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Avoiding Low-Voltage Grid Congestion using Smart Charging of Electric Vehicles based on Day-Ahead Probabilistic Photovoltaic Forecasts

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***Abstract*—Distribution System Operators (DSOs) can mitigate future grid congestion problems in low-voltage grids by applying smart charging algorithms to electric vehicles (EVs). However, application of real-time smart charging of EVs to mitigate local grid congestion could be problematic when aggregators cost-optimize EV charging by trading in electricity markets, as a deviation from the charging schedule for the provision of local grid services can lead to imbalance costs to the aggregator. Therefore, grid congestion problems should be forecasted, so aggregators can consider grid congestion in their electricity market bids and imbalance costs can be avoided. This study proposes a framework for mitigating grid congestion using EV smart charging, using probabilistic day-ahead forecasts of the grid load. The effectiveness of the proposed system in mitigating grid congestion is tested using day-ahead quantile regression forecasts for photovoltaic (PV) generation. Results indicate that transformer congestion problems reduce considerably when using probabilistic PV forecasts in EV scheduling. Considering a higher percentile in the PV generation forecast when scheduling EVs reduces grid congestion but marginally increases EV charging costs.**

***Index Terms*—EV Charging, Photovoltaic Generation Forecasting, Quantile Regression, Low Voltage Grid, Distribution System Operator**

I. Introduction

Efforts to decarbonize our energy and transport system result in high adoption of distributed energy resources such as photovoltaics (PV) and electric vehicles (EVs). The increasing penetration of these technologies increase the power flows in low-voltage (LV) grids, potentially causing cable and transformer congestion problems. Distribution System Operators (DSOs) can relieve congestion by grid and transformer reinforcements, or by actively managing the grid through the deployment of flexibility options. The latter option is preferable from a cost and emission perspective [1].

EVs are considered as an attractive technology for the provision of grid services. The share of EVs in the car fleet is expected to grow rapidly in coming years [2], stimulated by imposed governmental targets and price reductions for battery systems. Most EVs will be charged in LV grids, causing that a large number of EVs will be connected to the grid in the future. As the connection time to the charging station of EVs generally largely exceeds the time to fully charge the car, the charging schedules of these EVs can be altered in order to provide grid services [3]. The potential for using smart charging of EVs to solve local grid congestion problems has been studied in recent work [4], [5], but this work considered perfect foresight of grid loads and EV availability.

The stochastic nature of different grid loads, including PV generation, is one of the main barriers for using EVs for the provision of local grid services. An increasing share of the EVs cost-optimize their charging demand on the different electricity markets. Most of these markets have a closure time well in advance of real-time operation, causing that charging schedules should be determined at the moment of market closure. Supporting the DSO in mitigating grid congestion through a real-time alteration of the charging schedule from the submitted charging schedule to the electricity market results in imbalance costs. Ideally, grid congestion problems can be forecasted before the closure of the electricity market, so EV-owners or aggregators can consider this in their bids and no real-time alterations from the charging schedules are required to solve local grid congestion problems. In this way, imbalance costs can be avoided.

Different studies have proposed stochastic optimization models for EV or battery systems which consider the uncertainty in load or PV generation (e.g. [6], [7]). However, these studies added uncertainty to their models by creating noise around the actual load or PV generation using a probability density function, instead of using actual forecasting methods. As actual forecasts do not necessarily follow the probability density functions from these studies, these studies do not provide insight in how uncertainty in PV generation and load can be considered in real-life operation.

Other studies considered actual forecasts in smart charging algorithms for EVs and batteries, but focused on smart homes

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or medium-voltage (MV) grids [8], [9]. In addition, these studies used point forecasts for PV generation, which do not provide insights in the uncertainty around the forecasts. Given the large uncertainty in PV generation, probabilistic forecasts might be more appropriate. To the knowledge of the authors, no previous studies have looked into the potential of mitigating grid congestion problems in LV grids when considering actual probabilistic forecasts for PV generation.

This study presents a system for the mitigation of transformer congestion in LV grids using probabilistic forecasts of the transformer load, and provides insight in how DSOs can use probabilistic solar forecasts for the mitigation of grid congestion in LV grids using smart charging of EVs. Day-ahead quantile regression forecasts for PV generation are applied to EVs in a case study grid in order to obtain insight in the potential to mitigate transformer congestion problems using EV smart charging when considering day-ahead forecasts. In this way, no real-time corrections in EV charging schedules are required. The results of this analysis can be used by DSOs to get more realistic insight in the potential to mitigate grid congestion problems using EV smart charging, guiding them in grid investment decisions.

This work is outlined as follows. Section II discusses the quantile regression method used to generate probabilistic forecasts for PV generation. Section III outlines a system for the mitigation of transformer congestion in LV grids using EVs, based on forecasts of the transformer load. The data inputs used for modelling the proposed system are discussed in Section IV. The effectiveness of the proposed system is presented in Section V. Lastly, a discussion and conclusion are presented in Section VI.

II. Quantile regression

A widely applied and effective method to generate probabilistic solar forecasts is Quantile Regression (QR) [10], [11]. QR is a nonparametric forecast approach, which entails that it does not assume any particular probability distribution. Similar to linear regression, QR establishes a linear relation between the predictor variables and the expected output. In QR, these parameters are learned separately for each percentile τ by minimizing the sum of the absolute residuals over the asymmetrically applied weights error [12]. Subsequently, a probabilistic forecast is created by combining the estimates of each percentile. QR is described as:

$$\hat{y}_t(\tau) = \beta_0(\tau) + \beta_1(\tau)x_{1,t} + \ldots + \beta_m x_{m,t}, \tag{1}$$

where $\hat{y}$ is the expected PV power production per percentile, β are the regression coefficients per variable x, m is number of predictor variables included and t presents each 15-minute timestamp in 2016.

A. Data input

PV data is collected for a rooftop PV system located in the city of Utrecht, the Netherlands. The PV system has a rated capacity of 2,200 Wp, is oriented south (180°) with a tilt angle of 38°. PV power production measurements are available with a 2-second resolution [13], [14]. As this study simulates grid loads with a temporal interval of 15-minutes, the PV power measurements are resampled to 15-minute averages. Furthermore, the PV power production values are normalized to the system's rated capacity. Subsequently, the power production values are scaled to obtain production values for different PV penetration scenarios. The power measurements are available for the period 2014-2017. Moreover, 2014 and 2015 are used to train the QR forecast model. The solar power forecasts are generated for 2016.

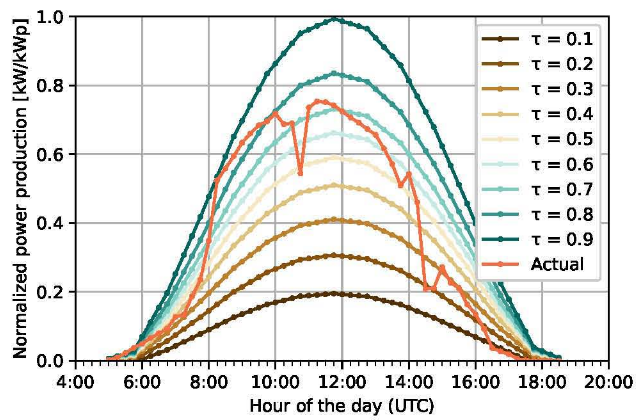

Fig. 1. PV power forecast results for September 16, 2016.

The QR model is fed with a number of predictor variables. These variables consider historical weather forecasts. These are obtained from the High Resolution Forecast Configuration (HRES) of the Integrated Forecast System (IFS), a Numerical Weather Prediction model developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) [15]. The collected variables are the global horizontal irradiance, air pressure, ambient and dewpoint temperature, zonal and meridional wind speed, precipitation, and low, mid, high and total cloud cover. These forecasts are collected at 12:00 UTC for each hour of the following day. As the forecasted values are given per hour, 15-minute values are found by assuming them to remain constant throughout each hour.

B. Evaluation

The quality of the QR forecast model is examined by means of the continuous ranked probability score (CRPS) [16]. The CRPS is preferred over alternatives as it is a common applied error metric that is able to evaluate both the sharpness and reliability of the forecast [10]. Moreover, the CRPS rewards a high concentration of the forecasted probability around the target value. A small CRPS value indicates a good forecast performance. The CRPS is calculated by:

$$CRPS = \frac{1}{T}\sum_{t=1}^{T}\int_{-\infty}^{\infty}(F_t(x) - \hat{F}_t(x))^2 dx, \tag{2}$$

where $F_t(x)$ and $\hat{F}_t(x)$ are the Cumulative Distribution Functions (CDFs) of the probabilistic forecast and observations and T represents the number of timesteps.

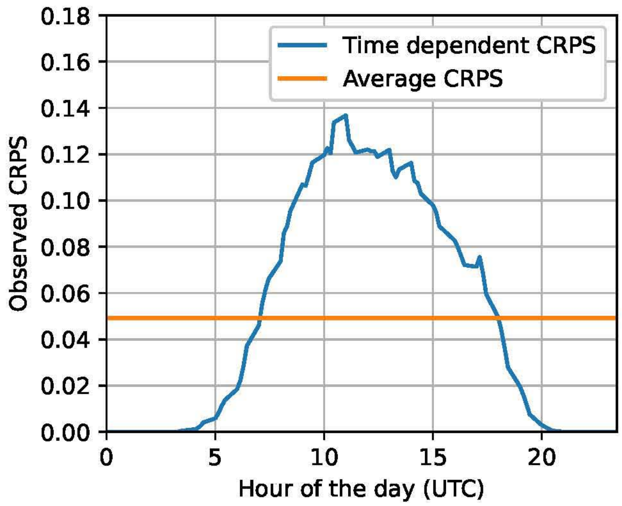

Fig. 2. The mean continuous ranked probability score (CRPS) per time of the day over the entire testing period, 2016.

C. Results

The PV power output forecasts for September 16, 2016, are depicted in Fig. 1. This figure shows the different forecasted percentiles, as well as the actual measurements. Over the entire test period, i.e. 2016, an average CRPS of 0.049 kW/kWp is found. Fig. 2 shows how the CRPS varies during the day. The highest error values are found during noon, where CRPS values of almost 0.14 kW per kWp are observed. This coincides with those moments where the greatest uncertainty occurs in the expected PV power production.

III. System design

A. System architecture

This research considers a system in which EVs mitigate transformer congestion problems in LV grids. Each considered LV grid connects different grid loads, including EV charging stations and PV systems, and is connected to the MV grid through a transformer. EVs cost-optimize their charging demand considering Time-of-Use (ToU) tariffs, while preventing that the power flows through the transformer exceed the transformer capacity by considering forecasts of the total grid load. The steps of the proposed system can be outlined as follows:

1) The DSO generates quantile regression forecasts for the transformer load for every timestep;
2) The DSO communicates these forecasts to the aggregator, which is responsible for the EV charging in the proposed system. These forecasts should be communicated well-before the closure time of the electricity markets. The DSO also communicates the range in the probabilistic forecast that aggregators should consider when determining the EV charging schedules;
3) The aggregator cost-optimizes the forecasted EV charging demand and submits bids to the electricity market. The aggregator makes sure that no transformer congestion occurs when considering both the upper and the lower limit of the range in probabilistic forecasts of the transformer load communicated by the DSO;
4) At real-time operation, grid congestion could occur when the actual transformer load is outside the range in load forecasts that the aggregator had to consider.

The analyses in this work only consider forecasts in PV generation.

B. EV charging model

The charging behavior of EVs in this study is simulated using an optimization model in which EVs cost-optimize their charging demand, while the transformer capacity is not violated for both the upper and the lower limit of the probabilistic forecast of the grid load.

a) Objective function:

EVs aim to minimize their charging costs:

$$\text{minimize} \sum_{t=1}^{T} \mathrm{c}_{\mathrm{ch},t}, \tag{3}$$

where c_{ch} is the electricity cost function for EV charging for the considered LV grid and T represents the end of the assessment timeframe.

The electricity cost function for EV charging considers the charging power for the set of charging transactions $n \in \mathcal{N}$ at the EV battery for each timestep t ($\mathrm{p}_{\mathrm{ch},n,t}$), the charging efficiency (η_{ch}), the duration of one timestep ($\Delta \mathrm{t}$) and the ToU-tariffs at each timestep (C_t):

$$\mathrm{c}_{\mathrm{ch},t} = \mathrm{C}_t \sum_{n=1}^{N} (\frac{1}{\eta_{\mathrm{ch}}} \mathrm{p}_{\mathrm{ch},n,t}) \Delta \mathrm{t} \ \forall t. \tag{4}$$

b) EV charging constraints:

The EV charging power is bounded by the maximum EV charging power of the specific charging transaction ($\mathrm{P}_{\mathrm{ch,max}}$):

$$0 \leq \mathrm{p}_{\mathrm{ch},n,t} \leq \mathrm{P}_{\mathrm{ch,max},n} \ \forall t \in \{t_{\mathrm{a},n}, t_{\mathrm{a},n} + \Delta \mathrm{t}, \ldots, t_{\mathrm{d},n}\}, n, \tag{5}$$

where $t_{\mathrm{a},n}$ and $t_{\mathrm{d},n}$ are the arrival and departure time of charging transaction n respectively.

In addition, the following constraint was added to assure that the charging demand of the charging transaction is met at the moment of departure:

$$\mathrm{e}_{\mathrm{ch,acc},t_{\mathrm{d},n},n} = \mathrm{E}_{\mathrm{req},n} \ \forall n, \tag{6}$$

where $\mathrm{e}_{\mathrm{ch,acc},t_{\mathrm{d},n},n}$ is the accumulated charging energy of a charging transaction at $t_{\mathrm{d},n}$ and $\mathrm{E}_{\mathrm{req},n}$ is the charging demand of charging transaction n.

The accumulated charging energy of a charging transaction is updated as follows:

$$\mathrm{e}_{\mathrm{ch,acc},t,n} = 0 \ \forall t \in \{t_{\mathrm{a},n}\}, n, \tag{7}$$

$$\begin{gathered} \mathrm{e}_{\mathrm{ch,acc},t,n} = \mathrm{e}_{\mathrm{ch,acc},t-\Delta\mathrm{t},n} + \mathrm{p}_{\mathrm{ch},t,n} \Delta \mathrm{t} \\ \forall t \in \{t_{\mathrm{a},n} + \Delta \mathrm{t}, t_{\mathrm{a},n} + 2\Delta \mathrm{t}, \ldots, t_{\mathrm{d},n}\}, n. \end{gathered} \tag{8}$$

c) Grid constraints:

The lower and the upper bound of the forecasted transformer load can be defined as follows:

$$\mathrm{p}_{\text{trans,lb},t} = \mathrm{P}_{\text{res},t} - \mathrm{P}_{\text{PV,ub},t} + \sum_{n=1}^{N} \frac{1}{\eta_{\text{ch}}} \mathrm{p}_{\text{ch},t,n} \ \forall t, \tag{9a}$$

$$\mathrm{p}_{\text{trans,ub},t} = \mathrm{P}_{\text{res},t} - \mathrm{P}_{\text{PV,lb},t} + \sum_{n=1}^{N} \frac{1}{\eta_{\text{ch}}} \mathrm{p}_{\text{ch},t,n} \ \forall t, \tag{9b}$$

where $\mathrm{p}_{\text{trans,lb}}$ and $\mathrm{p}_{\text{trans,ub}}$ are the lower and the upper bound of the forecasted transformer load, respectively, $\mathrm{P}_{\text{res},t}$ is the residential load in the studied LV grid and $\mathrm{P}_{\text{PV,ub},t}$ and $\mathrm{P}_{\text{PV,lb},t}$ are the upper bound and lower bound of the forecasted PV generation in the studied LV grid, respectively. Note that the lower bound of the forecasted transformer load depends on the upper bound in PV generation forecasts, as PV generation reduces the absolute transformer load.

The optimization model makes sure that both the lower and the upper bound of the forecasted transformer load do not exceeded the transformer capacity:

$$-\mathrm{P}_{\text{trans,max}} \leq \mathrm{p}_{\text{trans,lb},t} \leq \mathrm{P}_{\text{trans,max}} \ \forall t. \tag{10a}$$

$$-\mathrm{P}_{\text{trans,max}} \leq \mathrm{p}_{\text{trans,ub},t} \leq \mathrm{P}_{\text{trans,max}} \ \forall t. \tag{10b}$$

C. Evaluation

This study analyses the effectiveness of the proposed system in mitigating transformer congestion problems by considering the actual transformer load $\mathrm{p}_{\text{trans,actual},t}$, which is based on the actual PV generation $\mathrm{P}_{\text{PV,actual},t}$:

$$\mathrm{p}_{\text{trans,actual},t} = \mathrm{P}_{\text{res},t} - \mathrm{P}_{\text{PV,actual},t} + \sum_{n=1}^{N} \frac{1}{\eta_{\text{ch}}} \mathrm{p}_{\text{ch},t,n} \ \forall t. \tag{11}$$

IV. Data Inputs & Model Simulations

A. Case study

A 400 kVA transformer feeding a LV grid with 340 residential grid connections in the city of Utrecht, the Netherlands is used as a case study. Residential load profiles in this grid have been created by applying the total annual electricity consumption of all households in this grid to standardized NEDU profiles [17].

B. EV data

Future sets of EV charging transactions were generated using a probabilistic model outlined in [18]. The two inputs required for this probabilistic model are the total expected annual charging demand in one LV grid and distributions in the arrival time, connection time to the charging station, charging volume and charging power of EV charging transactions.

This study considers different adoption scenarios of EVs. The expected annual charging demand, which is used as an input in the probabilistic model for generating the charging transactions, is determined as follows:

$$\mathrm{E}_{\text{EV,total},s} = \mathrm{E}_{\text{EV,total,100\%}} \phi_s, \tag{12}$$

where $\mathrm{E}_{\text{EV,total},s}$ is the expected annual charging demand in the considered grid for scenario s, $\mathrm{E}_{\text{EV,total,100\%}}$ is the expected annual charging demand in the considered grid with 100% EV adoption and ϕ_s is the EV adoption rate in scenario s. This study used a value of 795 MWh for $\mathrm{E}_{\text{EV,total,100\%},s}$, based on an average car mileage of 13,000 km in the Netherlands [19], a car possession rate of 0.9 cars/household [20] and a driving efficiency of 0.2 kWh/km.

Charging transaction data for 1 January 2019 until 12 March 2020 from 277 charging stations with two charging sockets in residential areas in the province of Utrecht, the Netherlands was also used as an input in simulating the future charging transactions.

C. Scenario overview & model simulation

This study considers different EV adoption rates, installed PV capacities, transformer capacities and upper limits of probabilistic PV generation forecasts that aggregators should consider, in order to get broader insight in the usability of probabilistic PV generation forecast for grid management. The study considers EV adoption rates of 25%, 50%, 75% and 100% and total installed PV capacities of 100, 200, 300 and 400 kWp.

This analysis considers different upper limits for the PV generation forecasts that should be considered by the aggregators to identify its impact on transformer congestion levels and EV charging costs. Since the considered PV capacities are too low to induce transformer congestion by excess feed-in of electricity to the grid, no lower limits in PV generation forecasts are considered.

All optimizations are performed using the Gurobi optimization package for Python, using a high performance computing cluster. Day-ahead prices for the Netherlands in 2016 were used as ToU-tariffs in the analysis. All simulations of charging transactions and charging behavior were repeated five times, in order to obtain insight in the variability of results. This study used an charging efficiency (η_{ch}) of $\sqrt{0.87}$ [21].

V. Results

A. Grid load analysis

Figs. 3 and 4 provide insight in the effectiveness of the proposed system in avoiding grid congestion when considering PV generation forecasts. Grid congestion can be caused by PV generation forecasting errors. These figures present the number of hours of grid congestion in the studied grid with different installed PV capacities, EV adoption rates and considered percentiles of the PV generation forecast in EV scheduling.

Fig. 3 shows that considering probabilistic day-ahead forecasts of PV generation in the charging schedules optimization process leads to significant reductions in grid congestion. If EVs were allowed to charge freely without considering forecasts in PV generation, a 100% EV adoption would lead to 475 to 490 hours of transformer congestion per year, depending on the installed PV capacity. In contrast, the maximum number of hours with grid congestion is 61 if EVs consider grid congestion when determining their charging schedules.

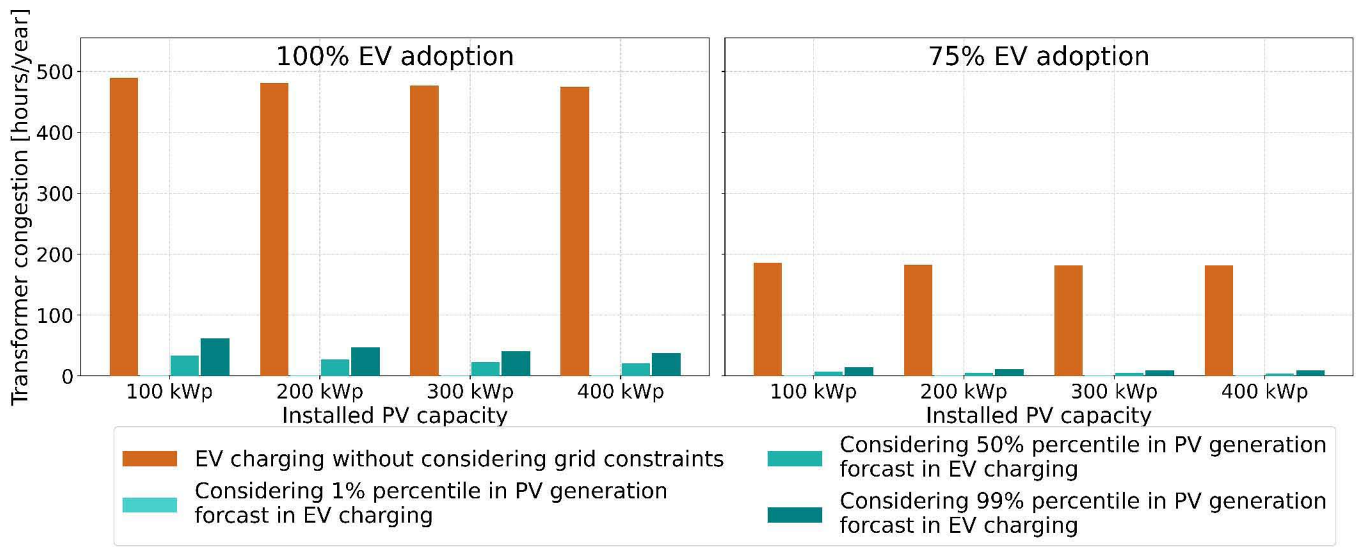

Fig. 3. Comparison of the average number of hours of transformer congestion between the proposed system and between a system in which EVs do not consider PV generation forecasts when scheduling their charging. Results are presented for different installed PV capacities, different EV adoption rates and different percentiles in the quantile regression PV generation forecasts that are used as upper bounds in the optimization algorithm.

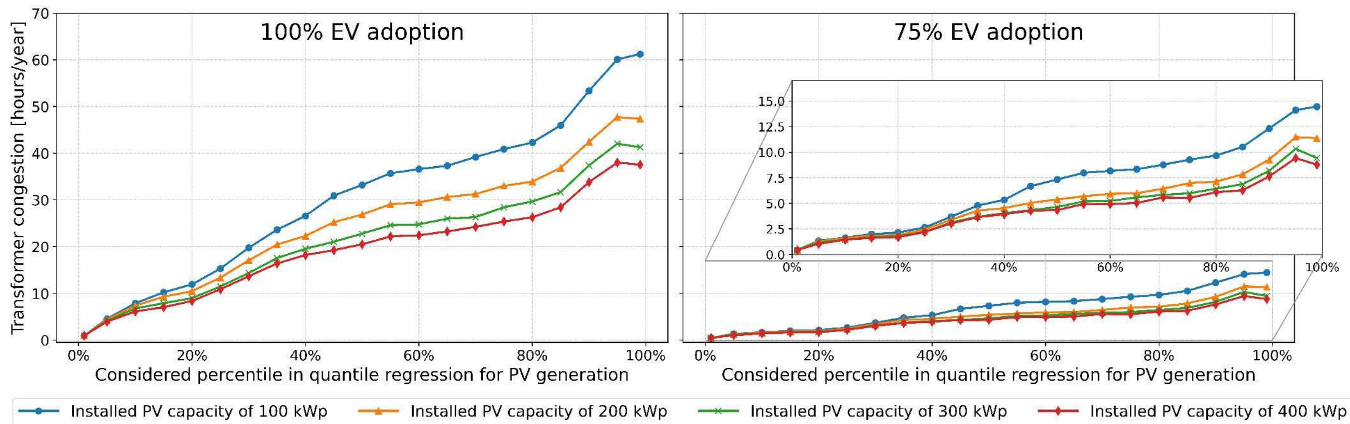

Fig. 4. Average number of hours of transformer congestion when using the proposed system, considering different installed PV capacities, different EV adoption rates and different percentiles in the quantile regression PV generation forecasts that are used as upper bounds in the optimization algorithm.

A detailed analysis of the effect of the considered percentile in the PV generation forecast on grid congestion levels is provided in Fig. 4. Using higher percentiles of the quantile regression forecast for PV generation in the scheduling of EVs results in more grid congestion. Using a higher percentile increases the chance that the forecast overestimates the PV generation, and thus increases the risk that the forecasted available grid capacity for EV charging is higher than the actual available grid capacity.

The number of hours with grid congestion decreases with higher EV adoption rates and higher total installed PV capacities in the considered LV grid. Transformer congestion levels when EVs do not consider grid constraints in their charging optimization reduces from a maximum value of 490 hours/year with a 100% EV adoption rate to a maximum value of 9 hours/year with a 50% EV adoption rate. No transformer congestion occurs with a 25% EV adoption rate. With higher installed PV capacities, EVs are in less cases constrained by the forecasted transformer capacity in their charging, as higher PV generation results in higher reductions in transformer load. Consequently, an overestimation in PV generation results in less cases in a violation of the transformer capacity.

TABLE I

INCREASE IN CHARGING COSTS WITH A 100% EV ADOPTION COMPARED TO THE CASE IN WHICH EVS DO NOT HAVE TO CONSIDER GRID CONSTRAINTS IN THEIR CHARGING OPTIMIZATION (0.0271 EURO/KWH).

Installed PV capacity	Considered percentile of PV forecast in EV scheduling				
	1%	20%	40%	60%	99%
100 kWp	0.353%	0.350%	0.347%	0.346%	0.339%
200 kWp	0.352%	0.346%	0.343%	0.341%	0.334%
300 kWp	0.351%	0.344%	0.340%	0.339%	0.331%
400 kWp	0.351%	0.342%	0.338%	0.337%	0.329%

B. Charging cost analysis

The charging costs of EVs are higher if grid constraints are considered in their charging optimization, as EVs can be restricted by the grid capacity to charge at moments with low ToU-tariffs. Table I presents the increase in EV charging costs compared to a situation in which EVs do not consider grid constraints. It indicates that EV charging costs only increase marginally when EVs consider grid load forecasts in their charging schedules. The maximum increase in charging costs equals 0.35%, corresponding to less than 0.0001 euro/kWh.

Considering higher percentiles of the PV generation forecast lowers charging costs, as the forecasted available transformer capacity for EV charging is higher with higher considered percentiles. Hence, EVs have more opportunities to charge at moments with low ToU-tariffs without being restricted by the transformer capacity. The difference in charging costs between the 1% and the 99% percentile is limited; the charging costs of the 99% percentile are at maximum 0.022% lower.

VI. Discussion & Conclusion

This study proposed a framework for using EV smart charging for the mitigation of grid congestion while considering probabilistic day-ahead forecasts of the grid load. The effectiveness of the proposed system was tested by using quantile regression forecasts of PV generation.

The results affirmed that considering day-ahead PV generation forecasts when scheduling EVs is effective in avoiding transformer congestion problems. The number of hours with transformer congestion decreases drastically when EVs consider grid load forecasts when scheduling their EVs; the number of hours with grid congestion are reduced by at least 87% at 100% EV adoption. Considering a higher percentile in PV generation increases the number of hours with grid congestion, but marginally decreases EV charging costs.

Although the results indicated that little transformer congestion occurs when scheduling EVs using day-ahead forecasts, this does not mean that day-ahead forecasts of transformer loads can be applied in practice. This study only considered forecasts in PV generation, but assumed perfect foresight for other grid loads. At residential areas, most EVs arrive in the beginning of the evening at the charging station, and the most beneficial electricity prices for this set of EVs usually occur in the middle of the night, at moments with low demand. Thus, the highest charging volumes occur at moments with no PV generation. Since perfect foresight has been assumed for all other loads, no grid congestion can occur at these moments. If the uncertainty in other loads was considered, forecasting errors for these loads could increase the number of hours with transformer congestion.

Lastly, this research only considered day-ahead forecasts, while the forecasting accuracy improves when using forecasts closure to real-time operation. The proposed system can be extended by updating the day-ahead forecasts with shorter-term forecasts, reducing the number of hours with grid congestion. Aggregators can correct for these updated forecasts by trading in intraday markets.

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