Stochastic modelling of the correlation between transformer loading and distributed energy resources in LV distribution networks

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Abstract: The rapid growth of distributed energy resources (DERs) poses operational challenges for the low-voltage (LV) distribution networks, such as overloading of the transformer and/or voltage violation. Many smart strategies based on flexibility and coordinated control of DER have been developed to address these issues. To facilitate this implementation, this study presents a stochastic modelling technique, based on the Monte Carlo approach, to analyse the correlation between transformer loading and voltage magnitudes measured at the point of connection (POC) of DER in the network. A case study has been performed using IEEE European LV test feeder and smart meter measurement from the Netherlands to reflect the realistic aspects of operational conditions. Advanced statistical modelling techniques are applied to generate a set of scenarios, consisting of solar irradiation, and electric vehicle charging and load consumption profiles. Simulation results reveal a strong linear relationship between transformer loading and voltage magnitudes at the POC of DERs. Thus, these findings can aid in implementing flexibility and coordinated control DERs for congestion management in the LV distribution network.

1 Introduction

The rapid growth of distributed energy resources (DERs), especially photovoltaic (PV) systems and electric vehicles (EVs), in the low-voltage (LV) distribution networks, poses operational challenges for the network operators [1]. A high level of PV penetration can result in overloading the transformer and/or voltage rise problems [2]. On the other hand, the integration of a large number of EVs will increase the overall energy consumption with a higher peak load, leading to congestions and/or serious voltage drops along the feeders. This warrants the deployment of smart strategies in the LV networks to deal with the challenges regarding transformer overloading and voltage rise problems, e.g. using flexibility and coordinated control of PV systems and/or EVs as presented in the literary works [3–7]. In these approaches, the control rules are based on voltage magnitude and/or transformer loading rate, to regulate the PV inverters and EV-charging behaviours.

Theoretically, the relationship between power injection and bus voltage magnitude and angle can be observed by applying the concept of the Jacobian matrix, which is derived from solving the nonlinear load flow using Newton–Raphson algorithm [8]. This relationship can be used to implement different coordinated control mechanisms in the network as presented in the literary works [9–12]. Authors in [9, 10] apply the Jacobian matrix to complement the active and reactive power control of PV inverters, respectively. In the work of Ali *et al.* [11], the Jacobian matrix-based method is proposed to fairly curtail PV power output for overvoltage mitigation. In the work of Mai *et al.* [12], the Jacobian matrix is utilised to aid the coordination of active and reactive powers of PV inverters to tackle overvoltage issues. However, the Jacobian matrix varies with instantaneous power flow and calculating such matrices requires gathering the information of the entire system/network [13]. Thus, observing the relationship by calculating the Jacobian matrix in an on-line manner is computationally demanding if not impossible. Due to the intermittent, unpredictable behaviours of EV charging and PV generation, an alternative approach is required to represent the correlation of power injection with voltage magnitude and angle. With this correlation being defined, power entering the transformer, e.g. transformer loading can be determined using measured voltage magnitude at point of connection (POC) of DERs. Hence, this can aid in implementing the flexibility and coordinated control DERs for congestion management in the LV distribution network.

Based on the above-presented discussion, this paper presents a stochastic modelling technique to determine the correlation between transformer loading and voltage magnitude in the LV distribution network with PV and EV integration. Based on the Monte Carlo approach, along with Pearson's correlation coefficient, the proposed method aims to investigate the correlation between the loading rate of the transformer and the voltage magnitude measured by the residential smart meters. A case study has been performed considering an IEEE European LV distribution feeder and real data measured in the Netherlands, i.e. solar irradiation measured in the field, smart meter measurements and PV system capacity of Dutch residential consumers, and EV battery specifications of Nissan Leaf 2018. Using the real set of data, advanced statistical modelling techniques are used to generate a set of scenarios, consisting of solar irradiation, EV-charging profiles and load consumption data. A simulation platform including Python and OpenDSS has been deployed to perform stochastic analyses with a high number of generated scenarios.

2 Stochastic modelling methodology

2.1 Stochastic modelling

The stochastic modelling involves the uncertainty of PV generation, EV charging and load consumption for the assessment of the correlation

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between transformer loading and voltage levels. Implementing the proposed methodology follows three main steps as listed below.

- First, a series of scenarios S including daily profiles of PV generation, EV charging and load demand for one year (8760 h) are generated. The households in the test network are then randomly assigned with the load profiles.
- Then, the penetration level (%) of PV systems and EV usage are defined. The houses having PV units and EVs are randomly allocated. It is assumed that PV units and EV have the same phase connection as the house.
- Next, simulations are executed for a series of scenario S. All resulting data from the simulation required for calculating the correlation metrics are gathered.

2.2 PV generation, EV charging, and load consumption profiles modelling

To model PV generation profiles, daily solar irradiation (W/m^2) profiles are developed following a random sampling method based on a Gaussian mixture model (GMM). The probability density function of the GMM is expressed by

$$f(x) = \sum_{k=1}^{K} \pi_k \mathrm{N}(x|\mu_k, \Sigma_k) \tag{1}$$

In (1), $\sum_{k=1}^{K} \pi_k = 1$ where k is the component, and $x = (1, \ldots, x_t, \ldots, x_\mathrm{T})$ denotes a solar irradiation profile with time step t and length T, while $\Sigma_k \in \mathbb{R}^\mathrm{T} \times \mathbb{R}^\mathrm{T}$ represents the statistical correlation of solar irradiation between time-steps. K for each PDF in (1) is the total number of component, which is determined using the Bayesian information criteria [14]. Based on this, the GMM generates the solar irradiation profiles for each month of a year, then the seasonality fluctuations during the year are considered.

For developing EV charging profiles, the normal distribution method discussed in the work of Minniti *et al.* [15] is fitted with the typical departure time and working hours of EV owners. For this, the real data of travelling behaviour from Dutch persons are utilised, while the EV battery specifications are derived from a commercial EV, which both are described in the next section.

To generate the residential load consumption profiles, a probabilistic method based on conditional copula is utilised. This method uses historical load consumption data derived from real smart meter measurement with 15-min resolution. The conditional copula applied in this paper can be mathematically presented as follows:

$$\begin{aligned} F(x_1, \ldots, x_t, \ldots, x_\mathrm{T}|\omega) = & C(F_{X_1|W}(x_1|\omega), \ldots, \\ & F_{X_t|W}(x_t|\omega), \ldots, F_{X_\mathrm{T}|W}(x_\mathrm{T}|\omega)) \end{aligned} \tag{2}$$

where $x = (1, \ldots, x_t, \ldots, x_\mathrm{T})$ represents a load consumption profile with time step t and length T, and $F_{X_t|W}(.)$ denotes the empirical continuous distribution function, while ω denotes the total annual energy consumption (kWh) of the households. The conditional copula allows the generated load consumption profiles to preserve the statistical correlation among the time steps, and also follow the appropriated total annual energy consumption.

2.3 Pearson's correlation coefficient

Pearson's correlation coefficient is applied to measure the statistical relationship between transformer loading (P_transf) and voltage levels at POC of residential houses (V). This type of coefficient, denoted by r, is most commonly used to indicate the strength of a linear relationship between two variables, e.g. P_transf and V, as given as follows:

$$r = \frac{\sum_{i=1}^{N} (P^i_\mathrm{transf} - \overline{P_\mathrm{transf}})(V^i - \overline{V})}{\sqrt{\sum_{i=1}^{N} (P^i_\mathrm{transf} - \overline{P_\mathrm{transf}})^2}\sqrt{\sum_{i=1}^{N} (V^i - \overline{V})^2}} \tag{3}$$

where N is a total number of observations, i.e. 8760.

3 Simulation setup

The test network is based on the well-known IEEE European test case as shown in Fig. 1. The test network is energised from a 250 kVA, 11/0.4 kV transformer with the secondary-side voltage level at 1.03 p.u., and supplies electricity to 55 households. These households are all single-phase users with a total number of 21, 19, and 15 households connected to phase A (phase 1), phase B (phase 2), and phase C (phase 3), respectively. Thus, the test network represents an unbalanced LV distribution network.

The smart meter measurements of real Dutch residential consumers provided by one Dutch DSO are used to generate the load consumption profiles following the procedure described in Section 2.1. The actual measured solar irradiation obtained from the Royal Netherlands Meteorological Institute in the work of Koninklijk Nederlands Meteorologisch Instituut (KNMI) [17] is used to generate the solar irradiation profile as discussed in Section 2.1. The capacity of PV systems is chosen based on typical Dutch residential-scale PV systems ranging from 4.06 to 6.27 kWp. Typical Dutch travelling information has been obtained from the Dutch Central Bureau for Statistics as used in the work of Minniti *et al.* [15], is utilised to simulate EV charging profiles. EV battery specifications of Nissan Leaf 2018 with battery capacity 40 kWh and level 1 charging power 1.5 kW are employed [18]. Simulations of one-year time-series power flow have been performed in Python-OpenDSS platform for three penetration levels, i.e., 20, 60, and 100%, of PV systems and EVs. A total of 10 scenarios per penetration level is analysed.

4 Numerical results

With no loss of generality, the relationship between the single-phase power of the transformer in phase A and the voltage magnitude measured at a POC of house no. 25 connected to the same phase is visualised in Fig. 2. This scatter plot along with the least-square lines show the linear relationship between these two variables in all penetration levels. The notable differences between the penetration levels are the angle of inclination. The inclination of the higher penetration levels is steeper than the smaller one.

Since the transformer power and the voltage level at the POC of households have a linear relationship, Pearson's correlation coefficient concept is employed to quantify the correlation between them. The correlation is measured in each phase for all POC, in which the single-phase power of the transformer and the voltage level at each POC in the same phase defines a pair of correlated variables. For the demonstration purpose, the resulting

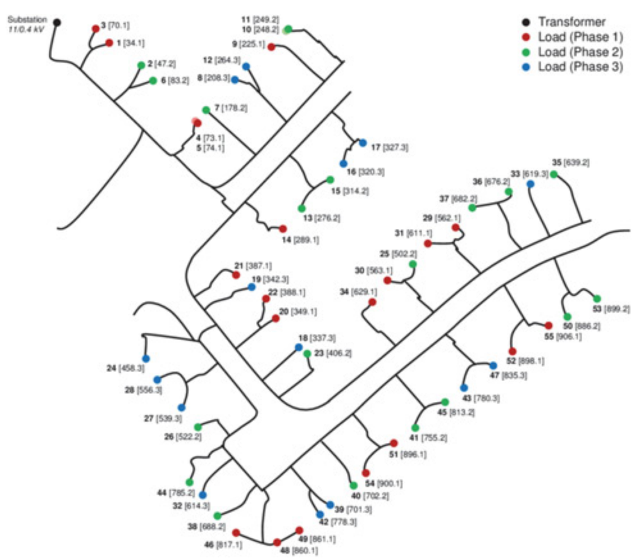

Fig. 1 *IEEE European test case, adopted from the work of Neumann [16]*

Pearson's correlation coefficients for phase A are shown in Fig. 3, where the index values in the horizontal axis, e.g. index 1, represents a pair of correlated variables, e.g. P_{transf} of phase A of the transformer and V_1 (measured at POC of house no. 1). As can be seen from Fig. 3, the calculated Pearson's correlation coefficients are all positive, high values, i.e. >0.99, in all cases of phases and penetration levels. This indicates that the linear relationship is strong and in an increasing direction.

Maximum values of Pearson's correlation coefficient (r_{max}) in different penetration levels for three phases are shown in Table 1, where P_{transf}–V_i depicts the pair of variables, in which V_i depicts voltage levels measured at house no. *i*. It is observed that with increasing penetration levels, the houses connected in phases A and B, and closer to the end of the feeder have the strongest association of their voltage levels and the transformer power. Meanwhile, for phase C with a 100% penetration level, the houses in the middle of the feeder, i.e. house no. 16, has the highest correlation coefficient. This might be caused by the unbalance of the network, in which phase C has only 15 households while phases A and B have 21 and 19 households, respectively.

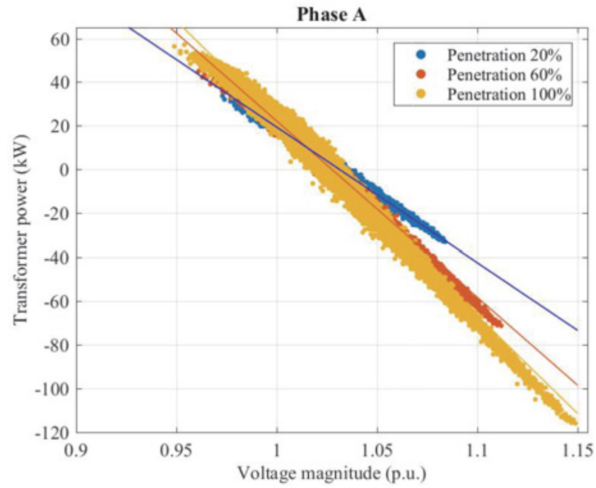

Fig. 2 *Scatter plot for transformer power of phase A and voltage magnitude measured at house no. 25*

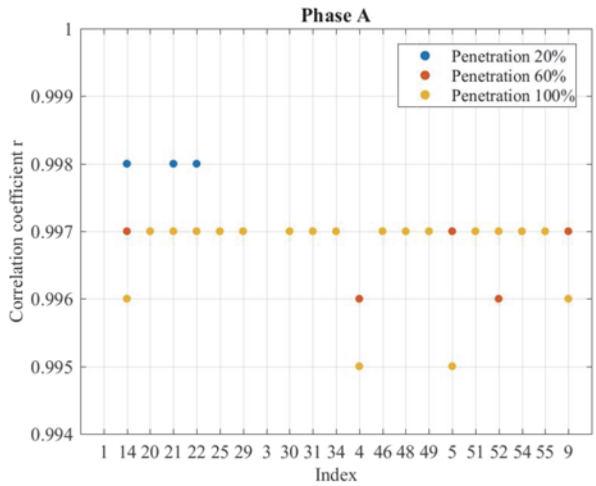

Fig. 3 *Pearson's correlation coefficients between phase A transformer power and the voltage level*

Table 1 Maximum Pearson's correlation coefficients in different penetration levels for different phases

Phase	Properties	Penetration levels		
		20%	60%	100%
A	r_{max}	0.9977	0.9971	0.9972
	P_{transf}–V_i	P_{transf}–V_{14}	P_{transf}–V_{22}	P_{transf}–V_{29}
B	r_{max}	0.9898	0.9961	0.9963
	P_{transf}–V_i	P_{transf}–V_{26}	P_{transf}–V_{23}	P_{transf}–V_{50}
C	r_{max}	0.8331	0.9852	0.9941
	P_{transf}–V_i	P_{transf}–V_{47}	P_{transf}–V_{47}	P_{transf}–V_{16}

Based on this strong linear association, i.e. $r_{max} \simeq 1$, the transformer loading can be estimated from DER location using the measured voltage magnitude at POC. This, thus, provides valuable insights for implementing flexibility and coordinated control DERs for congestion management in the LV distribution network.

5 Conclusion

This paper investigates the correlation of the transformer loading with voltage magnitude measured at the POC of DERs in the LV distribution network. To this end, a stochastic modelling technique, based on the Monte Carlo approach is proposed and Pearson's correlation coefficient is calculated. The obtained results show the strong linear relationship of transformer loading with voltage magnitudes at the POC of DERs. This linear relationship and the measured voltage magnitude at POC of DERs can be utilised to estimate transformer loading rate, then facilitating the flexibility and coordinated control DERs for congestion management.

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