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C6 Active Distribution systems and distributed energy resources  
PS1 Flexibility management in distribution networks

## Evaluating the Impact of New Technology Deployment on Future Congestion of LV Distribution Grids

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### SUMMARY

The electrification of end-energy use and the increasing integration of distributed energy resources (DERs) are significantly reshaping the landscape of low voltage (LV) distribution grids. However, many LV networks were originally designed without considering these transformative factors, potentially leading to congestion and overloads. Assessing the hosting capacity of these networks has become crucial, as it quantifies the ability of the distribution network to accommodate additional DERs while maintaining stable and reliable operations. In this context, we introduce the concept of *remaining* hosting capacity as a metric to evaluate LV distribution networks' capacity to absorb additional DERs, considering the existing DER deployment. We present two simulation methodologies: Gaussian mixture model-based stochastic power flow simulations that deliver a detailed network analysis, including specific current and voltage data but require substantial computational resources, and a data resampling simulation methodology that employs detailed load and DER profiles to rapidly approximate load demands at the transformer level. Furthermore, we conduct a sensitivity analysis for different levels of DER penetration to calculate the networks' capability to accommodate more DERs. The results obtained illustrate the effectiveness of GM models and the data resampling simulation methodology proposed in this work. The remaining hosting capacity concept provides essential insights into the networks' capabilities to accommodate additional DERs in the future, facilitating informed decisions for both Distribution System Operators (DSOs) and DER developers regarding grid operation, necessary upgrades, and sustainable DER expansion.

### KEYWORDS

Distributed Energy Resource, Monte Carlo Simulation, Gaussian Mixture, Network Congestion, Distribution Network.

## INTRODUCTION

The ongoing energy transition has a large impact on the operation of both medium voltage (MV) and low voltage (LV) distribution networks. Especially, LV networks are gaining more and more attention nowadays due to the accelerated adoption of distributed energy resources (DERs) technologies, such as photovoltaic (PV) panels, heat pumps (HP), and electric vehicles (EV) [1]. Most LV networks were designed and built without considering the presence of DERs and such a drastic increase in electricity offtake and injection. This leads to potential congestion problems related to over- and under-voltages, and overloading of distribution cables and transformers [2]. To address these challenges in the Netherlands, transmission, and distribution network operators (TSO and DSOs) have made significant investments in grid expansion to facilitate the integration of DERs. However, determining which networks require upgrading and to what extent reinforcement is needed to accommodate future DER adoption remains challenging.

As the energy transition is an ongoing and dynamic process, uncertainties exist regarding the adoption and deployment of various DER technologies and the associated increase in electricity demand. Therefore, robust planning for different transition scenarios becomes essential to address potential challenges. In this study, we aim to develop a decision-support tool for DSOs, simulating the capabilities of LV networks in the Netherlands to accommodate DER technologies, accounting for uncertainties in adoption and deployment. The concept of hosting capacity is mostly used in the literature to refer to the maximum DER penetration that can be accommodated in a network segment without violating its technical limits during operation [3], [4], [5]. While this metric is useful, it fails to consider the existing DER installations and does not account for the diversity and volatile nature of future DER expansions. The conventional, static hosting capacity approach poses a significant challenge for DSOs, who must ensure stable and reliable network operations under all plausible DER adoption scenarios.

To bridge this gap, we introduce the concept of remaining hosting capacity. This concept builds on the traditional hosting capacity by accounting for the current level of DER integration and providing a more accurate and actionable metric for DSOs. It offers a forward-looking capacity assessment that anticipates future growth patterns and operational fluctuations of DERs, thereby enabling more informed and resilient planning for network operation and expansion. Our approach focuses not just on the theoretical limits of DER integration, but on the practical and incremental capacity available for future enhancements within existing infrastructure. This dynamic, predictive model aligns better with the unpredictable trajectory of DER adoption and the strategic considerations of modern electrical distribution networks.

This paper presents two simulation models employed in evaluating the impact of DER technology adoption on future congestion in LV distribution networks considering the stochastic consumption and DER usage behavior: stochastic power flow simulations using Gaussian Mixture (GM) models and a data resampling simulation methodology. First, we use the Gaia LV Network Design software's probabilistic load flow module to model each LV network in full detail, from MV/LV transformer stations down to individual households. This allows detailed analysis of, e.g., specific current and voltage data but requires substantial computational resources (approximately 1 hour). Individual LV loads are represented by GM models, which vary per household based on available customer information and DER penetration in the networks. The GM models yield 2304 (96 quarters x 2 day types x 12 months) different probability distributions per year, capturing the behavior of the LV load. In this paper, we calculate the LV load of three networks.

The data resampling methodology employs detailed load and DER profiles to rapidly approximate load demands at the transformer level using Monte Carlo (MC) simulations, considering uncertainties in load profiles, PV generation, and EV charging within the network [6]. It is significantly faster, at 3-5 minutes per run. We simulate numerous scenarios of PV, HP, and EV profiles to evaluate potential congestion issues for each type of network based on the DER penetration of the year 2030, which is obtained from the growth and spread scenario provided by Dutch DSOs. Following this, we conduct a sensitivity

analysis for different levels of DER penetration to investigate the networks' capability to accommodate more DERs in the future.

The existing simulation approaches often evaluate the hosting capacity for a single type of DER, such as PV [2] or EV [7]. These approaches fail to capture the cumulative impact of multiple DER types, including HP, on the distribution network. Such an oversight can lead to inaccuracies in understanding the full spectrum of DER influence on network operations. To address this, our work introduces an alternative simulation approach that considers the interplay between various DER types, thereby providing a more realistic and practical simulation methodology to assess DER's impact on the distribution network. Additionally, the remaining hosting capacity offers a comprehensive view of the effects of varying levels of DER penetration on network operations. This forward-looking perspective equips DSOs with the knowledge of their limits for DER integration based on the current DER penetration level, allowing for better planning and management of network resources. Gaia LV Network Design software's probabilistic load flow module provides a high-resolution picture of the network's behavior including current and voltage analysis under current DER penetration levels, while the data resampling methodology allows a forward-looking approach for strategic planning enabling transformer-level analysis and the anticipation of future congestion arising from DER adoption.

In summary, the proposed methodologies enable us to

- (1) Identify LV networks with congestion problems and assess their severity;
- (2) Identify key elements causing grid congestion, such as increased demand or the penetration of DERs, and quantify their impact on network operation;
- (3) Provide insights into the networks' ability to accommodate additional DERs (i.e., the remaining hosting capacity).

This work is a steppingstone towards a decision support tool for DSOs and consumers, aiding informed choices regarding grid operation, network expansion, and DER investments. It offers valuable insights to network regulators to guide decision-making for sustainable and efficient LV network operation.

The remainder of this paper is organized as follows. First, we present the LV networks and GM models, followed by the simulation methodology with detailed profile data. After this, we provide the simulation setup with the necessary input data. Then, a results analysis is provided along with a sensitivity analysis. Finally, we conclude the paper by providing deployment recommendations.

## **LV NETWORKS AND GAUSSIAN MIXTURE MODELS**

### **LV networks modelling**

An LV network is represented in Gaia in a detailed way up to and including the MV/LV transformer. The external MV network is modeled in the form of an equivalent network (a voltage source in the simple cases considered here). An example of a LV network model is shown in Figure 1. LV cables are represented in detail with a 9-conductor model: three main conductors with a neutral wire, eventually three conductors for public lighting (PL) and their neutral wire, and Protective Earth (PE). Matrices of cable admittances are combined into the overall network admittance matrix taking into account the network topology and conductors connections. The connection of a household is modeled as it takes place in reality, i.e. single phase or three-phase, proper connection of the neutral and PE, etc. Households' electricity demand is represented in a stochastic form using GM models for active power of their baseload electricity demand and individual appliances. Dutch DSOs use network builders for automatic bulk generation of models of their LV distribution networks from Geographic Information Systems (GIS) and other databases.

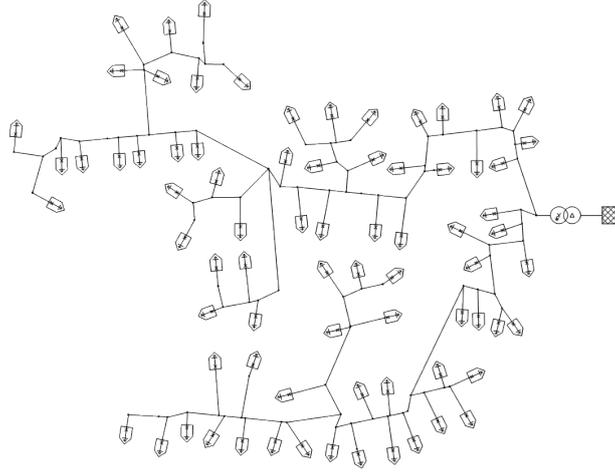


Figure 1. An example of LV network model

### Gaussian Mixture models and probabilistic load flow

Households are represented in a stochastic manner using GM models [8], [9]. A GM model is based on a combination of multiple normal (Gaussian) probability distributions:

$$f(x) = \sum_{j=1}^N \omega_j \cdot \frac{1}{\sqrt{2\pi}\sigma_j} \cdot e^{-\frac{(x-\mu_j)^2}{2\sigma_j^2}} \quad (1)$$

where  $N$  is the number of normal distributions that are used;  $\omega_j$ ,  $\sigma_j$  and  $\mu_j$  are the weighting coefficient, the standard deviation and the mean value of a normal distribution  $j$ . The use of multiple normal distributions allows approximating any empirical probability distribution of the measurement data.

Large appliances such as HP, PV, and EV are modelled separately and in a slightly different way than a base household load. Large appliances such as HP, PV, and EV are modelled separately and in a slightly different way than a base household load. The base household load is represented by up to 4 normal probability distributions. Appliances are modelled with 2 normal probability distributions, one of which has a fixed mean value nearly equal to zero and a small standard deviation (representing the switched-off/standby state of an appliance). Weighting coefficients for each component of a GM model vary with time, namely a quarter of an hour, working or weekend day, and a month of a year. This means that in total 2304 (96 quarters x 2 day types x 12 months) different GM probability distributions can be modelled over a year. An illustration of base load and PV GM models of a household at a specific time instant is given in Figure 2. The flowchart of GM model simulation is presented in Figure 3 (left).

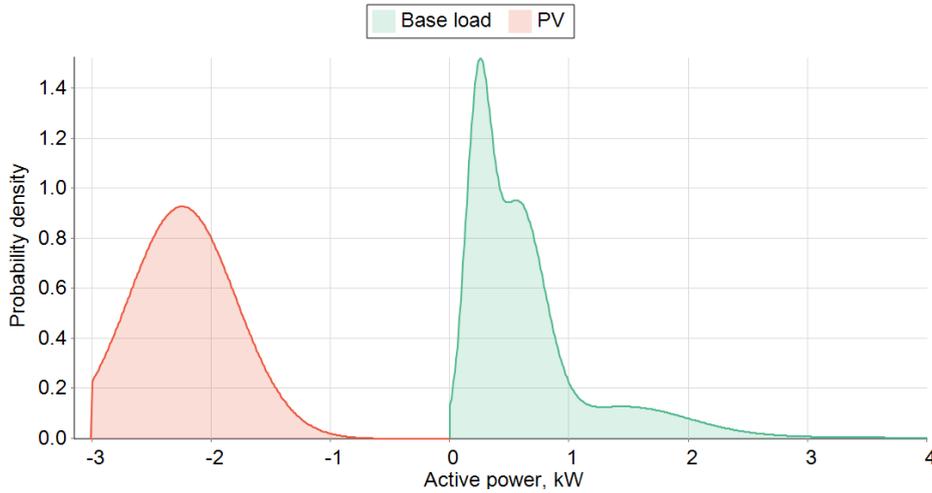


Figure 2. Probability distributions of base load and PV active powers of a household for a given time.

Parameters of GM models are obtained from the measurement data of smart meters or appliances, by using an expectation maximization algorithm. If smart meter data is used (in case of base load), it is assumed that the measurements are ‘clean’, i.e. excluding separately modeled appliances. If there are such appliances present, disaggregation techniques should be applied first. Further, the data has to be classified into separate types using clustering or other data science techniques. Currently, only standard annual energy consumption brackets are used for the classification. Measurement data of an appliance, necessary for determining GM model parameters, assumes that profiles for a specific type of appliance are provided.

After parameters of GM models are obtained, they can be coupled to a specific household connection, for instance, based on yearly energy consumption, type of house, and other criteria. In general, the number of different GM models is limited since the model of one type can be assigned to many household connections. Note that during the probabilistic power flow simulations (see below), the sampled electricity demand values for each house are different, even if they stem from the same GM model. Sampled values can either be uncorrelated (e.g. for base loads) or almost fully correlated (e.g., for PV). The remaining appliances (HP, PV, EV) are assigned according to specific allocation scenarios provided by DSOs. These local allocation scenarios are known as “growth and spread scenarios” because they are based on models of average technology uptake (growth) and regional differentiation (spread).

Finally, after GM models of base loads and appliances are coupled to each household, a probabilistic load flow can be executed. For this, MC simulation is used, and the solution of a deterministic nonlinear power flow problem for each random sample set of household powers in a network is obtained. Sampling of active powers of households and appliances is done according to the Latin hypercube principle [10] in order to reduce the number of random samples drastically and at the same time to cover the sampling space reasonably well. The empirically determined threshold is 1000 samples. After the MC load flow results are obtained, the statistical properties of powers, voltages, and currents for all network objects can be determined. Typically, specific percentile values of voltages at household connection points and currents through cables and transformers are of importance. However, in this work, only the loading of secondary substations has been considered. This provides a single-point estimate for the impact of a certain growth and spread scenario in a specific LV network.

## DATA RESAMPLING SIMULATION

We use a data resampling method with detailed load and DER profiles to evaluate the load demand at the transformer level for various DER penetration levels. Through MC analysis, we consider the

uncertainty of which house is equipped with which type of DERs, as well as the penetration of different DER types in the networks. A flowchart of the simulation methodology is presented in Figure 3 (right).

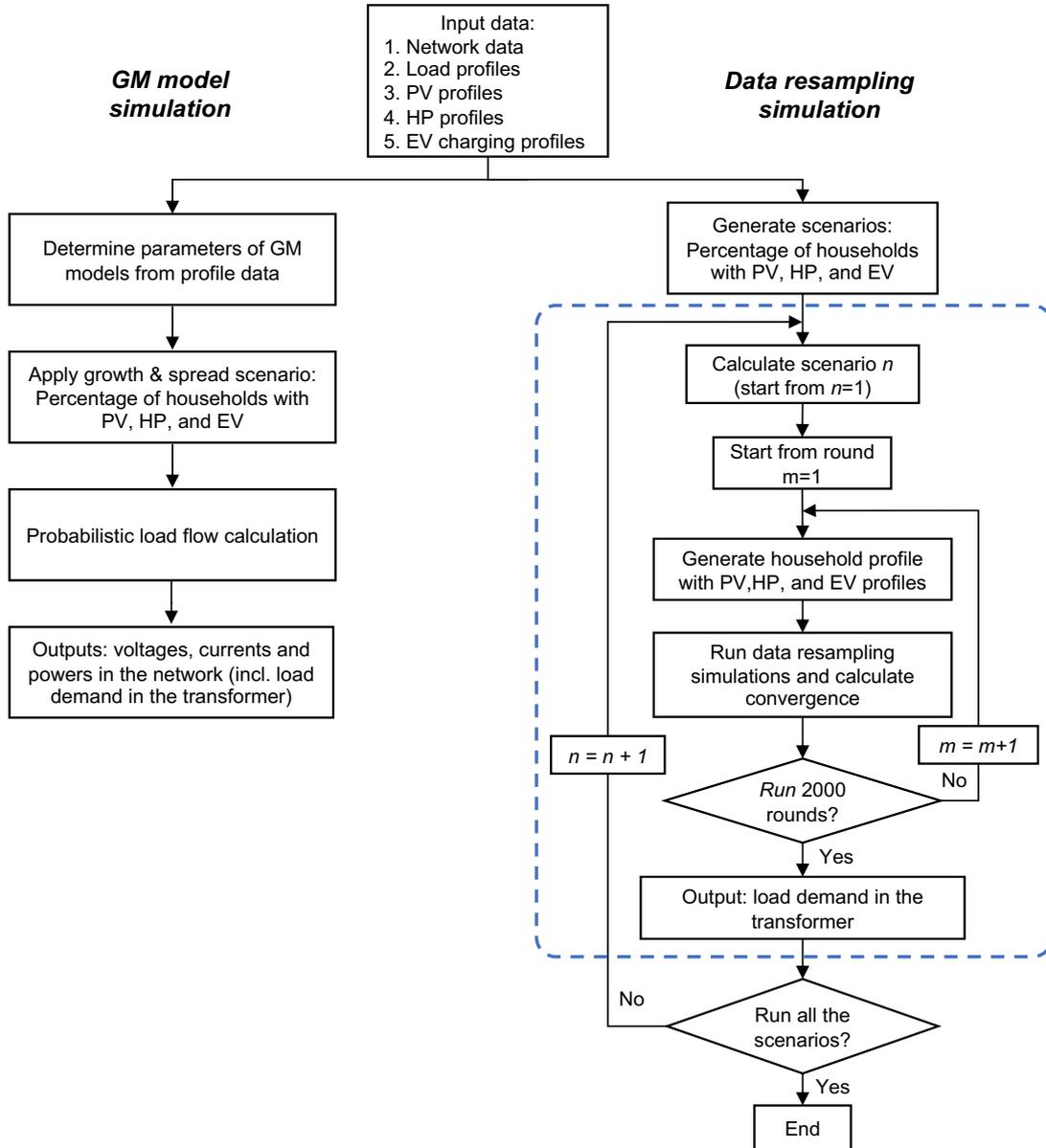


Figure 3. Simulation methodology flowchart for GM model simulation (left) and data resampling simulation (right)

The input data includes network models and datasets with profiles of base load, PVs, HPs, and EVs. Among them, the network model detailed information of each consumer in the network with annual load consumption and its corresponding DERs information, including installed PV and HP capacity, EV data with 4-digit postal code assumed in 2030. Based on this information, hourly consumption, and generation data of each household for the year is randomly selected from the given datasets, including load profiles, PV generation, HP, and EV consumption. The next steps involve (1) generate scenarios for various percentages of households with these DER technologies, (2) run data resampling simulation of each household to compute their power need from the network or power injection to the network and aggregate the load demand of all households in the network. To monitor the convergence of our simulations, we employ the Wasserstein Distance (WD) [11] to measure the difference between the distributions of transformer load after addition each simulated year. We conducted 2000 MC simulation rounds (i.e. years) and measured the WD between subsequent load distributions. Our observations revealed that after 1500 rounds, the WD begins to plateau, suggesting minimal changes in the

distributions thereafter. Based on this, we concluded that running the simulations for 2000 rounds is sufficient to ensure convergence, thereby providing a stable basis for analysis.

## REMAINING HOSTING CAPACITY

In the scientific literature, hosting capacity is defined as the amount of DER that a distribution network can accommodate without violating operation constraints [3], [4], [5]. Remaining hosting capacity is here defined as the network's capability to accommodate additional DERs based on the existing DER capacity within the network without violating its technical limits:

$$\text{Remaining hosting capacity} = \text{Total hosting capacity} - \text{installed capacity}$$

It's important to note that different DERs, such as PVs, EVs, and HPs, have distinct characteristics, with PV generation representing power injection into the grid, while EVs and HPs represent offtake profiles. The remaining hosting capacity is further split into two components: remaining injection hosting capacity and remaining offtake hosting capacity.

## SIMULATION SETUPS

We use the methodology introduced above to generate scenarios for several distribution networks. The networks are from the Dutch DSOs Alliander and Enexis. The growth and spread scenario for penetration levels of different technologies for the year 2030 of the three selected networks is summarized in Table 1.

Table 1: Growth and spread scenario for penetration levels of different technologies for the year 2030 of Networks Alliander and Enexis.

Networks	Household connections	EV (%) (charging capacity (kW) point	PV (%) (installed capacity (kW)	HP (%) (installed capacity (kW)	Transformer capacity (kW)
Alliander Arch5 Net2	246	15 (418)	100 (345)	5 (73)	400
Alliander Arch6 Net1	257	46 (1287)	100 (966)	13 (202)	400
Enexis Arch1 Net2	411	3 (132)	100 (585)	16 (367)	630

The base load data is obtained from the publicly open data from UK Smart Meters [12]. The HP data is developed by TNO [13]. PV profiles are obtained from the Network Revolution website [14]. The private EV charging sessions were generated by TNO and Elaad using a simulator called Albatross. Different characteristics of neighborhoods, such as location and their influence on EV charging behavior are considered there.

Based on these input data, we first randomly assign DER assets among the households, representing the uncertainty regarding the uptake of specific DER assets by individual households. However, we ensure the percentage of households with DERs aligns with predetermined values from the growth and spread scenario for the year 2030, as outlined in Table 1. This allows comparing the two methods above, and to identify whether the network has congestion problems. In a second set of simulations, set-up as an elaborate sensitivity analysis, we determine the remaining hosting capacity by gradually increasing the amount of DERs in the networks without congestion problems.

## RESULTS ANALYSIS

### Comparison between the results of stochastic power flow simulations using GM models and data resampling simulation

Figure 4 illustrates the relations between the 5<sup>th</sup> (left) and 95<sup>th</sup> percentile (right) of the loading of the transformer on each considered time step, as derived from the GM models and the resampling method.

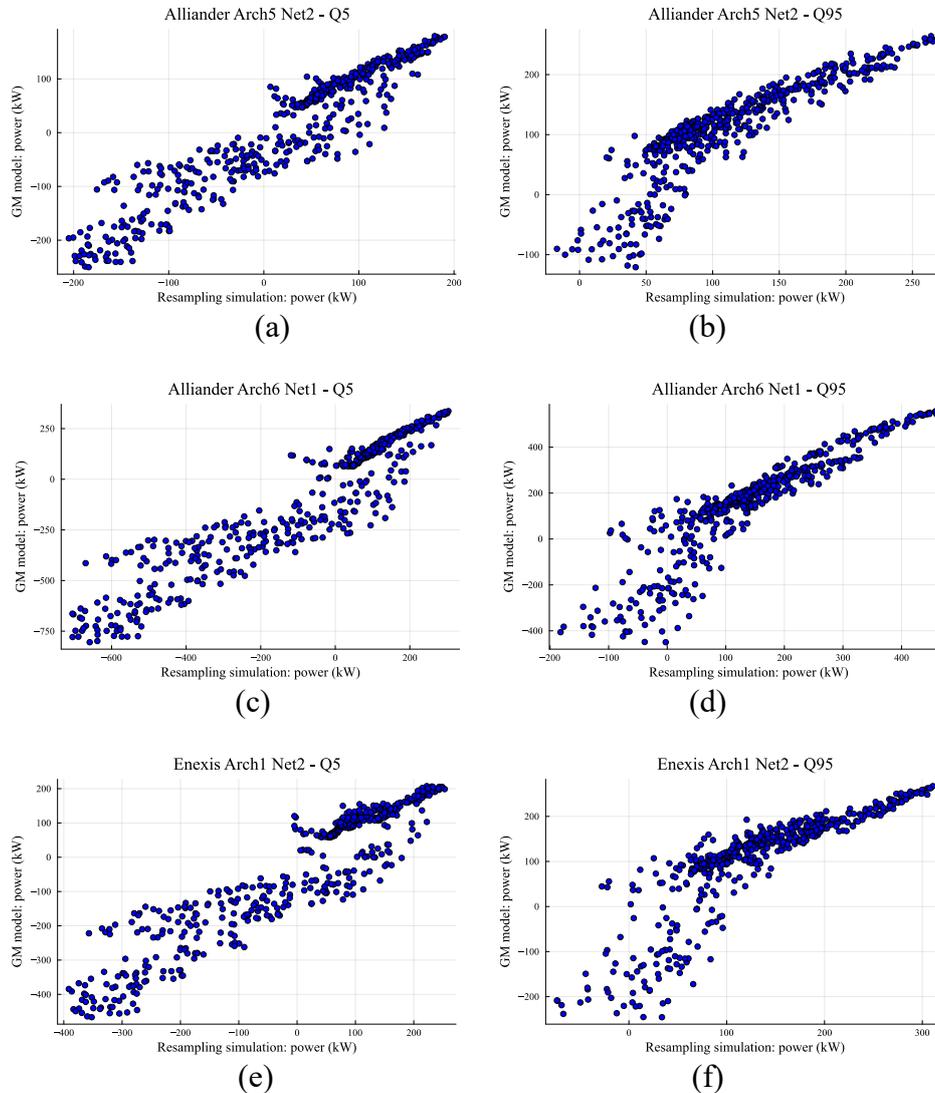


Figure 4. Comparison between the results of GM models and data resampling simulation, left: 5% percentile results, right: 95% percentile result.

The 5<sup>th</sup> percentile captures transformer loading during moments of high injections, while the 95<sup>th</sup> percentile results indicate the loading of the transformer during moments of high offtake. When examining the 5<sup>th</sup> and 95<sup>th</sup> percentile results, it is evident that the two simulations provide similar results (high correlation), although the results do not exhibit a perfect linear relationship. This correlation indicates that both models tend to respond similarly to the variables (such as PV, HP, and EV penetration) influencing network usage. Moreover, the Q5 results match well for large infeeds (negative numbers) - where the results are most critical for congestion analysis. Similarly, the Q95 results match well for large demands (positive numbers). It reinforces the value of utilizing diverse models in understanding network dynamics. Additionally, we calculate the minimum and maximum of the 5<sup>th</sup> and 95<sup>th</sup> percentiles of each day for the results obtained above of both models across each network, to obtain the distributions

of peak injections and offtakes. These distributions are depicted in Figure 5. Both of the results have the same conclusion that networks Alliander Arch5 Net2 and Enexis Arch1 Net2 are currently performing well within the DER penetration levels based on the growth and spread scenario given by DSOs. In contrast, the Alliander Arch6 Net1 network is experiencing congestion issues, primarily due to PV injection.

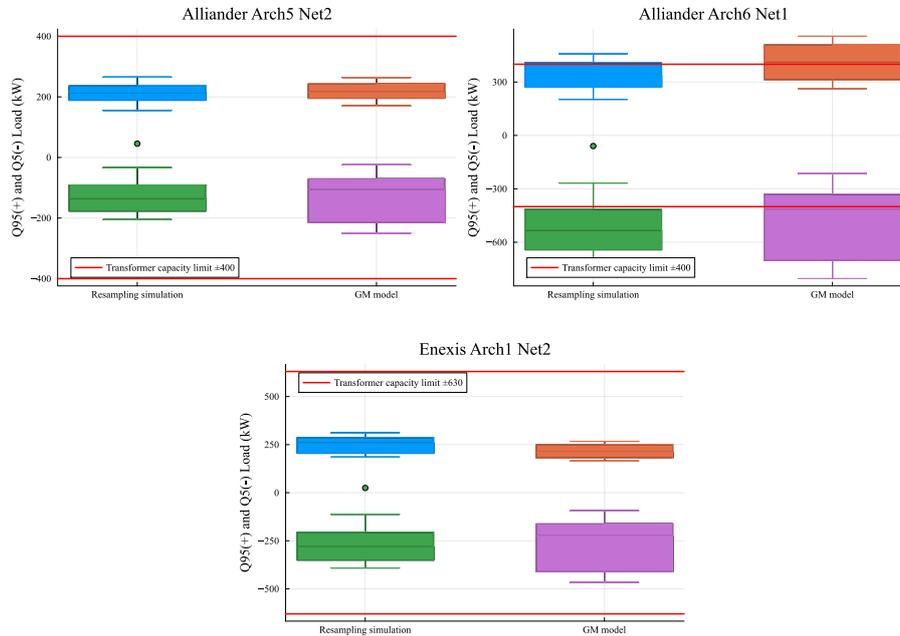


Figure 5. Distribution of minimum of 5% and maximum of 95% percentile values of each day for each network (red line represents for the transformer capacity limit)

### Remaining hosting capacity

We calculate the load demand at the transformer level for various percentages of PV, HP, and EV, starting from 0 up to 100% with a step of 10%. For this analysis, the forecast installed PV capacity was allocated to a subset of households (approx. 45% for the case analysed below), so that sensitivities to higher and lower penetration levels could be considered. Figure 6 summarizes the results, covering each DER penetration percentage scenario of the network Alliander Arch5 Net2 (for the other networks, results are similar). The x-axis corresponds to the percentage of HP, the y-axis to EV, and the z-axis to PV. The load demand for each unique combination of HP, EV, and PV penetration is denoted by circles within the graph. The green plane represents the maximal DER hosting capacity of the network. The results indicate that peak power injection to the network is mainly caused by PV installation at the households (see left panel). However, peak power offtake from the network is mainly influenced by the numbers of EVs and HPs installed in the households, as shown on the right panel.

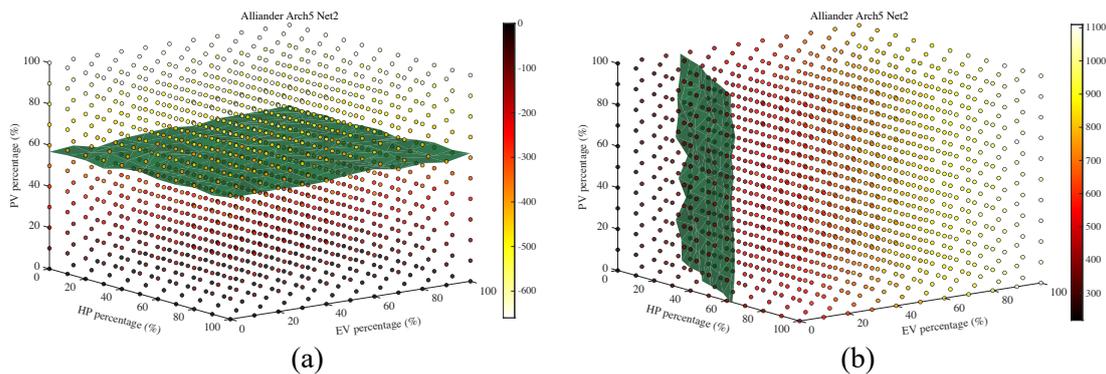


Figure 6. Minimal power injection (a) and maximal power offtake (b), as indicated by the different colors of the circles, from the data resampling simulation under various percentages of PV, HP, and EV in network Alliander Arch5 Net2. The green surface is the transformer capacity limit (400 kW for the example network).

We extract the 95<sup>th</sup> percentile of the maximum power offtake on each time step (or 95<sup>th</sup> percentile for injection) at the transformer level from the data resampling simulation of each DER penetration percentage scenario for the networks without congestion problems (Alliander Arch5 Net2 and Enexis Arch1 Net2). The results for the two networks are summarized in Figure 7.

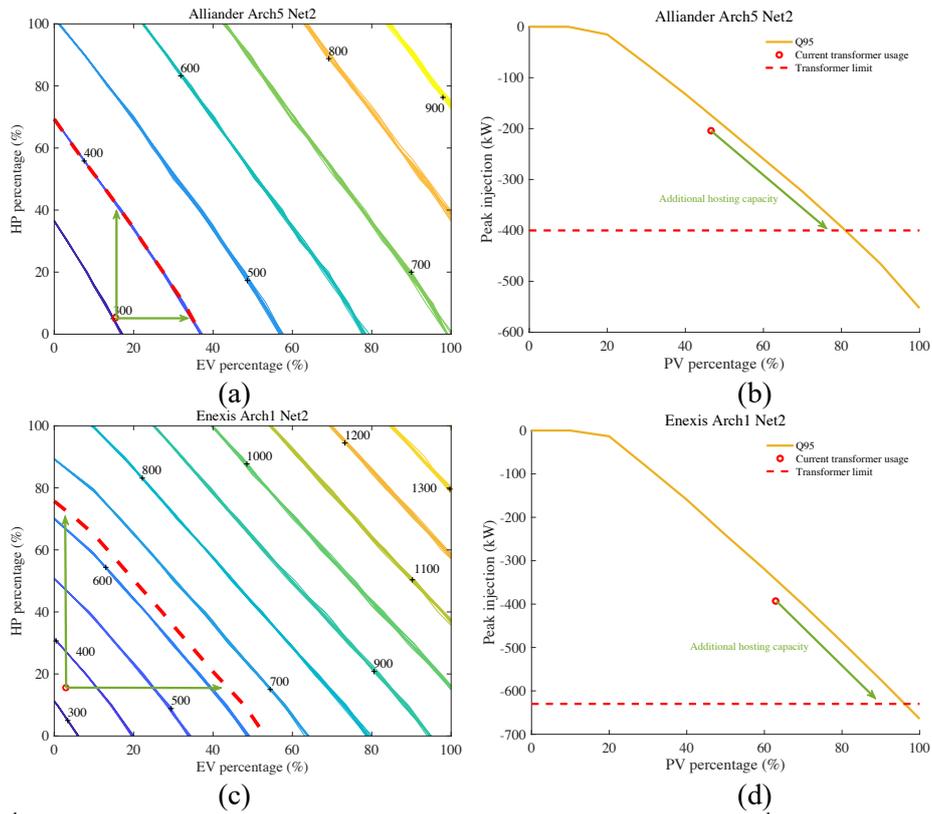


Figure 7. 95<sup>th</sup> percentile of the maximum offtake (left, contourlines) and 95<sup>th</sup> quantile of the minimum power injection (right, yellow line) under various DER penetration percentages for the two networks.

The remaining hosting capacity of DER technologies of the two networks is indicated by the green arrows. According to the specific growth and spread scenarios provided by DSOs, it is evident that networks Alliander Arch5 Net 2 has the capability to accommodate more DERs. The presented results are illustrative examples to demonstrate the functionality of the simulation methodology. Compared to GM models, the data resampling simulation approach offers a fast means to estimate power offtake and injection at the transformer, which informs the decision to test if the network is congested or not through detailed simulations. For networks without congestion problems, our sensitivity analysis assists in calculating remaining hosting capacity. This information equips DSOs with the insight required to take appropriate measures in response to various and dynamic situations.

## CONCLUSIONS

The dynamics of electricity distribution are rapidly evolving due to increased electrification and DER penetration, presenting unprecedented challenges for DSOs. For example, the unpredictable nature of DER adoption patterns requires strategic planning of network upgrades. In this paper, we use the concept of remaining hosting capacity as a metric to assess the ability of distribution networks to accommodate additional DERs, considering the current level of DER penetration. We explore two simulation

methodologies: the first employs probabilistic load flow simulations and GM models which provide detailed insight into the currents and voltages across network components, but are computationally intensive. The second is a data resampling method that leverages detailed load and DER profiles for a rapid assessment of loading of the transformer, thus swiftly pinpointing potential congestion issues and identifying the primary factors contributing to congestion. Our sensitivity analysis, built upon the resampling methodology, enables the calculation of the network's remaining hosting capacity. To demonstrate the efficacy of our methodologies, we conducted a case study on three Dutch networks. The findings confirm that both probabilistic power flow based on GM models and the resampling simulation methodology tend to respond similarly to the variables, illustrating the ability to use diverse models for understanding network dynamics. DSOs may choose the most suitable approach depending on their needs: whether it is to obtain a detailed network analysis for a given scenario or to quickly scan for possible congestion issue across a range of scenarios.

## **ACKNOWLEDGEMENTS**

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