EVALUATING VOLTAGE IMPACT DUE TO THE INSTALLATION OF DISTRIBUTED ENERGY RESOURCES IN LOW VOLTAGE NETWORKS

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ABSTRACT

The integration of Distributed Energy Resources (DERs) and Electric Vehicle Charging Points (EVCPs), in the Low Voltage (LV) networks, is creating several challenges to the Distribution System Operators (DSOs) as it may push the voltage magnitudes outside the regulated boundaries and/or increase its unbalance beyond the acceptable limits. In this paper, it is proposed a method capable of predicting the voltage impact of a new DER or EVCP installation without requiring network topology and, therefore, helping DSOs to optimise their LV networks.

INTRODUCTION

According to the International Energy Agency, the cumulative distributed solar Photovoltaics (PV) capacity in Germany increased from 28.4GW to 44.8GW (approximately 58%) between 2014 and 2020 [1, 2]. The same phenomenon is happening in other countries, mostly on a smaller, yet non-negligible scale, mainly due to economic reasons and environmental concerns.

With the transport electrification that has been occurring and will continue to be implemented over the next few years, it is expected that in 2030 more than 25% of the passenger-car and light-duty vehicle market share will be occupied by electric vehicles (contrasting with the 2.5% registered in 2019) [3].

While the production of energy in LV networks, using for instance solar panels, can increase the voltage magnitude, electric vehicle chargers can decrease the voltage magnitude across the feeder (considering exclusively grid to vehicle power flow). Therefore, the rapid growth of both PV and EVCPs in LV networks may drive voltage unbalance and magnitudes outside of the stipulated limits, if no action is taken. If the connection impacts of a DER or an EVCP are evaluated before its installation, the number of events where the voltage does not meet the regulated limits can be minimised by applying preventive measures recommended by the DSO. These measures could possibly include power curtailment (for DERs), load shifting (for EVCPs) and installation of equipment with lower-rated power.

Wang et al. suggested an approach capable of calculating the customer voltages for any intended operation of DERs by estimating the network impedances using the network topology and Smart Meter (SM) measurements and running three-phase power flows [4].

Traditionally, the energy flowed solely in the downstream direction which led the control and supervision to be concentrated at higher voltage levels. Additionally, the unreported changes that occurred on LV networks over time have led DSOs to not have accurate network topologies for most of these grids.

In this work, it is proposed a new method that evaluates the voltage impacts of a DER or EVCP installation, based on measurements taken by SMs, in an LV network without requiring its topology. The following section describes the proposed method and explains the steps to follow. After that, the forecasting model, which is one of the foundations of the method, is evaluated by performing several predictions and comparing them with the simulated data.

METHOD

The approach estimates the voltage measurements that could have been taken in each SM, if a certain DER/EVCP was already installed in the past. To do so, it estimates the voltage variations that could have been caused by the DER/EVCP and sums them with past voltage measurements.

The method can be divided into the following steps:

- SM data collection;
- SM data pre-processing and phase assignment;
- Forecasting model training;
- Selection of typical days;
- Voltage assessment.

Firstly, it is necessary to collect and pre-process SM measurements, as they are the main component of the method. Then, using the pre-processed data, a forecasting model is trained to predict the voltage variations at each timestamp. Finally, a set of days is selected from the history of measurements, the voltage at each SM is forecasted for these days according to the DER/EVCP parameters and its limits analysed.

SM data collection

In order to be able to forecast the connection of a DER or EVCP at any customer, the LV network must be totally covered by SMs. This also allows to forecast the voltage at each client and to ensure that the power and voltage variation relations between every SM are extracted.

Each SM must collect the following measurements:

- Voltage at each consumer connection phase;
- Energy/power consumption, preferably at each consumer connection phase.

SM data pre-processing and phase assignment

Data quality has a great impact on the model's performance, hence the need for a pre-processing step. This step can include the following actions:

- Removing null measurements and outliers;
- Dropping SMs with very low or constant measurements of energy/power consumption.

To train the previously stated model, it is also required to assign the SM connection phases to the secondary substation phases. This can be achieved either by supplying a list that contains the corresponding SM phases or running a classification algorithm [5] (which requires a monitoring system at the secondary substation as shown in figure 1).

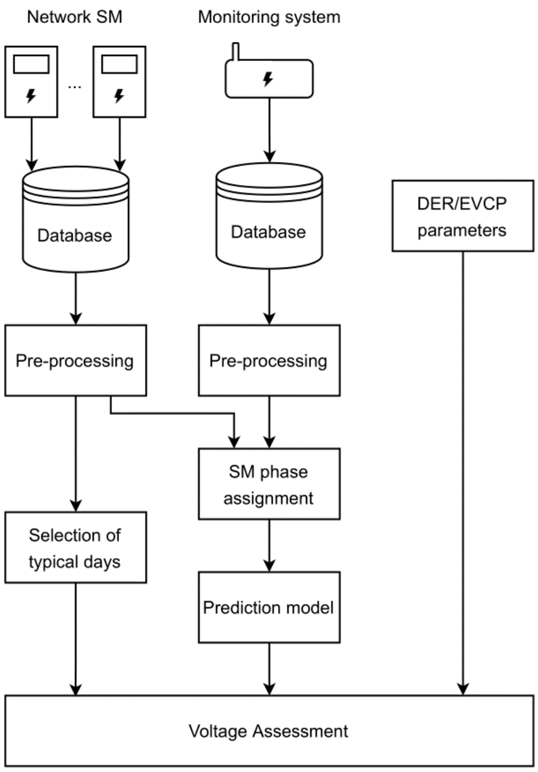

Figure 1: Block diagram representing the method.

Model training

Using the pre-processed voltage and power measurements, their variations between consecutive timestamps are calculated. These variations are then used to train the forecasting model. Additionally, a large historical sample of SM data will allow the forecasting model to better extract the underlying relations between voltage and power variations.

Selection of typical days

The voltage assessment can be based on the complete historical dataset or just a subset of days that represents distinct load profiles (typical days).

The analysis using typical days lets DSOs understand on which group of days there is a greater likelihood of voltage not meeting the regulated boundaries and, therefore, help the DSO to recommend specific measures. The days present in the historical dataset can be grouped using a clustering tool and the typical days obtained by getting the medoid of each cluster.

Voltage assessment

In order to evaluate the voltage impacts, it is necessary to forecast the voltage variations due to the connection of a DER or EVCP. This can be achieved by using the trained prediction model and defining the following parameters:

- Rated power;
- Typical profile (can be based on a real profile or other to predict the worst-case scenario, for instance);
- Connection location;
- Phase of installation (only necessary if it is intended to install a single-phase DER or EVCP on a three-phase consumer).

The forecasting model returns the expected voltage variations based on the power variations introduced on the network by the DER or EVCP, which correspond to the typical DER/EVCP profile defined. The predicted voltage at each SM with the installed DER or EVCP is calculated by summing the forecasted voltage variations with the voltage measurements taken during the typical days. With the forecasted voltages, it is possible to study if the aforementioned connection is expected to violate any established limit.

FORECASTING MODEL EVALUATION

To evaluate the errors of the model, several simulations were run for different network configurations and DER/EVCP parameters.

The first step consisted in defining the number of simulations and the degree of SM visibility. Each simulation performed the following actions:

1. Define the training and test period;
2. Select randomly a network;
3. Run a three-phase power flow for the selected network without the DER/EVCP installation for the training and test period;
4. Select randomly DER/EVCP parameters;
5. Run a three-phase power flow for the previously mentioned network with the DER/EVCP installation for the training and test period;
6. Calculate voltage variations using the results obtained in 2 and 4;
7. Train the forecasting model using the values obtained in 2 and following the steps mentioned in the previous section;
8. Get the predicted voltage variations by inputting the power variations for the test period in the trained model;

9. Calculate errors using the voltage variations for the test days calculated in 6 and returned in 8.

Simulated networks

The simulated networks were based on real networks built on OpenDSS and used on the Low Voltage Network Solutions project [6]. Neutral lines were added and approximately 20% of the consumers became three-phase connected loads in each network.
These grids contained a generator in the medium voltage network with variable voltage magnitude to mimic the upstream network. The medium voltage magnitudes used in the simulation were based on measurements collected by different sensors manufactured by ENEIDA.IO.
The load profiles of each network were randomly attributed to a selection of real SM measurements taken during the Low Carbon London project [7], which led to unbalanced networks.

Simulated DER/EVCP

For these simulations, it was considered that only PV panels or EVCP could be connected, and their rated power could be between 1kW and 10kW. The profiles from these installations were selected from the Customer-Led Network Revolution project [8] and then normalised.

Performance

To extensively evaluate the method, the performed simulations considered different SM visibility degrees and different training set sizes.
Since the voltage variations in DER/EVCP non-connection phases are very small, they were ignored. Therefore, the voltage variation errors were only analysed in the DER/EVCP connection phases.
The metrics used to assess the forecasting model performance were: Normalised Mean Absolute Error (NMAE), Normalised Root Mean Square Error (NRMSE) and Mean Bias Error (MBE). These metrics were calculated according to (1), (2) and (3).

$$NMAE = \frac{\sum_{t=1}^{n} |O_t - F_t|}{n} \times \frac{100\%}{\overline{O}} \quad (1)$$

$$NRMSE = \sqrt{\frac{\sum_{t=1}^{n} (O_t - F_t)^2}{n}} \times \frac{100\%}{\overline{O}} \quad (2)$$

$$MBE = \frac{\sum_{t=1}^{n} O_t - F_t}{n} \quad (3)$$

In (1), (2) and (3), n, O_t, F_t and $\overline{O}$ correspond to total number of samples, observed value at sample t, forecasted value at sample t and mean of the observed values, respectively.

The obtained metrics for the different simulations are shown in tables 1, 2 and 3. It is important to note that for the simulations performed the power measurements in each phase at three-phase SM were available.

Table 1: Metrics obtained for a set of 365 days of history (100 days of test).

	SM visibility				
Metrics	100%	~ 90%	~ 75%	~ 50%	~ 25%
NMAE (%)	3.83	5.22	7.62	8.43	5.90
NRMSE (%)	10.31	14.27	20.71	23.33	16.44
MBE (V)	0.01	0.02	0.03	0.03	0.03

Table 2: Metrics obtained for a set of 60 days of history (20 days of test).

	SM visibility				
Metrics	100%	~ 90%	~ 75%	~ 50%	~ 25%
NMAE (%)	5.89	5.86	7.40	8.31	7.44
NRMSE (%)	15.56	15.16	19.93	22.72	19.94
MBE (V)	0.03	0.03	0.03	0.04	0.04

Table 3: Metrics obtained for a set of 30 days of history (10 days of test).

	SM visibility				
Metrics	100%	~ 90%	~ 75%	~ 50%	~ 25%
NMAE (%)	7.56	6.80	12.01	11.62	8.95
NRMSE (%)	19.94	18.16	31.09	31.00	23.63
MBE (V)	0.02	0.03	0.04	0.06	0.04

According to the NMAEs calculated, the overall errors present in the predictions delivered by the forecasting model are low. In some timestamps, the model cannot provide forecasts of similar quality to most, as the NRMSE values show. Additionally, the model does not tend to underestimate or overestimate, as the MBEs calculated are close to 0V.
From the NMAEs and NRMSEs presented, it is possible to conclude that the forecasting errors tend to be higher when the length of the training set is smaller and the SM visibility is lower. This is to be expected as, by increasing the SM visibility and the length of historical dataset, a more representative view of the phenomenon at hand is given to the model.

CONCLUSION

A new method capable of predicting the voltage variations at each SM, due to the installation of an EVCP/DER, was developed. Unlike other methods, it does not require a network topology to predict the voltage impact.

It uses measurements taken by SMs during past days and the typical DER/EVCP profile to predict the voltage magnitudes during these days if a specific DER/EVCP was already connected.

Performing this type of analysis before installing a DER/EVCP in a LV network lets DSOs understand the possible consequences this installation brings at each customer and minimise them by enforcing preventive measures. Additionally, it can help DSOs decide which phase a single-phase DER/EVCP should be connected in a three-phase customer by forecasting the voltage impact in each phase and selecting the one that optimises the network operation.

The forecasting model provided predictions with low errors and did not show any overestimation or underestimation trend. Additionally, it was concluded that the model returned forecasts with higher accuracy when the length of the training set is larger and SM visibility are higher.

Therefore, the developed method can be seen as a useful tool for DSOs for the years to come due to the expected growth of DERs and EVs for the previously stated reasons. The forecasting model can possibly be improved by performing a pre-selection of input variables and by using other types of models to predict the voltage variations.

MISCELLANEOUS

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