging the vehicles (grid-to-vehicle electricity flow) and with the inverse flow due to V2G (vehicle-to-grid electricity flow) Maximum share of smart vehicles driving during peak hours
- Share of parked smart vehicles which are connected to the grid Electricity transfer capacity of the battery to grid connection in kW
- Capacity of the battery storage in MWh

2.2. Model of the district energy conversion systems

Osimo has significant distributed energy resources (DER), most of them being non-controllable renewables. In particular: 1.2 MW_e of the natural gas engine (that also operates in CHP mode), with a 39.9% electric efficiency serving the local district heating network (DHN), two mini-hydropower plants for a total size of 400 kW, approximately 31 MWp of PV systems. In particular, the local DHN thermal energy demand is met by heat recovered from the previously mentioned CHP system, with a 41.5% thermal efficiency, 13.5 MW_{th} of natural gas boilers with a 95% thermal efficiency and a 34.8 kW_e high-temperature heat pump with a coefficient of performance (COP) of 4.6. All these systems are monitored in real-time.

The rest of the electricity needs are met by drawing electricity from the national transmission network, while the heating needs (consisting both in domestic space heating and industrial use) are met mostly by individual solutions based on natural gas drawn from the national grid.

A graphical representation of a model of the case study is shown in Fig. 2.

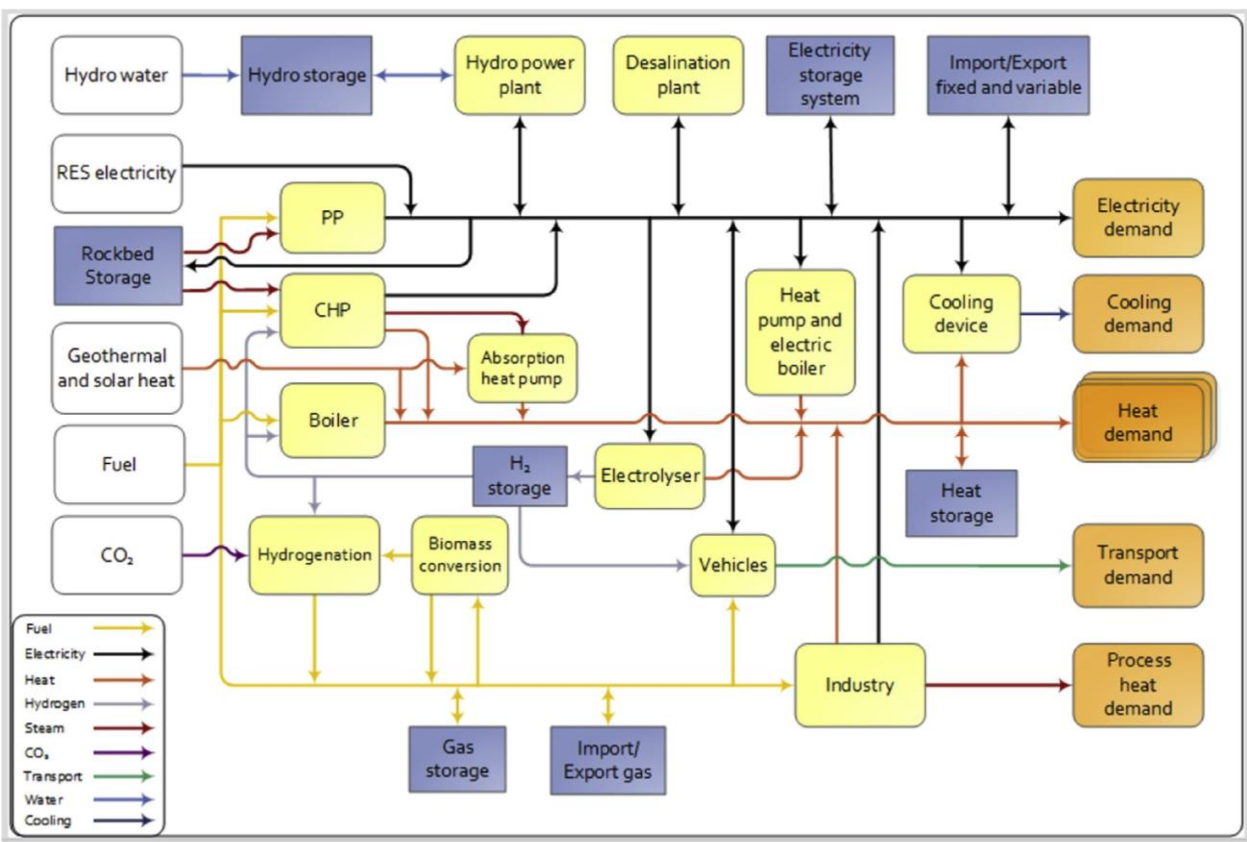

Fig. 1. EnergyPLAN model general structure. Screen dump from the model [33].

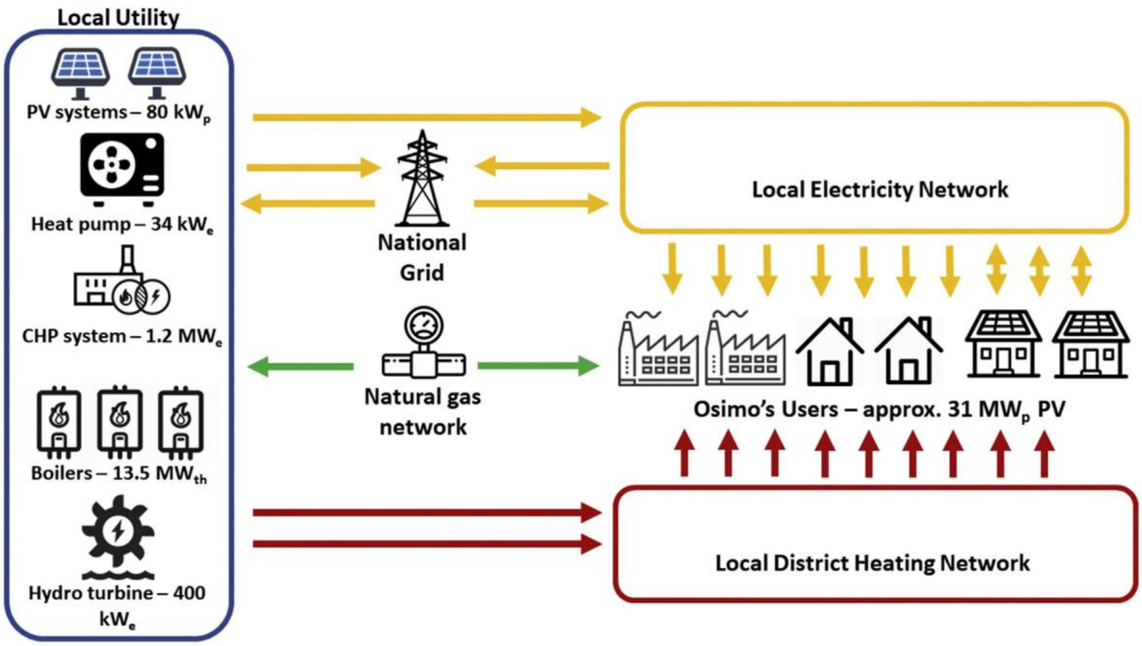

Fig. 2. Scheme of the representation of the local energy system under analysis.

Both the demands of the local DHN and the electricity exchanges with the national grid are provided with a 15-min resolution for the whole year of 2018 and

are shown in Fig. 3 and Fig. 4, respectively. As shown in Fig. 3, the heat demand peaks at around 9 MW in March and drops to around 1 MW in the summer months between June and September.

The additional natural gas demand (destined to both individual heating systems and industrial use) was instead provided as a yearly total, and in 2018, this demand amounted to 220 GWh.

Fig. 4 shows that the municipal microgrid injects a large amount

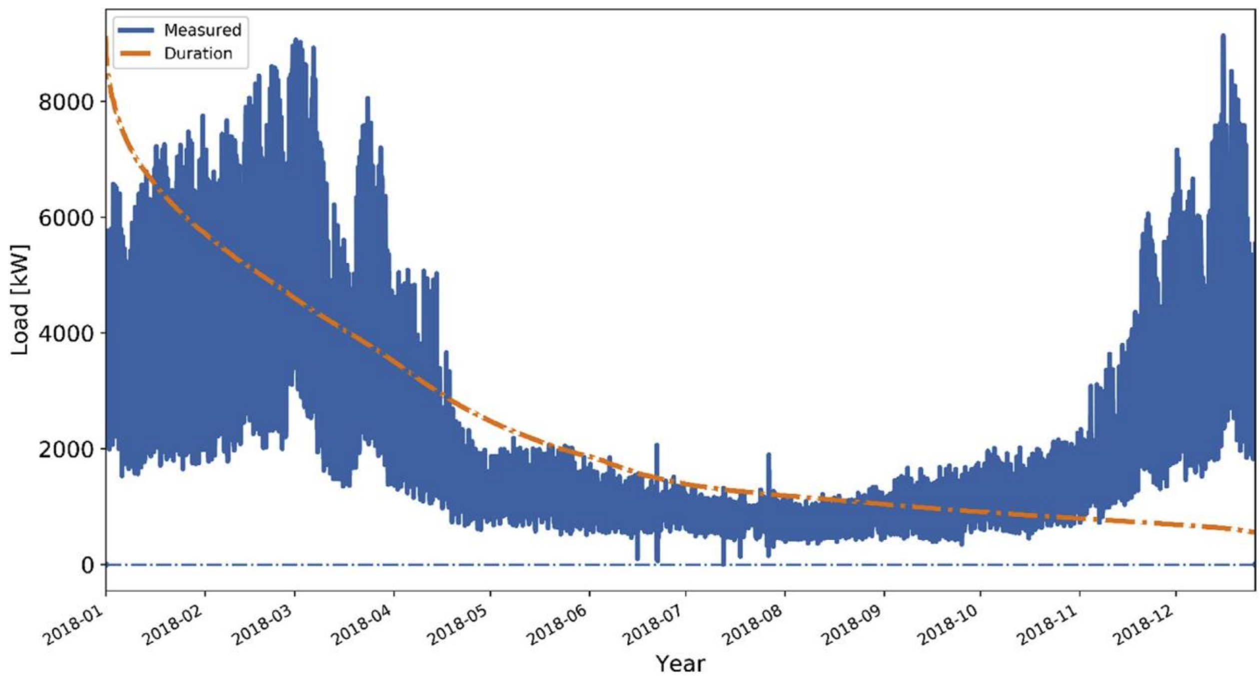

Fig. 3. Actual DHN demand in Osimo in 2018 with 15 min resolution (in blue) and corresponding duration curve (in orange). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

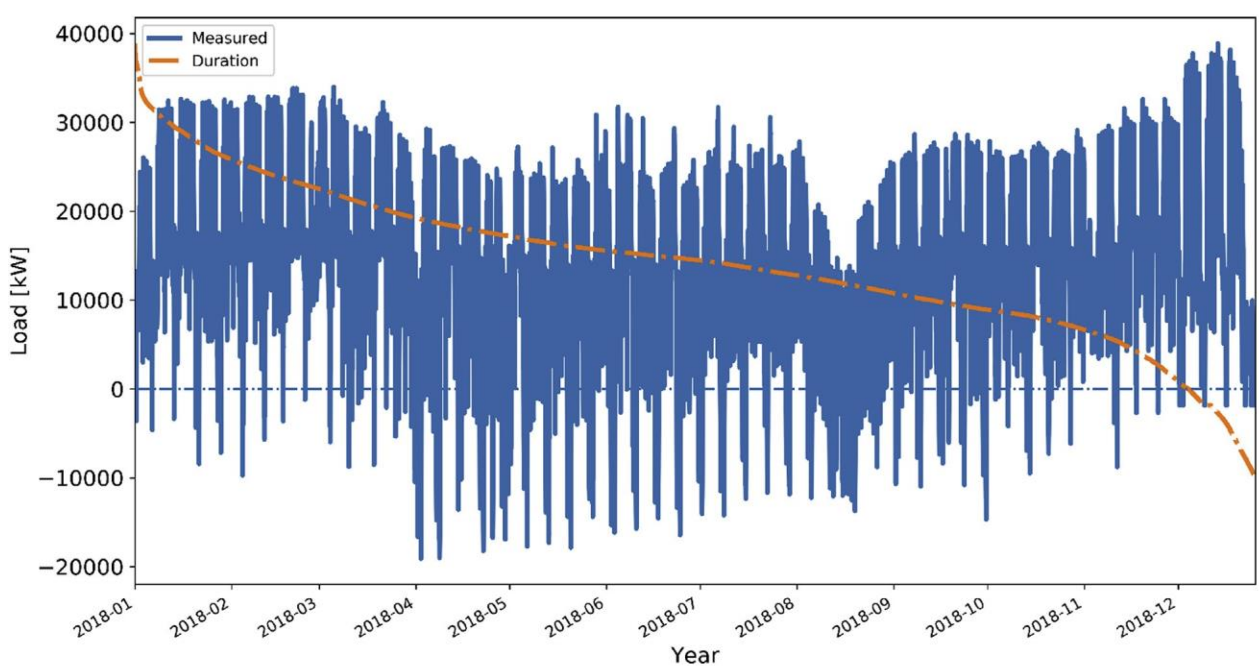

Fig. 4. Actual electricity load in Osimo in 2018 with 15 min resolution with respect to the national transmission grid (in blue) and corresponding duration curve (in orange). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

of electricity to the national grid (negative loads), mainly generated by the local PV systems. This happens very often on the weekends, and more pronouncedly during the summer. The feeding of electricity to the national grid in 2018 exceeded 4 GWh total, approximately 3.2% of the electricity which was drawn from the same grid in the same year.

2.3. Model of the conventional transport sector

In EnergyPLAN the conventional fossil-fueled transport sector is modeled by means of the yearly total demands of energy, distinguished by the type of fuel. In order to have a realistic estimate on the number of vehicles in Osimo a dataset containing all the registered vehicles in the Marche region [45] (where Osimo is located) has been used. The vehicles have been filtered to obtain the subsets which correspond to the fuels modeled in EnergyPLAN: diesel, petrol, natural gas, and GPL. The full-electric and hybrid vehicles already registered in the town have been neglected given their share of the total amount which was less than 1%.

Following the same classification proposed in Refs. [24], the fossil-fueled vehicles have been divided into different categories representing their size. An estimate of the yearly driven distance and the representative fuel consumption have been made for each size category according to Refs. [23,24,46]. All the values are reported in Table 1.

The demand shown in Table 1 is considered the baseline case for the fossil-fueled transport sector and the progressive penetration of EVs is considered distributed uniformly across all vehicle categories in Table 1.

2.4. Model of the electric vehicles′ demand and of their smart functionalities

For EVs, the total annual electricity demand as well as the hourly load distribution throughout a whole year is required for the EnergyPLAN simulations. This is needed to both represent the timevariant distribution of electricity demand and also as a basis to simulate the behavior of smart EVs.

In order to obtain a realistic demand for a given number of cars, a bottom-up approach has been used. First, the behavior of EV users in terms of charging patterns throughout the day is modeled by defining two probability distribution curves: one for a weekday, and one for a weekend day/public holiday. The curves are built by referring to a study summarizing the typical EV usage in the UK during 2018 [47]. The curves entail different types of EV usage patterns depending on the location of the charging station such as at the home, workplace, or at public stations.

Fig. 5 shows the probability distribution that described how likely is an EV owner to plug in its vehicles to start re-charging its batteries, throughout the whole day. The figure shows that for a weekday the majority of the charging events are started in the late afternoon when people start to get back home from work; this also indicates that the majority of the users based on which the dataset originates are of the residential type. The pattern obtained from a weekend/public holiday day is different in its shape, having a demand that is still higher in the late afternoon, but in a less pronounced way with respect to a weekday. In this case, there is also an increased need for charging in the central hours, from 08:00 to 16:00, returning a charging profile which is more evenly distributed over the day.

The curves shown in Fig. 5 provide the basis to simulate the

Table 1

Parameters for the existing conventional transport sector model, based on 2017 data.

	Category	Number of Vehicles	Yearly Distance (per car)	Fuel consumption [l/100 km]/[kg/100 km]	Yearly Demand [GWh]
Diesel	Small	2781	13900	4.79	18.5
	Medium	8361	13900	5.56	64.5
	Large	2321	13900	8.09	26.1
	Total	13463			109.3
Petrol	Small	6337	7400	6.19	25.8
	Medium	978	7400	6.79	4.4
	Large	150	7400	9.38	0.9
	Total	7465			31.1
Methane	Small	3019	7400	4.3	12.6
	Medium	748	7400	5.3	3.8
	Large	13	7400	5.3	0.1
	Total	3780			16.5
GPL	Small	1202	7400	4.3	2.6
	Medium	389	7400	5.3	1
	Large	33	7400	5.3	0.1
	Total	1624			3.7

charging process of a fleet of EVs. The actual charging load is determined following an algorithm that through a bottom-up approach builds a load profile dependent on the number of EVs and a set of other parameters which reflect the type of users which is particular to the local conditions of the fleet - Osimo in this case. The steps that are followed by the algorithm proceed as follows:

For the given day, a share of the fleet that is not in use is generated and thus, the EVs of this share will not demand electricity for the specific day.

For each EV that will be driving during the day a plug-in instant is sampled randomly from 24 hourly timeslots of the day according to one of the two probability distributions shown in Fig. 5, depending on if the day under consideration is a weekday or a weekend day.

Given a plug-in instant, two further values are generated to obtain a daily battery depletion value: the distance in km that was driven during the day prior to the plug-in instant, and the value of fuel economy, i.e. the amount of electricity that is consumed per km driven. The product of these two quantities returns the total electricity that is taken from the battery, which will have to be recharged by the charging station from the plugin timeslot onwards.

The charging process of a given EV proceeds to completely recharge the electricity that has been discharged during the day by charging with the maximum power allowed by the charging station from the plug-in timeslot until complete recharge. This is achieved by progressively adding up the loads of each timeslot for all the timeslots, considering the limits imposed by the maximum capacity of the charging stations.

As an example: an EV that requests a total of 6 kWh of electricity (as an example following a 30 km distance driven at a 0.2 kWh/km of fuel economy) and that plugs-in for recharge in the timeslot between 5 pm and 6 pm will add a 5 kWh of electricity demand in such timeslot provided that the charging station can actually provide such electricity in 1 h. If the electricity requested were to exceed the maximum amount that can be supplied by the charging station, as an example having the same 6 kWh charged by a 4 kW station, then the algorithm would put a 4 kWh demand on the 5 pme6 pm timeslot, and the remaining 2 kWh on the following 6

pme7 pm timeslot.

The algorithm proceeds in this way to compute the EV electricity demand throughout a whole year for the entire EV fleet. The same procedure can be defined to generate the load of any amount of EVs and according to different conditions by using appropriate

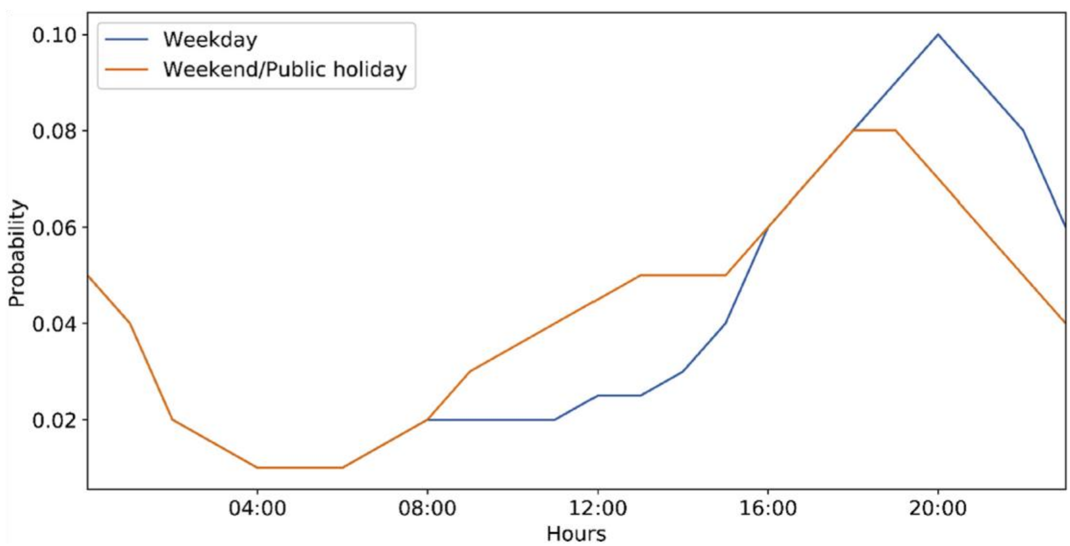

Fig. 5. Behavior of EV users over a weekday and a weekend/public holiday day expressed in terms of the probability that a charging process (vehicle plugged in for recharge) is initiated.

parameters. The parameters used in this study are set in order to reflect vehicle usage, and consequently, electricity load, conditions related to the Osimo test case. These are shown in Table 2. The number of EVs is then set to different values depending on the EV penetration rate that is investigated in each Scenario.

As an example, Fig. 6 shows the charging power requested by a fleet of 2600 EVs, representing a 10% substitution share of the 26000 vehicles in the town modeled in this study during a weekday and a weekend/public holiday day.

The same procedure can be followed to generate any number of profiles for any number of cars charging within the system to be investigated. The procedure is followed to generate plausible electricity demands for all the EV shares considered in this study: i.e. 10%, 20%, and 30%.

The electricity demand generated by the just described procedure is that of a fleet of EVs which is considered completely inflexible, as the charging process happens at the maximum power allowed by each charging station from the plug-in timeslot onwards until full recharge of the vehicles. Thus, in this way, it simply behaves as an additional electricity load that weighs on top of the regular electricity load. A passive EV electricity demand is needed also because a smart-charging enabled EV fleet is modeled in EnergyPLAN using an inflexible load profile as an input parameter.

In EnergyPLAN, the smart capabilities of “active” EVs are modeled by means of the parameters described in Paragraph 2.1, which in this study are set as follows:

Share of cars driving during peak hours: estimated to 20% [22]. Share of grid-connected parked cars during peak hours: assumed as 75% in order to represent a large diffusion of smart EV stations in the scenarios that consider it.

Table 2

Parameters used to model the EV charging load for the Osimo test case.

Parameter	Value	Source
Driving users [%/day]	80	[48]
Distance driven [km/day]	40	[48]
Fuel economy [kWh/km]	0.2	[49]
Charging power	10	[23,47]

Total electricity connection capacity: assumed as 10 kW per EV [49,50]. The same capacity per car is used both for the grid to car charging and V2G.

Total battery storage capacity: assumed as 40 kWh per EV [49]. Grid-to-battery/battery-to-grid electric efficiency: assumed as 90% for a one-way electricity transfer process. The battery-togrid electricity transfer (V2G) is allowed only in the scenarios allowing for V2G capability.

2.5. Model of the weather-related uncertainties

A further degree of uncertainty is added by considering the impact of the weather conditions on the local energy system, which affects the yield from the local PV plants. Since real measured meteorological data were available only for one year (2018), in order to model plausible weather conditions representative of several years’ time span, a simulated set of yearly weather data has been computed by means of the Renewables Ninja model [51].

This model can return weather data time series inferred from models using satellite observations from any location in the world [52,53] for a set of years ranging back to 2000. Moreover, it can simulate the electricity yield of PV systems of any size following the weather data. The variability in the PV system yield has been obtained directly from the portal by simulating a 1 kWp PV system for a period ranging from 2000 to 2018, thus for a total of 19 yearly profiles all in hourly temporal resolution.

The variability of the obtained PV plant yield is shown in Fig. 7 with twelve monthly boxplots representing the distribution of the daily average of the total system yield in kWh/kWp. The boxplots show the median (with the boxplots central line), the spread of the distribution and some outliers (the isolated points far from the lower/upper extremes).

Fig. 8 shows as an example the hourly yield obtained for four example days in the 19 yearly radiation time series obtained.

2.6. Model of the CO_2 emissions

To evaluate the CO_2 emissions generated by the energy system under investigation, the CO_2 contribution of both the local energy systems and the emissions associated to electricity import and

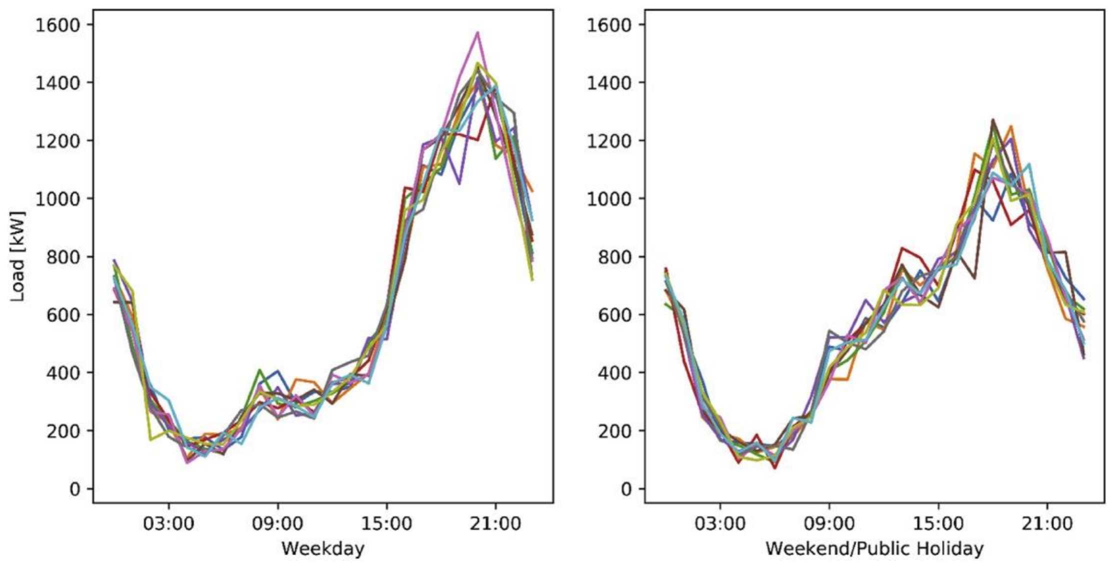

Fig. 6. Generated EV charging loads for weekdays and weekend/public holiday days for 2600 vehicles, representing a 10% EV penetration in the case study. Each line represents a different load for a given day, depending on the random charging initiation related to the probability distribution of Fig. 5.

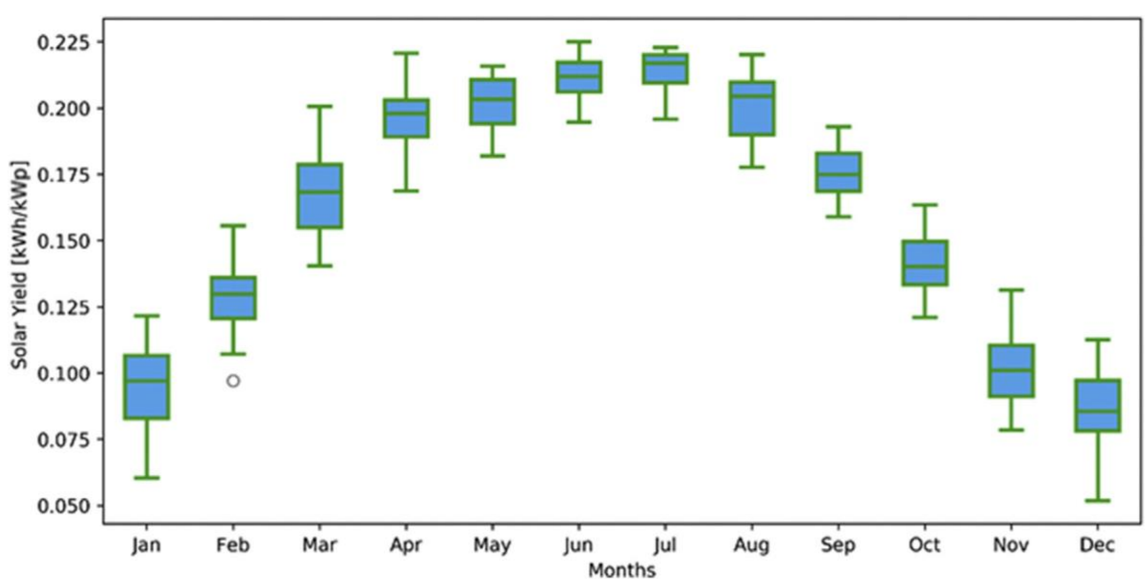

Fig. 7. Variability of the daily average total PV system yield for a 1 kWp system according to the simulated weather data.

export must be considered.

The CO_2 emissions generated by operating the local energy systems are returned as a simulation output for each EnergyPLAN simulation, specifically for the case study at hand they account for the emissions originated by operating the natural gas CHP engine and the boilers that feed the local DHN. The emissions due to the fossil fired transport sector and the additional natural gas demand are computed externally.

The quantification of the impact on emissions from power generation outside the system boundary must be computed externally from the total amount of electricity imported from and exported to the national grid, which are returned from each EnergyPLAN simulation. The emissions due to the usage of the national electricity grid are then accounted for on the mentioned data by means of the following formula.

$$CO_{2_{grid}} = \left(\frac{E^{+}_{grid}}{\eta_{grid}} - E^{-}_{grid} * \eta_{grid}\right) * c_{grid}$$

Where CO_{2grid} is the total amount of CO_2 emitted yearly by using the electricity grid, E^{+}_{grid} and E^{-}_{grid} are the total amounts of electricity in GWh drawn from and fed into the same grid respectively, η_{grid} is the transmission efficiency of the grid, which is set to 95% [54], and finally c_{grid} are the CO_2 emissions of the Italian electricity production system (considering both thermoelectric and other types of electricity generation), which is set to 0.308 $kgCO_2$/kWh of electricity [55].

In accounting for the effect on emissions outside the system boundary, the export of electricity is left unconstrained throughout all the simulations, meaning that no curtailments on such exports are considered. This is a conservative hypothesis that could alter

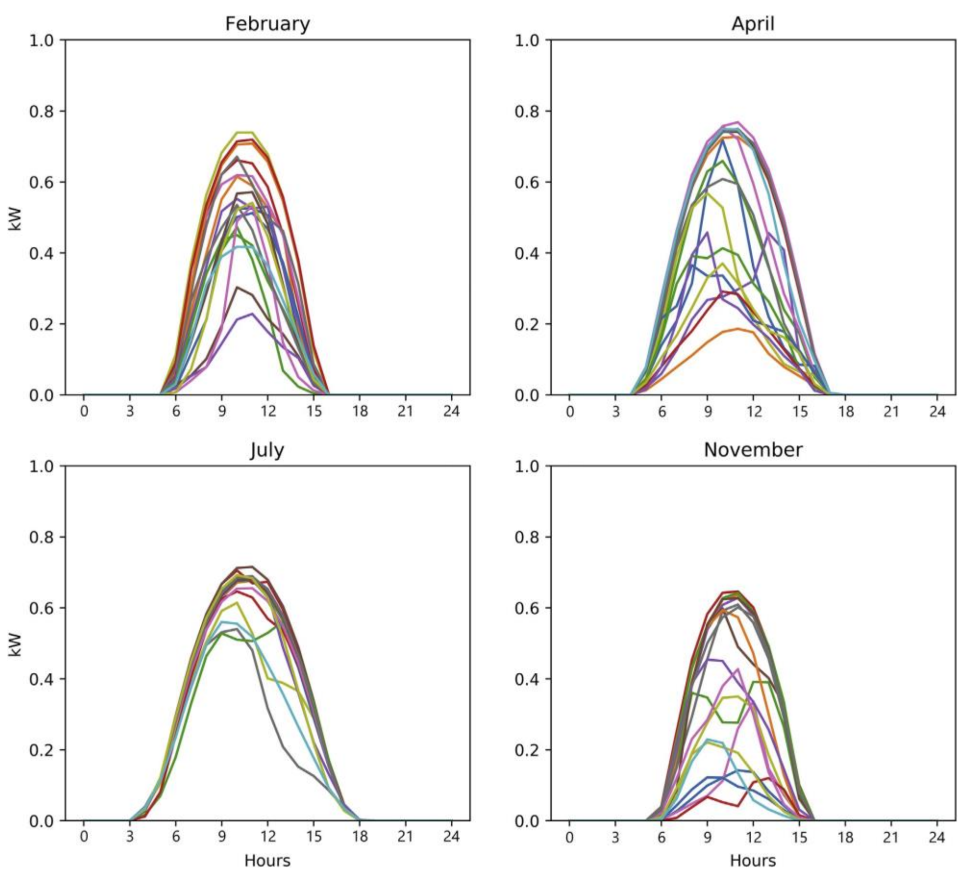

Fig. 8. Variability of the hourly average output power of a 1 kWp PV system over four months in the obtained profiles, considering a sample day of each month. Each separate line corresponds to data from a specific yearly dataset, It's possible to see the spread of the PV system yield that can be obtained from the same day over different years.

the evaluation of the CO_2 emissions of the district, also considering that curtailments due to non-controllable electricity generation happen in Italy at different levels [56]. To this end, also the curtailments happening within the Osimo system boundaries (meaning within the internal low voltage distribution network) should be considered. For this reason, the shifts in CO_2 emissions due to curtailments are treated separately in the conclusions with a sensitivity analysis.

3. Analytical framework & Scenario definition

This section describes the scenarios established for the analysis of the Osimo test case. Then, it summarizes the complete modeling framework including the description on how the components described in Section 2 are integrated and operated together in order to perform the analyses.

3.1. Scenario definition

The scenarios are established to assess how an increasingly large and active EV fleet can mitigate the impact related to high shares of non-controllable RES within an energy system. A single scenario expresses both the changes in PV system size and EV penetration and one of the three levels of EV smart capabilities, and three scenarios are defined in total.

For each Scenario three different levels of PV system capacity and four different levels of EV penetration are simulated. With regard to the PV, the capacities investigated are:

i) the current PV capacity of 31 MWp;
ii) an increase of þ50% on the current PV capacity (corresponding to a total of 46.5 MW_P);
iii) a doubling of the current PV capacity (þ100% corresponding to a total of 62 MW_p).

The levels of the EV penetration are:

i) 0%, corresponding to the present situation in which the presence of EVs is negligible;
ii) 10% of EVs (corresponding to 2600 EVs);
iii) 20% of EVs;iv) 30% of EVs.

The latter value has been indicated in an official report from the Italian TSO Terna [54], which indicates 30% as the maximum likely penetration of EVs in Italy within 2030. The three scenarios are thus defined as follows:

Scenario 1 demonstrates the impact of passive EVs on the local energy system under varying PV system sizes. The EVs simply behave as an additional non-elastic electricity demand with hourly resolution.

Scenario 2 analyses the benefits of equipping the same fleet of EVs from Scenario 1 with a smart charging infrastructure. This is achieved by running the same simulations with the active EVs settings described in Section 2.3 except for the enabling of vehicle-to-grid electricity flow. It is then possible for the grid to partially manage the charging process over time.

Scenario 3 finally completes the active functionalities of the EV fleet by enabling V2G: with respect to Scenario 2, in this scenario it is also possible to discharge the EVs batteries providing electricity to the local grid.

Following the uncertainties modeling described in Paragraphs 2.3 and 2.4. there is potentially a large number of simulations to run for every combination of PV size, EV penetration and EV smart functionalities. From the weather uncertainty model there is a total of 19 yearly profiles, while the EV load patterns that can be generated are potentially infinite in number due to the presence of random components in their generation procedure. For this study the amount of different EV load profiles to be tested is arbitrarily set to three for each of the 19 weather years, returning a total of 57 simulations for each combination of PV size and EV penetration, for each scenario. In order to summarize the variability embedded in each group of 57 simulations, a boxplot representation is used as a visualization.

3.2. Structure of the analytical framework

All the inputs and the described modeling efforts are managed by a framework developed in the Python programming language. This framework is also in charge of calling the EnergyPLAN software externally to launch simulations, in a similar way as what has been done in Ref. [57].

For each simulation an EnergyPLAN model is imported in Python using standard data structures and modified to include the parameters of interest. These can be listed as: PV penetration, EV penetration, EV smart functionalities, EV load profile and weather profile (influencing both the PV system yield and the DHN demand). Once modified the Python-encoded model is re-encoded into an EnergyPLAN input file and its simulation is launched from within inside the Python environment.

The result output is a standard EnergyPLAN output file, from which the quantities of interest in the analysis can be extracted and formatted into tables, visualized or analyzed further. The quantities analyzed in this work are the yearly electricity imports and exports and the total yearly emissions (broken down by sector).

A graphical representation of the framework is shown in Fig. 9.

4. Results

Paragraph 4.1 highlights to what extent the EV fleet can aid in locally self-consumption of the electricity surplus generated by the local PV system. Given that Osimo relies on both importing and exporting electricity from the national transmission network this is achieved by analyzing the total amounts of electricity both imported (due to the lack of sufficient production capacity from the local systems) and exported (due to the inability of timely consumption/storage) within a year. This type of analysis is performed particularly to investigate the impacts of a smart charging infrastructure with respect to a fleet of passive EVs.

Paragraph 4.2 analyzes the effects of the increasing penetration of both PV and EVs on the emissions generated by the city. This is analyzed also by considering different potential scenarios of solar generated electricity curtailments, both of the exported electricity and happening within the Osimo energy system boundaries.

4.1. Impacts on the renewables self-consumption capabilities of the district

The self-consumption capabilities are determined by referring to Fig. 10: panels (a.1) to (a.3) show the total yearly electricity export in Scenario 1, 2 and 3 respectively, while panels (b.1) to (b.3) do the same for the electricity import.

Fig. 10-(a1) shows the limited impact on export reduction by deploying non-smart vehicles. This is due to the lack of synchronization between PV production and EV charging patterns, with the PV reducing its output in the late afternoon (as in Fig. 8) when the majority of the EV charging events start (as in Figs. 5 and 6).

The comparison of (a.2) and (a.3) with (a.1) shows the significant effects of the smart capabilities of the EVs in reducing the need to export electricity. A 30% share of EVs with V2G can completely remove the need for such export even with a doubling the PV capacity with respect to the one currently deployed and, at the current PV capacity, even a 10% penetration can achieve the same effect. The reduction effect is limited if only the smart charging is used, as in Fig. 10 e (a.2), thus furtherly proving the benefits of V2G.On the other hand, the electricity imports steadily increase with the increasing number of passive EVs, as shown in Fig. 10 e (b.1). By switching to active EVs the need to import starts to decrease with respect to the reference case without EVs both with smart charging in Scenario 2 as in (b.2), and even more so with V2G in Scenario 3 as in (b.3).

It is worth noticing the u-shaped trend of the electricity imports in Fig.10 e (b.3) happening for large capacities of PV, specifically for the cases with a 50% and 100% increase. By comparing with the same cases in (b.1) it can be seen that at the lowest level of EV penetration of 10% the electricity imports decrease, only to start growing again by increasing the number of EVs to a 30% penetration share (which is ultimately an increase in electricity demand).

In these cases, the imports of electricity have a minimum suggesting that the increased usage capability of the PV generated electricity enabled by V2G is saturated. Consequently, increasing even more the number of EVs will only increase the need to import electricity.

It can be deduced that there is an optimal combination of PV system size and EVs penetration that optimally exploits the V2G capability of the EVs.

By summarizing the results is clear that there are significant benefits to harness from a local fleet of EVs in terms of increasing the self-consumption capabilities of non-controllable RES sources. But under the EVs usage patterns that emerged so far this must happen through a smart charging infrastructure: that is operating EV as active components by managing the charging process of grid connected vehicles in time and even better by enabling flows of electricity from the vehicles to the grid with V2G.

4.2. Impacts on the district's CO_2 emissions

This paragraph analyzes the impact of the three quantities of interest in the study on the total emissions of the Osimo energy system. Fig.11 shows the emissions across the different levels of PV capacity and EV penetration in Scenario 1, thus with passive EVs.

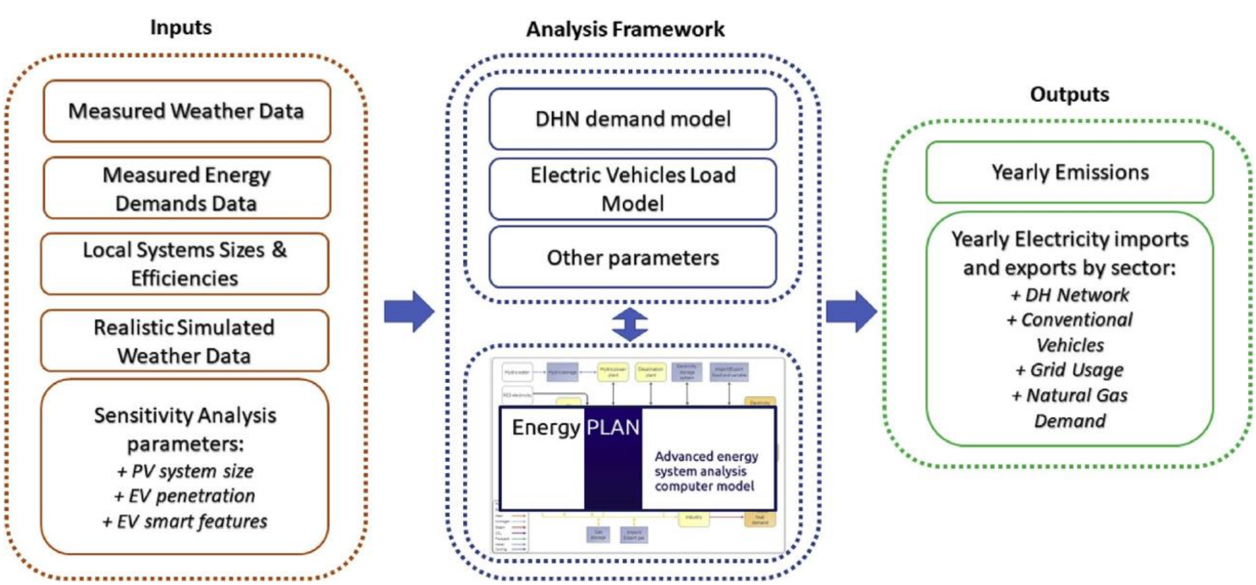

Fig. 9. Graphical representation of the applied analytical framework.

Fig. 12 on the other hand reports the breakdown of such emissions, by referring to the median value of the boxplot. Here they are divided across four sources: the emissions due to the natural gas demand, the operation of the DHN network, the conventional transport and the national grid usage.

From both the two figures is possible to immediately see how both the PV and EV participate to the reduction in CO_2 emissions. By referring to the medians of the boxplots a 50% increase in PV size can grant approximately a 7.4 kt reduction in CO_2 emissions, while a 10% increase in EVs approximately 4.7 kt. For the scenario having the largest PV capacity and EV penetration, the reduction in emissions amounts to 23.2 kt/year, which is a 17.6% reduction with respect to the current situation.

The breakdown in Fig. 12 also allows visualizing the impact of the EVs by splitting the reduction in emissions of the transport sector (due to the removal of fossil-fueled vehicles) and the modified usage of the national grid. The higher penetration of passive EV, the PV power capacity being equal, has a twofold effect: on the one hand it lowers the emissions of transport the sector (since 4.7 kt/year of CO_2 are avoided for each 10% EV increment); on the other hand it increases the demand of electricity from the national grid by 1.7 kt every 10% of EV increment.

From Fig. 12 it is also possible to see that a large share of the emissions keeps being related to the natural gas demand serving privately owned heating solutions and the industry, ranging from 33% to 40% of the total amount in the scenarios. This indicates that in order to achieve a deeper reduction of the carbon emissions this is a sector that inevitably needs to be considered in a cross-sector energy system integration.

As shown in Fig.12 by increasing the EV penetration the relative importance of the emissions source shift from the transport sector to the usage of the national electricity grid. This is confirmed also by Scenario 2 and 3 for “active” EVs, both in absolute and relative terms, though with slight changes.

Adding a smart charging capability in Scenario 2 allows for more electricity produced from the PV system to be used to charge the EVs (thus meeting an internal electricity demand) instead of being exported, as seen by comparing Fig. 10 e (a.1) with (a.2). This provides moderate decreases in the CO_2 emissions generated by Osimo's energy system with respect to Scenario 1 using completely passive EVs. To give an order of magnitude the decrease in emissions range from 0.06 yearly median kt of CO_2 to 0.23 kt depending on the PV system size and EV penetration, with the highest reduction of 0.23 kt happening for the cases with the highest PV capacity and EV penetration among the tested ones. Using V2G in Scenario 3 on the other hand slightly increases the emissions with respect to the case with passive EVs of Scenario 1. V2G allows for the EVs within Osimo to be used as batteries, which inevitably introduces losses due to the charging and discharging process. According to the parameters used in this study the roundtrip efficiency due to using the EVs batteries as storage is of 81%, causing 19% of the electricity produced to be lost. While on the other hand feeding the surplus into the national grid implies transmission losses of 5%. However, as previously highlighted the impossibility of timely using the variable electricity production, which in this study is represented by need to export electricity away from the Osimo system, is susceptible to curtailments which can happen both inside and outside the Osimo system boundary. According to Fig.10 e (a.1) to (a.3), Scenario 3 (V2G vehicles) is then the one which is less susceptible to curtailments being the one with the lowest need to export electricity (considered to be proportional to the need of timely usage of the non-controllable electricity production), followed by Scenario 2 and Scenario 1. This evaluation is shown graphically in Fig. 13.

The three diagrams in Fig. 13 focus on the scenario with the highest PV capacity across the three levels of EV penetration and investigate a realistic pattern of how the total yearly emissions would vary by increasingly curtailing the electricity that has to be exported outside of the district. Each subfigure shows how the emissions increase due to the increasing curtailment, and from all the three subfigures it is possible to see that having an EVs fleet equipped with active capabilities (even better with V2G) clearly reduces the CO_2 emissions. In particular, a curtailment threshold is highlighted in red, showing what is the level of curtailment over which the Osimo district test case with the V2G equipped fleet produces the least CO_2 emissions. The thresholds range between 15% and 25% with the considered EV penetration levels, all values which are significantly above 2% which has been registered in Italy in 2018 as a national average at the transmission level [56]. In any case Scenario 3, having V2G is less susceptible to potential curtailments given it self-consumes all the non-controllable electricity production.

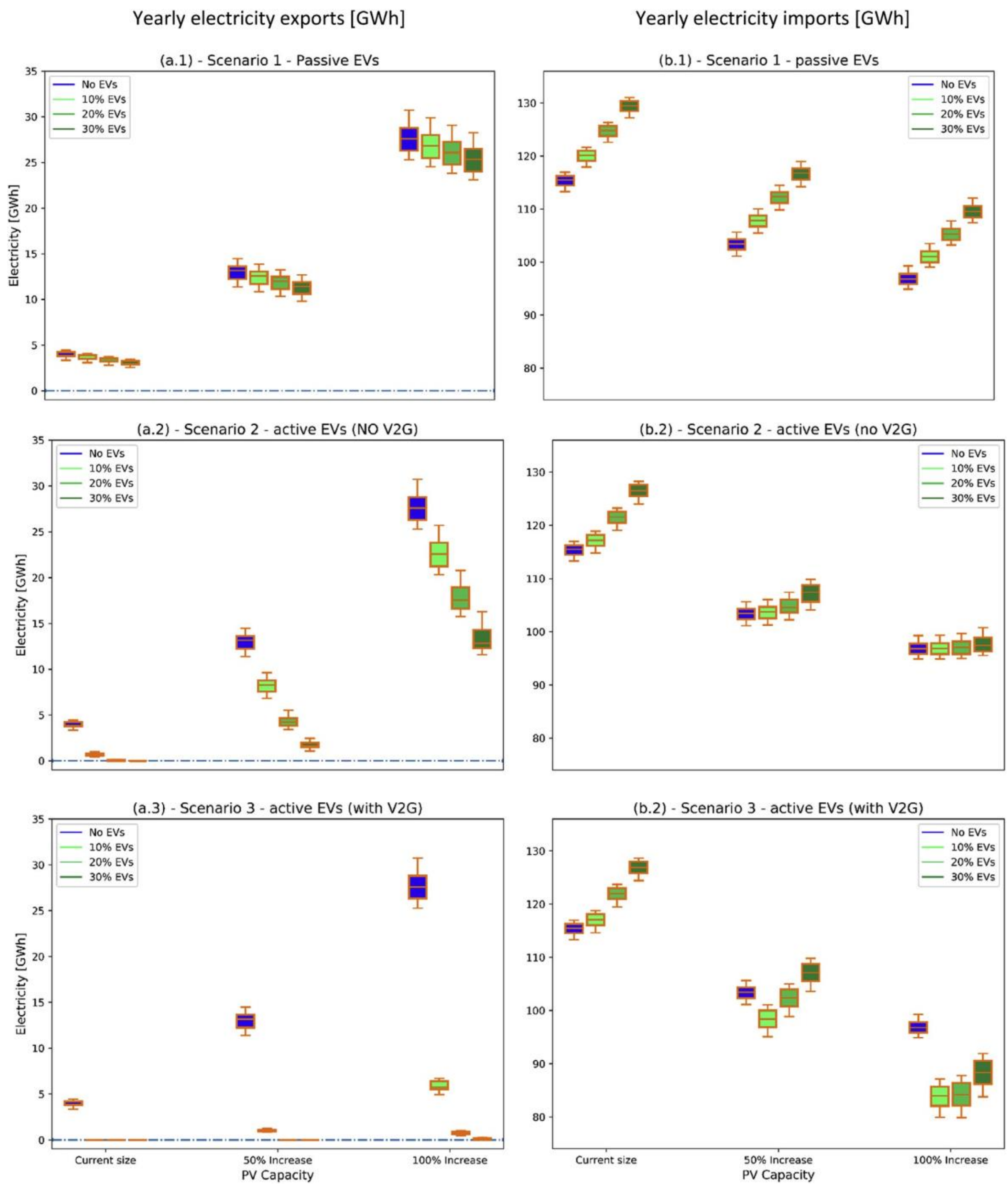

Fig. 10. Yearly electricity exports and imports across the three scenarios.

A last necessary remark would be on the curtailments happening in the microgrid (e.g in Osimo's low voltage distribution network), towards which the presence of "active" EVs is surely helpful. This is not accounted for in the present simulations, but it is possible to obtain an order of magnitude by comparing the emissions obtained in Scenario 1 and Scenario 3 in the case with the largest PV system capacity and EVs penetration. With respect to the case with passive EVs (Scenario 1) adding smart charging and V2G increases the emissions of 0.34 yearly kt of CO_2, a 0.3% increase. According to the parameters used in Paragraph 2.6 such amount of CO_2 would be emitted by the national grid following an electricity production of 1.1 GWh; which for the 62 MWp PV system capacity that would be 1.73% of the annual median yearly yield considered in this study. Under the hypothesis that a curtailment of this magnitude would be avoided by having EVs,

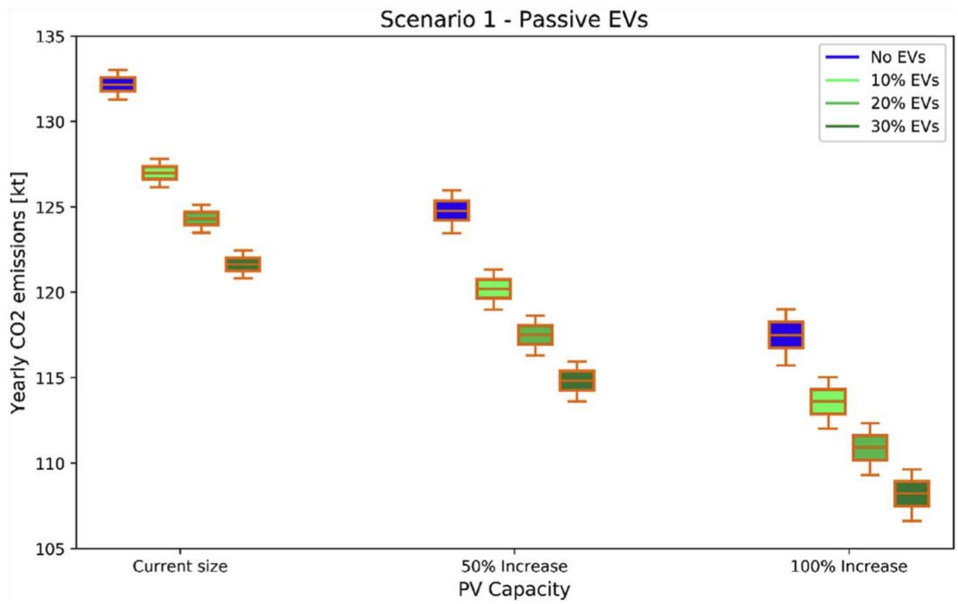

Fig. 11. Yearly CO_2 emissions generated by the city test case for different levels of EV penetration and PV plant capacity in Scenario 1. The present PV level is 31 MWp.

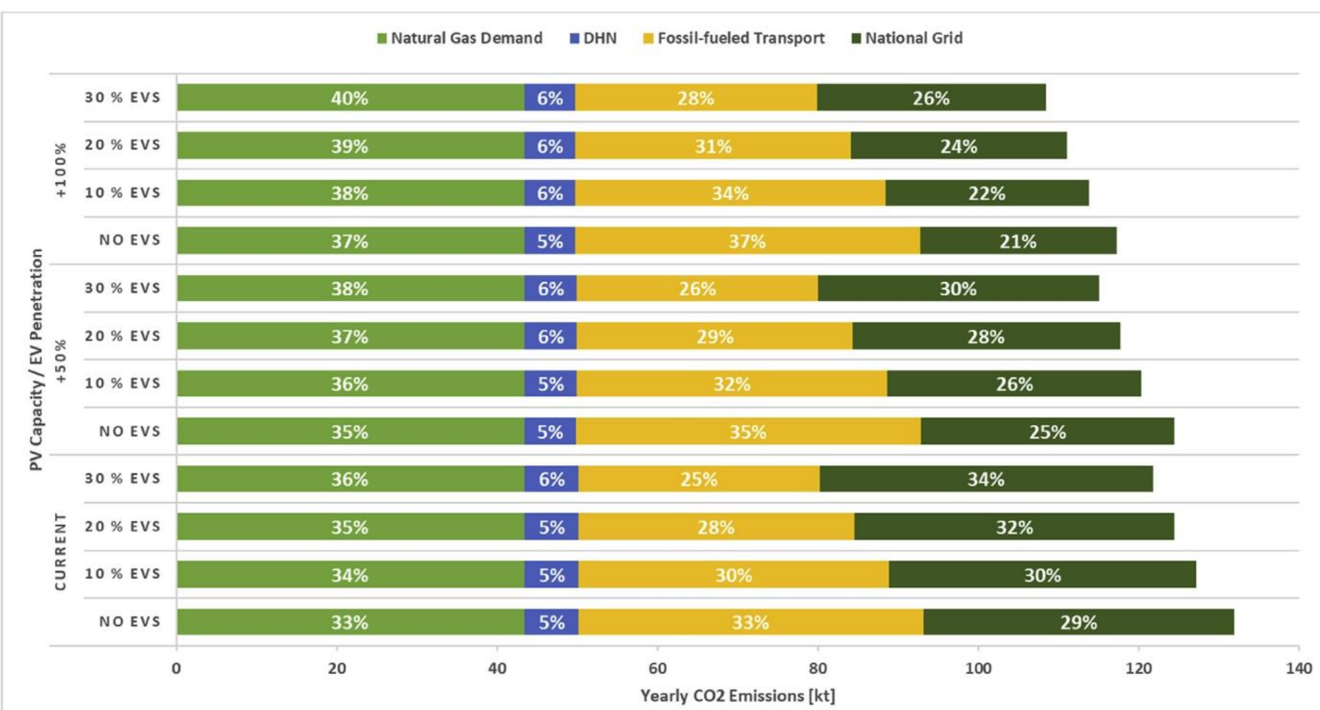

Fig. 12. Category breakdown of the emissions in Scenario 1, both in absolute terms (yearly kt of CO_2 emitted) and in relative terms with respect to the total.

thus avoiding drawing (or not exporting) such amount of electricity from the national grid, it can be stated that for the present case study EVs are also beneficial to the overall CO_2 emissions of the district for internal curtailments above the presented quantities.

It is shown that V2G has significant benefits to harness, but as pointed out by several authors [58e60] and as highlighted in the introduction, V2G comes with a set of technical and regulatory barriers that must be addressed in order to achieve widespread adoption of such technology, which is the case of the scenario analyzed in this study.

The barriers lie both on the technical integration of EVs with V2G, which entail a set of additional costs for hardware and software (with respect to a purely passive EV scheme) that are needed to establish the infrastructure that could allow its deployment [60]. A further aspect to be considered lies in the business models and regulatory frameworks that could allow the deployment by also aiding in mitigating the mentioned costs. In this study, the EVs have been considered as being completely privately owned by local users, substituting the current fossil-fueled vehicles following the same ownership model, but the effectiveness of any on the just mentioned facilitating actions could change in the presence of novel ownership models. Moreover, also the scale of the V2G integration could lead to completely different regulation models, such as for example with the participation in intraday balancing markets. In this sense, the presence of established best practices and business models is still underdeveloped, with applications being confined to a few pilot projects [60].

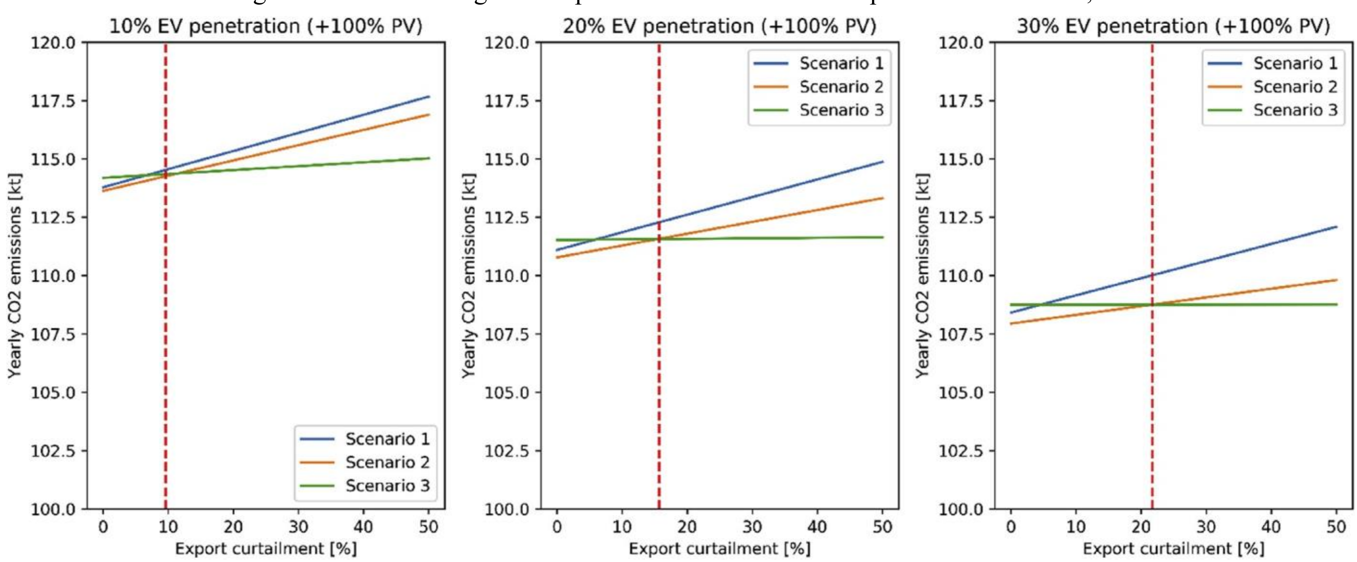

Fig. 13. Susceptibility to electricity export curtailments across the three scenarios considering a doubled PV capacity with respect to the current situation.

For the test case at hand, with a single municipal community providing and/or managing the provision of different energyrelated commodities to the user with a geographically limited area this could be facilitated with the establishment of a local compensation/regulation scheme, such as the just mentioned pilot projects.

From a techno-economic perspective, also other types of local authorities (such as municipalities) could encourage the installation of EV charging points directly by the users' households. Another option would instead rely on the wider deployment of public and/or workplace charging stations (which are mostly used in the central hours of the day from 08:00 to 14:00 [47]), still towards the goal of increasing the flexibility of the local grid and avoid otherwise necessary investments aimed at increasing the flexibility of the local grid. In any case, investments in grid flexibility enhancing equipment (for example in batteries and higher capacity transformers), could be avoided with compensation schemes that leverage local conditions: which for the case at hand is an excess of electricity production driven by solar in the central hours of the day.

5. Conclusions

In this paper, an analysis of a local energy system with both a high penetration of RES and EVs is investigated. The scope of the analysis is to understand to which extent a fleet of EVs can aid in increasing the self-consumption capability of a district with respect to high and increasing penetration of non-controllable RES, specifically PV. Moreover, it investigates the impacts of both the EVs and RES penetration on a district's production of CO_2 emissions.

Three different smart vehicle functionalities are introduced in the model: from totally non-smart vehicles (passive users) to full V2G capabilities (fully active users). The study refers to an energy district context, with multiple energy sectors and conversion technologies being analyzed at the same time in order to batter evaluate cross-sector interactions. The analyses are performed only from a technical point of view, thus only considering the energy balances and demands to be met across different sectors.

The case study under analysis is a multi-energy municipal micro-grid in central Italy with a very high share of distributed electricity production resources (32%), of which mainly noncontrollable renewables (29%).

The analyses are performed by means of a framework that uses the EnergyPLAN energy systems model as a simulation engine. The framework also characterizes a set of diverse sources of uncertainty both by using available measured data and simulated weather data from a web-based model to obtain more robust results. Specifically, the uncertainties which are considered are related to the weather and the EV demand pattern.

The results show that the presence of EVs can be of great help in integrating higher shares of PV production into the local energy system, even considering all the mentioned uncertainty sources, and particularly by equipping the EVs with smart charging and vehicle-to-grid enabled infrastructure. At the current PV capacity, a 10% EV penetration (2600 vehicles for the case study at hand) with V2G already allows eliminating the need of exporting electricity surplus to the national grid. By doubling the PV capacity, the EV share needed to obtain the same effect is 30%. Without a smart charging infrastructure, and particularly V2G, the benefits that can be harnessed in terms of self-consumption capabilities from the presence of EVs are significantly lower.

Regarding the emissions of the local energy system, the analyses show that for the considered energy sectors, electricity, and private transports, the presence of an EV fleet is also significantly beneficial. Removing fossil-based vehicles already entails significant benefits, these amount to 0.47 yearly kt of CO_2 removed for every 1% of EV penetration (approximately 260 vehicles). But the benefits are also significant due to the increased capability of selfconsuming the excess of electricity produced in the district from non-controllable RES. These are progressively larger by increasing the share of surplus electricity which must be curtailed either after being exported to the national electricity system or due to curtailments happening within the modeled local energy system. Overall the presence of EVs, coupled with large PV capacities, can lead to CO_2 emissions reductions of 17.5%.

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References

[1] United Nations. Transforming our world: the 2030 agenda for sustainable development. 2016. https://doi.org/10.1201/b20466-7.

[2] Intergovernmental Panel on Climate Change. IPCC report global warming of 1.5 C: summary for policymakers. 2018. Available at: https://www.ipcc.ch/sr15/chapter/spm/.

[3] McKinsey. Global energy perspective 2019: reference case. Available at: https://www.mckinsey.com/industries/oil-and-gas/our-insights/globalenergy-perspective-2019; 2019.

[4] IRENA International Renewable Energy Agency. Renewable power generation costs in. 2018. https://doi.org/10.1007/SpringerReference_7300. 2018.

[5] Bunsen Till, Cazzola P, D'Amore L, Gorner M, Scheffer S, Schuitmaker R, et al. Global EV Outlook 2019 to electric mobility. Available at: www.iea.org/publications/reports/globalevoutlook2019/; 2019.

[6] Engel H, Hensley R, Knupfer S, Sahdev S. The potential impact of electric vehicles on global energy systems. McKinsey Cent Futur Mobil; 2018. p. 8. Available at: https://www.mckinsey.com/industries/automotive-andassembly/our-insights/the-potential-impact-of-electric-vehicles-on-globalenergy-systems.

[7] Denholm P, O'Connell M, Brinkman G, Jorgenson J. Overgeneration from solar energy in California: a field guide to the duck chart (NREL/TP-6A20-65023). Tech Rep 2015:46. Available at: http://www.nrel.gov/docs/fy16osti/65453. pdf.

[8] Brown EG. Demonstrating plug-in electric vehicles smart charging and storage supporting the grid California energy commission. 2018. Available at: http://smartgrid.ucla.edu.

[9] Shepero M, Munkhammar J, Widen J, Bishop JDK, Bostr om T. Modeling of€ photovoltaic power generation and electric vehicles charging on city-scale: a review. Renew Sustain Energy Rev 2018;89:61e71. https://doi.org/10.1016/ j.rser.2018.02.034.

[10] Hoarau Q, Perez Y. Interactions between electric mobility and photovoltaic generation: a review. Renew Sustain Energy Rev 2018;94:510e22. https://doi.org/10.1016/j.rser.2018.06.039.

[11] Altmann M, Brenninkmeijer A, Lanoix J-CDE, Crisan A, Hugyecz A, et al. Decentralised energy systems. 2010. Available at: http://www.europarl.europa.eu/activities/committees/studies.do?language¼EN.

[12] Alanne K, Saari A. Distributed energy generation and sustainable development. Renew Sustain Energy Rev 2006;10:539e58. https://doi.org/10.1016/j.rser.2004.11.004.

[13] Mancarella P. MES (multi-energy systems): an overview of concepts and evaluation models. Energy 2014;65:1e17. https://doi.org/10.1016/j.energy.2013.10.041.

[14] Lund H, Østergaard PA, Connolly D, Mathiesen BV. Smart energy and smart energy systems. Energy 2017;137:556e65. https://doi.org/10.1016/j.energy.2017.05.123.

[15] Wouters C, Fraga ES, James AM. An energy integrated, multi-microgrid, MILP (mixed-integer linear programming) approach for residential distributed energy system planning - a South Australian case-study. Energy 2015;85: 30e44. https://doi.org/10.1016/j.energy.2015.03.051.

[16] Renaldi R, Friedrich D. Techno-economic analysis of a solar district heating system with seasonal thermal storage in the UK. Appl Energy 2019;236: 388e400. https://doi.org/10.1016/j.apenergy.2018.11.030.

[17] Koirala BP, van Oost E, van der Windt H. Community energy storage: a responsible innovation towards a sustainable energy system? Appl Energy 2018;231:570e85. https://doi.org/10.1016/j.apenergy.2018.09.163.

[18] Liu X, Yan Z, Wu J. Optimal coordinated operation of a multi-energy community considering interactions between energy storage and conversion devices. Appl Energy 2019;248:256e73. https://doi.org/10.1016/j.apenergy.2019.04.106.

[19] Bagheri M, Delbari SH, Pakzadmanesh M, Kennedy CA. City-integrated renewable energy design for low-carbon and climate-resilient communities. Appl Energy 2019;239:1212e25. https://doi.org/10.1016/j.apenergy.2019.02.031.

[20] Fischer D, Harbrecht A, Surmann A, McKenna R. Electric vehicles' impacts on residential electric local profiles e a stochastic modelling approach considering socio-economic, behavioural and spatial factors. Appl Energy 2019;233e234:644e58. https://doi.org/10.1016/j.apenergy.2018.10.010.

[21] Cabrera P, Lund H, Carta JA. Smart renewable energy penetration strategies on islands: the case of Gran Canaria. Energy 2018;162:421e43. https://doi.org/10.1016/j.energy.2018.08.020.

[22] Lund H, Kempton W. Integration of renewable energy into the transport and electricity sectors through V2G. Energy Pol 2008;36:3578e87. https://doi.org/10.1016/j.enpol.2008.06.007.

[23] Bellocchi S, Gambini M, Manno M, Stilo T, Vellini M. Positive interactions between electric vehicles and renewable energy sources in CO 2 -reduced energy scenarios: the Italian case. Energy 2018;161:172e82. https://doi.org/ 10.1016/j.energy.2018.07.068.

[24] Bellocchi S, Klockner K, Manno M, Noussan M, Vellini M. On the role of electric€ vehicles towards low-carbon energy systems: Italy and Germany in comparison. Appl Energy 2019;255:113848. https://doi.org/10.1016/ j.apenergy.2019.113848.

[25] Bellocchi S, Manno M, Noussan M, Giacomo M. Electrification of transport and residential heating sectors in support of renewable penetration : scenarios for the Italian energy system. Energy 2020;196:117062. https://doi.org/10.1016/ j.energy.2020.117062.

[26] Good C, Shepero M, Munkhammar J, Bostrom T. Scenario-based modelling of€ the potential for solar energy charging of electric vehicles in two Scandinavian cities.Energy 2019;168:111e25. https://doi.org/10.1016/ j.energy.2018.11.050.

[27] Pfeifer A, Dobravec V, Pavlinek L, Krajacic G, Duic N. Integration of renewable energy and demand response technologies in interconnected energy systems. Energy 2018;161:447e55. https://doi.org/10.1016/j.energy.2018.07.134.

[28] Bacekovic I, Østergaard PA. Local smart energy systems and cross-system integration. Energy 2018;151:812e25. https://doi.org/10.1016/ j.energy.2018.03.098.

[29] Comodi G, Caresana F, Salvi D, Pelagalli L, Lorenzetti M. Local promotion of electric mobility in cities: guidelines and real application case in Italy. Energy 2016;95:494e503. https://doi.org/10.1016/j.energy.2015.12.038.

[30] Mavromatidis G, Orehounig K, Carmeliet J. A review of uncertainty characterisation approaches for the optimal design of distributed energy systems. Renew Sustain Energy Rev 2018;88:258e77. https://doi.org/10.1016/ j.rser.2018.02.021.

[31] Mavromatidis G, Orehounig K, Bollinger LA, Hohmann M, Marquant JF, Miglani S, et al. Ten questions concerning modeling of distributed multienergy systems. Build Environ 2019;165:106372. https://doi.org/10.1016/ j.buildenv.2019.106372.

[32] Keirstead J, Jennings M, Sivakumar A. A review of urban energy system models: approaches, challenges and opportunities. Renew Sustain Energy Rev 2012;16:3847e66. https://doi.org/10.1016/j.rser.2012.02.047.

[33] EnergyPLAN nd. https://www.energyplan.eu/.

[34] Østergaard PA. Reviewing EnergyPLAN simulations and performance indicator applications in EnergyPLAN simulations. Appl Energy 2015;154:921e33. https://doi.org/10.1016/j.apenergy.2015.05.086.

[35] Østergaard PA. Wind power integration in Aalborg Municipality using compression heat pumps and geothermal absorption heat pumps. Energy 2013;49:502e8. https://doi.org/10.1016/j.energy.2012.11.030.

[36] Østergaard PA. Comparing electricity, heat and biogas storages' impacts on renewable energy integration. Energy 2012;37:255e62. https://doi.org/ 10.1016/j.energy.2011.11.039.

[37] Østergaard PA, Lund H. A renewable energy system in Frederikshavn using low-temperature geothermal energy for district heating. Appl Energy 2011;88:479e87. https://doi.org/10.1016/j.apenergy.2010.03.018.

[38] Sperling K, Moller B. End-use energy savings and district heating expansion in€ a local renewable energy system - a short-term perspective. Appl Energy 2012;92:831e42. https://doi.org/10.1016/j.apenergy.2011.08.040.

[39] Brandoni C, Arteconi A, Ciriachi G, Polonara F. Assessing the impact of microgeneration technologies on local sustainability. Energy Convers Manag 2014;87:1281e90. https://doi.org/10.1016/j.enconman.2014.04.070.

[40] De Luca G, Fabozzi S, Massarotti N, Vanoli L. A renewable energy system for a nearly zero greenhouse city: case study of a small city in southern Italy. Energy 2018;143:347e62. https://doi.org/10.1016/j.energy.2017.07.004.

[41] Østergaard PA, Jantzen J, Marczinkowski HM, Kristensen M. Business and socioeconomic assessment of introducing heat pumps with heat storage in small-scale district heating systems. Renew Energy 2019;139:904e14. https://doi.org/10.1016/j.renene.2019.02.140.

[42] Marczinkowski HM, Østergaard PA. Residential versus communal combination of photovoltaic and battery in smart energy systems. Energy 2018;152: 466e75. https://doi.org/10.1016/j.energy.2018.03.153.

[43] Marczinkowski HM, Østergaard PA. Evaluation of electricity storage versus thermal storage as part of two different energy planning approaches for the islands SamsØ and Orkney. Energy 2019;175:505e14. https://doi.org/ 10.1016/j.energy.2019.03.103.

[44] Aalborg University. EnergyPLAN documentation V15. Available at: https:// www.energyplan.eu/training/documentation/.

[45] Agenzia per l'Italia Digitale. Parco Circolante dei Veicoli - regione Marche n.d. https://www.dati.gov.it/dataset/parco-circolante-dei-veicoli-manutenzione.

[46] Petrolifera Unione. Previsioni di domanda energetica e petrolifera italiana 2019-2040. Available at: https://www.unionepetrolifera.it/download/ previsioni-domanda-energetica-e-petrolifera-2019_2040/.

[47] Element Energy. EV charging behaviour study. 2019. Available at: http:// www.element-energy.co.uk/wordpress/wp-content/uploads/2019/04/ 20190329-NG-EV-CHARGING-BEHAVIOUR-STUDY-FINAL-REPORT-V1EXTERNAL.pdf.

[48] Abitudini UnipolSai. Di guida degli Italiani. Available at: http://www. unipolsai.com/sites/corporate/files/pages_related_documents/cs_ osservatorio-unipolsai-2018.pdf.

[49] EVDB. Electric vehicle database n.d. https://ev-database.org/cheatsheet/ energy-consumption-electric-car.

[50] Netherlands Enterprise Agency. Electric vehicle charging: definitions and explanation. 2019. p. 12. Available at: https://www.rvo.nl/sites/default/files/ 2019/01/Electric%20Vehicle%20Charging%20-%20Definitions%20and% 20Explanation%20-%20january%202019_0.pdf.

[51] Pfenninger S, Staffell I. Renewable ninja n.d. https://www.renewables.ninja/.

[52] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224e39. https://doi.org/ 10.1016/j.energy.2016.08.068.

[53] Pfenninger S, Staffell I. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 2016;114: 1251e65. https://doi.org/10.1016/j.energy.2016.08.060.

[54] Terna SpA. Analisi dei dati elettrici 2016. 2017. Available at: https://www. terna.it/it/sistema-elettrico/statistiche/pubblicazioni-statistiche.

[55] Fattori ISPRA. Di emissione atmosfertica di gas a effetto serra nel settore elettrico naizonale e nei principali Paesi Europei. Available at: https://www. isprambiente.gov.it/files2019/pubblicazioni/rapporti/R_303_19_gas_serra_ settore_elettrico.pdf.

[56] IRENA. Solutions to integrate high shares of renewable energy. 2019. p. 28. Available at: https://www.irena.org/publications/2019/Jun/Solutions-tointegrate-high-shares-of-variable-renewable-energy.

[57] Prina MG, Cozzini M, Garegnani G, Manzolini G, Moser D, Filippi Oberegger U, et al. Multi-objective optimization algorithm coupled to EnergyPLAN software: the EPLANopt model. Energy 2018;149:213e21. https://doi.org/ 10.1016/j.energy.2018.02.050.

[58] Pearre NS, Ribberink H. Review of research on V2X technologies, strategies, and operations. Renew Sustain Energy Rev 2019;105:61e70. https://doi.org/ 10.1016/j.rser.2019.01.047.

[59] Noel L, Zarazua de Rubens G, Kester J, Sovacool BK, Noel L, Zarazua de Rubens G, et al. The technical challenges to V2G. 2019. https://doi.org/ 10.1007/978-3-030-04864-8_3.

[60] fei Chen C, Zarazua de Rubens G, Noel L, Kester J, Sovacool BK. Assessing the socio-demographic, technical, economic and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. Renew Sustain Energy Rev 2020;121:109692. https://doi.org/10.1016/ j.rser.2019.109692.