Sustainable Cities and Society 72 (2021) 103043

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Probabilistic load flow analysis of electric vehicle smart charging in unbalanced LV distribution systems with residential photovoltaic generation

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ARTICLE INFO

Keywords:
Probabilistic load flow
Smart charging
Electric vehicle
Unbalanced residential grid
Photovoltaics

ABSTRACT

Several studies have presented electric vehicle smart charging schemes to increase the temporal matching between photovoltaic generation and electric vehicle charging, including a smart charging scheme with an objective to minimize the net-load variance. This method has proved, through simulations, that the self consumption could be increased, but the benefit of the approach has not been tested on a low voltage distribution system. To increase the quality of grid impact analyses of the smart charging scheme, probabilistic methods that include input and spatial allocation uncertainties are more appropriate. In this study, a probabilistic load flow analysis is performed by modelling the variability of electric vehicle mobility, household load, photovoltaic system generation, and the adoption of photovoltaic system and electric vehicle in society. The results show that the smart charging scheme improves the low voltage distribution system performance and increases the correlations between network nodes. It is also shown that concentrated allocation has more severe impacts, in particular at lower penetration levels. This paper can form the basis for the development of probabilistic impact analysis of smart charging to allow society to integrate more electric vehicles and photovoltaic systems for a more sustainable future.

1. Introduction

Societal awareness of greenhouse gas emissions and their impact on the environment has led to an increase in the adoption of both photovoltaic (PV) and electric vehicles (EVs) as sustainable alternatives, both of which are predicted to have a vital share of the future energy mix (Comello, Reichelstein, & Sahoo, 2018; International Energy Agency, 2018). The currently increasing penetration of these technologies in residential buildings poses potential challenges to distribution grid operation due to the temporal mismatch between on-site power consumption and production (Fachrizal & Munkhammar, 2020). This mismatch may lead to voltage deviation problems, component overloading and increases in power losses (Aleem, Suhail Hussain, & Ustun, 2020; Khalid, Alam, Sarwar, & Asghar, 2019).

These adverse effects of PV power generation and EV charging, consequently, limit the adoption of these technologies in the electricity system and could prevent the transition of the society towards a sustainable future. One of the efforts to solve or to mend the issue is by improving the synergies between PV power generation and EV charging. Previous studies have shown that improved on-site matching between PV power generation and EV charging load could effectively decrease the negative impacts on the power system resulting from PV and EV deployment (Fachrizal, Shepero, van der Meer, Munkhammar, & Widén, 2020; Luthander, Widén, Nilsson, & Palm, 2015).

Two of the most commonly used metrics for load matching are self-consumption (SC) and self-sufficiency (SS). SC is defined as the percentage of total self-consumed PV power generation to the total PV power generation and SS is defined as the percentage of total self-consumed PV power generation to the total load consumption (Luthander et al., 2015). Several methods have been introduced to increase the load matching, including energy storage and demand side management (DSM) (Luthander et al., 2015).

DSM can be defined as activities that are planned to affect the use of electricity at the customer side. DSM requires active residential customer engagement and a novel communications framework for information exchange and control, which are also considered to be some of the main components in smart grids (Gelazanskas & Gamage, 2014).

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https://doi.org/10.1016/j.scs.2021.103043
Received 9 December 2020; Received in revised form 3 May 2021; Accepted 21 May 2021
Available online 25 May 2021

Nomenclature

Abbreviations

DSM	demand side management
EMS	energy management systems
EV	electric vehicle
GHI	global horizontal irradiance
LV	low voltage
P/L	PV generation to load
PLF	probabilistic load flow
PV	photovoltaics
SC	self-consumption
SS	self-sufficiency

Variables

η	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)
Corr	correlation coefficient
Cov	covariance
D	daily EV driving distance (km)
E	daily EV charging demand (kWh)
I_t	solar irradiance at time t (W/m^2)
l_t	household load at time t (W)
s_t	solar PV generation at time t (W)
$\mathrm{SoC}_{\mathrm{arr}}$	state of charge on arrival (kWh)
$\mathrm{SoC}_{\mathrm{target}}$	targeted state of charge (kWh)
$x_{\max}$	maximum EV charging rate (W)
x_t	EV charging load at time t (W)

Controlling EV charging load, so-called smart charging, is one such DSM strategy that can also be employed at the residential customer to increase the load matching (Fachrizal et al., 2020).

In Fachrizal and Munkhammar (2020), a distributed smart charging scheme was developed for EVs with an objective to minimize the net-load variance for residential buildings with a PV system and EV charging demand. This method proved, through simulations, that the SC could be increased and peak loads could be reduced. However, the benefit of this method has not been tested on an actual LV distribution system, which is one of the gaps that this paper intends to fill.

Studying the impact of smart EV charging on LV distribution systems can be straightforwardly done by solving the power flow equations for the system (Green, Wang, & Alam, 2011). For realistic grid impact analyses, it is important to take into account both so-called aleatory and epistemic uncertainties of the modelled systems. The aleatory uncertainties arise from natural randomness and inherent variability, while the epistemic uncertainties arise from lack of information (Mulenga, Bollen, & Etherden, 2019).

The uncertainty in power flow analysis comes from both nature, e.g., solar irradiance, and also from society. Some examples of uncertainties from society are electricity consumption behaviour, EV mileage, EV mobility, and the adoption dynamics of PV and EVs (Heymann et al., 2019; Palm, 2017; Ramadhani, Shepero, Munkhammar, Widén, & Etherden, 2020).

The uncertainty arises both temporally, from randomness in the timing of events such as EV arrivals or departures and clouds shading the PV systems, and spatially, e.g., because these events do not take place simultaneously at all buildings, and because the studied systems differ between buildings. To capture both temporal and spatial variation, a probability distribution function (PDF) of the intended parameter is often used (Bollen & Rönnberg, 2017; Ramadhani et al., 2020). Alternatively, a time-series model with a proper temporal diversity can be utilized (Bollen & Rönnberg, 2017; Ramadhani et al., 2020).

At higher voltage levels, the adoptions were observed to be unevenly distributed and concentrated pockets due to peer effects were found (Bernards, Morren, & Slootweg, 2018; Graziano & Atkinson, 2014). Concentrated allocation has more severe impacts on the grid while randomly distributed allocation might result in an under-investment during early PV and EV adoption (Heymann et al., 2019). Despite that, the impacts of concentrated PV and EV allocation in low voltage networks, to the best of the author's knowledge, have rarely been considered. The impact of smart charging with different allocation methods has not been studied in detail either.

Hence, probabilistic methods that include these input uncertainties are often more appropriate than the otherwise commonly used deterministic worst-case approaches (Ramadhani et al., 2020). This is also another gap that this study intends to fulfill.

1.1. Previous works on grid impacts of smart charging

In review papers Fachrizal et al. (2020) and Rahman, Vasant, Singh, Abdullah-Al-Wadud, & Adnan (2016) several studies on the smart charging using optimization methods were presented. The objectives of the smart charging varied from maximizing the technical perspectives such as minimizing the grid impacts (Clement-Nyns, Haesen, & Driesen, 2010; Liu et al., 2015), peak load shaving (Ioakimidis, Thomas, Rycerski, & Genikomsakis, 2018; Weckx & Driesen, 2015), and minimizing the load variance (Crozier, Morstyn, & McCulloch, 2020; Jian et al., 2013; Shang, Liu, Shao, & Jian, 2020; Weckx & Driesen, 2015), to the economical perspectives such as maximizing profit (Meer, Mouli, Mouli, Elizondo, & Bauer, 2018) and minimizing the charging cost (Jeon, Cho, & Lee, 2020; Nour, Said, Ali, & Farkas, 2019; Quddus, Shahvari, Marufuzzaman, Usher, & Jaradat, 2018; Sachan & Adnan, 2018; Ul-Haq, Azhar, Mahmoud, Perwaiz, & Al-Ammar, 2017).

Some of the aforementioned smart charging studies have included grid impact analysis as can be seen in Table 1. In Weckx and Driesen (2015), smart charging grid impacts were simulated in a Belgian LV network, and the grid losses were reduced by 28%. Paper (Liu et al., 2015) assessed the smart charging with an objective to reduce the impact on the power grid in an example of commercial building micrograds. In Clement-Nyns et al. (2010), the grid impacts were evaluated for the IEEE 34-bus test feeder, where the losses were reduced from 2.4% to 2.1%. Paper (Shang et al., 2020) simulated the grid impact of smart charging in a campus grid, and compared with uncoordinated charging. The smart charging increased the peak shaving and self-consumption by 17.5% and 258.7%, respectively. In Crozier et al. (2020), smart charging reduced the percentage of distribution networks that required a reinforcement. In Nour et al. (2019) smart charging successfully lower the peak load, loading, and voltage violation. Paper (Sachan & Adnan, 2018) suggested to redesign the weakest feeder to support more EVs in the system.

From the aforementioned smart charging grid impact studies, some studies have employed, to some extent, probabilistic approaches by considering the uncertainties of the input. In Clement-Nyns et al. (2010), the load profile uncertainty was modeled using a normal distribution. That study utilized a random allocation method for three penetration levels. The papers Shang et al. (2020) and Nour et al. (2019) considered the uncertainty of EV mobility parameters, but did not vary the allocation and penetration. The study in Crozier et al. (2020) utilized Monte Carlo simulation by randomly adding different household load and EV charging Other examples of probabilistic studies of EVs in LV distribution systems in a wider context without smart charging optimization can

Table 1
Comparison of the proposed PLF study with other works in smart charging grid impacts analysis.

	Parameters in optimization formulation				SC Objectives	Simulated grid	Allocation method	Penetration method	Correlation analysis
	PV	EV	Load	Time					
This study	✓	✓	✓	✓	Minimizing net-load variance	IEEE European LV test feeder, unbalanced	Epistemic, concentrated and distributed, 5 sets for each method	Ten penetration levels	✓
Weckx and Driesen (2015)	✓	✓	✓		Minimizing the peak load and the load variance	A Belgian LV network	Epistemic, evenly distributed	One penetration level, all houses have PV and half of houses have EV	
Liu et al. (2015)	✓	✓	✓	✓	Improve PV self consumption and reduce the impact on the power grid	An example of commercial building microgrids	Not applicable	Not applicable	
Clement-Nyns et al. (2010)		✓	✓	✓	Minimizing the residential grid losses	IEEE PES Distribution Test Feeders, 34-bus Feeder	Aleatory, random	Three penetration levels	
Shang et al. (2020)	✓	✓	✓	✓	Load flattening and improving self-consumption	Medium voltage, SUSTech campus grid	Epistemic, known locations	One penetration level	
Crozier et al. (2020)		✓	✓	✓	Load flattening	Transmission and distribution grid in Great Britain	Aleatory, random	One penetration level, forecasted penetration level	
Nour et al. (2019)		✓	✓	✓	Cost minimization	Distribution grid in Egypt, balanced	Unknown	One penetration level, 50%	
Sachan and Adnan (2018)		✓		✓	Cost minimization and grid stability	Distribution grid	Epistemic	Depends on the feeder strength	
Jeon et al. (2020)	✓	✓		✓	Cost minimization	MV grid network in Jeju Island	Epistemic, known locations	Epistemic, forecasted penetration level	

be found in Anastasiadis, Voreadi, and Hatziargyriou (2011), Chen, Yan, Pei, and Wu (2016), Shariff, Essa, and Cipcigan (2016), Ul-Haq et al. (2017).

As shown in Table 1, even though the allocation method can be modelled as epistemic or aleatory, previous works rarely varied the allocation. Hence, the uncertainty from the different possible allocations was not captured. Mainly, the smart charging studies presented in the mentioned papers focused solely on EV charging without PV generation. However, some of them also considered PV generation, for example (Jeon et al., 2020; Liu et al., 2015; Shang et al., 2020; Weckx & Driesen, 2015).

Power system input variables are dependent on each other to some extent, including EV charging loads (Ramadhani et al., 2020). The state of charge of the battery, for example, is correlated positively with daily travelled distances (Pashajavid & Golkar, 2014). Hence, it also impacts the voltage at the network bus both temporally and spatially (Mu, Wu, Jenkins, Jia, & Wang, 2014). Ref. Mu et al. (2014) also observed that the EV charging load in a larger network system was also spatially correlated, with the peak spatially concentrated in the residential area. However, the impact on the correlation from smart charging schemes has rarely been discussed. Additionally, grid impact simulation studies of EV charging and PV generation are also encouraged to include the impact on unbalanced networks (Shepero, Ramadhani, Munkhammar, & Widén, 2019). Paper Shepero et al. (2019) investigated the impacts of single-phase charging and single-phase PV generation on a residential electricity distribution system and found that in the unbalanced system, the losses were 12% higher and the minimum voltage was 0.03 pu lower.

1.2. Contributions

To fill the gaps in previous research outlined above, in this paper we perform a probabilistic load flow (PLF) analysis of smart charging with an objective to reduce the net-load variability in an unbalanced LV distribution system considering the uncertainties of the systems. This study performs probabilistic analysis of smart charging by capturing both temporal and spatial variability of EV mobility pattern, human activities at home, PV system generation, and the dynamics of PV system and EV adoption in society.

The temporal variability is captured by generating synthetic one-year time-series profiles of the EV mobility, load, and PV generation for typical Swedish consumers, considering the uncertainty from stochastic behaviour of human activities and PV system sizes. Then, PLF analyses are carried out with Monte-Carlo simulations, considering ten different penetration levels. It allows us to observe the impact of smart charging in a wide range of penetrations.

Two different methods of PV and EV allocation are compared, namely random distributed and concentrated allocation, to analyze the impact of the spatial allocation uncertainties. To capture the spatial variability, five different sets of allocation scenarios are utilized for each method at every penetration level. PLF simulations with and without a smart charging scheme, aimed at reducing net-load variability, are then performed for an unbalanced LV network. The operational performance and the correlation between nodes are investigated. The results for the uncontrolled and controlled cases are then compared to analyze the advantages of adopting a smart charging scheme. The contributions of this paper are summarized as follows:

1 The grid impact of smart charging is evaluated with an objective to reduce the net-load variability in unbalanced LV distribution systems with residential PV generation.
2 Both aleatory and epistemic uncertainties are explained and considered in probabilistic simulations with ten different penetration levels, a wide range of PV system sizes, and considering the temporal and spatial variability.
3 The impact of the varying ways in which society might adopt PV systems and EVs is studied by simulating both randomly distributed and concentrated residential PV and EV allocations in the low voltage network.
4 The impact of smart charging on the correlation between network nodes is investigated as an indicator of diversity among load and generation patterns in the grid.

1.3. Paper organization

The paper is structured as follows: Section 2 describes the models, methods, and data used in this study. Section 3 presents the results for both uncontrolled charging and smart charging, each with two different allocation methods. The results are then discussed in Section 4, and conclusions are drawn in Section 5.

2. Methods

A schematic overview of the methodology used in this paper is shown in Fig. 1. The inputs for the PV generation model were irradiance data and PV sizes, which were scaled from PV generation to load (P/L) ratio and household load profile. The household load and PV generation models, together with EV mobility patterns, distances, and EV parameters, were then used as inputs to the EV smart charging optimization model that generated EV smart charging load profiles. In the case of an EV uncontrolled charging load profiles, PV generation model and load model were not considered as input.

The EV charging load profile, household load, and PV generation models were then used as inputs to the load flow calculations with ten penetration levels and two allocation methods. For each method at every penetration levels, five different sets of allocation scenarios were considered. The load flow calculation results included the voltages, phase unbalance, peak loading, and total losses. The result from smart charging were then compared to the result from uncontrolled charging.

2.1. Uncertainties considered

This study considers both aleatory and epistemic uncertainties. The aleatory uncertainties, also known as random or statistical uncertainties, arise from natural stochastic behavior. For example, the uncertainty in predicting the outcome of flipping a coin is considered as an aleatory uncertainty. This type of uncertainty is difficult to reduce. The epistemic uncertainties, also known as knowable uncertainties, arise from inadequate knowledge. The variability of this uncertainty can be reduced with more information (Ülkümen, Fox, & Malle, 2016).

To capture the varying behaviours of aleatory uncertainties in the system in this study, synthetic profiles were generated for stochastic residential load, mobility demand, and PV generation. The steps in these processes are explained in the next section.

Usually, PV sizes, phase selection for single-phase connections, PV penetration levels, and the location of houses with PV are included as epistemic uncertainties, unless the uncertainties are estimated from measured data or from previously used probability distributions. These epistemic uncertainties remain a research challenge and, in a lot of cases, they are a matter of assumption (Mulenga et al., 2019).

In this study, PV system sizes were chosen based on the P/L ratio. The distribution of the P/L ratios was assumed to be the same as the P/L ratios of buildings in Ratnam, Weller, Kellett, & Murray (2017). In the simulations, the single-phase load, PV generation, and EV charging load were connected to the connection phase of the customers as given in the IEEE test feeder data explained in the next section. Because the distribution of PV sizes and phase connections were assumed to be the same as in the existing scenarios given by paper (Ratnam et al., 2017) and by the IEEE test feeder data, these variables were considered to be known and were not treated as epistemic uncertainties (Mulenga et al., 2019).

A variety of penetration levels, defined as the number of houses with PV systems and EVs, were considered, ranging from 5 to 50 houses out of 55 houses. As regards the PV and EV allocation, previous studies often assigned a set of random locations (Ma, Azuatalam, Power, Chapman, & Verbič, 2019; Mulenga et al., 2019). However, as discussed in the previous section, this study aims to analyse the impact of concentrated adoption of PV and EVs that may happen due to a peer effect. Hence, both concentrated and randomly distributed allocation are simulated and then compared.

For each method, five different sets of allocation scenarios are utilized for every penetration level. For the concentrated distribution, the five sets of allocation scenarios are concentrated on five equally distributed locations i.e., one set of allocation is concentrated near the substation, one set is concentrated at the end of the network and the others are concentrated between them. For the distributed scenarios, the five sets of allocation are randomly generated.

2.2. Correlation between network nodes

In addition to voltage profiles, phase unbalance, peak loading, total losses, and net-load variability, this paper also investigates the impact of smart charging on the correlation between network nodes. For evaluating the correlation, the Pearson correlation coefficient is used. How to use the Pearson correlation coefficient for modelling correlation in load flow studies is explained more deeply in Ramadhani et al. (2020).

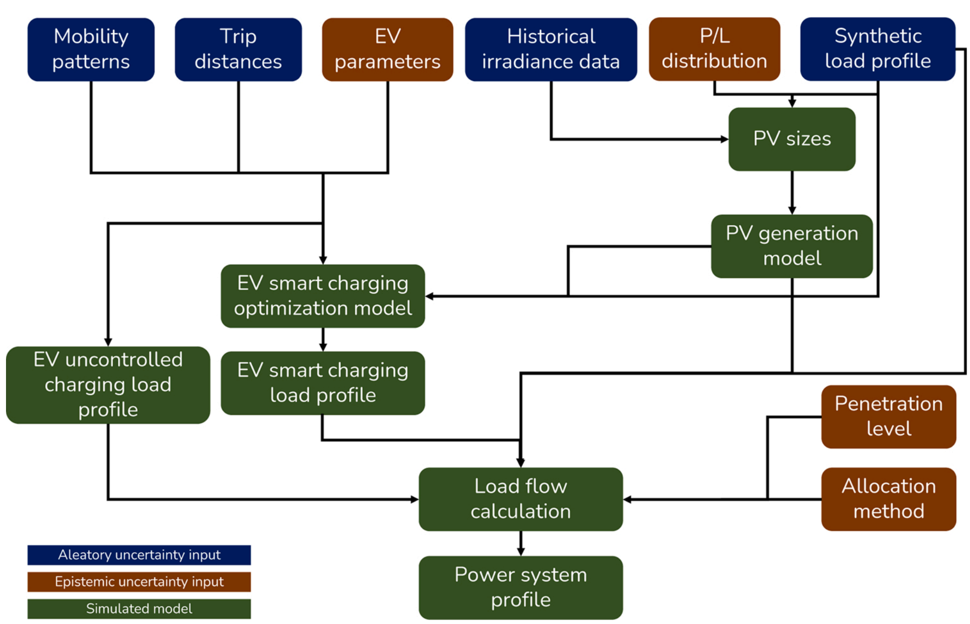

Fig. 1. Schematic overview of the paper. Two EV charging load profiles generated from different inputs (smart charging and uncontrolled charging) are used for the comparison. Ten penetration levels are considered, from five houses to fifty houses. Two different allocation methods are used: concentrated and distributed. Five different sets of allocation scenarios are utilized for each method at every penetration.

Per definition, the correlation coefficient is the normalized covariance, which represents the joint variability of two variables. A positive correlation coefficient value explains that higher values of one variable coincide with higher values of the other variable, and vice versa. For two random variables X and Y with a sample size of N, the covariance of is:

$$\mathrm{Cov}(X,Y)=\sum_{i=1}^{N}\frac{(x_i-\bar{x})(y_i-\bar{y})}{N}, \tag{1}$$

where $\bar{x}$ and $\bar{y}$ are the mean of X and Y respectively. The correlation coefficient is then described as:

$$\mathrm{Corr}(X,Y)=\frac{\mathrm{Cov}(X,Y)}{\sigma_x\sigma_y}, \tag{2}$$

where σ_x and σ_y are the standard deviations of X and Y respectively. The average correlation used in this paper is based on all correlations of all pairs of bus nodes. For this part of the study only the 100% penetration level of PV and EVs was analyzed. Hence, there is no allocation method applied in this analysis.

2.3. Data and case study

2.3.1. Residential load

Synthetic household electricity profile data were generated with the Widén model (Widén & Wäckelgård, 2010). This is a Markov chain based model that generates electricity profiles based on Swedish occupant activity profiles. The model was trained to generate electricity use profiles without electric heating for detached houses with two adult inhabitants per household. The load was assumed to have a constant power factor of 0.95.

2.3.2. Mobility pattern and charging demand

The mobility model and the charging demand were based on Swedish travel survey data from 2006 (RES, 2007). The arrival and departure times, the origin and the destination locations of the trips, and the distance traveled within the trips were available in the survey data.

The arrival and departure times were randomly sampled with a Monte Carlo method. The daily charging demands were calculated as

$$E=\eta\times D, \tag{3}$$

where η is the specific consumption of EVs (kWh/km) and D is the daily driving distance (km). η was set to 0.15 kWh/km, while D was calculated by doubling a randomly sampled distance from the travel survey data. This distance represented the round-trips from and to home, assuming that each EV travels in two equally long trips a day, such as from home to workplace and back to home. The maximum usable energy in the battery was set to 30 kWh. This was assuming that the battery could provide sufficient energy for the trips by EVs within a city.

Home-work-home mobility patterns were used to define the arrival and departure times and the charging demands in weekdays, while home-other-home mobility patterns were used for weekends. See Shepero and Munkhammar (2018) for information about which trips were considered ending at the categories work and other. The user mobility statistics that was used in this study is illustrated in Fig. 2.

2.3.3. PV generation

PV power generation profiles were based on global horizontal irradiance (GHI) data for Stockholm, Sweden (latitude 59.3° N and longitude 18.0° E), from 2018, recorded by the Swedish Meteorological and Hydrological Institute (SMHI) (SMHI, 2018). The PV system in this study was scaled relative to the total yearly electricity demand, i.e., P/L ratios. The PV generation profile in this study was calculated by directly multiplying the GHI with a factor which made the yearly PV electricity production satisfy the given P/L ratios. The PV power generation s_t at time t can be expressed as

$$s_t=\eta_{\mathrm{pv}}\times I_t, \tag{4}$$

where η_{pv} is the PV system efficiency factor times area in m^2, and I_t is the incident solar radiation which in this case is the GHI. GHI data are used as the incident solar radiation profile for simplicity reasons, as the exact generation profile is not crucial. The PV system efficiency factor times area η_{pv} can be written as

$$\eta_{\mathrm{pv}}=\frac{\sum_{t=1}^{35040}l_t\Delta t\times P/L}{\left(\sum_{t=1}^{35040}I_t\Delta t\right)}, \tag{5}$$

where l_t is the electric load at time t, Δt is the time step which in this case is 15 minutes, and P/L is the ratio of yearly electricity production to yearly electricity consumption. In this case, the electricity demand included both the household load and the EV charging demand. The PV power generation was assumed to have a constant power factor of 1.

2.3.4. LV distribution grid data

For power flow analysis, the IEEE European LV test feeder was used (IEEE, 2021). It represents a single feeder from a real LV grid in the UK and has been used before in, e.g., (Gruosso, Gajani, Zhang, Daniel, & Maffezzoni, 2019; Ni, Nguyen, Cobben, Van den Brom, & Zhao, 2018). It includes 55 customers with a single phase connection. The grid is supplied by an 800 kVA 11 kV/0.416 kV transformer. The grid topology and the phase connection are shown in Fig. 3. The voltage on the low voltage side was set to 1.04 pu at all times. The unbalanced power flow was simulated in OpenDSS using a fixed-point iterative method known as normal mode in OpenDSS.

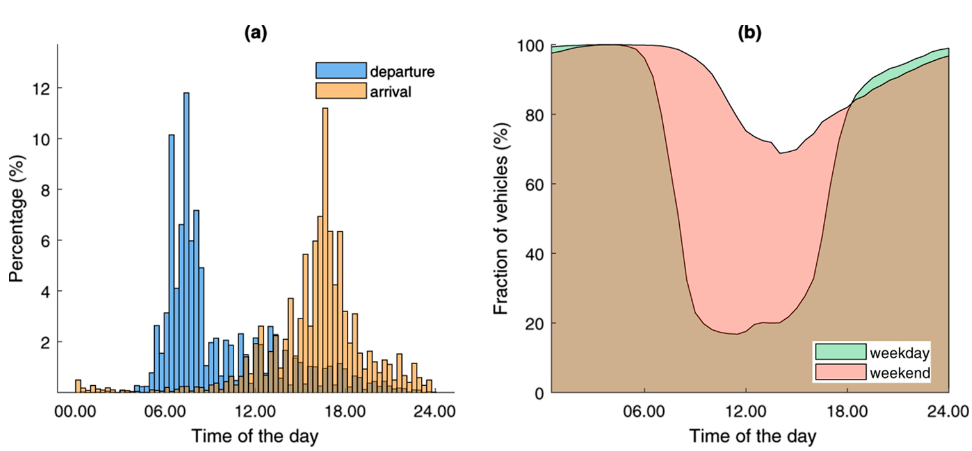

Fig. 2. User mobility statistics: (a) home-arrival and home-departure times and (b) mean daily fraction of vehicles parked at residential areas. In (b), the light green area represents the weekday fraction, the light red area the weekend fraction, and the brown area just the intersection area between the two fractions.

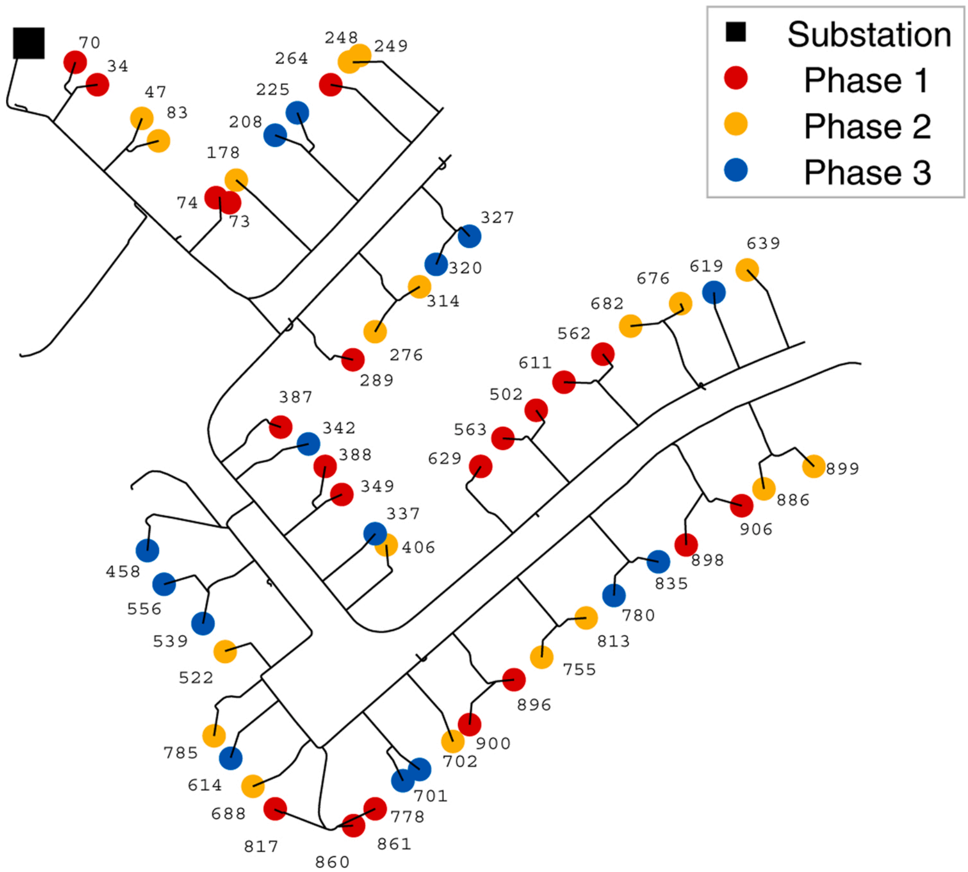

Fig. 3. IEEE European LV test case used in this study.

2.4. EV charging scheme

This section describes the two charging schemes considered, i.e., uncontrolled charging and smart charging. The two charging schemes were included in order to compare the worst and best case scenarios of EV integration in the residential distribution grid. The uncontrolled charging scheme represents the worst case scenario since there is no coordination between EV charging and generation-load patterns, which most likely leads to increased peak load and low local PV utilization. The smart charging scheme represents the best case scenario where the charging scheme attempts to increase the PV self-consumption and not to increase the peak load based on the mobility pattern of the users. The expected mean daily load and PV generation with uncontrolled and smart charging profiles are shown in Fig. 4.

Since the comparison is intended to assess the highest improvement potential by the smart charging scheme on the residential distribution grid operation, it was assumed that all EVs always charge at home. In addition, it was also assumed that the EVs charge only once a day, which was motivated by the finding in Quiros-Tortos, Navarro-Espinosa, Ochoa, and Butler (2018) that the majority of EVs are charged once a day. The maximum charging power was set to 3.7 kW which is a typical home-charging power (Cundeva, Krkoleva, & Bollen, 2018). The

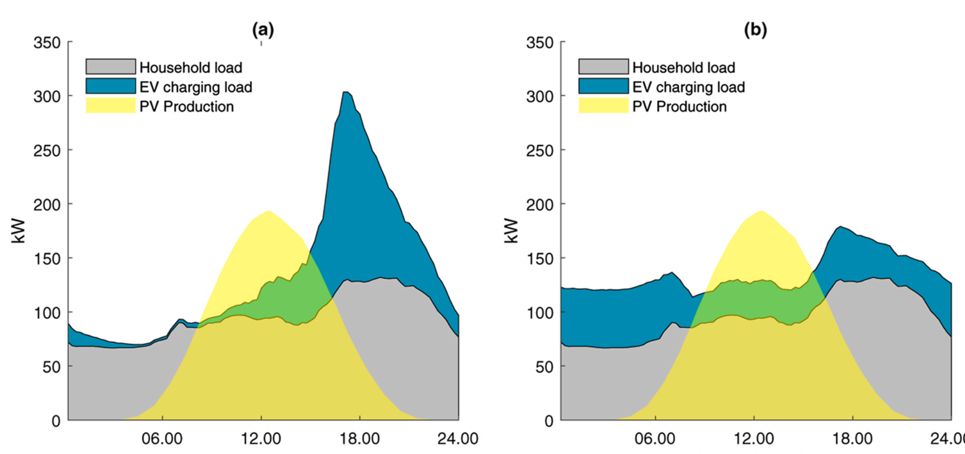

Fig. 4. Mean daily load profile with (a) the uncontrolled charging scheme and (b) the smart charging scheme. The figures were generated for a case of a community with a P/L = 0.5.

charging efficiency was set to 90% which referred to the average efficiency of Level 2 chargers (Sears, Roberts, & Glitman, 2014). It was assumed that the efficiency is constant regardless of the charging power rate. The resolution of the simulations was 15-min. The following subsections further describe each charging scheme.

2.4.1. Uncontrolled charging scheme

In the uncontrolled charging scheme, it is assumed that EVs start charging upon arrival with rated charging power. The charging will finish when the EV battery state-of-charge (SoC) meets the targeted SoC, which in this case is maximum SoC or fully charged battery. If the targeted SoC has not been reached when the EV is to depart, the charging is stopped at the departure time.

2.4.2. Smart charging scheme

The smart charging scheme is based on a distributed smart charging scheme developed in Fachrizal and Munkhammar (2020). In the smart charging scheme, the charging process does not always start immediately upon arrival and with the rated charging power. The scheme considers the parking period duration, the energy demand of the EV, and forecasts of PV power generation and electricity consumption, which in this case was assumed to be perfect forecasts, thereby representing an upper limit case. Fig. 5 shows an overview of the proposed smart charging scheme. Since the charging is distributed, only local parameters are considered. From these inputs, the scheme is employed to minimize the net-load variability of an individual household. Minimizing the load variability in each individual household can contribute to a decrease in the load variability in a local distribution grid or even a regional grid (Jian et al., 2013). Since the smart charging is expected to lower the power transfer from the grid to the household and vice versa, it will be unnecessary to include grid constraints. This will also simplify the scheme which can be beneficial for practical implementation since grid data is difficult to obtain.

The net-load variability was quantified with a population variance equation. However, the denominator part was not included as it is constant and would not affect the optimization result. The optimization problem of the smart charging scheme can be written as

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

$$\text{s.t.} \quad \eta_x \sum_{t=t_{\mathrm{arr}}}^{t_{\mathrm{dep}}} x_t \cdot \Delta t = \mathrm{SoC}_{\mathrm{target}} - \mathrm{SoC}_{\mathrm{arr}}, \qquad 0 \le x_t \le x_{\max}, \tag{7}$$

where 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 EV charging load. In the constraint, η_x is the charging efficiency, Δt is the time step, which in this case is 15 min, $\mathrm{SoC}_{\mathrm{target}}$ is the targeted state of charge (kWh) of the battery, $\mathrm{SoC}_{\mathrm{arr}}$ is the state of charge (kWh) of the battery on arrival and $x_{\max}$ is the maximum charging power rate. As can be seen in Eqs. (6) and (7), the optimization formulation in this study is in a quadratic programming form, thus a convex problem. The optimization problem was solved using MATLAB quadprog with the interior-point-convex algorithm. For more details about the optimization problem, see (Fachrizal & Munkhammar, 2020).

3. Results

This section first presents the result of the probabilistic grid impact analysis of smart charging in terms of voltage profiles and phase unbalance. Secondly, peak loading and total losses are also compared. The phase unbalance is defined as the maximum deviation, among the three phases, between phase and average line voltage (IEEE, 2002). After that, the relation between the grid performance and the main objective of the smart charging, i.e., minimized net-load variability, is presented. Finally, in the last part, the correlation between network nodes in terms of voltages and EV charging loads is analyzed.

3.1. Voltage profiles

The voltage profiles in the LV distribution grid obtained when the PV and EV penetration level was increased for both allocation methods are shown in Fig. 6 and Table 2. The voltage deviation increased across all phases when increasing the PV and EV penetration. In both the concentrated and distributed allocation scenarios, the voltage deviation and range of uncontrolled charging were higher than those of smart charging. On average, the voltage standard deviation and voltage range in the smart charging case with distributed allocation were 0.001 pu and 0.031 pu lower than in the uncontrolled one, respectively. In the smart charging with concentrated allocation scenarios, the average voltage standard deviation and voltage range were 0.001 pu and 0.039 lower than in the uncontrolled one, respectively.

The impact of different allocation methods on the voltage deviation was higher for the lower penetration levels. When PV and EV penetration were less than 55%, the voltage deviation for concentrated allocation was higher than for distributed allocation.

Concentrated allocation also gave higher maximum voltages for the lower penetration levels. The maximum voltages started to exceed the allowed level of 1.1 pu when the penetration was equal to 40 buildings in the case of distributed allocation, but exceeded 1.1 pu when the penetration was equal to 25 buildings, i.e., 3 penetration levels earlier, in the case of concentrated allocation. This happened for both the smart and uncontrolled charging schemes. This is likely because the EVs were

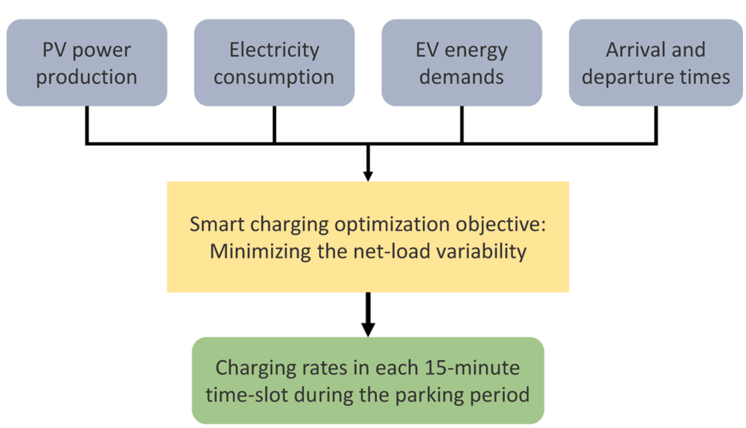

Fig. 5. Overview of the smart charging scheme.

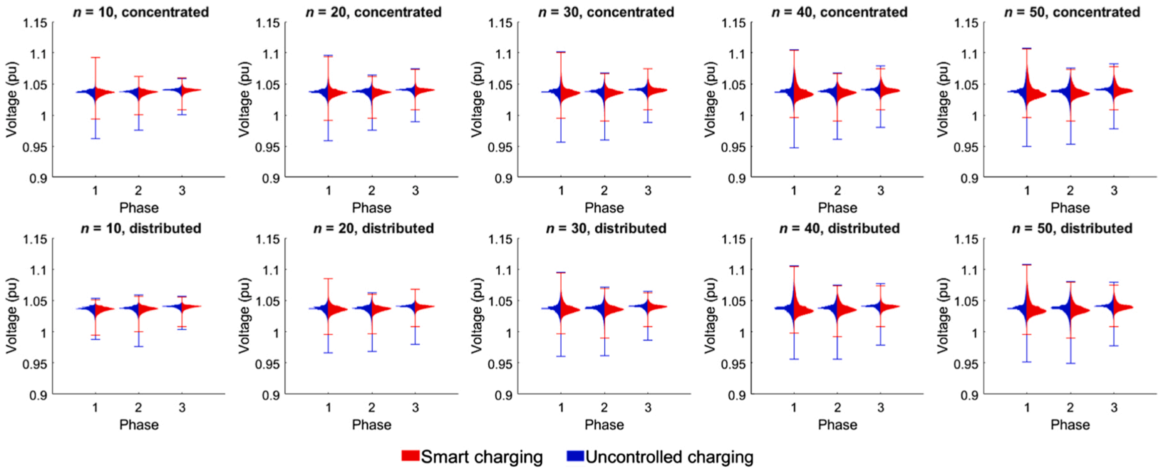

Fig. 6. Comparison of violin plots of the phase voltages for different charging schemes (smart and uncontrolled charging) and different allocation methods (concentrated and distributed). Five out of ten penetration levels were presented for a simpler presentation (even *n* only), with *n* being the number of houses with PV and EV. The horizontal marks of each violin plot represent the minimum and maximum values. The differences between smart and uncontrolled charging were bigger in higher penetration levels, but the differences between concentrated and distributed were bigger in lower penetration levels.

Table 2
Mean, minimum (subscript), and maximum (superscript) values in p.u of the voltages for different charging schemes ('S' = smart and 'U' = uncontrolled charging) and different allocation methods ('C' = concentrated and 'D' = distributed). Ten penetration levels were considered.

'n' houses	5	10	15	20	25	30	35	40	45	50
U, D	$1.037_{0.989}^{1.051}$	$1.037_{0.987}^{1.053}$	$1.037_{0.975}^{1.070}$	$1.037_{0.966}^{1.085}$	$1.037_{0.948}^{1.091}$	$1.038_{0.961}^{1.096}$	$1.038_{0.966}^{1.094}$	$1.038_{0.956}^{1.106}$	$1.038_{0.951}^{1.109}$	$1.038_{0.952}^{1.108}$
S, D	$1.037_{0.993}^{1.051}$	$1.037_{0.994}^{1.051}$	$1.037_{0.993}^{1.069}$	$1.037_{0.996}^{1.084}$	$1.037_{0.992}^{1.089}$	$1.038_{0.996}^{1.093}$	$1.038_{0.996}^{1.094}$	$1.038_{0.997}^{1.104}$	$1.038_{0.996}^{1.107}$	$1.038_{0.996}^{1.106}$
U, C	$1.037_{0.981}^{1.085}$	$1.037_{0.962}^{1.093}$	$1.037_{0.955}^{1.098}$	$1.037_{0.959}^{1.096}$	$1.038_{0.956}^{1.104}$	$1.038_{0.956}^{1.102}$	$1.038_{0.950}^{1.101}$	$1.038_{0.947}^{1.105}$	$1.038_{0.949}^{1.106}$	$1.038_{0.950}^{1.108}$
S, C	$1.037_{0.993}^{1.085}$	$1.037_{0.994}^{1.093}$	$1.037_{0.993}^{1.098}$	$1.037_{0.992}^{1.094}$	$1.038_{0.993}^{1.101}$	$1.038_{0.994}^{1.101}$	$1.038_{0.997}^{1.099}$	$1.038_{0.996}^{1.103}$	$1.038_{0.996}^{1.104}$	$1.038_{0.996}^{1.106}$

rarely available during midday, when the PV power generation was highest and, hence, smart charging was rarely applied during that time.

The minimum voltage in the uncontrolled charging cases was always lower than that in the smart charging cases and the difference was increasing with increasing PV and EV penetration. In addition, the minimum voltage in the case of uncontrolled charging with concentrated allocation was always lower than with distributed allocation. For the highest penetration cases, the minimum voltage for smart charging was 0.996 pu. For the same penetration, the minimum voltage for uncontrolled charging was 0.950 pu with concentrated allocation and 0.952 with distributed allocation. This likely happened at the peak load time when the EVs were charging.

During most of the time in the higher penetration cases, the voltages were within ±5% of the rated value. For smart charging, the 5% percentiles were 1.025 with both allocation methods and the 95% percentiles were 1.057 pu with distributed allocation and 1.058 with concentrated allocation. For uncontrolled charging, the 5% percentiles were 1.019 with both allocation methods and the 95% percentiles were 1.057 pu with distributed allocation and 1.057 with concentrated allocation.

3.2. Phase unbalance

The phase unbalance with respect to increasing PV and EV penetration on the tested system is shown in Fig. 7. The mean values of the phase unbalance are given in Table 3. It can be observed that increasing the PV and EV penetration amplified the phase unbalance, and the phase unbalance with concentrated allocation was higher than with distributed allocation.

In all PV and EV penetration scenarios, smart charging helped reduce the phase unbalance. The average phase unbalance with smart charging was always lower than that in the uncontrolled case for the same penetration level. Smart charging also significantly decreased the maximum phase unbalance and the number of events in which the phase unbalance was higher than 3%, which is considered as the safe limit (Arghavani & Peyravi, 2017). This safe limit, however, was exceeded more often with concentrated allocation than with distributed allocation.

With distributed allocation, the average number of events per year in which this safe limit was exceeded was reduced from 7608 events in the uncontrolled charging scenarios to 265 events in the smart charging

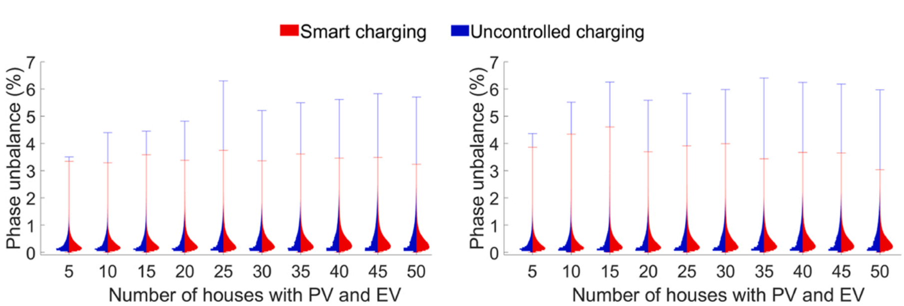

Fig. 7. Comparison of violin plots of the phase unbalance for different charging schemes: (smart and uncontrolled charging) and different allocation methods (distributed and concentrated). The left and right figures represent distributed and concentrated allocation, respectively. Ten penetration levels were considered. Red and blue represent smart charging and uncontrolled charging, respectively. The horizontal mark of each violin plot represents the maximum value. Smart charging reduces the phase unbalance. In lower penetration levels, the phase unbalance of concentrated allocation were higher.

Table 3
Mean values in % of the phase unbalance for different charging schemes (smart and uncontrolled charging) and different allocation methods (concentrated and distributed). Ten penetration levels were considered.

Houses with PV	5	10	15	20	25	30	35	40	45	50
Uncontrolled, distributed	0.32	0.35	0.39	0.43	0.49	0.50	0.51	0.58	0.61	0.60
Smart, distributed	0.30	0.31	0.34	0.37	0.42	0.41	0.41	0.47	0.48	0.44
Uncontrolled, concentrated	0.35	0.39	0.45	0.47	0.51	0.53	0.53	0.58	0.57	0.59
Smart, concentrated	0.34	0.36	0.41	0.41	0.43	0.45	0.42	0.46	0.43	0.43

scenarios. With concentrated allocation, the number was reduced from 10,811 events in the uncontrolled charging scenarios to 2455 events in the smart charging scenarios.

During most of the time, the phase unbalance was lower than 3%. The 95% quantile of the phase unbalance of uncontrolled charging ranged from 0.87% for the lowest penetration level to 1.70% for the highest penetration level.

It is interesting to note that even though the trend of the maximum phase unbalance is to increase with respect to increasing PV and EV penetration, in some cases the maximum phase unbalance was lower at higher penetration. For example, the maximum phase unbalance for the case of 40 houses with PV and EV was lower than for the case of 35 houses with PV and EV. This is likely because of the random allocation of PV locations, which shows the importance of the choice of PV allocation approach in grid impact analysis.

3.3. Peak loading and total losses

The peak loading and losses for all cases and penetrations are presented in Fig. 8. As expected, the loading and losses increased with increasing PV and EV penetration.

As regards the peak loading, the smart charging impact was insignificant at lower penetration levels, i.e., the peak load was almost the same. The impact of smart charging was increasing with increasing penetration level. At the maximum penetration level, the peak load was reduced up to 57%.

The increase in the penetration levels of PV and EVs also leads to higher losses regardless of the charging schemes, as shown in Fig. 8. This is due to the higher net-load variance and higher power magnitudes in the higher penetration level scenarios.

When it comes to the reduction of losses due to the smart charging scheme, this is less significant in the low penetration scenarios compared to the higher penetration scenarios. This is basically due to fewer flexible loads, i.e., EVs, involved in the lower penetration scenarios than in the higher penetration scenarios. For the active power, the loss reduction ranged from 59 kWh for the lowest penetration level to 795 kWh for the maximum penetration level.

In terms of allocation methods, the concentrated allocation scenarios have higher losses and peak load in all uncontrolled charging scenarios and higher losses in the smart charging scenarios. For the peak load in the smart charging scenarios, however, the differences were insignificant. This implies that the reduction of peak load due to the smart charging scheme is higher with concentrated allocation.

3.4. Net-load variability

In this study, the objective of the smart charging scheme was to reduce the net-load variance. Thus, it is important to measure the performance of the smart charging from the perspective of the objective and how significantly this parameter correlates with grid parameters. Fig. 9 shows the net-load variability, quantified by the square-root of the variance, i.e., the standard deviation. Regardless of the charging scheme, it can be seen that the higher the penetration of PV and EVs the higher the net-load variability. Clearly, the smart charging scheme reduced the variability. However, the reduction did not increase significantly when the penetration increased. One probable reason is

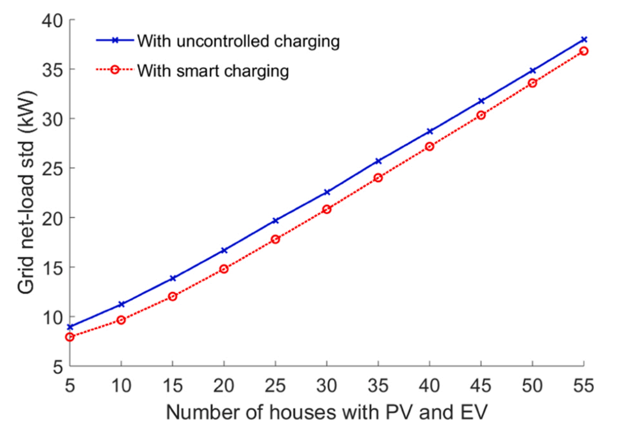

Fig. 9. Standard deviation of system net load for eleven penetration levels with uncontrolled and smart charging. In all cases, smart charging reduced the net-load standard deviation.

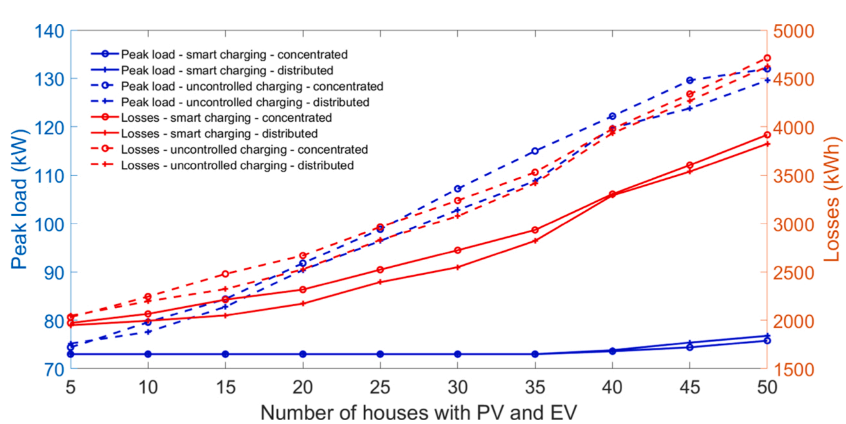

Fig. 8. Peak load and losses for different charging schemes (smart and uncontrolled charging) and different allocation methods (concentrated and distributed). Ten penetration levels were considered.

that there was more unconsumed PV power when the number of houses with PV was higher. A large amount of unconsumed PV power leads to a high net-load variability.

3.5. Correlation between network nodes

The average values of the correlation coefficients for EV charging load and voltages, respectively, between all pairs of bus nodes, are given in Table 4 for uncontrolled charging and smart charging. It can be observed that smart charging increases the correlation between nodes for both EV charging load and voltages, even though there is no communication between nodes applied, as in the case of centralized smart charging. This is due to the PV power generation being completely correlated between buildings, so controlling the charging to match the PV generation leads to more correlated charging profiles. The correlation between the EV charging load and the PV generation is given in Table 5. Similarly, the correlation is higher in the smart charging scheme than in the case of uncontrolled charging.

4. Discussion and implementation

The results presented in Section 3 are summarized in Table 6. The results showed that the smart charging scheme improved the operational performance of the LV distribution system by decreasing the voltage deviation, reducing the phase unbalance, shaving the peak load, and lowering the total losses. In general, the impacts of smart charging were increasingly noticeable with the increase of the PV and EV penetration. The results also showed that concentrated allocation leads to more severe impacts in all of these respects, particularly for voltage profiles at lower penetration levels. This corresponds to those findings from previous studies on higher voltage networks. Smart charging had similar impacts with both concentrated and distributed allocation, but the peak load reduction and minimum voltage increment due to the smart charging were higher with concentrated allocation. Smart charging was also found to increase the correlation between nodes without any node communication, due to simultaneous shifting of charging to times with available PV generation.

In terms of voltage, the results indicated that the smart charging scheme increased both the minimum voltage and the 5% quantiles of voltage. At the maximum penetration level with concentrated allocation, the minimum voltage increased from 0.950 pu to 0.996 pu and the 5% quantiles increased from 1.019 pu to 1.025 pu. This shows that the smart charging scheme reduces the undervoltage problems more significantly than it reduces the overvoltage problems. This is due to the limited number of EVs available at homes during midday when PV generation peaks.

The results also indicated the ability of smart charging to reduce the phase unbalance. The maximum values of phase unbalance were reduced by up to 50% and the phase unbalance violation events were reduced from 10,811 events to 2455 events with concentrated allocation. For peak loading, the results showed that the smart charging cut the peak loading more significantly for higher penetrations and with concentrated allocation, up to 57% at the maximum penetration with concentrated allocation. The ability of smart charging to lower the total losses was also shown for all penetration levels with a mean reduction of 14%.

Table 4
Averages values of the correlation coefficient for EV charging load and voltages, respectively, evaluated and averaged over all pairs of the 55 network nodes for both uncontrolled charging and smart charging.

Variables	Uncontrolled charging	Smart charging
EV charging load	0.103	0.164
Voltages	0.987	0.995

Table 5
Correlation between EV charging load and PV generation for uncontrolled charging and smart charging.

Uncontrolled charging	Smart charging
0.007	0.141

The result showed that there was an almost perfect correlation between grid parameters and net-load variability, which the smart charging scheme minimized. Reduced net-load variability implies reduced system losses and voltage deviations. Thus, employing a smart charging scheme that has as its main objective to reduce the net-load variability will result in reduced system losses and voltage deviations.

The correlation study showed that the correlation between network nodes is higher in the smart charging scheme. In the uncontrolled charging scheme, the EVs start charging upon arrival, which is a random variable. The charging finishes as soon as the battery SoC meets the targeted SoC, which makes it directly related to the arrival time as well. Hence, the correlation of EV charging load is just related to the random arrival time and have no correlation to the PV generation as shown in Table 5.

In a smart charging scheme, the EV charging load is optimized to the PV generation and hence the two variables are correlated. The PV generation, although decorrelation was found in irradiance at the bigger area (Widén, Shepero, & Munkhammar, 2017), was assumed perfectly correlated here because the geographical information was not utilised in the simulation. This made the EV charging loads between nodes more correlated and, as a consequence, the voltages between nodes became more correlated as well. Further studies should include geographic diversity in the PV generation due to spatial decorrelation, which might change the simultaneity of smart charging.

Although this study has successfully shown the benefit of the proposed smart charging, the implementation of this charging scheme requires several technologies and adaptation of behaviour among grid customers. Firstly, the state of the charge of the EV's battery has to be known. Secondly, in a real setting, the future PV and load conditions are not known. Hence, a forecast is needed. The impact of the forecast accuracy on this smart charging scenario is an interesting topic for further studies. Further studies on the impact of the forecast accuracy on the proposed smart charging scheme should be conducted.

Lastly, the smart charging scheme requires user participation to voluntarily state the length of the period that the car is available for charging. One of the risks is if the user urgently needs the car in the middle of the night, for example, when the battery may not be fully charged. Another challenge is that this smart charging scheme ignores the customer's economical benefit. Some smart charging technologies with the objective to maximise the customer profit are already available on the market (Hildermeier et al., 2019). This kind of smart charging, however, needs extra storage technologies that are more costly for the customer. In addition, the grid owner needs to utilize proper pricing strategies to get the benefit of these technologies (Huang et al., 2020). Hence, the smart charging proposed in this study is better to be promoted by the grid owner. One of the examples is by providing the EV owner to use this type of charging gratis. Future studies could include more variables that are applicable to LV distribution systems, such as energy storage, or compare several smart charging schemes with different objectives using the same performance metrics.

5. Conclusions

The work presented in this study investigated the probabilistic impact of EV smart charging with the purpose of increasing the load matching in unbalanced LV distribution systems.The probabilistic analysis is performed by including both the temporal and spatial variability of EV charging demand, household load, PV system generation,

Table 6
A relationship matrix between charging algorithms (smart and uncontrolled charging), allocation methods (concentrated and distributed), and penetration levels (low and high) in terms of the negative impacts of PV system generation and EV charging in LV distribution system based on the results presented in Section 3. Relationship between different variables, e.g., charging algorithms-allocation methods, describes the impact of varying these two variables together. Relationship between the same variables, e.g., charging algorithms-charging algorithms, represents the impact of varying this variable alone.

	Charging algorithms	Allocation methods	Penetration levels
Charging algorithms	Smart charging reduces the negative impact and increase the correlation between nodes compared to uncontrolled charging.	Smart charging benefit is more significant in reducing the peak load and increasing the minimum voltage with concentrated allocation.	Smart charging benefit is higher at higher penetration.
Allocation methods		Concentrated allocation has more severe impacts compared to distributed allocation.	The impact of concentrated allocation is higher at lower penetration levels.
Penetration levels			Higher penetration levels has more severe impact compared to lower penetration levels.

and the dynamic of PV system and EV adoption in society. Several conclusions can be drawn from this study:

1. The smart charging scheme, which has as its main objective to reduce the net-load variability, improves the LV distribution system performance by decreasing the voltage deviation, reducing the phase unbalance, shaving the peak load, and lowering the total losses.
2. The smart charging scheme has a more noticeable impact in terms of improving the LV distribution system performance at the higher penetration levels, where more houses have PV systems and EV charging. Therefore, smart charging is more beneficial at higher penetration levels.
3. The concentrated allocation was shown to result in more dramatic impacts from PV systems and uncontrolled charging than the distributed one, in particular at lower penetration levels. Hence, assuming a distributed allocation of PV systems and EV charging load in the distribution electricity system could underestimate the negative impact during early PV and EV adoption.
4. Smart charging had similar impacts with both concentrated and distributed allocation, except in terms of peak load reduction and voltage drop mitigation, where the impacts were higher with concentrated allocation.
5. Smart charging was also found to increase the correlation between network nodes without any node communication. The correlation was due to more simultaneous charging during periods with PV power availability.

This paper can form the basis for the development of probabilistic impact analysis of smart charging to allow society to integrate more electric vehicles and photovoltaic systems for a more sustainable future.

Conflict of interest

The authors declare no conflict of interest.

Acknowledgements

This work was funded through SweGRIDS, by the Swedish Energy Agency and Vattenfall. This work also forms part of the Swedish strategic research programme StandUp for Energy.

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