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Combined PV–EV hosting capacity assessment for a residential LV distribution grid with smart EV charging and PV curtailment

Reza Fachrizal *, Umar Hanif Ramadhani, Joakim Munkhammar, Joakim Widén

Built Environment Energy Systems Group, Department of Civil and Industrial Engineering, Uppsala University, Sweden

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A B S T R A C T

Photovoltaic (PV) systems and electric vehicles (EVs) integrated in local distribution systems are considered to be two of the keys to a sustainable future built environment. However, large-scale integration of PV generation and EV charging loads poses technical challenges for the distribution grid. Each grid has a specific hosting capacity limiting the allowable PV and EV share. This paper presents a combined PV–EV grid integration and hosting capacity assessment for a residential LV distribution grid with four different energy management system (EMS) scenarios: (1) without EMS, (2) with EV smart charging only, (3) with PV curtailment only, and (4) with both EV smart charging and PV curtailment. The combined PV–EV hosting capacity is presented using a novel graphical approach so that both PV and EV hosting capacity can be analyzed within the same framework. Results show that the EV smart charging can improve the hosting capacity for EVs significantly and for PV slightly. While the PV curtailment can improve the hosting capacity for PV significantly, it cannot improve the hosting capacity for EVs at all. From the graphical analysis, it can be concluded that there is a slight positive correlation between PV and EV hosting capacity in the case of residential areas.

1. Introduction

The power and transport sectors have been two of the major greenhouse gas emitters since the industrial revolution era [1]. The transition towards cleaner and more sustainable technologies in these sectors has been promoted globally in recent years [2]. Renewable energy sources (RES) such as photovoltaic (PV) systems and electric transportation, including electric vehicles (EVs), integrated in the built environment are considered two of the keys to a sustainable future in the power and transport sectors [3,4]. As a result, the adoption of both PV systems and EVs has increased significantly in recent years [2,5].

However, large-scale integration of PV systems and EVs poses technical challenges for the local power grids. Large-scale addition of PV systems can lead to large surplus generation and overvoltage problems [6]. On the other hand, the addition of large-scale EV charging can lead to high loads and undervoltage problems [7]. Furthermore, both surplus generation and increased loads can lead to component overloading and an increase in system losses [8,9]. A power grid has a specific hosting capacity for each type of added new generation such as PV systems, and for loads such as EVs, below which the mentioned problems can be avoided. By definition, the hosting capacity is the maximum amount of new generation or load that can be connected without endangering the reliability or quality for other customers [10]. There are several performance indices that can be used to define the hosting capacity, such as voltage deviations, component overloading, losses and harmonics. In recent studies, voltage deviations and component loading have been the most common performance indices for evaluating the hosting capacity [11].

An increased synergy between local generation and load is able to reduce the net load on the grid, and thereby increase the hosting capacity. In the case of residential buildings, deploying battery energy storage systems (BESS) has the potential to improve the synergy between PV generation and EV charging [12]. However, it can be very costly and not economically feasible [13]. Deploying energy management systems (EMS) is another option to improve the synergy between generation and load [14].

Supply side management (SSM) has been the most common EMS used in the electric power grid, since commonly the majority of electricity delivered to the customers comes from centralized generation plants. In that case, the generation is operated to follow the load patterns. However, such SSM is impractical for PV systems without battery storage since they are not fully dispatchable power sources. They cannot adjust their power output to follow the load at all times due to the variable nature of the solar irradiance. However, the generation from PV systems can still be dispatched downward, i.e., curtailed, when there is surplus generation. Thus, PV curtailment using a smart inverter is still useful to increase the power grid hosting capacity for PV [15,16].

* Corresponding author.
E-mail address: reza.fachrizal@angstrom.uu.se (R. Fachrizal).

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Nomenclature

Abbreviations

BESS	Battery Energy Storage Systems
DSM	Demand side management
DSO	Distribution System Operator
EMS	Energy management systems
EV	Electric vehicle
GHI	Global horizontal irradiance
LV	Low voltage
PV	Photovoltaics
RES	Renewable energy sources
SSM	Supply side management
V2G	Vehicle-to-grid

Variables

η_{EV}	EV specific consumption factor (kWh/km)
η_{PV}	PV system efficiency factor times array area (m^2)
η_x	EV charging efficiency
μ_{tpark}	Mean net-load during the parking period (W)
D	Daily EV driving distance (km)
E_{EV}	Daily EV charging demand (kWh)
I_t	Solar irradiance at time t (W/m^2)
L_{EV}	Annual EV charging demand (kWh)
L_H	Annual household electricity consumption (kWh)
l_t	Household load at time t (W)
P_{PV}	Annual PV electricity production (kWh)
R_{EV}	Annual EV charging demand per annual existing household electricity consumption (%)
R_{PV}	Annual PV generation per annual existing household electricity consumption (%)
$s_{tr,max}$	Maximum allowed PV power transfer from a household to the grid
s_t	Solar PV generation at time t (W)
SoC_{arr}	State of charge on arrival (kWh)
SoC_{target}	Targeted state of charge (kWh)
t_{arr}	Arrival time (h)
t_{dep}	Departure time (h)
x_{max}	Maximum EV charging rate (W)
x_t	EV charging load at time t (W)

With the increased share of intermittent decentralized RES such as local PV plants, demand side management (DSM) is becoming more common [17,18]. In this case, the load is operated to follow the generation patterns. In the case of EVs in a residential distribution grid, the EV charging will have the greatest impact on the grid when the peak charging demand coincides with the peak household demand which usually happens between 6 and 7 pm [19]. Thus, a DSM scenario for EVs, a so-called EV smart charging scheme, which shifts the EV charging load in time to the non-peak load periods will be beneficial for avoiding overloading problems [20]. Furthermore, several studies have shown that EV smart charging schemes can improve the synergy between PV generation and EV charging load [21]. A smart charging scheme for a residential area with a financial objective was proposed in [22]. It was shown that such a smart charging scheme can reduce the peak loads. In [23], a smart charging scheme to minimize the net-load variability at residential buildings with PV systems was proposed. In that paper, it was shown that reduced net-load variability led to both an increase in PV self-consumption and a peak load reduction. Reduced peak loads will likely lead to higher EV hosting capacity and improved PV self-consumption will likely lead to higher PV hosting capacity.

1.1. Related works and motivation

PV and EV integration in the distribution grid has been a major topic within the research on energy systems in the built environment in recent years. Considerable amounts of research on the grid impacts of both PV and EV penetration in the distribution grid have been carried out. For example, the impacts of residential PV penetration in distribution grids was studied and presented in [24,25]. The impacts of a large share of EV loads in residential distribution grids were investigated in [26–28]. Most of the studies presented the grid impacts from individual technologies, i.e., from PV only or from EV only. There were more limited numbers of existing papers presenting the grid impacts by both PV and EV together. For example, combined PV–EV grid integration studies were conducted with case studies of a Swedish distribution grid in [29] and a Italian distribution grid in [30].

Studies explicitly focusing on determining the grid hosting capacity are comparatively more recent and are currently gaining a high interest from both researchers and practitioners in the field of power systems engineering. Considerable amounts of research related to grid hosting capacity for PV and EV have been carried out in recent years. For example, in [31,32], PV hosting capacity assessments of Swedish distribution grids were investigated with the voltage deviation level as the performance index. In [33,34], different PV hosting capacity assessment methodologies were proposed and discussed. The enhancement of PV hosting capacity using EMS schemes was simulated in [24,35].

A few review papers have summarized the existing research in the area. For example, the state of the art within hosting capacity assessments for distributed generation, from historical development to enhancement strategies, was reviewed in [16]. The strategies to improve the PV hosting capacity were recently reviewed in [15]. In [11], the PV hosting capacity quantification was reviewed comprehensively and it was concluded that voltage deviations and component loading are the most common performance indices.

The concept of hosting capacity is not as commonly used for EV integration as it is for PV. EV hosting capacity was investigated in [32] for a case study in a Swedish grid, in [36] for a case study in a Macedonian grid, and in [37] for a case study using IEEE 33-node network. These three papers used voltage deviation level as the performance index. In [32], a hosting capacity assessment method for new large power-consuming equipment was introduced, with EV charging load as one of the case studies. In [36], a sensitivity analysis of the hosting capacity of a LV urban grid for single-phase EV chargers was presented. In [37], an analytical-based probabilistic approach to estimate the hosting capacity in a distribution for EV was proposed.

It is important to note that studies of hosting capacity and grid impact can utilize either a time-series approach, as in [31,38], or a probability distribution approach, as in [32,36]. Detailed time series for both consumption and generation can be obtained from historical data or from stochastic models. Historical time series are close to reality, but these data are often difficult to get access to and have low flexibility to introduce a new technology or scheme. Methods for generating stochastic time series are able to introduce new scenarios but may require complex modeling efforts. The probability distribution approach is the simplest one, but the accuracy of this method should be further evaluated [32].

Generally, combined hosting capacity assessments for two different technologies are comparatively scarce. A combined hosting capacity assessment for PV and wind power, i.e., two different generation technologies, has been conducted in [39]. In [32], both PV and EV hosting capacity assessments were conducted individually for the same distribution grid; however, the impact of one technology on the other's hosting capacity was not included. Neither was an assessment of the possible hosting capacity enhancements with EMS strategies such as smart charging schemes and curtailment methods included in the mentioned study.

1.2. Aims and structure of the paper

Following the research gaps discussed in Section 1.1, this paper aims to complement previous research by assessing the grid impacts and hosting capacity of combined PV–EV integration with different combinations of two EMS strategies; smart charging of EVs and PV curtailment. Four scenarios with respect to the use of EMS are simulated in this paper: (1) without EMS, (2) with EV smart charging only, (3) with PV curtailment only, and (4) with both EV smart charging and PV curtailment. The EV smart charging scheme developed in [23] is used, in which the objective is to minimize the net-load variability. As a limitation, no vehicle-to-grid (V2G) scheme is included in the charging scheme. It has been shown that the proposed smart charging scheme can increase the PV self-consumption and reduce the peak load. However, the scheme has not been tested for grid integration and hosting capacity assessments. In the case of PV curtailment, when the PV hosting capacity without curtailment has been estimated, the optimal curtailment strategy will be later defined. This is in order to make the voltage still within the tolerable limit without curtailing a large share of the electricity. The following topics are investigated in this study:

1. The impact of the integration of PV and EVs in a distribution grid, with various annual PV and EV shares, and with the four EMS scenarios (1)-(4) defined above.
2. The grid hosting capacity for PV and EVs with the four EMS deployment scenarios, assessed by considering undervoltage and overvoltage occurrences.
3. The trade-offs between voltage rise and PV electricity utilization with respect to PV curtailment.

The combined hosting capacity for PV and EVs is presented with a novel graphical analysis approach. This enables assessment of the combined PV–EV hosting capacity within the same framework, which has not been done in previous studies.

This paper is organized as follows: Section 2 presents the methodology, including case studies, EV smart charging and curtailment algorithms, simulation scenarios and hosting capacity measures. Section 3 presents the results for the grid impact studies, the combined PV–EV hosting capacity assessments and the optimal curtailment analysis. In Section 4, highlights of the results are discussed, and the main conclusions are presented.

2. Methodology

2.1. Data and case studies

For this study, the authors have chosen to utilize detailed stochastic time series for both generation and consumption, instead of probability distributions or historical time series. The main advantage of using stochastic time series is that it allows introducing several different scenarios. Stochastic household load, PV generation, and EV charging demand, are explained below, followed by the LV grid information.

2.1.1. Household electric load

The Widén Markov-chain stochastic model was used for generating synthetic household electricity use profiles. The model was developed in [40], and was trained on Swedish occupant activity patterns and validated against Swedish electricity use data. The model was set to generate electricity profiles without electric heating for a detached house with two inhabitants per household, The number of inhabitants is based on the mean value of the number of inhabitants in Swedish single-family buildings [41]. The household load in this study was assumed to have a constant power factor of 0.95.

2.1.2. PV power generation

PV power generation was modeled based on solar irradiance time-series data for 2018 from Stockholm, Sweden, with latitude 59.3° N and longitude 18.0° E, recorded by the Swedish Meteorological and Hydrological Institute (SMHI) [42]. The PV generation was modeled as

$$s_t = \eta_{PV} \times I_t, \tag{1}$$

where s_t is solar PV generation (W) at time t, η_{PV} is the PV system efficiency factor times array area (m^2), and I_t is the incident solar radiation (W/m^2) at time t. The PV power generation was assumed to have a constant power factor of 1. GHI data are used as the incident solar radiation profile for simplicity reasons, as the exact generation profile is not crucial. The PV systems were scaled relative to the total annual household electricity demand, based on the ratio of the total annual PV generation to the annual household electricity demand R_{PV}, which can be defined as

$$R_{PV} = \frac{P_{PV}}{L_H}, \tag{2}$$

where P_{PV} is the annual PV electricity production and L_H is annual household electricity consumption. Thus, the PV system efficiency factor times array area η_{PV} was calculated so that the annual PV electricity production P_{PV} satisfied the given R_{PV} ratios, which is a parameter that is used to define the PV hosting capacity. A list of R_{PV} ratios used is included in Section 2.4. The PV system efficiency factor times array area η_{PV} can be defined as

$$\eta_{PV} = \frac{L_H \times R_{PV}}{(\sum_{t=1}^{t_{end}} I_t \Delta t)}. \tag{3}$$

2.1.3. Mobility patterns and charging demand

The charging demand was modeled based on Swedish mobility data for 2006, obtained from the Swedish travel survey [43]. The times of arrival and departure, the origin and the destination locations of the trips, and the distance traveled were available in the survey data. Home–work–home mobility patterns were used to define the times of arrival and departure and the charging demands in weekdays, while home–other–home mobility patterns were used for weekends. More information about trips that were considered ending at the categories work and other can be found in [44]. From this survey data, a Monte Carlo method was used to generate user mobility patterns, which were then used as inputs for the simulations. Fig. 1 shows the histogram of the time of home-arrival and home-departure and the fraction of vehicles parked at home in this study, respectively.

The daily charging demands E_{EV} were calculated as

$$E_{EV} = \eta_{EV} \times D, \tag{4}$$

where η_{EV} is the specific consumption of EVs (kWh/km) and D is the daily driving distance (km). η_{EV} was set to 0.16 kWh/km, while D was calculated by doubling a randomly sampled distance from the travel survey data. This distance represents the round-trips from and to home, with an assumption that each EV travels

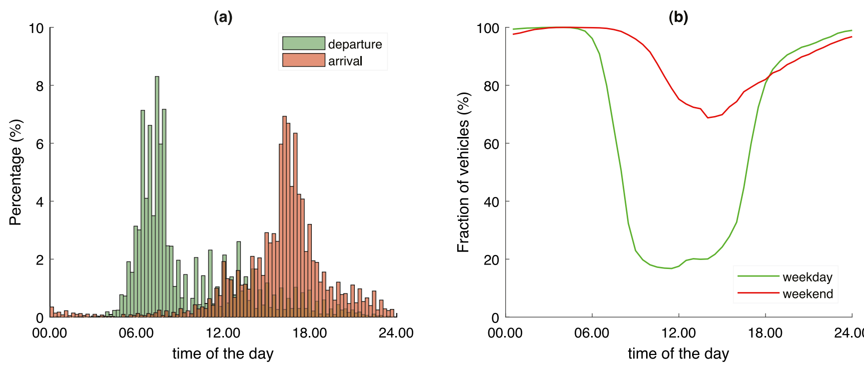

Fig. 1. Statistics of user mobility from [43]: (a) histogram showing time of arrival at home and departure from home, (b) mean daily fraction of vehicles parked at home.

in two equally long trips a day, such as from home to office to home again. The maximum usable energy in the EV battery was set to 30 kWh. This was assuming that the EV battery capacity was sufficient to be used for trips within a city. The maximum charging power was set to 3.7 kW which was based on the power of typical home charger [36]. The charging efficiency was set to 90%, which conforms to the average of Level 2 charging efficiency [45]. It was assumed that the charging efficiency was constant regardless of the charging power. The EV charger was assumed to have a constant power factor of 1. With these mobility and charging demand models, if each household hosts one EV, the annual charging demand will be equivalent to 50% of the household load. The ratio of the annual charging demand to the annual household electricity use R_{EV}, which is a parameter that was used to define the EV hosting capacity in this study, is defined as

$$R_{EV} = \frac{L_{EV}}{L_H}, \tag{5}$$

where L_{EV} is the annual charging demand and L_H is the annual household electricity use.

2.1.4. LV distribution grid

The power flow computation and hosting capacity assessment in the simulated case studies was performed using the IEEE European LV Test Feeder [46]. The grid is operated in a radial structure and has 55 household loads in total. The LV network distribution area is approximately 0.023 km^2, while the total connection length of the network excluding individual connection from the main grid to each customer is approximately 600 m. Based on several quantitative indicators of electricity distribution systems in Europe [47], the studied network can be classified as a small LV network in a highly dense neighborhood, typically found in major cities. The number of LV customers per unit area in the network is approximately 2700 consumers/km^2, compared to median and mean values of 400 and 50 consumers/km^2 respectively. It has an LV circuit length per LV consumer of 0.01 km/consumer, compared to median and mean values of 0.025 and 0.03 km/consumer. The circuit length per unit area of the network is approximately 27 km/km^2, compared to median and mean values of 5 and 1 km/km^2 respectively.

Even though the grid has three-phase connections, each customer only has a single-phase connection. Thus, the grid is by default unbalanced. The grid is supplied by a 800 kVA 11 kV/0.416 kV transformer. The grid topology is shown in Fig. 2. The voltage in the substation was by default set to 1.04 pu all the time. The power flow was simulated in OpenDSS using a fixed-point iterative method known as normal mode in OpenDSS.

2.2. EV charging schemes

2.2.1. Uncontrolled charging

In the uncontrolled charging scheme, the charging always starts upon the arrival of the EV at home, with the rated charging power (3.7 kW). Since the charging scheme is uncontrolled, it does not consider the household load and PV generation. The charging is stopped when the EV battery state of charge (SoC) meets the targeted SoC, which in this case corresponds to the battery being fully charged with 30 kWh. If the EV should depart from home when it has not met the targeted SoC, the charging is stopped at the departure time. From this scheme, a time-series of uncontrolled EV charging loads over a full year is generated.

2.2.2. Distributed smart charging

The smart charging scheme used in this study was based on a distributed smart charging scheme presented in [23]. In this smart charging scheme, the charging does not always start upon the arrival of an EV at home nor always with the rated charging power. The charging can be delayed and the charging rate can be adjusted considering the EV charging demand and the forecast of household load and PV generation within the parking periods. Since the simulations in this study used a perfect forecast, results from the smart charging scheme would be a best-case approximation. It should be noted that the charging scheme is distributed and not centralized. Thus, the smart charging scheme only considers the local or single household parameters, not the neighborhood or grid parameters. From these inputs, the charging scheme will minimize the net-load variability of a single household with the constraints of targeted SoC and maximum charging rate. Minimizing the net-load variability implies reducing both peak loads and excess generation, in other words, making the net-load flatter. The net-load variability is represented with a population variance equation. However, the denominator part is not included as it is constant and will not affect the optimization results. The optimization formulation of the smart charging scheme can be written as

$$\min_{x} \sum_{t=t_{arr}}^{t_{dep}} (x_t + l_t - s_t - \mu_{tpark})^2, \tag{6}$$

$$\begin{aligned} \text{s.t.} \quad & \eta_x \sum_{t=t_{arr}}^{t_{dep}} x_t \cdot \Delta t = SoC_{target} - SoC_{arr}, \\ & 0 \le x_t \le x_{max}. \end{aligned} \tag{7}$$

In the objective function (Eq. (6)), t_{arr} and t_{dep} are the arrival and departure times of the car, respectively, x_t is the charging power rate at time t, l_t is the household load at time t, s_t is the solar power production at time t, μ_{tpark} is the mean net-load during the parking period including the EV charging load. In the constraint (Eq. (7)), η_x is the charging efficiency, Δt is the time step, which in this case is 15 min, SoC_{target} is the state of charge (kWh) targeted in the battery, SoC_{arr} is the state of charge (kWh) in the battery on arrival and x_{max} is the maximum charging power rate. The mean net-load during the parking period μ_{tpark} is defined as

$$\mu_{tpark} = \frac{\left(\sum_{t=t_{arr}}^{t_{dep}} (l_t - s_t) \cdot \Delta t\right) + SoC_{target} - SoC_{arr}}{t_{dep} - t_{arr}}. \tag{8}$$

It should be noted that the charging scheduling for the scheduled parking period is conducted only at the time of arrival t_{arr}. The optimization output is a vector containing $x_{t_{arr}}, x_{t_{arr+1}}, \ldots, x_{t_{dep-1}}, x_{t_{dep}}$ which is the time-series of the smart EV charging load.

2.3. PV curtailment

The power curtailment method was based on the PV power generation and load at each customer. The full curtailment was used as the benchmark, which represented the best-case scenario of maximum voltage at the customer and PV hosting capacity. In the full curtailment, no excess PV electricity transfer from the household to the grid was allowed. The generated PV power after full curtailment $s_{curt,t}$ can be defined as

$$s_{curt,t} = \min(s_t, l_t + x_t). \tag{9}$$

Simulation results from the scenario with full curtailment were compared to the results from other scenarios, i.e., without EMS and with smart charging. After the PV hosting capacity in the scenario without curtailment was obtained, partial curtailment was introduced to find out the trade-offs between voltage rise and PV electricity utilization. In the case of partial curtailment, excess PV electricity transfer from the household to the grid was allowed but limited. The limitation was based on the maximum transferred power that did not violate the maximum voltage limit. When the PV power excess was not higher than the power transfer limit, no power was curtailed. The curtailment started if the excess PV power exceeded the power transfer limit. The generated PV power after optimal curtailment $s_{opt,t}$ can be defined as

$$s_{opt,t} = l_t + x_t + \min(s_t - (l_t + x_t), s_{tr,max}), \tag{10}$$

where $s_{tr,max}$ is the maximum allowed PV power transfer from a household to the grid. This value was obtained after the PV hosting capacity was estimated.

2.4. Simulation scenarios

In this section, the simulation scenarios and algorithms used in this study are described. Full-year time-series simulations with different PV–EV shares and EMS strategies were conducted.

2.4.1. PV and EV shares

Several PV and EV share scenarios were simulated. The PV and EV shares were quantified with the ratio of PV annual electricity and EV annual charging demand to the existing annual household electricity consumption, R_{PV} and R_{EV}, which were defined earlier in Eqs. (2) and (5). The annual existing electricity consumption was 228 MWh. This yields 11.4 kWh per household per day on average. Both R_{PV} and R_{EV} simulated in this study were 0%, 25%, 50%, 75% and 100%. Thus, there were 25 combined PV–EV scenarios. Evenly distributed PV and EVs were assumed in the network in order not to underestimate nor overestimate the hosting capacity.

Given the heterogeneous distribution of social groups in a geographical area and the nature of the diffusion process, the adoption dynamics of PV and EVs can result in complex patterns [48,49]. Previous research found that the adoption was heterogeneously distributed at higher voltage levels [50]. Different PV and EVs allocation schemes will have different impacts on the grid. In a large grid, there can be a phenomenon of concentrated pockets, where integration of PV and EVs are concentrated among customers at a certain spot [51]. Based on the previous study [50], the factors which are considered significant in PV and EV adoption were peer effects, income, household age, and household composition. In this study, however, household income, age, and composition were not varied between customers. In terms of peer effects, concentrated pockets due to peer effects were found under 1 mile (1.6 km) in [52], and within 100 meters in [50]. Hence, as the total grid area in this study is smaller than 150 m × 150 m and, thus, the largest spatial separation between two buildings is only around 150 m, the peer effects might be less relevant. Based on these considerations, evenly distributed PV and EVs were assumed in the grid. The possible impacts of this assumption are discussed further in the discussion part in Section 4.

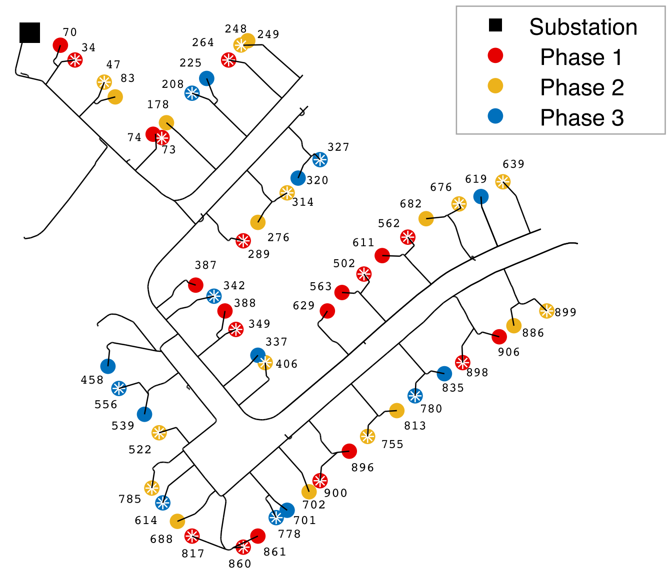

Fig. 2. IEEE European LV test case used in this study. White-starred customers are customers which have one EV in 25% EV share scenario while the others have none, and have two EVs in 75% EV share scenario while the others have one.

While an even distribution for PV was straightforwardly obtained due to the scalability of PV systems, an even distribution for EVs was not as easy to achieve since two customers could not divide one EV load equally in the case of low EV penetration. As mentioned earlier in Section 2.1, one EV annual charging demand equals 50% of the annual electricity consumption of one household. Thus, one EV load per two households yields 25% EV share penetration in the grid. Three EV loads per two household yields 75% EV share penetration in the grid. Fig. 2 shows the studied grid and the EV allocations to make the EV distribution as even as possible.

2.4.2. Energy management systems

Four scenarios with respect to the use of two different EMS, i.e., smart charging of EVs and PV curtailment, were simulated in this paper. The four scenarios are: (1) without EMS, (2) with EV smart charging only which was described in Section 2.2.2, (3) with PV curtailment only which was described in Section 2.3, and (4) with both EV smart charging and PV curtailment. All combined

PV–EV shares were applied to the scenario without EMS. The scenario with 0% EV cannot be applied to the scenario with EV smart charging since there were no EVs to be charged. The scenario with 0% PV cannot be applied to the scenario with PV curtailment since there was no PV power to be curtailed. Likewise, the scenario with both 0% PV and 0% EV cannot be applied to the scenario with both EV smart charging and PV curtailment. In total, there were 81 simulation scenarios combining PV–EV shares and EMS scenarios.

2.4.3. Simulation algorithms

Flowcharts of the simulation in the four different EMS scenarios are shown in Fig. 3. As can be seen in Fig. 3(a) and (c), mobility profiles and vehicle-specific consumption were the inputs for the EV uncontrolled charging model which generates EV uncontrolled charging profiles, while for the smart charging model, two additional inputs, i.e., household electric load and PV generation profiles, were needed to generate smart charging load profiles, as shown in Fig. 3(b) and (d). The PV curtailment took into account three inputs, i.e., household load, EV charging load and PV generation profiles, as shown in Fig. 3(c) and (d). That implies that the curtailment process was conducted in real-time after final EV charging load was defined, whereas EV smart charging was planned hours ahead and considered the PV generation forecast before curtailment. The final household load, EV charging, and PV generation profiles were then used as the inputs for the load flow calculation to generate power system profiles such as voltages and system losses.

2.5. Hosting capacity quantification

Voltage violation is considered the main problem for high penetration of distributed generation or load [16]. Thus, the voltage deviation level was chosen as hosting capacity performance index in this study, being one of the most common measures, and usually the most relevant one, for defining the grid hosting capacity [11]. According to the European standard [53], rms voltages in a LV distribution system must be within the range of 0.90 – 1.10 pu during 95% of the time, on a weekly basis. Voltage levels outside this range are considered voltage violations.

Three allowed voltage deviation levels were used in this study. The first one was 10% allowed voltage deviation which means that the voltage at the customer level must be within 0.90–1.10 pu. This range conforms to the commonly used standard [53]. The second one was 9% allowed voltage deviation which means that the voltage at the customer level must be within 0.91–1.09 pu, representing a somewhat safer voltage range. The third one was 10% allowed voltage deviation but with the lowest and highest 0.01% of voltage population excluded; in other words, only the range between the 0.01th and 99.99th percentiles of the voltage population was included. The interpretation of this last case should be that the grid tolerates very rare occurrences of overvoltage and undervoltage, but still conforms to the standard [53].

It is important to note that the probability distribution of the resulting voltage in this study represents the probability distribution of all time-series and not the probability distribution of the worst-case voltage magnitude that has sometimes been used in other studies, e.g., in [32].

To evaluate whether the performance limit has been reached or not, the number of PV systems and EVs should be increased step by step. The resolution of the increment, however, can vary greatly between studies. In this study, as described in Section 2.4.1, the resolution is 25%. The maximum and minimum voltages between selected PV and EV shares were estimated with a linear regression fitting method. To evaluate the combined EV and PV hosting capacity, a graphical-based method is proposed.

3. Results

As mentioned earlier, high net loads and surplus generation lead to systems losses and voltage violations. The voltage violations define the hosting capacity of the grid. In this section, load profiles, system losses and voltage profiles obtained from the simulations with several PV and EV shares are presented. Then the grid hosting capacity and the optimal levels of curtailment are estimated. As described in Section 2.4.1, the PV and EV shares in this study are based on the ratios of annual PV generation and EV charging demand to the total annual existing household load. It should be noted that the present analysis is based on a small LV network in a highly dense neighborhood typically found in major cities as described in Section 2.1.4 [47].

3.1. Load profiles

Fig. 4 shows the net-load profiles in different EMS scenarios with 50% PV and 50% EV shares. In the daily net-load profiles shown in Fig. 4(a), it can be seen that the daily peak loads increased significantly when EVs were introduced in the households. However, with the smart charging, the peak loads were significantly lower than with the uncontrolled charging scheme.

In the scenarios without EMS and with EV smart charging only, there were negative net loads, indicating surplus PV generation. The surplus generation in the scenario with smart charging was slightly lower than the one without EMS. This surplus could be handled by the PV curtailment strategy. As can be seen, the scenarios that included PV curtailment did not have the negative net-loads. The annual peak load and generation values can be obtained by observing the full-year net-load duration curves, which are shown in Fig. 4(b). It can be seen that when both EV smart charging and PV curtailment were deployed, both peak loads and peak surplus generation were reduced.

3.2. System losses

Fig. 5 shows the annual electrical losses in different combined PV–EV shares and EMS strategies. As it is already known that the electrical losses are proportional to the square of the current flowing in the line [54], both higher net load and higher net generation lead to higher electrical losses. Thus, the scenarios with the net load close to zero had less electrical losses and indicate a more favorable balance between the local generation and load.

By observing Fig. 5(a)–(d), it can be concluded that the higher the EV share, the higher the electrical losses, since the overall electricity consumption was higher. By comparing Fig. 5(a) and (b), it can be seen that the EV smart charging scheme reduced losses due to lower peak loads. In the scenarios without PV curtailment shown in Fig. 5(a) and (b), the curves of annual losses are convex-shaped with respect to the PV shares. This implies that the losses decreased when a low PV capacity was initially integrated in the grid, but that the losses started to increase when the PV share reached higher levels. It can also be seen that when the EV share was higher, the optimum PV share in terms of losses was shifted to higher values. For example, the optimum PV share was around 25% for the scenario without EV loads, while the optimum PV share was between 50% and 75% for the scenario with 100% EV load additions.

When PV curtailment was included, the higher the installed PV share, the lower the electrical losses. This is because in the case of peak PV production, the net-load did not reach below zero since the production was curtailed. However, it should be noted that generally the curtailed electricity is actually energy losses and it can be much higher than the electrical losses. In

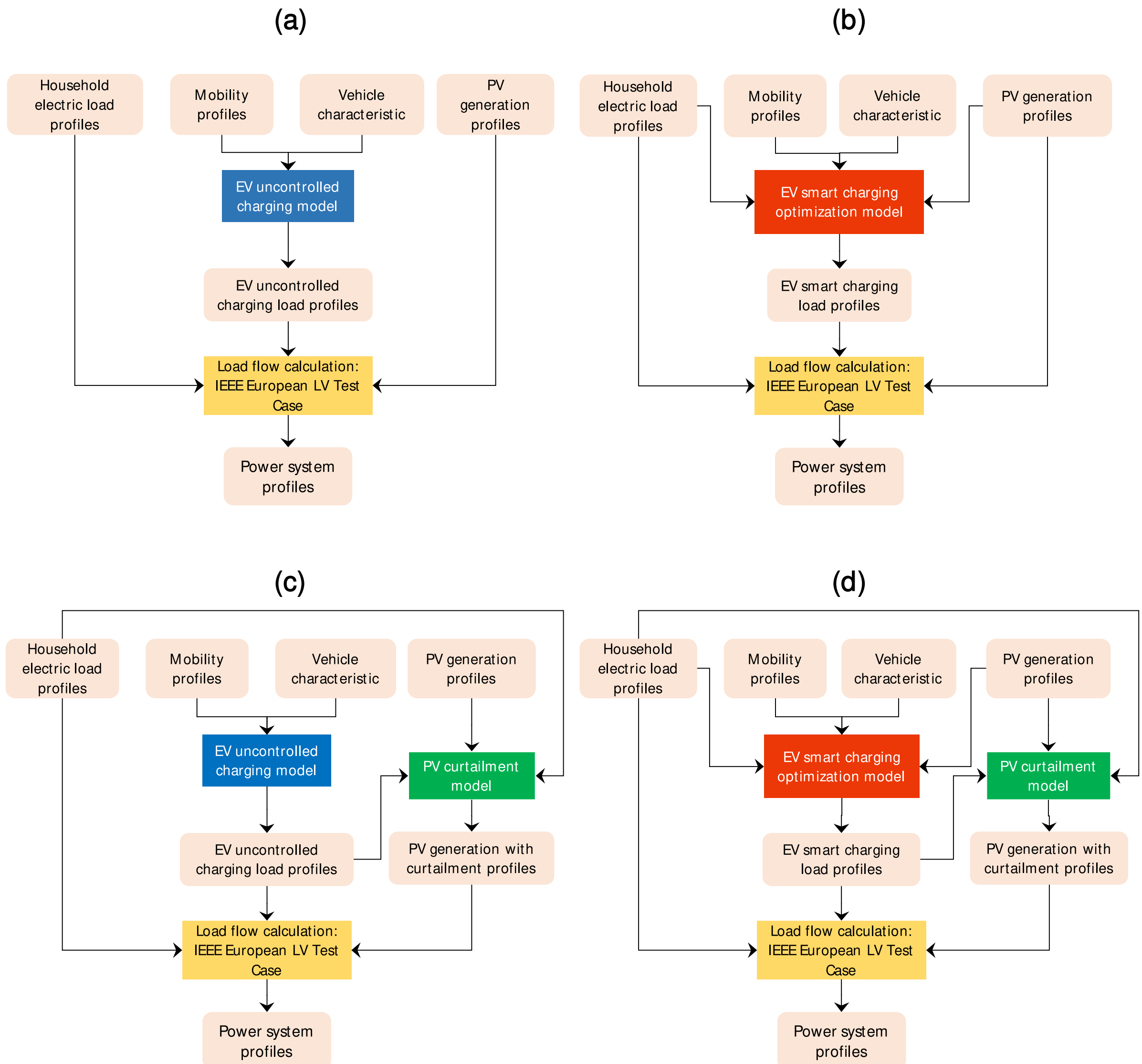

Fig. 3. Simulation algorithms for scenario (a) without EMS, (b) with EV smart charging only, (c) with PV curtailment only, (d) with both EV smart charging and PV curtailment.

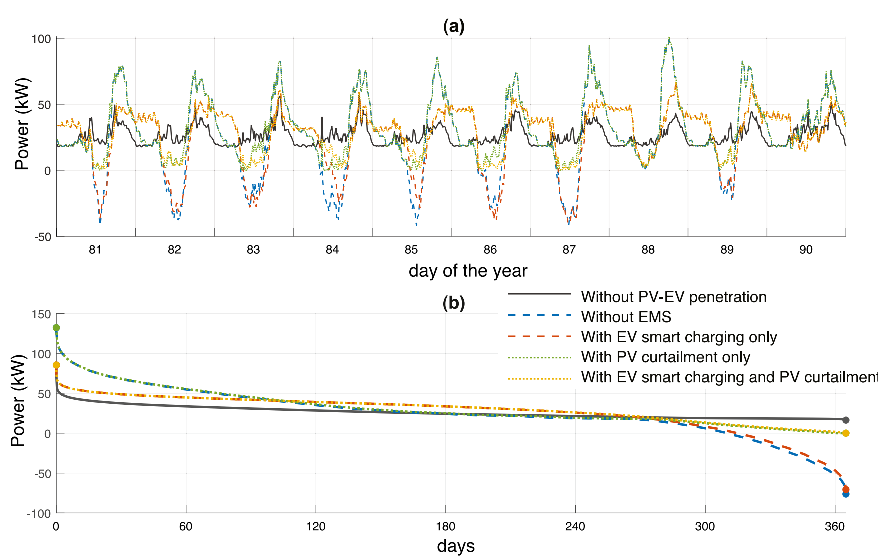

Fig. 4. Net-load profiles with 50% PV and 50% EV shares in different EMS strategies compared to the one without PV and EV penetration: (a) daily net-load profiles in selected spring days, (b) net-load duration curves. Positive values indicate net-load and negative values indicate net-generation.

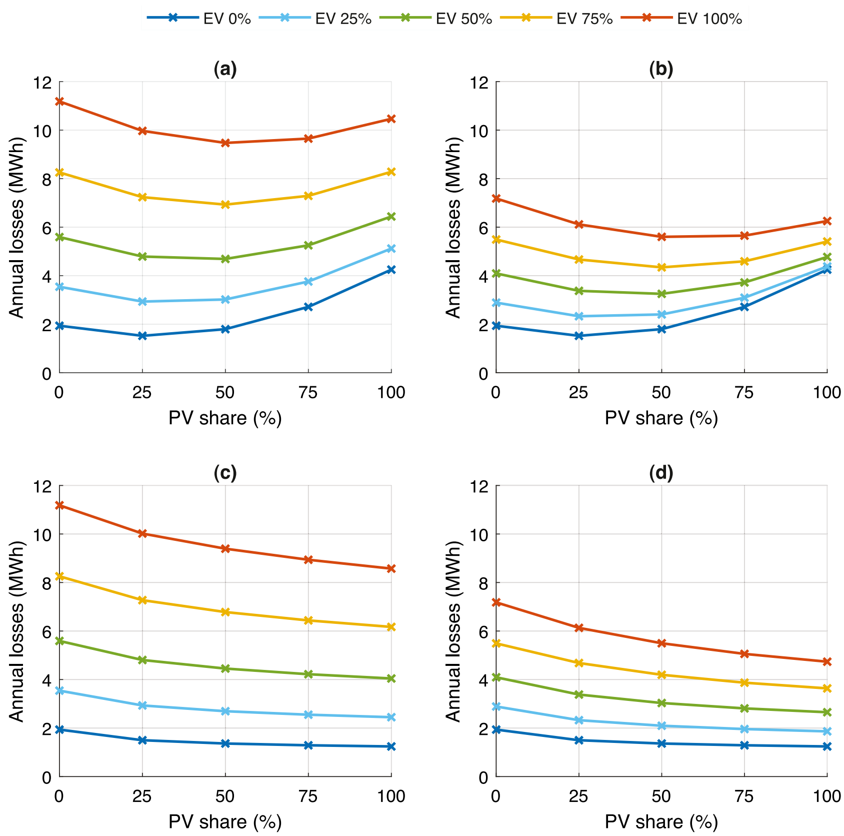

Fig. 5. Annual electrical system losses in different PV and EV integration scenarios: (a) without EMS, (b) EV smart charging only, (c) PV curtailment only, (d) EV smart charging + PV curtailment.

case the customers do not have a battery energy storage systems and do not get any compensation from transferring excess PV power to the grid, they will not be negatively affected by the full curtailment and the DSO (Distribution System Operator) will have fewer voltage rise problems. When the customers are allowed to transfer the excess PV power and get compensation from that, the full curtailment will be a wasteful option if the voltage at the customers is still far from the upper prescribed limit. In that case, an optimal level of curtailment should be identified. The voltage profiles from different scenarios in relation to the optimal curtailment are discussed in more detail in Section 3.3 and Section 3.5 respectively.

3.3. Voltage profiles

Before proceeding to the results from the combined PV–EV integration assessment, the integration of PV only and EVs only was simulated to see the individual impacts of PV and EVs as well as of the relevant EMS strategies, i.e., PV curtailment for PV and smart charging for EVs. It should be noted in the test grid used as case study, the voltage in the substation was by default kept at 1.04 p.u. all the time.

The voltage medians and ranges with PV addition only and EV addition only are presented in Fig. 6(a) and (b), respectively. It can be seen that the PV curtailment gave lower maximum voltages when the installed PV share was increased. However, the median values were approximately the same regardless of the curtailment. As for EV impacts on the voltage profiles, it can be seen that compared to the voltages in the uncontrolled charging scheme, both minimum and maximum voltages in the smart charging scheme were further from the prescribed voltage limits. However, the smart charging scheme had a more significant impact on keeping the minimum voltage above the lower limit than on keeping the maximum voltage below the upper limit.

In Fig. 7, violin plots show the probability distributions of the customer voltage in the different EMS scenarios and with different combinations of PV–EV shares. Each row corresponds to a specific PV share and each column corresponds to a specific EV share. From the figures, it can be seen that PV curtailment reduced the voltage rise problems and EV smart charging schemes reduced the voltage drop problems.

It can also be seen that the minimum voltages in the scenarios with only PV curtailment were similar to the ones in the scenarios without EMS, which is the worst scenario in terms of voltage range. On the other hand, the maximum voltages in the scenarios with only EV smart charging were similar to the ones in the scenarios without EMS. However, there were some exceptions in the scenarios with 25% PV share, especially when the EV share is higher. In those cases the maximum voltages were lower. This indicates that the EV smart charging was able to also reduce the voltage rise due to PV power production, but only if the installed PV share was low. In higher PV share scenarios, the voltage rise problems could not be solved by the smart charging alone with driving patterns unchanged, which was an assumption in this study. The driving patterns are limiting in this sense due to the low fraction of vehicles present at residential buildings during peak solar power production, which can be excessively high for high PV shares.

In an unbalanced three-phase distribution system, higher load in one phase leads to a voltage drop in that phase but induces voltage rise in the other two phases. Similarly, higher generation in one phase leads to a voltage rise in that phase but induces voltage drop in the other two phases [32]. In the case of EV charging, the magnitude of the load for uncontrolled charging

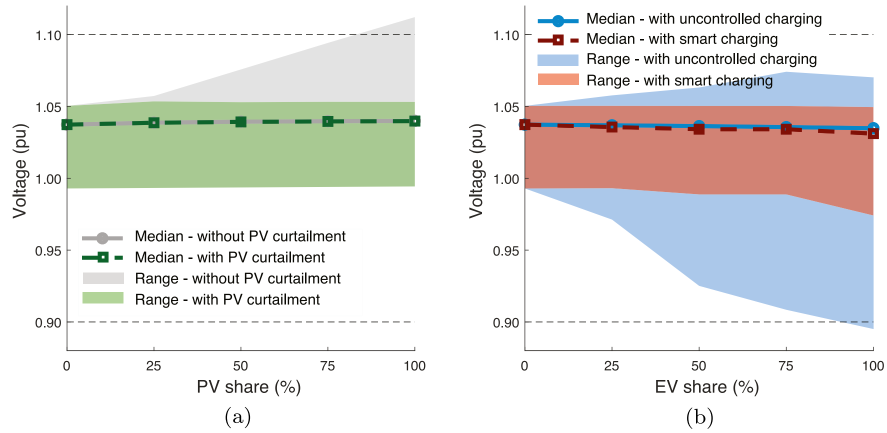

Fig. 6. Median, minimum, maximum voltages in (a) different PV share scenarios without EVs and (b) different EV share scenarios without PV.

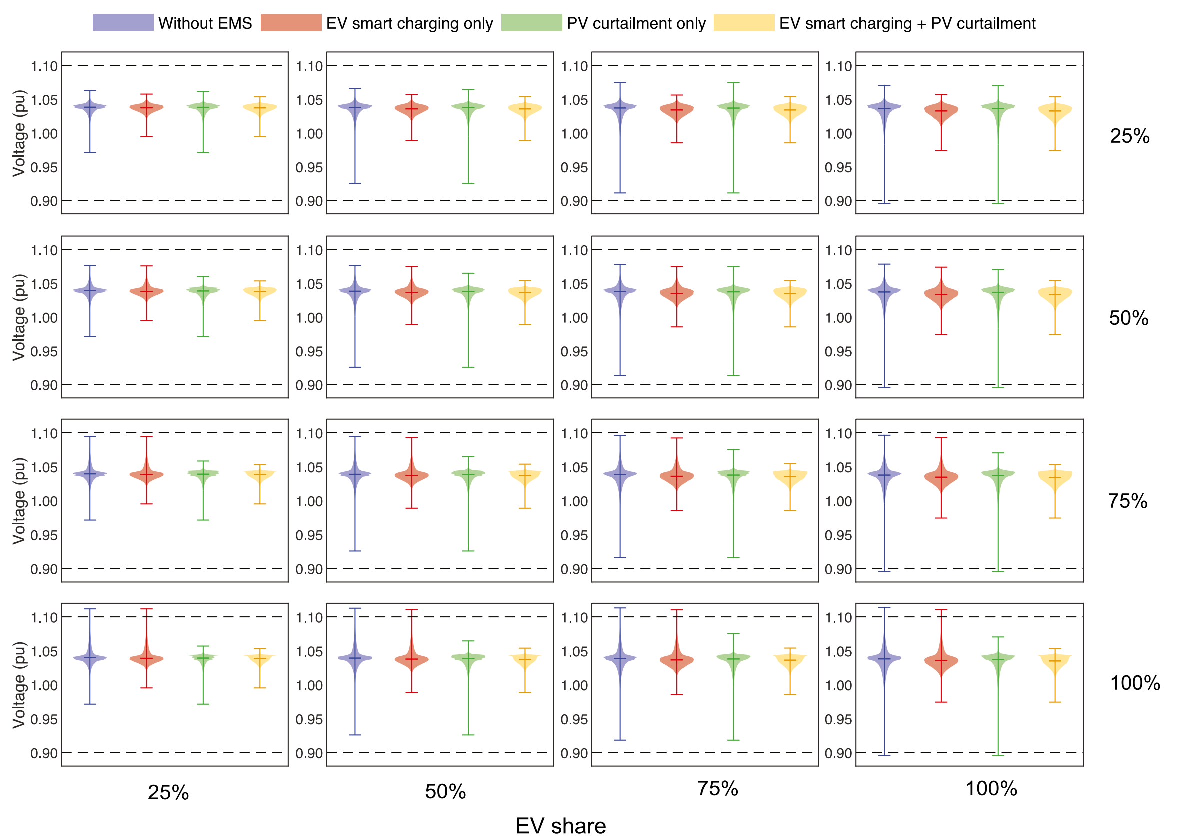

Fig. 7. Voltage probability distributions in different EMS scenarios and with combined PV–EV shares.

was generally higher than for smart charging, and lowering it thus has an impact both on the voltage rise and the voltage drop. This is why the maximum voltages in the scenarios with both EV smart charging and PV curtailment are lower than the ones with PV curtailment only. In the case of PV generation in this study, the effect is less visible since PV systems were evenly distributed among customers and there is high generation coincidence in different phases. Thus, when the generated PV power was high at one of the customers with a certain phase, it was also high at other nearby customers connected to the other two phases. This is why, in the scenarios with both EV smart charging and PV curtailment, the minimum voltages are similar to the ones with smart charging only. In these scenarios voltage drops are mainly affected by the EV smart charging scheme.

From Fig. 7 it can be seen that, in the scenarios with 100% PV share, there were times when the voltage at customers exceeded the upper tolerable limit (overvoltages) if no EMS or only the smart charging scheme was deployed. In the 100% EV share scenarios, there were times when the voltage exceeded the lower tolerable limit (undervoltages) if no EMS or only the PV curtailment strategy was deployed. These results were used as the basis to estimate the combined hosting capacity, which is presented and discussed in more detail in Section 3.4.

3.4. Graphical analysis of combined PV–EV hosting capacity

In this section, the grid hosting capacity for combined PV–EV integration was estimated from the voltage profiles. In order to estimate the hosting capacity, the minimum and maximum voltages should be obtained or at least estimated. In this study, the minimum and maximum voltages as functions of PV and EV shares were estimated using linear regression models. Fig. 8(a) and (b) show the maximum and minimum voltages from the simulated PV and EV shares and their linear estimations in scenarios without EMS and with EV smart charging only. From Fig. 8, it can be seen that the linear estimations are close enough with the values from full power flow simulations, especially the ones near the prescribed voltage limits. By observing Fig. 8, it can be estimated that the hosting capacity for EVs in the scenario without EMS was between 80% and 100%, while with smart charging the grid could host more than 100% EVs. Both scenarios without and with smart charging had similar estimated PV hosting capacity, the one for the smart charging scenario being slightly better.

With these linear models, the combined PV–EV hosting capacity was estimated, with a resulting graphical analysis shown in Fig. 9. Fig. 9(a) shows the combined hosting capacity estimations with a 10% allowed voltage deviation, which means that the grid could tolerate a voltage variation within 0.90–1.10 pu. Fig. 9(b) shows the combined hosting capacity estimations with a 9% allowed voltage deviation (0.91–1.09 pu), which represents a safer voltage range. Fig. 9(c) shows the combined hosting capacity estimations with the 10% allowed voltage deviation (0.90–1.10 pu), but with the lowest and highest 0.01% of the voltage population excluded, or, in other words, only including the part of the voltage population between the 0.01th and 99.99th percentiles. This implies that the grid would tolerate a few very rare occurrences of overvoltage and undervoltage. The exclusion of the lowest and highest 0.01% voltage can also be seen as a way not to underestimate the hosting capacity, since the probability is low for the lowest and highest 0.01% voltages to occur.

The filled areas are the tolerable PV–EV shares considering the prescribed upper and lower voltage limits. Different colors represent different EMS strategies. Blue colors are for the scenario without EMS (scenario 1), red colors are for the scenario with EV smart charging only (scenario 2), green colors are for the scenario with PV curtailment only (scenario 3) and yellow colors are for the scenario with both EV smart charging and PV curtailment (scenario 4). The venn diagram color legend and the guide on the shown colors in the figure are included since there are intersections between different colors. The area of PV–EV shares which is not covered by a certain color, is beyond the hosting capacity of the EMS strategy represented by that certain color.

It can be seen from Fig. 9(a)–(c) that the areas for scenario 1 without EMS are also covered by all other scenarios (scenarios 2–4). All areas in scenarios 1–3 are also covered by scenario 4, while part of the area for scenario 4 in the higher ranges of PV and EV shares is not covered by any other scenario. This means that the combined PV–EV hosting capacity was very high in scenario 4 (both EV smart charging and PV curtailment). Compared to scenario 1 without EMS, scenario 2 (EV smart charging only) increased the hosting capacity for EVs significantly (significantly larger coverage of the area horizontally) and for PV slightly (slightly larger coverage of the area vertically). Scenario 3 (PV curtailment only) increased the PV hosting capacity significantly (significantly larger coverage of the area vertically) but did not increase the EV hosting capacity (no change of coverage of the area horizontally).

In scenario 1, it can be seen that when all the voltage population was included, the increased share of PV did not increase EV hosting capacity and vice versa, as shown in Fig. 9(a) and (b) where the edges of area (1) are vertically and horizontally flat. However, if the lowest and highest 0.01% of the voltages were excluded, as shown in Fig. 9(c), a correlation between the shares of PV and EVs and the hosting capacity of the opposite technology can be seen. That is, the edge of the area is shifted towards higher

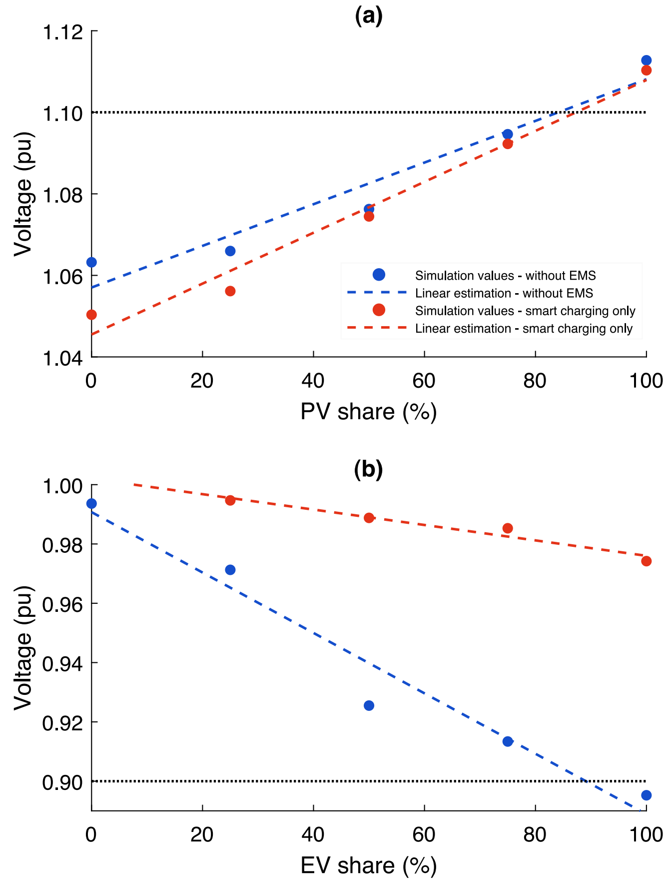

Fig. 8. (a) Maximum and (b) minimum voltages from the simulated PV and EV shares and fitted linear models.

PV share when the EV share is higher and vice versa. This implies that the increased PV share improved the EV hosting capacity and the increased EV share improved the PV hosting capacity. It can also be seen in Fig. 9(c) that the exclusion made the EV hosting capacity higher, exceeding 100%, while for PV there was almost no difference. This means that the simulated minimum voltages shown in Fig. 7 for 100% EV share were uncommon, being entirely part of the excluded values, while the simulated maximum voltages for the 100% PV share represented the expected conditions. This is because the irradiance data that the PV profiles were based on were the same for all customers, which is a reasonable assumption due to the high PV generation coincidence at the neighborhood level (cf. [55]). Thus, when the PV power was high at one of the customers, it was also high at other nearby customers. For the EVs, however, it was unlikely that all the users charged their EVs at the same time. The lowest voltage in the grid therefore likely happened due to the coincidence of many EVs charging at nearby customers far from the substation, which is a rare occasion.

As mentioned earlier, EV smart charging can improve the EV hosting capacity significantly. However, it should be noted that the EV smart charging was simulated based on perfect forecasts of PV production and load. Thus, the minimum voltage in scenario 2 with EV smart charging represented an identified upper limit case for the minimum voltage. In the case of PV curtailment, the full curtailment made the maximum voltage similar to the scenario without the addition of PV, which resulted in very high PV hosting capacity. The maximum voltage in scenario 3 with full PV curtailment represented an identified lower limit case for the maximum voltage. However, it should be noted that in this case

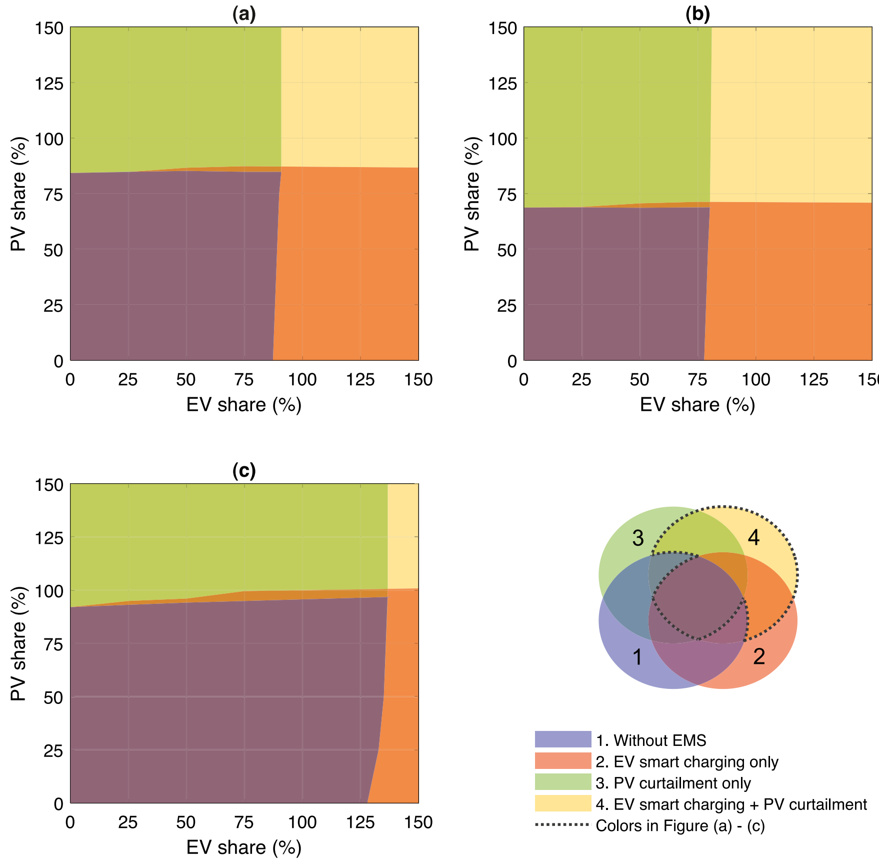

Fig. 9. Graphical analysis of combined PV–EV grid hosting capacity with (a) 10% allowed voltage deviation, (b) 9% allowed voltage deviation, (c) 10% allowed voltage deviation within 0.01th and 99.99th percentiles.

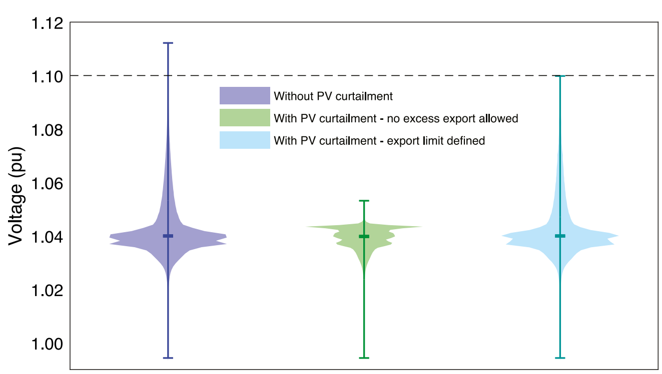

Fig. 10. Voltage distributions in different curtailment scenarios.

the PV hosting capacity is in terms of installed quantity, not the amount of PV power flowing within the grid, since the hosting capacity is improved by curtailing the excess power.

3.5. Optimal curtailment and PV electricity utilization

When the customers are allowed to transfer some of the excess electricity to the grid, the maximum voltage will increase but the utilization of the PV systems will be higher. As long as the voltage does not exceed the prescribed limit, full curtailment can be avoided. The trade-offs between PV electricity utilization and voltage rise are presented and discussed in this section.

Fig. 10 shows the voltage probability distribution with a 100% PV share in three different curtailment scenarios: without PV curtailment (export of all the generated electricity is allowed and not limited), with full PV curtailment (no electricity export allowed), and with partial curtailment (electricity export allowed but limited). As discussed in Section 2.3, Eqs. (9) and (10) were used to generate the PV profiles for full and partial curtailment, respectively. In the case of partial curtailment, the maximum transferred PV power $s_{tr,max}$ in Eq. (10) was chosen from the simulation result on the maximum PV power transfer in the scenario without curtailment with 75% PV share. This is motivated by the fact that in that scenario there was no occurrence of overvoltage yet, as shown in Figs. 6 and 7. In the scenario without curtailment, there were overvoltage occurrences when 100% PV share was simulated. By implementing the partial curtailment strategy, the prescribed upper voltage limit was not violated when a 100% PV share was simulated, as shown in Fig. 10.

Fig. 11 shows the PV electricity relative to the existing load in different curtailment scenarios. In Fig. 11(a), system annual consumed PV electricity per total load or so-called self-sufficiency is shown. In Fig. 11(b) and (c), the exported and curtailed PV electricity per total load are shown. The sum of consumed, exported and curtailed PV electricity is equal to the PV share, which is shown on the x-axis of Fig. 11. The sum of consumed and exported PV electricity can be considered as the utilized electricity, while the curtailed PV electricity can be considered as the wasted electricity. While the full curtailment excelled in terms of maximum voltage, it was much poorer in terms of utilized electricity.

In Fig. 11(a), it can be seen that the grid self-sufficiency in the full curtailment scenario was lower than the ones in the no and partial curtailment scenarios, which were identical. The lower grid self-sufficiency is a drawback since the excess electricity from a customer could actually be used by the other nearby customers within the distribution grid. Thus, the partial curtailment was beneficial in not decreasing the grid self-sufficiency.

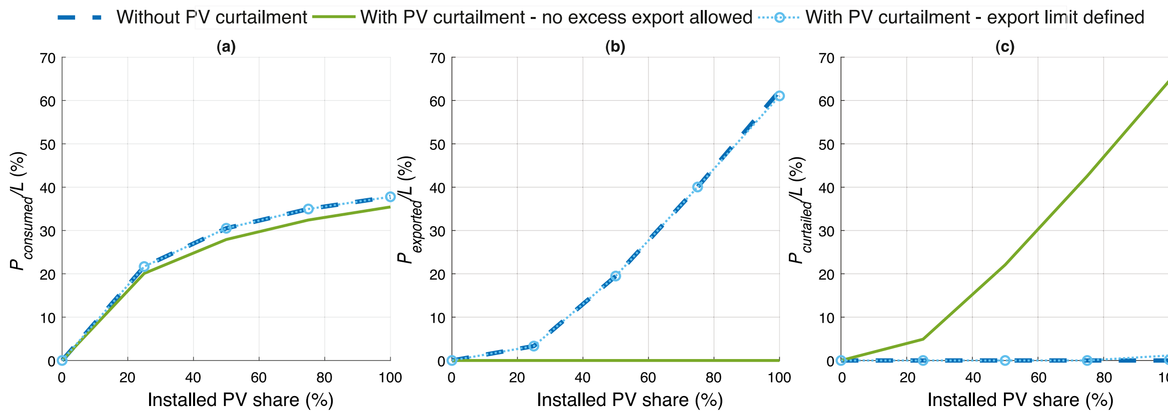

Fig. 11. Different PV electricity utilization relative to the existing load: (a) system annual consumed PV electricity per total load, i.e., self-sufficiency, (b) system annual exported PV electricity per total load, (c) system annual curtailed PV electricity per total load. Results from different curtailment strategies are shown in each subfigure.

In the scenario with full curtailment, there was no exported excess electricity as shown in Fig. 11(b). The exported excess electricity in the scenario with partial curtailment was slightly lower than one in the scenario without full curtailment when the installed PV share was higher than 75%. However, the difference was very insignificant. In the full curtailment scenario, starting from 25% PV share, the curtailed electricity was linearly proportional to the installed PV share as shown in Fig. 11(c). More than 50% of PV electricity was curtailed when the installed PV share was around 80%. In the scenario with partial curtailment, there was no curtailment except from the 75% to higher installed PV share. The curtailed electricity with 100% PV share in the partial curtailment scenario was very small and much lower than the one with the full curtailment scenario. From these results, it can be concluded that the PV electricity utilization could be close to the scenario without PV curtailment, but in this case without violating the upper voltage limit.

4. Discussion

With the proposed combined hosting capacity approach, the hosting capacity of both PV and EVs can be assessed together within the same framework. With this approach, it is also possible to analyze the impact of PV integration on the EV hosting capacity and vice versa. Furthermore, the framework can also illustrate the combined PV–EV hosting capacity enhancement with various applied EMS strategies. The framework can be used by DSOs or other relevant stakeholders to analyze the impact of grid integration of one technology on another one, as well as the impact of various EMS deployments. This might be useful for grid operation, grid reinforcement planning or asset management, since it illustrates how much new distributed generation and/or loads can be integrated into the network, and which EMS scenario will be suitable, so that grid reinforcement can be avoided.

In the case study in this paper, results show that in the scenario without EMS, there was a slightly positive correlation between the PV and EV shares and the opposite hosting capacity. In that case, the addition of PV increased the EV hosting capacity and the addition of EVs increased the PV hosting capacity. However, the increases were not significant due to low vehicle availability in the midday when the solar power peaked.

Results also show that with the simulated smart charging scheme, the voltage drops due to EVs could be significantly reduced following reduced peak loads. The voltage rises could also be slightly reduced following an improved PV–EV synergy by the smart charging scheme, despite the low vehicle availability at homes at midday when the PV power production peaked. This led to a significantly improved EV hosting capacity and a slightly improved PV hosting capacity when the smart charging was deployed. However, it should be noted that the simulated smart charging scheme in this study was based on perfect forecasts. Less reliable forecasts are expected to reduce the smart charging scheme's effectiveness. To which extent is left for future studies to investigate. It is also recommended for future studies to deploy different smart charging objectives such as smart charging with a financial objective, which can be more beneficial and practical for the customers.

As discussed in Section 3, PV curtailment can improve the PV hosting capacity in terms of installed capacity. However, PV curtailment cannot improve PV utilization in terms of self-consumed electricity.In the full curtailment scenario, when the installed PV capacity is high, the majority of the PV electricity is curtailed. This is indeed an economical disadvantage, since the idea of installing a PV system on the building is commonly to utilize the PV electricity within the building and reduce the electricity purchase from the grid. When an optimal curtailment strategy was deployed instead of full curtailment, a large share of the curtailment can be avoided, without violating the upper voltage limit. However, it still does not improve the self-consumed electricity; instead the excess electricity is fed into the grid, as in the scenario without curtailment. If the users get a compensation by feeding in electricity, the economical disadvantage of having excess PV electricity can be minimized. If there is no such compensation, the economical disadvantage can be reduced only by improving the PV self-consumption. This can be achieved with BESS and DSM [14]. Future studies on PV hosting capacity involving BESS and DSM strategies other than EV smart charging are recommended. Including the economic aspect is encouraged, especially for studies involving BESS, due to their high cost. In that case, the economical trade-offs between curtailment and BESS investment should be analyzed.

As mentioned previously, the hosting capacity of a given network depends on several conditions [16,32]. Details such as at which location the PV or EVs will be integrated, whether the connection is single-phase or three-phase, and to which phase the PV or EVs are connected in case of a single-phase connection, are all examples of conditions that affect the hosting capacity. Most of the time these details are unknown. Thus, hosting capacity assessments are usually subject to several uncertainties [32]. The temporal uncertainty was covered in this study since full-year stochastic simulations were conducted. However, in terms of PV–EV allocation, this study relied on the simplification of having an even PV–EV distribution among the customers.

In reality, there are numerous possible and more or less likely combinations of PV and EV allocation. For example, as mentioned previously, PV–EV adoption might be concentrated to one spot due to peer effects or just random allocation, and this would indeed alter the hosting capacity shown in Fig. 9. The change would, theoretically, depend on the location of the concentrated allocation. If the concentrated allocation of PV and EVs occurred in a bus with a higher electrical distance from the substation, the PV–EV tolerable areas in Fig. 9 are expected to be shifted to the left and bottom, resulting in lower combined PV–EV hosting capacity. In the future, probabilistic impact analysis within this proposed framework, taking also the spatial uncertainty of the allocation method into account, would be interesting.

In this paper, only home-charging is considered. This is motivated by the finding in a recent survey in [56], which states that more than 80% of EV users in Europe charge their EVs at home due to the lack of charging infrastructure in other locations and the fact that many EVs can be charged using a regular home socket. In another study in [57], it was shown that the EV charging peak load occurred in the evening, indicating that most private EV users charge their EVs at home after they arrive from work. This is reasonable since the longest inactive parking period usually occurs at home [58]. Given the current trend, the DSOs should pay closer attention to the residential grid in terms of EV charging demand increase. However, the trend might change and alter the charging behaviors in the future. Based on that, further studies should also consider the potential changes of occupancy and mobility patterns in the future, for example possible behavioral changes due to the global pandemic in 2020, which might change mobility patterns and choice of transportation as well as future PV and EV adoption due to impacts on the global economy.

The validity of a PV–EV hosting capacity study will always depend on how representative the data or the models compared to the real conditions. Other conditions could be studied with the use of stochastic models for mobility and EV charging, such as the models in [44], with parameters updated to represent altered conditions. With altered mobility patterns, it is expected that the charging profile will change as well. This will lead to different power flow computation results for the hosting capacity performance indices, such as voltage and component loading profiles. Furthermore, the impact of EVs to PV hosting capacity and vice versa, as well as the impact of the smart charging application on both hosting capacities are expected to change.

In this paper, the studied network is based on the IEEE European LV Test Feeder, which can be categorized as a distribution network in a dense neighborhood. Thus, the results from this paper might give insights on PV–EV hosting capacity in other similar networks with similar set-ups. However, regardless of the similarity of this network to other networks, it should be noted that a hosting capacity assessment in a specific network with certain assumptions, will only be valid for that specific network with those specific assumptions [16,32]. Therefore, in such hosting capacity assessment, DSOs should use the data from their own network in order to have a valid result for their distribution system planning [32]. Regardless of the scenario or the network studied, as long as the required data are available, the proposed framework and approach could be used by DSOs or other stakeholders to assess the combined PV–EV hosting capacity in their networks.

Even though this paper is focused on a specific case study, the same framework has a broader applicability and could be used for other types of combined hosting capacity assessments. In future studies, it would be interesting to assess the combined hosting capacity for other technologies other than PV–EV within the same framework using this approach. This includes other generation–load technologies such as wind–EV or PV–heat pump, generation–generation technologies such as PV–wind, load–load technologies such as EV–heat pump, and generation–load–storage technologies such as PV–EV-battery. It should be noted that the proposed framework is most effective in assessing the hosting capacity of two technologies of generation and/or load at the same time since it is based on a two-dimensional figure. Having more than two dimensions is a problem from a visualization perspective. However, the inclusion of energy storage will not need an additional dimension, since its role is similar to DSM such as EV smart charging. Different storage sizes will rather require using different colors in the figure.

In addition to assessments for different technologies, future grid studies and hosting capacity assessments for different parts of the built environment, e.g., non-residential distribution grids, or city-scale grids, are also recommended. In that case, the mobility and occupancy patterns will not be limited to residential buildings.

5. Conclusions

This paper presented a combined PV–EV integration and hosting capacity assessment in a residential distribution grid with EV smart charging and PV curtailment. The hosting capacity assessment was conducted with a novel framework that allows both PV and EV hosting capacity to be assessed together within the same framework. With this approach, the impact of PV penetration on the EV hosting capacity and the impact of EV penetration on the PV hosting capacity can be analyzed. In this study the framework was used to analyze a case study for a residential distribution grid with PV generation, household electricity use and EV charging profile for Swedish conditions.

The results show that with the PV curtailment, the hosting capacity for PV system increased, but it did not have an impact on the EV hosting capacity. The results also show that with the EV smart charging scheme, peak loads were significantly decreased and surplus generation was also slightly decreased. This led to a significantly higher EV hosting capacity, and a slightly higher PV hosting capacity. The insignificant impacts from smart charging on increasing PV hosting capacity was due to the low vehicle availability at homes at midday when the PV power production peaks. The combination of smart charging and PV curtailment resulted in low peak loads and low surplus generation led to the highest combined PV–EV hosting capacity among the simulated scenarios. It is expected that improved synergy between PV and EVs can make both PV and EV hosting capacity increase even more. This can be achieved, for example, by deploying BESS or changing the mobility behavior.

The proposed framework allows the DSO or other relevant stakeholders to analyze the impact of grid integration of different technologies with various EMS strategies, which might be useful for grid operation or grid reinforcement planning. Although this paper presents a specific case study for PV–EV hosting capacity, the framework can be used for other combined technology deployments. This includes generation–generation technologies, e.g., PV–wind, or generation–load technologies, e.g., wind–EV and PV–heat pump, or generation–load–storage technologies such as PV–EV-battery.

CRediT authorship contribution statement

Reza Fachrizal: Conceptualization, Methodology, Software, Data curation, Visualization, Formal analysis, Writing - original draft. **Umar Hanif Ramadhani:** Software, Visualization, Writing - review & editing. **Joakim Munkhammar:** Supervision, Writing - review & editing. **Joakim Widén:** Supervision, Funding acquisition, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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