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Impact of rapid PV fluctuations on power quality in the low-voltage grid and mitigation strategies using electric vehicles

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ABSTRACT

Cloud transients cause rapid fluctuations in the output of photovoltaic (PV) systems, which can significantly affect the voltage levels in a low-voltage (LV) grid with high penetration of PV systems. These voltage fluctuations may lead to violation of the existing power quality standards. This study estimates the impact of rapid PV output fluctuations on the power quality in an existing LV grid by performing load flow analyses for scenarios in the years 2017, 2030 and 2050 using PV data with 20-second resolution. In this study, we propose a system for the mitigation of PV output fluctuations by altering the charging processes of electric vehicles (EVs) and we assess the effectiveness of the proposed system. Results indicate that PV output fluctuations have minor impact on the voltage levels in the year 2030, but PV output fluctuations induce considerable voltage fluctuations in the year 2050. The magnitude of the voltage fluctuations is dependent on the location in the grid, the installed PV capacity and the grid configuration. These voltage fluctuations can induce visible and annoying light flicker for a significant part of the day in the year 2050. Implementing the proposed system shows that EV technology can contribute in reducing the amount of visible and annoying light flicker considerably, however at the expense of increased charging costs for EV owners.

1. Introduction

The ongoing surge in photovoltaic (PV) generation capacity in low voltage (LV) grids poses unprecedented challenges to distribution system operators (DSOs). Passing clouds induce short-term variability in the output of PV systems. Fluctuations of 45–90% of the rated PV capacity per minute induced by passing clouds have been reported for a large PV plant in Portugal [1] and fluctuations of 63% of the rated PV capacity per minute have been measured in a Hawaiian PV plant [2]. Cloud transients also result in considerable PV output fluctuations on a shorter time-scale; PV output fluctuations of 80% of the installed PV capacity per 2 seconds have been observed in Spain [3].

The intermittent nature of PV generation is the source of power quality issues. The main power quality problems associated with rapid PV output fluctuations are voltage fluctuations and light flicker, which is induced by voltage fluctuations [4]. Voltage fluctuations and flicker can cause damage to electrical appliances connected to the grid [5] and light flicker can cause annoyance and health problems to people exposed to it [6,7]. For this reason, European DSOs must comply to the EN-50160 power quality standards [8]. The relationship between PV power output fluctuations and light flicker has been addressed in multiple studies, with inconclusive results. A Malaysian case study demonstrated a positive relationship between the installed PV capacity and flicker values, and reported flicker values induced by PV power output fluctuations that violate the local flicker limits [9]. In addition, a study using a measurement setup for 69 PV modules concluded that fluctuations in PV generation can lead to considerable light flicker values, depending on the metric used to measure flicker values [10]. However, an empirical analysis of a 1.41 MW PV plant in Florida reported a low correlation between PV power output and measured flicker values [11], but this study did not look into the correlation between fluctuations in PV generation and flicker values. Similarly, Stewart et al. [12] concluded based on Hawaiian solar irradiance data that PV generation does not cause violation of the light flicker standards. The flicker values in this study were determined by using the flicker threshold values for 1-second and 2-second voltage fluctuations

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Nomenclature

Abbreviations

aFRR	automatic frequency restoration reserves
BEV	battery electric vehicle
DoD	depth-of-discharge
DSO	distribution system operator
EMS	energy management system
EV	electric vehicle
GPLK	gepantserde papier-lood kabel (paper-lead covered cables)
LV	low-voltage
MPPT	maximum power point tracking
MV	medium-voltage
OLTC	on-load tap changer
PHEV	plugin-hybrid electric vehicle
PMU	phasor measurement unit
PV	photovoltaic
SoC	state of charge
V2G	vehicle-to-grid
VSV	very-short voltage variation index

Indices & sets

$g \in \mathscr{G}$	grid connections in the LV grid
$n \in \mathscr{N}$	charging transactions in assessment period
$t \in \mathscr{T}$	time steps in the assessment period

EV charging model parameters

$t_{plug-in,n}$	plug-in time of transaction$n$
$t_{plug-out,n}$	plug-out time of transaction$n$
t_b	individual time step between $t_{plug-in}$ and $t_{plug-out}$
c_t	electricity price at time step t [€/kWh]
Δt	duration of one time step [h]
$P_{ch,n,max}$	maximum charging power of transaction n [kW]
$P_{disch,n,max}$	maximum discharging power of transaction n [kW]
$E_{req,n}$	required charging energy of transaction n [kWh]
$\eta_{roundtrip}$	V2G roundtrip efficiency [−]
$P_{rl,g,t}$	residential load of grid connection g at time step t [kW]
$P_{hp,g,t}$	heat pump load of grid connection g at time step t [kW]
$P_{PV,g,t}$	PV generation of grid connection g at time step t [kW]
R_{max}	maximum allowable residual load ramp rate [kW/Δt]
β	share of EV battery that can be used for V2G-functions [%]
$E_{cap,n,min}$	battery capacity of smallest EV battery on the market of the EV type of transaction n [kWh]

EV charging model variables

$p_{ch,n,t}$	charging power of transaction n at time step t [kW]
$p_{disch,n,t}$	discharging power of transaction n at time step t [kW]
$e_{V2G-losses,n}$	V2G efficiency losses of transaction n [kWh]
$p_{residual,t}$	residual load at time step t [kW]

and by using 1-second and 2-second PV generation data, but this study did not consider the fact that PV output fluctuations on a longer timescale can also induce light flicker [6]. Lastly, a study in a small Finnish LV grid indicated that only fluctuations in PV generation do not induce flicker values that cause violation of power quality standards, but that a combination of fluctuating PV power output with continuously connecting and disconnecting loads could result in power quality problems [13].

With higher PV penetration levels in the future, DSOs might need to deploy mechanisms for mitigation of power quality problems induced by rapid PV output fluctuations to ensure future compliance to power quality standards. Several mechanisms have been proposed in scientific literature. On-load tap changers (OLTCs) at transformer stations can be used for voltage control in the LV grid, but have limited effect at the end of feeder lines and cannot mitigate rapid voltage fluctuations [14,15]. Dump loads [16] and diesel generators in combination with battery systems [17] are undesirable for PV fluctuation mitigation, since dump loads result in dissipation of renewable energy and diesel generators have negative environmental impacts. PV power output fluctuations can also be mitigated through reactive power control in PV inverters [13,18], but this can have adverse effects on the inverter lifetime [19]. In addition, advanced Maximum Power Point Tracking (MPPT) algorithms in combination with DC-DC converters in PV inverters can reduce the voltage drop in case a PV system is partially shaded [20–22]. Multiple studies have proposed the utilization of energy storage systems for fluctuation mitigations, including battery systems [16,23–27] and capacitors [28,29]. However, the capacity of capacitors is limited, while battery systems have relatively high investment costs.

Electric vehicle (EV) batteries are recently considered as an attractive technology for fluctuation mitigation. With high EV adoption rates in the future, a large pool of EV batteries will be connected to the grid when EVs are charging. If the DSO can use part of the battery capacity for grid services through aggregators which combine a pool of EVs [30], this will reduce the required investments by the DSO and will limit the societal costs. The mitigation of PV output fluctuations by EVs is addressed in different studies. References [31–33] propose systems in which the EV charging station for one EV or an EV parking lot is placed behind the PV inverter to capture fluctuations in PV generation. These systems do not provide a system-wide solution; one set of EVs can only stabilize the output of one PV inverter. A system in which EVs adapt their charging power to compensate for the lower PV power injected during a cloud transient is proposed by Aly et al. [34]. Garcia-Villalobos et al. [35] and Ali et al. [36] propose multi-objective EV charging algorithms, with minimization of voltage fluctuations as one of the objectives. A combined system of an EV and a stationary battery system to mitigate fluctuation problems is proposed by Eldeeb et al. [37]. The work by Cheng et al. [38] proposes an extensive mitigation strategy for rapid voltage fluctuations by using EVs, based on detailed solar forecasts and alterations of the OLTC tap positions. Lastly, Foster et al. [15] determine the increase in charging costs for EV owners in a small 4-bus system, based on a charging algorithm in which EV charging costs are minimized while mitigating rapid PV output fluctuations by EVs.

The goal of this study is twofold. Firstly, this study aims to create insight in the voltage fluctuations and power quality in a LV grid for future scenarios in 2017, 2030 and 2050. The analysis considers rapid PV output fluctuations, as well as other contributors to voltage fluctuations, such as charging EVs and heat pumps. The contribution of this study compared to previous studies on PV output fluctuations is that this study: (i) looks at a large, existing LV grid with a high number of busbars, (ii) makes realistic estimations of the voltage fluctuations in the future based on the expected future PV and EV integration rates in an existing grid and (iii) looks at the effect of PV output fluctuations on the voltage levels in different seasons. Secondly, this study proposes a system using EVs for the mitigation of power quality problems caused by PV output fluctuations in the LV grid. The effectiveness of the proposed system is assessed through a case study. In contrast to other proposed systems using EVs, this system mitigates PV output fluctuations in the whole LV grid and does not require OLTCs or stationary battery systems for the mitigation of PV output fluctuations.

The paper is structured as follows. Section 2 presents a system design for the mitigation of PV output fluctuations through EVs. The proposed system is applied to a case study, which is described together with all data inputs in Section 3. The simulation results are presented in Section 4. The paper ends with discussion in Section 5 and conclusions in Section 6.

2. System design

2.1. System architecture

The mitigation of PV output fluctuations through EVs requires involvement of different groups of actors and different system components. As the objectives differ among actors and rapid information exchange is required between the different actors, the total system architecture is complex. Fig. 1 provides a schematic overview of the different system components, involved actors and the required information flows between the different actors and system components.

The proposed system covers a single LV grid, which is connected to the medium-voltage (MV) grid through a MV/LV transformer. The LV grid connects a set of buildings, of which some are equipped with heat pumps and/or PV systems. A smart meter in every building logs the net load and communicates this data to the DSO at every timestep. Furthermore, a number of EV charging stations is connected to the grid. Each charging station or EV connected to the charging station contains an energy management system (EMS), which can be controlled by an aggregator.

Aggregators are the first group of actors with a central role in the proposed system and can be defined as “organizations that can combine distributed energy resources into a single system resource that can be utilized for the provision of flexibility services” [39,p. 534]. In this system, aggregators combine different EVs for mitigation of rapid PV output fluctuations, and thus provide ancillary services to the DSO. In the proposed system, aggregators are responsible for collecting EV charging data and sending it to the DSO, as well as determining the optimal EV charging schedules and communicating them to individual EVs. All data in the proposed system architecture is transmitted through a secured internet connection.

The main role of the DSO in the proposed system is to comply with the power quality standards. In the proposed system architecture, the DSO procures ancillary services from aggregators for the mitigation of power quality issues induced by rapid PV output fluctuations. This requires real-time monitoring of the power quality by the DSO. In case of violation of the power quality standards, the DSO demands the aggregators to provide ancillary services.

The last group of actors involved in the proposed system architecture are system users (i.e., consumers and prosumers connected to the grid). Their role is the provision of information and allowing this information to be used for system control. EV owners with EVs connected to the grid must specify their expected plug-out time, desired charging objective (e.g. smart charging or uncontrolled charging) and charging demand to the aggregator before charging. As inflexible load for grid connections is assumed in this system, the only role of individual grid connections is that they allow the DSO to use their smart meter data to monitor the residential load, heat pump load and PV generation.

In the proposed system, the following actions are executed:

- *At the plug-in moment*: Each EV owner specifies its specific charging requirements to their aggregator. The aggregator calculates the optimal charging schedule for the specific EV based on the input of the EV owner and the time-of-use electricity tariffs.
- *Real-time*: The aggregator sends the real-time charging power of each EV to the DSO. Meanwhile, the DSO collects real-time load data from smart meters and real-time charging data from all aggregators, and calculates whether the power quality is endangered. If this is the case, a signal is sent to the aggregators, which update the charging schedules and communicate the updated schedules to the EVs and the DSO.
- *After real-time operation*: Aggregators receive financial compensation from the DSO for deviating from the optimal charging schedule.

2.2. EV charging model formulation

This study assumes that all EV charging strategies are based on smart charging, in which aggregators try to minimize the charging costs of EV owners. Different EV smart charging strategies are identified in this study, distinguishing between charging strategies with and without vehicle-to-grid (V2G) functions and distinguishing between charging strategies with and without mitigation of PV output fluctuations by EVs.

This section proposes a generic EV charging model that can be applied to all considered EV charging strategies. The proposed model is formulated as a linear programming optimization problem, which is a well-established method for energy scheduling optimization [40,41]. The model can be applied to all considered scenarios.

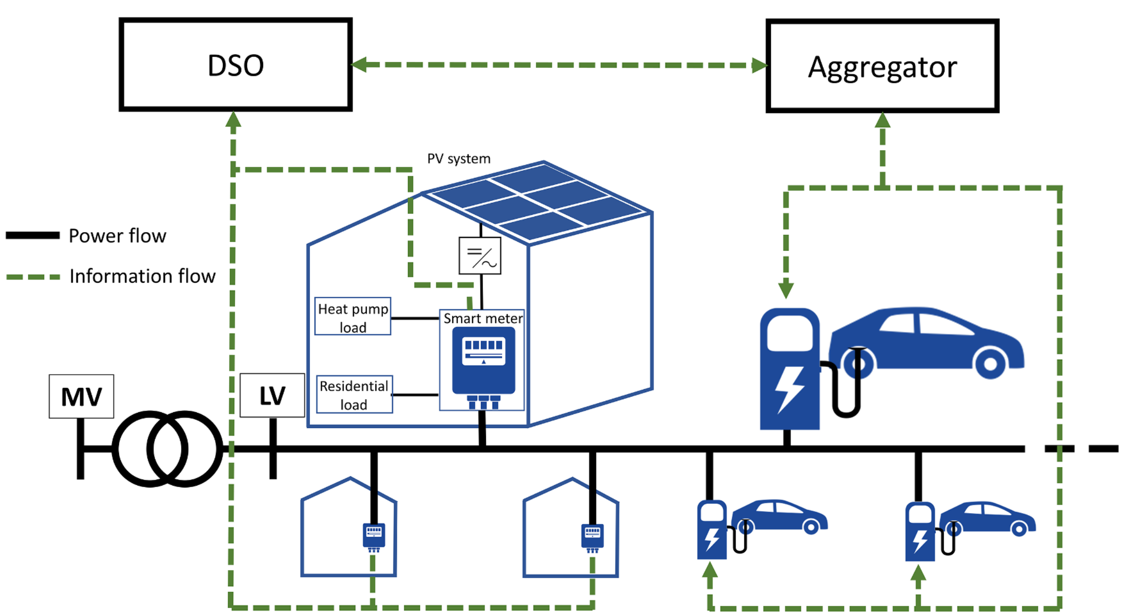

Fig. 1. Schematic overview of the power and information flows in the proposed system architecture.

2.2.1. Objective function

In all scenarios, the aggregator aims to minimize the total charging costs of all charging transactions $n \in \mathcal{N}$ in the assessment timeframe:

$$minimize\left(\sum_{n=1}^{N} \sum_{t=t_{plug-in,n}}^{t_{plug-out,n}} (c_t * (p_{ch,n,t} - p_{disch,n,t}) * \Delta t)\right). \quad (1)$$

2.2.2. General constraints

Different constraints apply to all considered charging scenarios. As EV battery systems and charging stations can only manage a specific range of charging and discharging powers, the charging power and discharging power are bounded as:

$$0 \le p_{ch,n,t} \le P_{ch,n,max} \ \forall \ t, \ n, \quad (2)$$

$$0 \le p_{disch,n,t} \le P_{disch,n,max} \ \forall \ t, \ n. \quad (3)$$

In addition, each EV should have met its charging demand before unplugging in all optimization scenarios. The charging balance constraint is formulated as follows:

$$\sum_{t=t_{plug-in,n}}^{t_{plug-out,n}} (p_{ch,n,t} - p_{disch,n,t}) * \Delta t = E_{req,n} + e_{V2G-losses,n} \ \forall \ n. \quad (4)$$

When V2G-functions are provided in a transaction, the total required charging energy increases, as EV discharging and charging comes with efficiency losses which should be compensated ($e_{V2G-losses,n}$) [42]. Note that the charging efficiency can be disregarded for $E_{req,n}$, as $E_{req,n}$ represents the required charging volume at the charging station, and thus already considers the charging efficiency. $e_{V2G-losses,n}$ is formulated as follows:

$$e_{V2G-losses,n} = \left(\frac{1}{\eta_{roundtrip}} - 1\right) * \sum_{t=t_{plug-in,n}}^{t_{plug-out,n}} (p_{disch,n,t} * \Delta t) \ \forall \ n. \quad (5)$$

2.2.3. PV output fluctuations mitigation constraints

In the scenarios in which EVs mitigate PV output fluctuations, aggregators alter the charging schedule of EVs based on fluctuations in the total residual load in the LV grid, as voltage levels in the grid are directly related to the residual load in the grid [43]. Residual load can be defined as the net load in the grid and is formulated below:

$$p_{residual,t} = \sum_{n}^{N} (p_{ch,n,t} - p_{disch,n,t}) + \sum_{g}^{G} (P_{rl,g,t} + P_{hp,g,t} - P_{PV,g,t}) \ \ \forall \ t. \quad (6)$$

The fluctuations in residual load are constrained by an absolute value R_{max}:

$$- R_{max} \le (p_{residual,t} - p_{residual,t-1}) \le R_{max} \ \forall \ t \in \{2. \,..T\}. \quad (7)$$

As the residential load, heat pump load and PV generation are assumed to be inflexible, this constraint can only be met by alterations in EV charging behavior. The total residual load should be communicated by the DSO to the aggregators in every time step to allow aggregators to meet this constraint. This constraint looks at residual load fluctuations for the whole LV grid and not at the fluctuations per specific feeder line, as (i) power flows are redistributed among feeder lines at the transformer station and at distribution sub-stations and (ii) this would mean that the charging model is infeasible at any moment with PV output fluctuations when no EV is charging at a specific feeder line, causing underestimation of the potential of EVs to mitigate voltage fluctuations.

2.2.4. V2G constraints

This section formulates a set of constraints for studies considering V2G-functions when the battery capacity of EVs and the initial battery State-of-Charge (SoC) are unknown. The first V2G constraint limits the total amount of energy injected to the grid per charging transaction, as the battery degradation per cycle grows exponentially with a higher Depth-of-Discharge (DoD) [44]. The total discharging volume is constrained by a share β of the battery capacity of the smallest EV battery on the market of the EV type (i.e., battery electric vehicle (BEV) or plug-in hybrid (PHEV)) of transaction n ($E_{cap,n,min}$):

$$\sum_{t=t_{plug-in,n}}^{t_{plug-out,n}} (p_{disch,n,t} * \Delta t) \le \beta * E_{cap,n,min} \ \forall \ n. \quad (8)$$

The second V2G constraint avoids that an EV injects electricity to the grid when the EV battery is empty during the charging process, due to an empty battery at $t_{plug-in,n}$ or due to high volumes of electricity injected to the grid throughout the charging process. For every time step between $t_{plug-in,n}$ and $t_{plug-out,n}$, referred to as t_b, this constraint assures that the EV discharging energy is smaller than the EV charging energy:

$$\sum_{t=t_{plug-in,n}}^{t_b} (p_{disch,n,t} * \Delta t) \le \sum_{t=t_{plug-in,n}}^{t_b} (p_{ch,n,t} * \Delta t) \ \forall \ n. \quad (9)$$

The last V2G constraint avoids that the battery overcharges (i.e., the total net charged energy exceeds the required charging energy) at every time step during the EV connection period:

$$\sum_{t=t_{plug-in,n}}^{t_b} ((p_{ch,n,t} - p_{disch,n,t}) * \Delta t) \le E_{req,n} + e_{V2G-losses,n,t_b} \ \forall \ n. \quad (10)$$

The value of $e_{V2G-losses,n,t_b}$ is determined according to equation 5, replacing $t_{plug-out,n}$ in this equation with t_b. To limit the computational time when dealing with very high data resolution, the constraints in equations 9 and 10 can also be applied to a limited number of time steps between $t_{plug-in,n}$ and $t_{plug-out,n}$, instead of to all time steps.

3. Case study and simulation data inputs

3.1. Case study introduction

The described framework is applied to an existing LV grid in the Lombok district in the city of Utrecht, the Netherlands to determine the effect of PV output fluctuations and adaptations in EV charging behavior on voltage levels in the LV grid. The investigated grid serves 340 grid connections in a residential area originating from the end of the 19th century. It has a radial outline and consists of 19 feeder lines. Most of the feeder lines are *GPLK*[1] cables with cross-sectional areas ranging from 25 to 95 mm^2, as specified in Appendix I.

3.2. Scenario development

To get a comprehensive view of the future impact of PV output fluctuations on voltage levels in the LV grid, scenarios are set up for the years 2017, 2030 and 2050. For each studied year, estimations are made about the PV adoption rate, number of EV transactions in the investigated grid and the heat pump adoption rate, as displayed in Table 1. Additionally, the effect of different seasons and different levels of PV output fluctuations on voltage fluctuations is studied by considering a day with high PV output fluctuations and a day with low PV output fluctuations for both summer and winter for each studied year.

The following section discusses the selected values in Table 1 and other data inputs.

3.3. Data inputs

3.3.1. PV generation profiles

The installed PV capacity in the investigated grid in 2017 equaled 52 kWp, with a rooftop potential of 886 kWp (based on [45]). The estimated total installed PV capacity for 2030 and 2050 is based on projections in literature ([46–50]). The installed PV capacity per grid connection for 2030 and 2050 is determined using a database of the current installed PV capacity per grid connection in the district of the

[1] 'Gepantserde Papier-Lood Kabel', which translates to 'paper/lead-covered cables'. The core is made of copper. This cable type is not installed anymore since the 1970s.

Table 1
Assumed PV capacity, heat pump adoption rate and number of EVs charging in the different scenarios.

	Installed PV capacity [kWp]	Share of households with a heat pump [%]	Number of local EVs charging in the investigated grid per week	Number of visiting EVs charging in the investigated grid per week
2017	52	hybrid: 0%, all-electric: 0%	BEV: 3, PHEV: 4	BEV: 4, PHEV: 10
2030	222	hybrid: 15%, all-electric: 5%	BEV: 23, PHEV: 19	BEV: 34, PHEV: 49
2050	440	hybrid: 0%, all-electric: 20%	BEV: 99, PHEV:0	BEV: 144, PHEV: 0

investigated grid. The installed PV capacity from a randomly selected grid connection in this database is assigned to a random grid connection in the investigated grid without PV until the total estimated PV capacity for 2030 and 2050 of the investigated grid is reached.

The PV generation profiles are determined using a database from the Dutch Solar Forecasting and Smart Grids project [51,52]. This database contains PV generation profiles of over 200 PV systems in the province of Utrecht, the Netherlands with a 2-second resolution. A cluster of four PV systems, all equipped with MPPT control algorithms, is selected from this database. This cluster could fit within the size of the investigated grid when respecting the original distance between the selected PV systems. Subsequently, four one-day PV generation profiles with a 20-second resolution are extracted from the database, representing days with high and low PV output fluctuations in summer and winter. These PV generation profiles are normalized to kW/kWp. Each grid connection with PV is assigned the PV generation profile of the nearest of the four PV systems from the dataset when the selected cluster is projected on the investigated grid.

3.3.2. EV transactions

The current number of EVs charging per week in the investigated grid is based on a database with EV charging transactions in the district of the investigated grid from the Smart Solar Charging research project [53]. A distinction is made between PHEVs and BEVs, and between local and visiting EVs[2]. The number of EVs charging per week in 2030 and 2050 in Table 1 is based on the methods described in Appendix II.

The average number of EVs charging per week in the investigated grid is converted to a set of EV transactions for a week, consisting of the plug-in time, plug-out time, required charging volume and EV type, using the Smart Solar Charging EV charging database and a probabilistic model described in [54].

3.3.3. Residential load and heat pump load

The residential load per grid connection (i.e., total load of a grid connection excluding PV generation, EV load and heat pump load) is determined for 2017, 2030 and 2050 based on the measured annual electricity consumption per grid connection in the investigated grid in 2017, standardized electricity profiles [55] and an annual load reduction factor of 1.5% [56].

The assumed heat pump adoption rate for 2017, 2030 and 2050 in Table 1 is based on projections in literature [46,57–61], but the ambiguity about the future heat pump adoption rate in these projections is high. A moderate adoption rate of heat pumps is assumed for the investigated grid, as most houses in this district are relatively old and unsuitable for heat pumps. The simulated set of heat pumps is randomly distributed among grid connections. Their electricity demand profile is determined by converting the natural gas demand over time to heat pump demand over time, using a natural gas boiler efficiency of 95% [62] and the coefficient-of-performance of heat pumps at different temperatures described in [58]. The natural gas profile over time is based on standardized natural gas profiles[3] in the Netherlands [55] and the measured natural gas consumption per grid connection in 2017.

3.4. Model simulations

The PV generation, EV transaction data, residential load and heat pump load serve as input to the EV charging model described in Section 2.2. The model is solved using the Gurobi Modeling and Optimization package [63] for Python [64], using 20-second time steps and using Dutch aFRR withdrawal prices as input [65]. Part of the simulations are performed using the SurfSARA LISA supercomputing service [66], due to the high time resolution considered in this study. The assessment timeframe in the analysis equals one day. Charging transactions starting one day before the assessment timeframe are also included in the model, to assure that there are sufficient EVs charging at the beginning of the assessment timeframe. In addition, the model is run for three extra days after the assessment timeframe to allow EVs that connected shortly before the end of the assessment timeframe to finish their charging transaction. The model determines the EV charging power per timestep per EV transaction. Subsequently, every EV transaction is assigned to individual EV charging stations, considering the availability of charging stations. The number of EV charging stations is left unconstrained, meaning that it is directly based on the maximum number of EVs charging simultaneously. The location of individual charging stations is determined randomly. The used V2G-roundtrip efficiency equals 73% [42] and the share of the battery that can be used for V2G-functions (β) is limited to 20% of the battery capacity, as battery degradation is low when the DoD stays below 10–20% [44].

The voltage levels in the grid are determined by performing load flow analyses with the DIgSILENT Powerfactory software package [67], using the Newton-Raphson method [68,69]. A load flow analysis is a widely-used simulation method (e.g., [40,41,70]) within the field of power system analysis to determine power flows, cable and transformer loadings and voltage levels in electricity grids. Perfect balance between all three phases is assumed, as (i) this saves computational time and (ii) there is high uncertainty about to which phase future PV systems and EV charging stations will be connected.

4. Simulation results

4.1. No EV PV fluctuation mitigation

The simulated voltage levels for 2017, 2030 and 2050 for a summer day with very high PV fluctuation levels are presented in Fig. 2 for four different locations in the investigated grid: next to the MV/LV transformer, next to a distribution sub-station, at the end of a feeder line with an average installed PV capacity and at the end of a feeder line with a high installed PV capacity. The correlation between PV output fluctuations and voltage fluctuations for two locations is presented in Fig. 3.

The figures show an increasing level of variability in voltage levels between 2017 and 2050 at all locations in the grid. Fluctuations in PV generation are a major contributor to these voltage fluctuations;

[2] Gerritsma et al. [54] describe the method used for determining whether an EV is a local or visiting EV.

[3] Standardized natural gas profiles are based on outside weather conditions. The average temperature, insolation and wind speed of three years for each hour of the year from the Royal Netherlands Meteorological Institute [82] is used in the analysis.

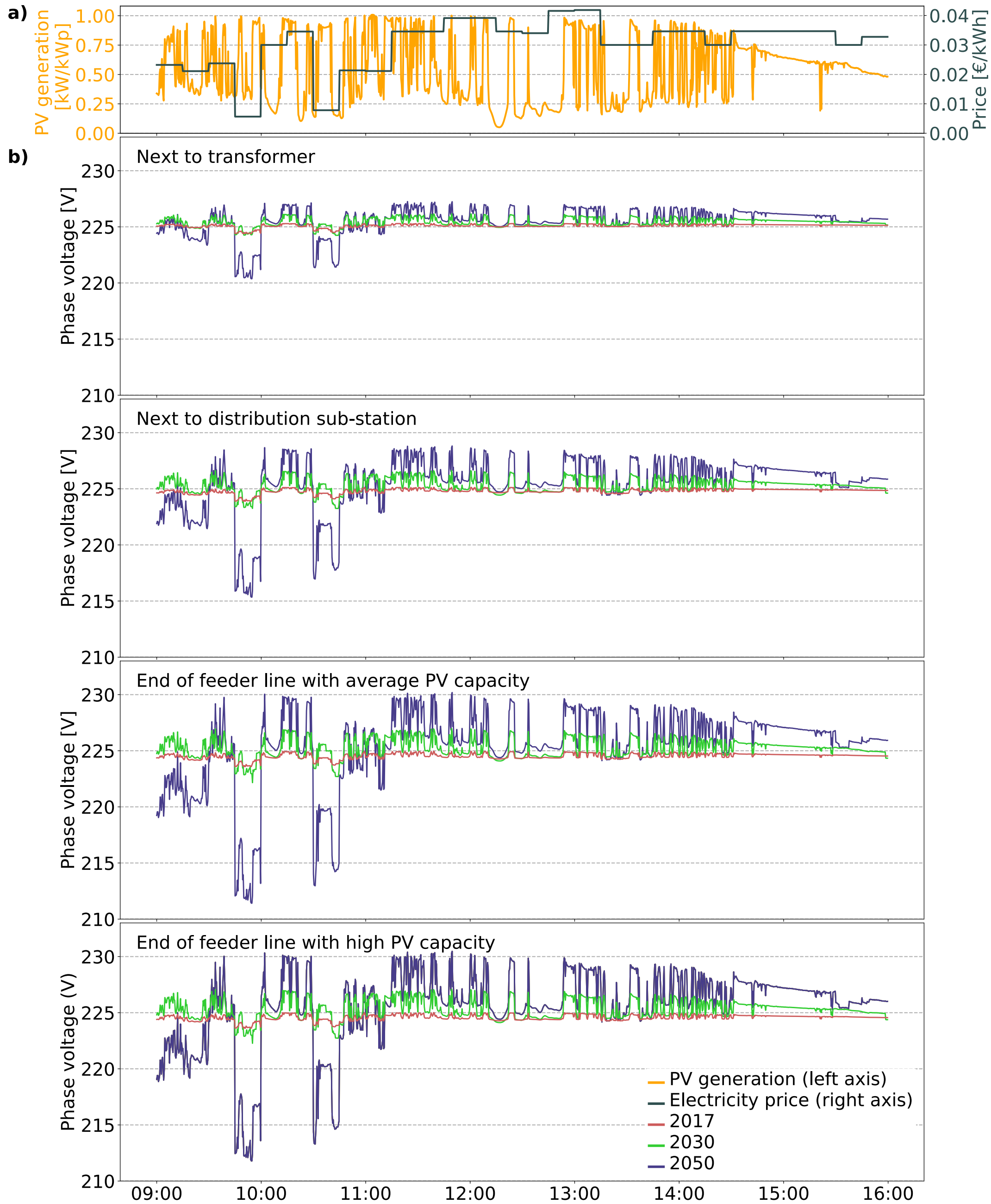

Fig. 2. (a) Normalized PV generation profile and aFRR prices over time on a summer day with high PV output fluctuations. (b) Phase voltage levels at different locations in the considered grid in 2017, 2030 and 2050 on a summer day with high PV output fluctuations without considering V2G-functions.

comparing Fig. 2a and b shows that voltage fluctuations and PV output fluctuations follow almost identical patterns and Fig. 3 shows a high correlation between PV and voltage fluctuations. Therefore, the increase in voltage variations between 2017 and 2050 can to a large extent be attributed to the increase in installed PV capacity between 2017 and 2050. The higher PV feed-in induced by a higher PV capacity is the cause of the higher average voltage levels in 2030 and 2050 in Fig. 2. The voltage drops at the beginning of the day in the 2050 scenarios in Fig. 2 and the few data points outside of the main cluster of data points in Fig. 3 can be explained by EVs charging simultaneously, triggered by a low electricity price.

Both figures indicate that the level of voltage fluctuations differs between locations in the grid, with the highest voltage fluctuations at the end of feeder lines and the lowest voltage fluctuations next to the transformer. The low voltage fluctuations next to the transformer can be explained by two factors: (i) the transformer is located quite far from most PV systems, causing that most PV output fluctuations have been absorbed by previous cables before reaching the transformer; (ii) the transformer connects different feeder lines, causing voltage fluctuations to be absorbed by other feeder lines. Similarly, the voltage fluctuations next to a distribution sub-station, which splits one feeder line into multiple feeder lines, are less considerable than at the end of feeder lines, due to the possibility to redistribute power flows among feeder lines at a distribution sub-station. Fig. 2 also indicates that the installed PV capacity on a feeder line has minor impact on voltage fluctuations; the voltage fluctuations at the end of the feeder line with a high installed PV capacity are similar to the voltage fluctuations at the feeder line with an average installed PV capacity.

A potential consequence of the reported voltage fluctuations is light flicker, which depends on the frequency and the value of voltage fluctuations. With the studied time resolution of 20 s, voltage fluctuations of at least 0.7% of the nominal voltage (1.6 V/20 s) result in visible

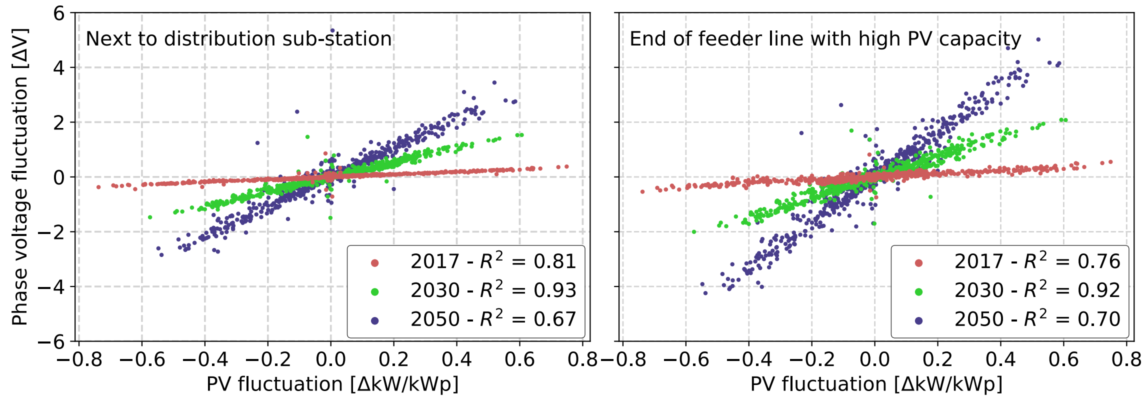

Fig. 3. Scatter plot showing the relationship between PV output fluctuations and voltage fluctuations at two locations in the grid, for a summer day with high PV output fluctuations without considering V2G-functions using a 20-second time resolution. Data points with voltage fluctuations > 6 V or < −6 V (three in left figure, four in right figure) are not included in the fig. to increase the readability of the figure.

Table 2
Share of time between 9:00 and 17:00 with visible light flicker (> 1.6 V/20 s) and annoying light flicker (> 3.6 V/20 s) at the end of a feeder line with a high installed PV capacity for different scenarios. Charging strategy: smart charging excluding V2G.

		> 1.6 V/20s	> 3.6 V/20s
2017	Summer, high PV fluctuations	0.0%	0.0%
	Summer, low PV fluctuations	0.0%	0.0%
	Winter, high PV fluctuations	0.0%	0.0%
	Winter, low PV fluctuations	0.0%	0.0%
2030	Summer, high PV fluctuations	1.4%	0.0%
	Summer, low PV fluctuations	0.1%	0.0%
	Winter, high PV fluctuations	0.3%	0.0%
	Winter, low PV fluctuations	0.0%	0.0%
2050	Summer, high PV fluctuations	12.8%	2.1%
	Summer, low PV fluctuations	0.6%	0.3%
	Winter, high PV fluctuations	3.5%	0.1%
	Winter, low PV fluctuations	0.0%	0.0%

light flicker, and voltage fluctuations of at least 1.6% of the nominal voltage (3.6 V/20 s) result in annoying light flicker [6]. Tables 2 and 3 show in what share of the 20-second time steps between 9:00 and 17:00 visible and annoying light flicker occurs for different scenarios at different locations in the investigated grid.[4]

From these tables can be concluded that PV output fluctuations hardly induce visible and annoying light flicker until 2030. Higher flicker values are reported for 2050, due to the higher installed PV capacity in that year. The occurrence of light flicker in 2050 depends on the location and the level of PV output fluctuations. Figs. 2 and 3 show that voltage fluctuations are limited next to the transformer and next to the distribution sub-station. Table 3 shows that these voltage fluctuations also result in low flicker values at these locations. However, at the end of feeder lines, visible light flicker can occur up to 12.8% of the time between 9:00 and 17:00, and annoying light flicker up to 2.1% of the time.

4.2. *Effect of PV fluctuation mitigation by EVs*

To test the effectiveness of the proposed fluctuation mitigation strategy in Section 2, the EV charging model was run eleven times for each scenario. For each model run, a new set of EV transactions is generated, using the methods in Section 3.3, and a set of historical aFRR prices from between 2015 and 2017 in summer and winter is selected

Table 3
Share of time between 9:00 and 17:00 with visible light flicker (> 1.6 V/20 s) and annoying light flicker (> 3.6 V/20 s) at different locations in the grid on a day with high PV output fluctuations in 2050. Charging strategy: smart charging excluding V2G.

	> 1.6 V/20s	> 3.6 V/20s
Next to transformer	0.0%	0.0%
Next to distribution sub-station	0.1%	0.0%
End of feeder line with avg. PV capacity	12.3%	1.5%
End of feeder line with high PV capacity	12.8%	2.1%

Table 4
Share of time between 9:00 and 17:00 with visible light flicker (> 1.6 V/20s) and annoying light flicker (> 1.6 V/20s) at two locations in the grid with different maximum allowable residual load ramp rates. Charging strategy: smart charging excluding V2G-functions.

Max. allowable ramp rate	End of feeder line with avg. PV capacity > 1.6 V/20s	> 3.6 V/20s	End of feeder line with high PV capacity > 1.6 V/20s	> 3.6 V/20s
No max. allowable ramp rate	*12.3%*	*1.5%*	*12.8%*	*2.1%*
1 kW/20s	7.1%	0.0%	6.1%	0.0%
2 kW/20s	5.8%	0.0%	4.7%	0.0%
6 kW/20s	3.2%	0.0%	3.1%	0.0%
8 kW/20s	3.0%	0.0%	2.8%	0.0%
10 kW/20s	3.0%	0.0%	2.8%	0.0%
15 kW/20s	2.5%	0.0%	2.0%	0.0%
20 kW/20s	1.2%	0.0%	0.8%	0.0%
25 kW/20s	0.8%	0.0%	1.1%	0.0%
30 kW/20s	1.5%	0.0%	1.6%	0.0%
40 kW/20s	1.7%	0.0%	2.4%	0.0%
50 kW/20s	2.3%	0.0%	3.1%	0.0%

randomly[5], to assess how the potential of EVs to mitigate PV output fluctuations and the impact on charging costs is affected by specific EV availability and the used pricing set. The model runs showed that the EV fleet size is not always sufficiently large for mitigation of residual load fluctuations until 2030; in some model runs for 2030, EVs can only limit the ramp rate to 89 kW/20 s without V2G-functions, and to

[4] This study cannot determine whether the flicker values in the EN-50160 standards are violated, as this requires measurements at a very short timescale (< 1s) [6], while this study reports the voltage levels on a 20-second timescale.

[5] As there is no seasonality in EV charging behavior [83], the same EV transaction input data is used for all scenarios (summer/winter days with high/low PV output fluctuations) of a particular model run of the same year. The same set of aFRR prices are used for all scenarios of a respective season of a specific model run.

64 kW/20 s with V2G-functions, due to a low number of connected EVs at the time steps with the most extreme PV output fluctuations. In 2050, EVs can mitigate residual load fluctuations to 1 kW/20 s in all model runs, due to the high EV adoption rate in 2050.

The effect of limiting fluctuations in the total residual load through EVs on flicker in the LV grid is presented in Table 4. This table shows the occurrence of visible and annoying light flicker between 9:00 and 17:00 with different imposed maximum allowable ramp rates at two locations in the grid.

All studied maximum allowable residual load ramp rates lead to a reduction in time with visible and annoying light flicker. Least light flicker seems to occur with a maximum allowable ramp rate between 20 and 25 kW/20 s. Higher maximum allowable ramp rates limit flicker induced by PV output fluctuations to a limited extent, whereas lower maximum allowable ramp rates require continuous alterations in charging power of EVs to avoid large fluctuations in residual load. This erratic charging behavior of EVs can cause local voltage fluctuations, as EVs alter their charging behavior based on the residual load fluctuations in the whole LV grid, and not on the residual load fluctuations of the specific feeder line.

Lower maximum allowable ramp rates require more deviations from the optimal EV charging schedule and therefore negatively affect EV charging costs. Fig. 4 shows the average increase in EV charging costs with different maximum allowable ramp rates on days with different levels of PV output fluctuations in different seasons. As expected, the increase in charging costs compared to the optimal charging scenario is higher on days with high PV output fluctuations. Although PV output fluctuations are higher in summer than in winter, the increase in charging costs is not always higher in summer, due to the higher volatility of aFRR prices in winter. The scenarios with V2G-functions have a higher increase in charging costs; an EV with V2G-functions that is forced to charge to mitigate PV output fluctuations at a moment with high electricity prices not only increases its charging costs, but also loses the opportunity to generate revenue by injecting electricity to the grid.

4.3. Sensitivity analyses

Multiple sensitivity analyses are performed to investigate how the results would change under different circumstances. As the ambiguity about the estimated installed PV capacity for 2050 in literature is high, the installed PV capacity is varied in the first sensitivity analysis between the estimated value of 440 kWp for 2050 and the rooftop potential in the studied area of 886 kWp. Table 5 shows that the time with visible and annoying light flicker increases considerably with a higher installed PV capacity.

Table 5
Share of time between 9:00 and 17:00 with visible light flicker (> 1.6 V/20s) and annoying light flicker (> 3.6 V/20s) at the end of a feeder line with a high installed PV capacity with different total installed PV capacities. Scenario: summer day in 2050 with high PV fluctuations.

Installed PV capacity	> 1.6 V/20s	> 3.6 V/20s
440 kWp (base)	12.8%	2.1%
600 kWp	16.6%	7.2%
700 kWp	18.8%	9.7%
797 kWp	20.0%	10.9%
886 kWp	21.8%	12.1%

The grid strength varies between different residential areas in the Netherlands. Therefore, the effect of the grid configuration on the perceived levels of flicker is simulated in the second sensitivity analysis, as shown in Table 6. A weak grid configuration is simulated by replacing all original cables in the load flow analysis configurations in PowerFactory with cable types with approximately 50% the cross-sectional area, while a strong grid configuration has been simulated by replacing all cables with the cable type with the highest-available capacity (4 × 150mm^2 aluminum cables). From Table 6 it can be concluded that the grid configuration is an important determinant for light flicker; the number of light flicker occurrences increases considerably with a weak grid and decreases with a strong grid.

5. Discussion

5.1. Methodological considerations for the load flow analysis

Different assumptions in the load flow model could affect the

Table 6
Share of time between 9:00 and 17:00 with visible light flicker (> 1.6 V/20s) and annoying light flicker (> 3.6 V/20s) at the end of a feeder line with a high installed PV capacity with different grid configurations. Scenario: summer day in 2050 with high PV output fluctuations.

	> 1.6 V/20s	> 3.6 V/20s
Weak grid configuration	12.8%	2.1%
Original grid configuration	17.4%	7.8%
Strong grid configuration	7.5%	0.2%

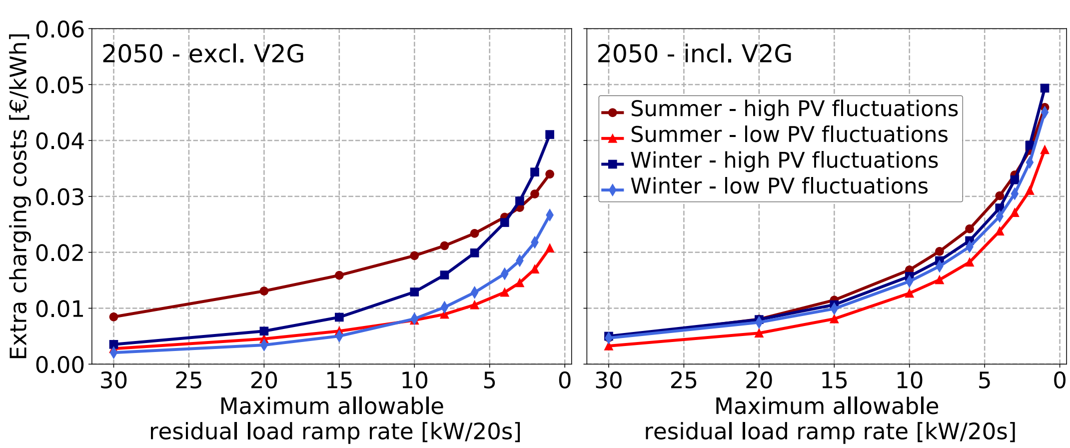

Fig. 4. The average increase in charging costs in different scenarios in 2050 compared to the optimal charging scenario for 11 model runs when applying different maximum allowable ramp rates of the residual load in the LV grid.

reported flicker values. This study assumed a constant voltage level in the MV grid, while the MV voltage levels fluctuate considerably in practice. As voltage fluctuations in the MV grid induce voltage fluctuations in the LV grid, the reported flicker values could be higher in practice. Additionally, a balanced load flow model was used in the load flow simulations, assuming perfect distribution of loads and PV systems among all three phases. A perfect load distribution among the three phases is unrealistic, thus the simulated voltage fluctuations could in practice be higher for one or multiple phases. Lastly, the used flicker threshold values are based on human perception studies using incandescent light bulbs. Due to the ban of sales of incandescent light bulbs in the EU[6], no incandescent light bulbs will be in use in 2050. Sharma et al. [71] indicated that non-dimmable LEDs are more sensitive to light flicker than incandescent light bulbs, whereas dimmable LEDs exhibit less flicker sensitivity.

5.2. Methodological and practical considerations for the EV charging model

The study showed that EVs are a reliable technology for the mitigation of flicker induced by PV output fluctuations, due to the high number of EVs that are expected to connect to the LV grid in 2050. However, rapid developments in autonomous vehicles or hydrogen vehicles would reduce the number of EV charging transactions in the LV grid and rapid developments in car sharing would reduce the average connection time of EVs, resulting in a lower mitigation potential of rapid PV output fluctuations by EVs and higher costs for the mitigation of flicker through EVs. Similarly, EVs are currently also considered for the provision of other grid services, including the provision of balancing services [72,73] and peak shaving services [74,75]. This would reduce the number of EVs available for fluctuation mitigation.

The used EV charging model assumed perfect foresight; when optimizing the model, the PV generation profile for the whole simulation period is already known to the model. This is only realistic when extensive and accurate PV forecasting models are applied to LV grids by DSOs or aggregators. If such models are not available in 2050, the ramp rate mitigation potential will decrease and the increase in charging costs when EVs provide grid support services will be higher.

Crucial to successful implementation of the proposed system architecture is data exchange on a short time scale between components in the grids, aggregators and DSOs. Investments in data communication and data processing infrastructure are a prerequisite for implementation of the proposed system. In the proposed system architecture, DSOs need access to real-time smart meter data. Currently, regulations do not allow DSOs to collect the smart meter data continuously on the required time scale [76]. Alternatively, DSOs could monitor the power quality in the LV grid through phasor measurement units (PMUs).

5.3. Discussion of results

The results showed that PV generation fluctuations can lead to visible and annoying light flicker for a considerable share of the day. However, different studies indicated that PV output fluctuations will not lead to violation of EN-50160 flicker standards [11–13]. Cloud transients take a few seconds, while the flicker standards values are for a large extent based on voltage fluctuations with a shorter duration. Therefore, the current power quality standards will not be exhaustive with higher levels of PV penetration in the future and additional flicker standards should be considered to ensure stable power quality in the future. Such a method could for instance be based on the very-short voltage variation (VSV) index, proposed in [77] and used in, among others, [10,78] and [79] to assess voltage fluctuations induced by PV output fluctuations.

The remaining question is whether EVs are a better ramp rate mitigation option than alternatives, such as grid reinforcements, battery systems or capacitors. Different studies have looked at the costs and mitigation potential of different technologies [16,17,26], but as these studies looked at incomparable systems with different pricing mechanisms, further studies are required to determine the best mitigation technology.

6. Conclusion

Cloud transients can cause rapid fluctuations in the output of PV systems, which may affect the power quality in LV grids. First, a realistic estimation of the impact of rapid PV output fluctuations on voltage levels in a LV grid for 2017, 2030 and 2050 was made. Second, a system was proposed for the mitigation of PV output fluctuations in the investigated LV grid by altering the charging processes of EVs. The extent that EV technology can mitigate voltage fluctuations induced by PV output fluctuations was determined by using smart charging strategies including the V2G concept.

The simulation outcome showed that PV output fluctuations can cause voltage fluctuations in the LV grid, which can result in visible and annoying light flicker for a considerable part of the day. However, no major voltage fluctuations are expected until 2030 given the assumptions of this study. The impact of large PV output fluctuations is highest at the end of feeder lines, whereas the impact is minor close to the transformer. Other major determinants are the total installed PV capacity in the grid and the grid strength.

The second part of the analysis showed that EVs will be able to limit fluctuations in residual load to low values in 2050, when voltage fluctuations will potentially become problematic. The simulation results indicate that all tested maximum allowable residual load ramp rates lead to lower visible and annoying light flicker at almost all locations, but do not fully eliminate voltage fluctuations and light flicker. A maximum allowable ramp rate between 20 and 25 kW/20s results in the lowest time with light flicker in the investigated grid. However, the increase in charging costs is higher with maximum allowable ramp rates between 20 and 25 kW/20s compared to higher maximum allowable ramp rates. Therefore, the maximum allowable ramp rate that should be applied when implementing the proposed system architecture depends on the willingness-to-pay for flicker mitigation by the DSO and the maximum allowable levels of flicker by the DSO, regulator and consumers.

The results of this study were based on different assumptions, including a constant MV level, full-availability of EVs for the mitigation of PV-fluctuations, perfect foresight in PV-generation and flicker threshold values based on incandescent lights. Future studies could elaborate on these assumptions by considering more-sophisticated inputs.

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Declaration of Competing Interest

The authors declared that there is no conflict of interest.

[6] EC Directive 245/2009.

Appendix I. Cable types in the investigated grid

(See Table 7)

Table 7
Cable types in investigated grid.

Cable type	No. of grid connections connected to cable type
Aluminum 4 × 6 mm^2	7
GPLK copper 4 × 25 mm^2	160
GPLK copper 4 × 50 mm^2	77
GPLK copper 4 × 70 mm^2	76
GPLK copper 4 × 95 mm^2	20

Appendix II. Assumptions in determining future number of EVs charging in the grid.

1. The number of local passenger cars remains constant, using the car possession rate in [80].
2. All passenger cars in 2050 will be BEVs, based on the Dutch governmental target to have a 100% zero-emission car fleet by 2050 [81].
   a. The EV fleet (BEV + PHEV) will increase linearly between 2017 and 2050.
   b. The ratio PHEV/BEV will decrease linearly from the ratio in 2017 to a ratio of 0 by 2050.
3. The share of the total number of local EVs performing a charging transaction in the investigated grid in a week remains constant over time for each type of EV.
4. The growth rate of the number of visiting BEVs and PHEVs per week is assumed to be the same as the growth rate of local BEVs and local PHEVs respectively.

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