Modelling the Hosting Capacity of Orion's Low Voltage Network for EV Charging

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EEA Conference & Exhibition 2021, 30 June – 1 July, Wellington

Abstract

Forecasting future electricity demand on low voltage (LV) distribution networks is particularly challenging in the face of new technologies such as Electric Vehicles (EVs) where the uptake and charging behaviours are highly uncertain. To support their planning processes, Orion has undertaken a staged assessment of LV network performance in the face of increasing levels of EV charging. The first stage of EV modelling involved a high-level deterministic simulation of all Orion's LV networks to identify areas that may be more vulnerable to constraints. From the results of the first stage, a smaller subset of vulnerable LV networks was selected for further modelling. This paper focuses on the second stage of the assessment process where 236 selected distribution transformers and their downstream LV networks were modelled using a probabilistic methodology developed by the EPECentre. This model captures a wide range of scenarios and encompasses data from New Zealand-centric inputs, including national travel surveys, household smart meter demand profiles and the current NZ EV fleet composition. In order to meet the large simulation burden required of a probabilistic methodology, a fast power flow solver was developed. This paper reports the forecast congestion levels and probabilities that these selected circuits may face as EV charging increases on Orion's network. The learnings and challenges of working with imperfect distribution asset data sets to develop these models are also shared, such as approximating LV phase imbalance and electricity demand profiles with only the LV distribution transformer's Maximum Demand Indicator (MDIs) measurements.

1. Introduction

Light passenger Electric Vehicles (EVs) have roughly doubled in the last two years from 13,000 in 2019, up to 26,000 in March 2021 [1]. This growth has been fuelled by a combination of reducing prices for EV technology and greater choice, particularly of pure EV models with larger battery capacities. The majority of EV charging is anticipated to occur at home. Ownership of light pure-electric EVs is skewed heavily towards individuals with 77%, compared to just 19% owned by companies [1]. This raises the question as to how low voltage (LV) networks will respond to this significant increase in residential load.

This paper discusses Orion's pioneering approach to understanding the effect of EV charging on their distribution network. A methodology is presented to assess a subset of circuits that are expected to be most at risk of overloading using a probabilistic analysis developed by the EPECentre. Data challenges and approaches to best represent the base loading and capture the uncertainty of what EV charging may look like are discussed. LV monitoring data is presented for an example subnetwork, to benchmark the power flow simulations and processes before EV loads are added. Detailed results for the example subnetwork and aggregated results for the subnetworks investigated are presented. A subnetwork is defined as the circuits downstream of and including the LV distribution transformer.

2. Motivation and Background

Traditionally, distribution companies have taken a largely reactive approach to managing their LV assets. This strategy typically involves tracking transformer peak loadings, but otherwise relies on customers to report localised power quality issues. In the past, this strategy was effective as residential loads could be easily predicted, thereby identifying networks to be upgraded accordingly. However, distributors are beginning to see a rise in uptake of Distributed Energy Resources (DERs) such as photovoltaic (PV) panels and EVs as customers seek to decarbonise. These technologies have the potential to disrupt traditional household demand patterns and cause high levels of congestion on LV networks, if not suitably managed.

To assess the impacts of a growing EV population, Orion collaborated with the EPECentre on a high-level deterministic study in 2019 (Phase 1). In that study, over 10,000 LV subnetworks were assessed to provide an indication of the quantity of transformers, cables and lines that could experience some form of current or voltage constraint under increasing EV load. Considering the size of the data set and the deterministic approach, the variability in load profiles was not be taken into account, thereby giving no indication of how frequently constraints could occur.

From the results of the Phase 1 study, 236 of the most vulnerable LV subnetworks were selected for a more targeted probabilistic study (Phase 2). The sensitivity of the selected LV subnetworks to factors such as phase imbalance, battery sizes, travel distances and charging times. A fast power flow solver was developed to speed up the analysis.

3. Methodology

3.1. Probabilistic Modelling Approach

The goal of probabilistic modelling is to capture the temporal diversity in both base loads and EV charging loads and to depict numerous EV load scenarios, with varying EV models, charger ratings and a range of EV user behaviours. This diversity of load scenarios captures a richer view of the possible network performance at the cost of increased computation. This modelling uses a time resolution of a half-hour (HH) and looks at the loads across a worst-case winter week (336 HHs). The number of EVs in a subnetwork is increased from zero (the base load case), to EV penetrations of 10, 20, 30, 40, 50, 75 and 100%. The EV penetration is defined as the percentage of residential ICPs with an EV.

The probabilistic nature of the modelling means that a large number of simulations are undertaken for each EV penetration for each subnetwork; typically 2,000 scenarios with differing combinations of base loads, EV loads and locations. This results in a distribution of values for each quantity of interest. To simplify these results, key percentile values are presented as depicted in Figure 1. For currents and transformer powers, the higher percentiles right of the median are used e.g. P85.7, P99.4, P99.97 to understand asset overloading. For voltage the bottom percentiles are used, i.e. P0.03, P0.6, P14.3 as for EV charging we are looking at voltage drop along circuits. The percentiles are also interpreted in terms of the number of half-hour (HH) trading periods for which the quantity is expected to be above (or below) a given value in the study week. Note the 0.1HH is a one in ten chance that the quantity could be above or below the specified value in a week.

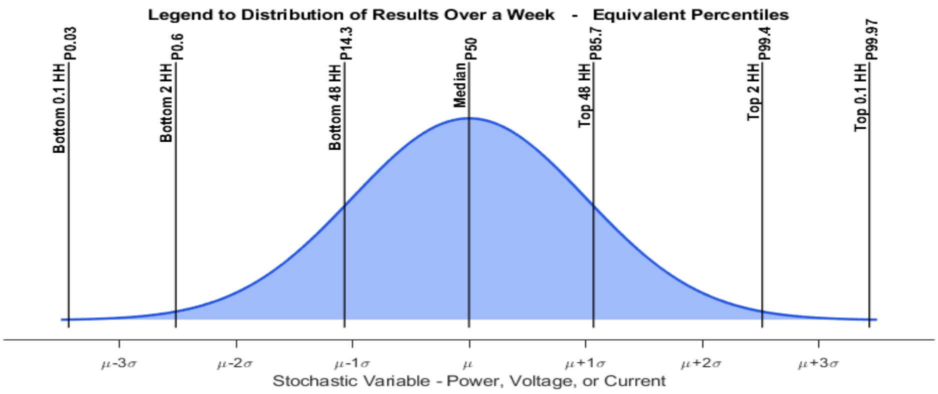

Figure 1: Graphical representation of the statistical results presented, identifying the percentiles of interest and the equivalent number of half-hours (HH) out of a week (336 HHs).

3.2. **Power Flow Approximation Method**

To analyse the 236 subnetworks of interest, would require in excess of 1 billion power flows to be solved. The speed of recursive power flow solvers, is found to be too slow. Instead, an approximation method was developed, which improves speeds by a factor of 10. This method uses Taylor Series expansions, formed around known solutions of the power flows or initial points. The two key observations related to this method are as follows. First, the accuracy of the approximation is dependent on the number of initial points based on which the approximations are made. Second, a linear approximation is normally applied for solutions, but as the power, voltage and current limits are approached, a quadratic approximation is applied for improved accuracy.

3.3. **Network Data Inputs and Challenges**

3.3.1. **LV network topology**

Orion provided a database that detailed the LV asset types, connectivity and loads (both commercial and residential) for 236 subnetworks of interest. While this data was sufficient to recreate the subnetworks to allow power flow modelling to be undertaken, it also presented several challenges.

To reduce the number of nodes along LV branches, Orion's geographic information system (GIS) does not record precise connection points. Instead, ICPs' positions are represented in GIS graphics, but only associated with a branch in the underlying connectivity model. Therefore, ICPs were modelled with connections at evenly spaced intervals along the length of the branch. The phase connection for ICPs is also not recorded is the GIS.

Due to the age of some areas of Orion's network, several branches are recorded as 'unknown'. For the subnetworks of interest, the branch type was unknown for 19% of branches and the number of phases for a branch were unknown for 6%. These unknown branches are typically short and usually occur at tee-offs to single customer premises, thereby having a minor impact on modelled results. However, in some instances, an unknown branch can occur along the main trunk of an LV feeder and affect downstream results.

3.3.2. **Base Load Assignment**

To model the 'worst case' week, the base load profile (ICP load at 0% EV penetration), for each subnetwork needed to be established. Transformer maximum demand indicators (MDIs) provided peak phase current magnitudes for each subnetwork during winter. However, the demand profile over a week is not recorded. Due to the low volume of EVs on Orion's network (<2% network wide), it has been assumed that MDI values do not include EV load.

Residential load profiles were assigned from an anonymised set of half-hourly smart meter data from ~1800 Christchurch-based households from 2015. The highest network load week (21-28 June) was selected for simulation. To ensure simulated loads matched those on the subnetworks, MDI data from the 2019 winter season was used as a reference point. Algorithms were developed to assign different ICPs to each phase based on transformer MDI values and select smart-meter load data based on peak load characteristics. Load data was categorised by the maximum demand peak in a week and subsets of residential smart-meter data were used for restricting load allocation to better align loads to match the given MDI's. A minimum subset of 500 households was maintained to ensure sufficient diversity.

3.3.3. Commercial ICP Load Representation

To accurately assign load profiles to ICPs on a feeder, it was important to have representative commercial load profiles, particularly for the large commercial loads. Orion provided half-hourly load data for the commercial ICPs where available, and where unavailable, representative data was used based on the Australian and New Zealand Standard Industrial Classification (ANZSIC) code and scaled by its monthly consumption data. Commercial ICPs were assigned fixed load profiles in the simulations, across all scenarios and EV penetration levels.

3.3.4. EV Load Scenarios Distributions

As this study was targeted at residential EV uptake, EV loads were only assigned to residential connections. For each scenario, EV load profiles over a week were generated for each household assigned an EV. Characteristics of the EV, such as battery capacity, charger rating, charging behaviour and the EV's travel over a week were randomly assigned according to distributions. The scenario selection process is depicted in Figure 2. Additional factors such as anxiety factor and EV preheat were also included.

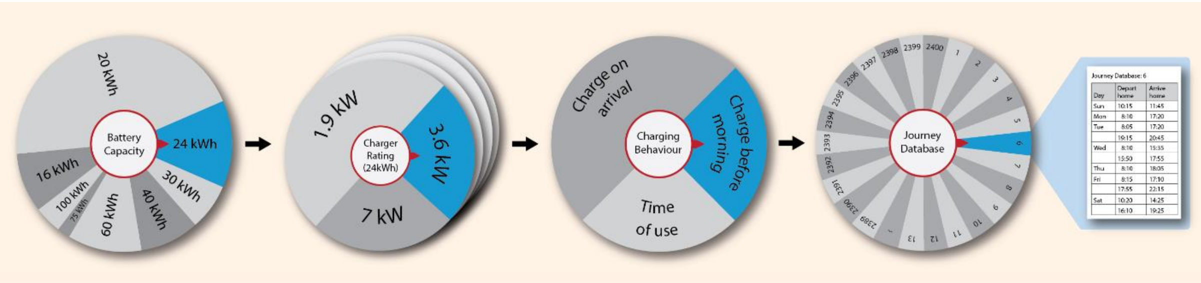

Figure 2: Scenarios were selected to create an EV Load profile based on distributions such as battery capacity, charger rating, charging behaviour and a set of journeys undertaken over a week.

The distribution of EV battery capacities was calculated from "electric only" NZTA fleet data as at 30 June 2020 [2] and binned into eight discrete battery capacities between 16kWh to 100kWh. EV capacity degradation was excluded, except for the Nissan Leaf model, where battery degradation of 3% per year was assumed from the date of manufacture. The most common battery capacity was 20kWh largely consisting of degraded Nissan Leafs. A distribution of EV charger ratings was established for both single phase and three phase connections for each battery capacity of interest taking into account the maximum on-board charger rating of EV models and some Orion user surveys [3]. EV journeys were modelled from the NZ Ministry of Transports journey data surveys for light transport between 2015-2018 [4]. This assumes that the fossil-fuelled journeys are representative of EV journeys. The data set contained over 3700 households, with multiple vehicles. High error rates in the survey data resulted in a significant reduction in the useable data, leaving ~ 2500 vehicles for the study.

4. Model Validation

In 2019, Orion initiated a programme to roll-out LV monitoring at distribution transformer sites, particularly targeting those with a higher risk of congestion. Of the 236 subnetworks modelled, 20 had over a year's worth of monitoring data available, which provided the opportunity to compare the distributions of modelled MDI-scaled base load to measured winter week data. This section examines an example subnetwork, with LV monitoring installed, as depicted in Figure 3. The example subnetwork was selected due to its high proportion of residential ICPs, mix of overhead and underground reticulation and available monitoring data.

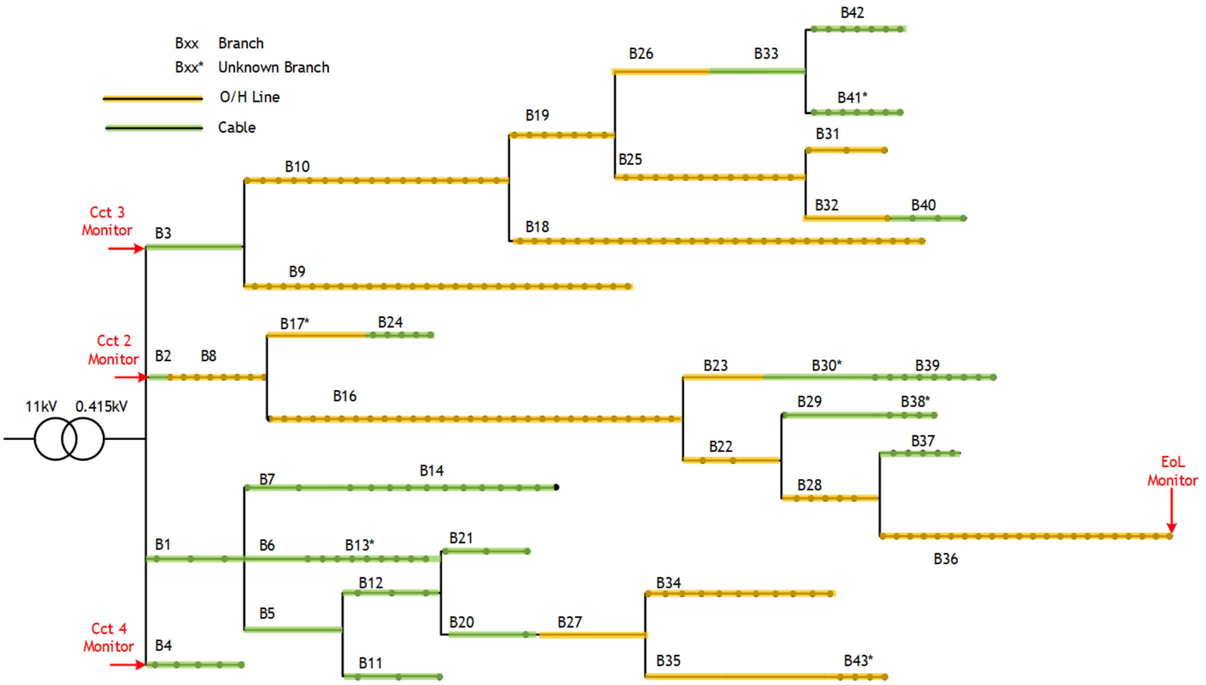

Figure 3: Schematic for subnetwork #129 with 265 ICPs, including 10 commercial ICPs and the remaining residential ICPs.

Figure 4 illustrates the distribution of measured current values for circuit 2 over the peak winter week for the example subnetwork in comparison to the percentile values produced by the base load probabilistic model. Table 1 summarises the variances in percentiles for the currents of the three circuits that were monitored.

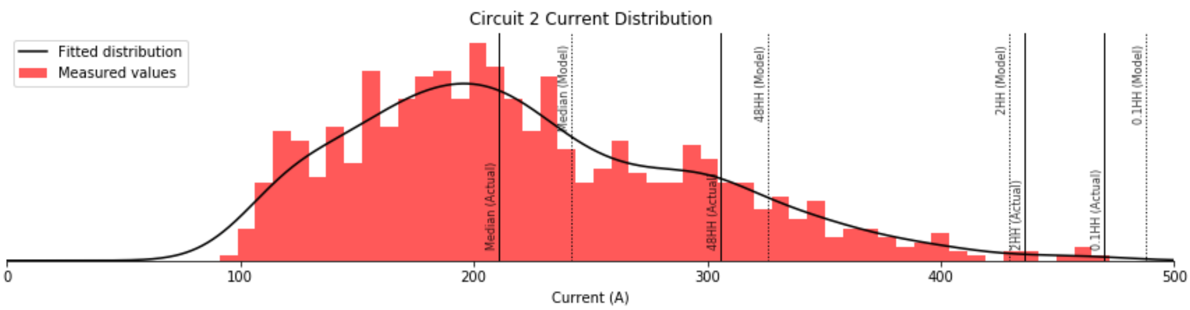

Figure 4: Comparison of modelled vs actual current distributions for circuit 2 over the peak winter week.

Table 1: Comparison of modelled versus actual current percentiles for the peak winter week, for circuits 2,3 and 4.

	Circuit 2 I (A)			Circuit 3 I (A)			Circuit 4 I (A)		
	Model	**Actual**	**Variance**	**Model**	**Actual**	**Variance**	**Model**	**Actual**	**Variance**
Median	241.7	210.6	15%	137.9	153.5	-10%	16.3	14.0	16%
Top 48HH	325.9	305.9	7%	177.3	193.6	-8%	25.2	23.5	7%
Top 2HH	429.6	435.7	-1%	224.9	243.4	-8%	40.3	41.3	-3%
Top 0.1HH	487.7	470.2	4%	255.2	269.7	-5%	49.9	45.9	9%

Due to the range of possible ICP configurations with the information given, it is not expected that the modelled distribution will align perfectly with measured results. This is particularly evident in the variance in median values, which could be due to attempting to load match from only a maximum value (the MDI). However, when comparing the top 2HH current values (highlighted in the table) across all three measured circuits, the variance between modelled and actual values were consistently below 10%, which show a good translation from transformer MDI values to ‘peak’ circuit loadings. Current sensors for circuit 1 were not installed last winter, so transformer and circuit 1 loadings are unavailable.

Voltage measurements at the LV bus during peak winter week load, show good agreement with modelled values. However, there were much larger variances in end of line (EoL) voltages on circuit 2 (Table 2). Regulations stipulate that voltages should remain within 6% of the nominal voltage (230V), therefore variances of up to 7% between the modelled and actual EoL values should be questioned. A potential cause of this variance may be due to EoL readings being taken after the typical winter peak (August rather than July peak assumed by the model). This hypothesis is supported by the variance in bus voltage distributions between July and August (Figure 5), an effect which would only be exacerbated at the EoL.

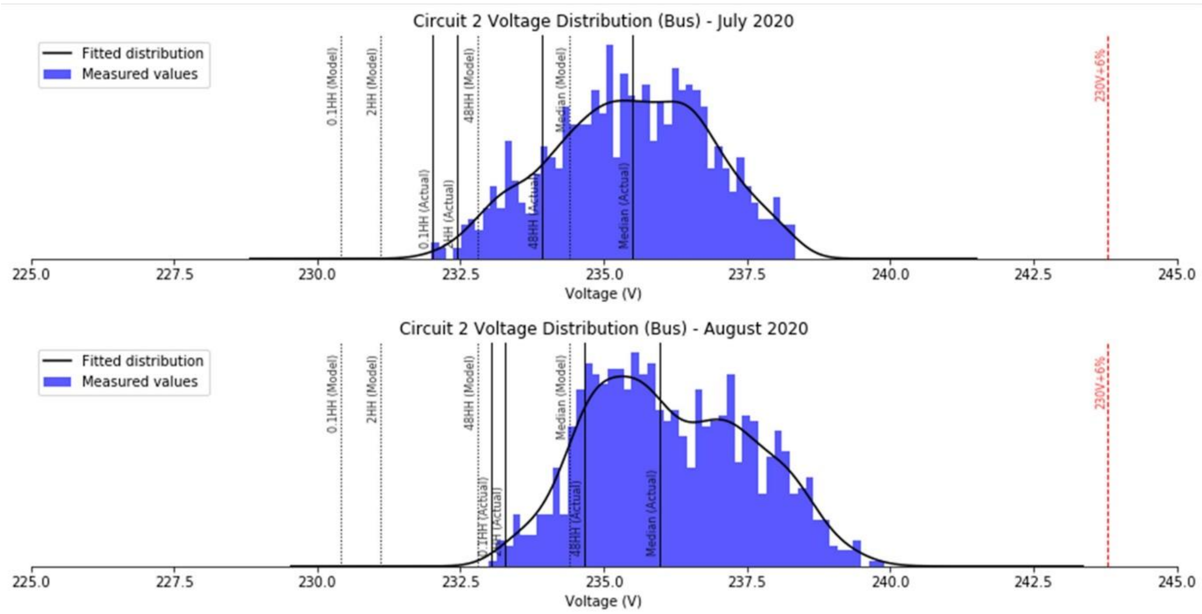

Figure 5: Comparison of modelled vs actual bus voltage distributions over winter week showing July/August variability

Table 2: Comparison of modelled versus actual current percentiles for LV bus (or close to) and circuit 2 (EoL)

	Bus (V)					Circuit 2 EoL (V)		
	Model	Actual (July)	Variance (July)	Actual (August)	Variance (August)	Model	Actual (August)	Variance (August)
Median	234.4	235.5	-0.5%	236.0	-0.7%	217.1	225.7	-3.8%
Bottom 48HH	232.8	233.9	-0.5%	234.7	-0.8%	209.4	219.6	-4.7%
Bottom 2 HH	231.1	232.4	-0.6%	233.3	-0.9%	199	210.6	-5.5%
Bottom 0.1HH	230.4	232.0	-0.7%	233.1	-1.1%	193	207.6	-7.0%

5. Results

This section reports probabilistic modelling results for the example subnetwork validated in the previous section and aggregated results for the 236 subnetworks assessed in the study.

5.1. Example Subnetwork Results

From the recorded winter MDI values, it is noted that phase A has a 20% higher MDI current than phase B or C. Figure 6 shows box and whisker plots of the distribution of maximum phase currents for the 2,000 scenarios modelled per EV penetration. The measured MDI values are marked with a black dash. The 50th percentile is at the centre of each box with the edges representing the 25th and 75th percentiles. The whiskers extend to the 1st and 99th percentiles and the outliers are represented as dots with the three lowest and highest outliers presented for clarity. It is noted that the MDI is close to the median result for phase A, while for phase B and C the median is slightly below the MDI values. At 100% EV penetration, the median maximum current for phase A has increased by 26%.

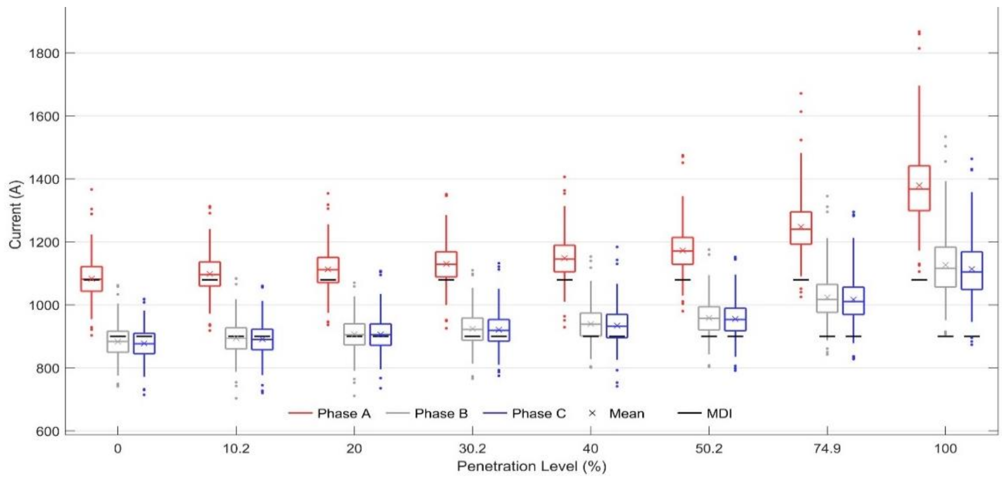

Figure 6: Distribution of maximum phase currents over all the scenarios for the subnetwork as a function of EV penetration.

Results for the voltages for three worst case branches are presented in Figure 7 as a function of EV penetration for the various distribution values of interest. Note that the 48HH voltages lie below the 0.94 p.u. regulated voltage limit for all EV penetration levels indicating a risk of sustained undervoltage during the peak winter week without any EVs present.

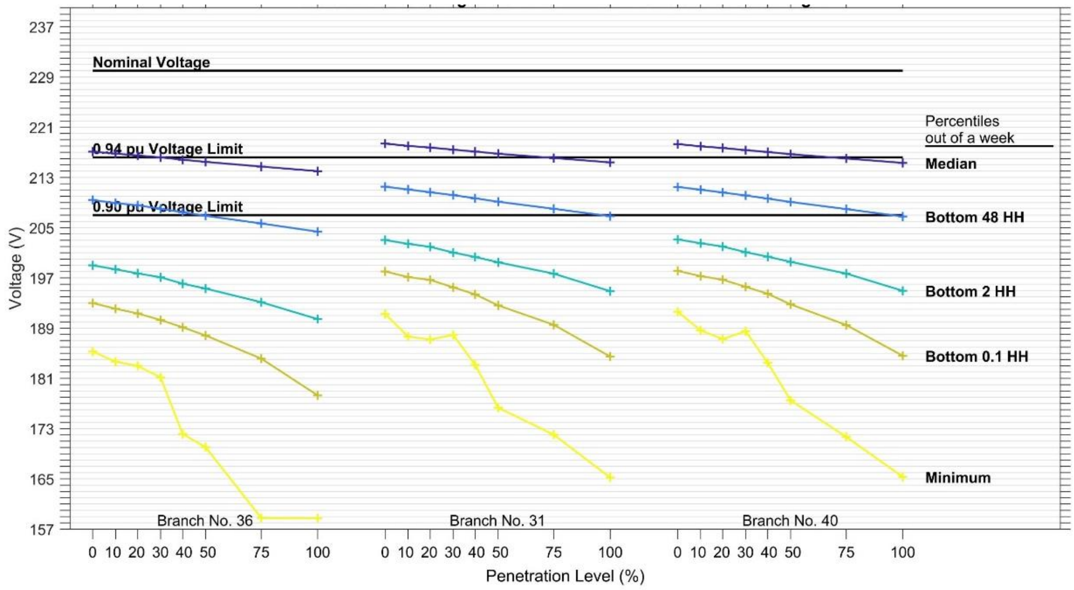

Figure 7: Voltage results for worst three branches on the example subnetwork as a function of EV penetration.

5.2. **Aggregated Results**

Aggregated results include the analysed 236 subnetworks (4,189 branches). The transformer constraints do not appear to be significant, so only voltage and branch current constraints are presented. Figure 8 shows that a significant number of branches have some level of voltage constraint, even before EV load is added to the model. Looking at the 2HH constraint, 20% of branches have a constraint, rising to 30% at 100% EV penetration. If the more rigid 0.1HH constraint is considered, at 100% EV penetration, this rises to 44% of branches.

Figure 9 presents the combined results for all branches in the 236 subnetworks that register current constraints in the simulations. Comparing Figure 9 to Figure 8, the current constraints are significantly fewer. Again, looking at the 2HH distribution results, the percentage of constrained branches changes from ~ 4% to ~8% with increasing EV penetration.

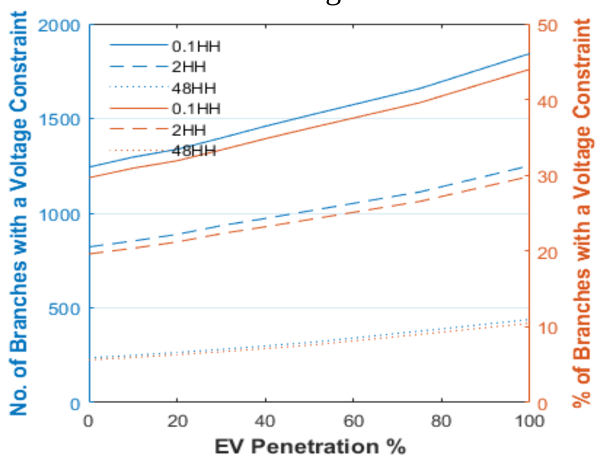

Figure 8: Number of branches with voltage constraints for 0.1HH, 2HH and 48HH as a function of EV penetration, aggregated over the 236 subnetworks. The right axis shows the percentage of branches constrained as a function of EV penetration.

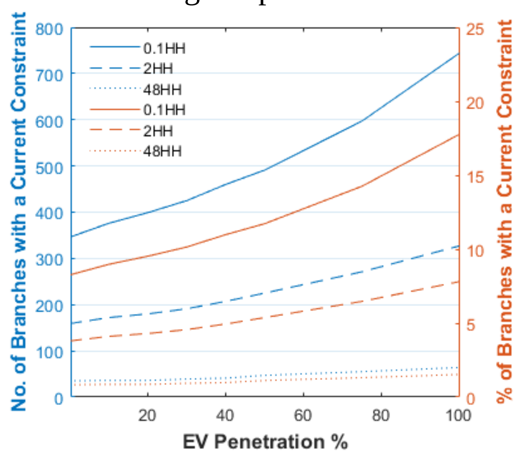

Figure 9: Number of branches with current constraints for 0.1HH, 2HH and 48HH as a function of EV penetration, aggregated over the 236 subnetworks. The right axis shows the percentage of branches constrained as a function of EV penetration.

Figure 10 and Figure 11 present the available hosting capacities for the 236 subnetworks assessed, based on 2HH voltage and current constraints, respectively. These show that the majority of subnetworks are likely to experience voltage below 0.94 p.u. during peak base load conditions. However, analysis of the example subnetwork indicate that modelled volt drop may be conservative. Causes for voltage discrepancies are discussed further in Section 6.2.

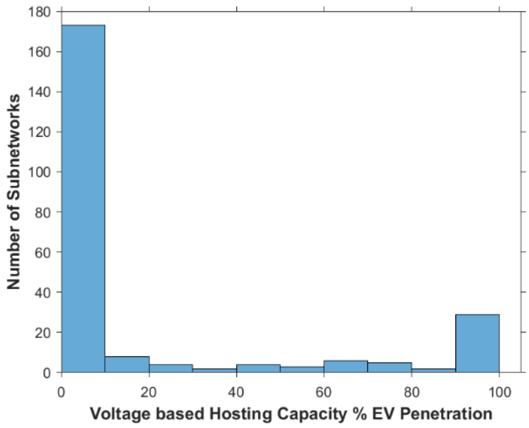

Figure 10:Voltage based hosting capacity distribution for the 236 subnetworks using 2HH threshold

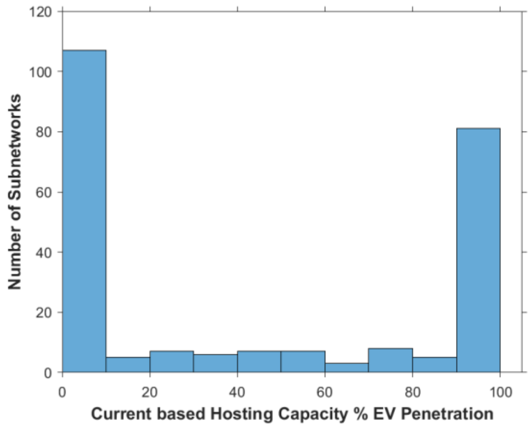

Figure 11: Current based hosting capacity distribution for the 236 subnetworks using 2HH threshold

6. Discussion

6.1. Data Quality

Source data quality was a challenge, due to data gaps and standardisation. Unknown branch types, phasing and ICPs loads required algorithms to approximate realistic configurations. Results for networks with a high percentage of unknown types have a higher degree of uncertainty and give a driver to audit these areas to fill data gaps.

EV load profiles have not been studied extensively in the local context, but this study has drawn upon Orion's knowledge and national travel data to create a reasonable approximation. By implementing a probabilistic approach and assigning residential load profiles to match MDI peaks, the impacts of individual assumptions are minimised due to the number of scenarios carried out. The resulting statistical outcomes provide a robust indication of potential network congestion on Orion's LV network.

6.2. Validation

Considering the limitations around data quality, the modelled current results for the example subnetwork were within 16% of the measured values. This is a positive result given that only the three-phase transformer MDI current is being matched. The EoL voltages modelled were within 7% of measured values despite some misalignment with the highest loaded week. Although this is a significant difference when compared with the voltage regulation band ($\pm$6%), it is reasonable when reviewed in the context of the limited data available.

The load profile of the entire subnetwork is replicated from three phase transformer MDI values. There are many potential sources of inaccuracy, including the different integration periods being used for recording MDI values (which can be between 8 and 30 minutes), differences in modelled to actual phase assignments of ICPs to name a few. While further work could be undertaken to pin these down more accurately, this would require extensive LV monitoring, which may not be financially feasible.

The key benefit of the modelling work is to identify potential congestion points in the LV distribution network, being able to rank their severity, and demonstrate how constraints increase as the EV penetration rises.

6.3. **Network Impacts**

The first step to determining network impacts will be to establish appropriate thresholds for voltage and current limits. EEA power quality guidelines [5] advise that voltage should remain at 230V ± 6%, assessed based on 10 min r.m.s. readings using the 99th percentile and 1st percentile values as upper and lower bounds in a one-week period (i.e. no more than ten readings outside of ± 6% in a week). This is relatively close to the 2HH (P0.6 & P99.4) thresholds presented in this paper, although modelling results use the equivalent of 30 minute averages.

Cables, conductors and transformers have some tolerance for short-time overloads of their thermal capacity. For example, buried XLPE cables can operate 9% above nominal rating for periods of up to 36 hours, not more than three times per year [6]. For these cases, the 48HH (85.7 percentile) may be a more appropriate measure.

The aggregated results in this study clearly show a significant number of 2HH voltage constraints before EV load is added. This is reflective of the lack of LV network visibility, which has led to a reactive approach to LV network improvements in the past. In both cases, the increase in constraints is gradual between 0% and 100% EV penetration (10% increase in 2HH voltage constraints and <1% increase in 48HH current constraints).

7. **Conclusions**

In this paper, a probabilistic method was presented for forecasting the transformer, voltage and current constraints experienced on LV distribution networks as a function of EV penetration. A fast power flow solver was developed by the EPECentre to combine Orion network data with NZ-specific EV inputs to model numerous load scenarios and determine the likelihood of exceeding network limits. Establishing base loads presented a significant challenge due data quality issues such as gaps in network topology records, erroneous MDIs and the variability of commercial loads.

Results indicate that maintaining voltage within regulations is likely to be the primary network challenge as EV uptake increases. The model approximates that 20% of branches may have existing voltage constraints for 2HH of a peak winter week, rising to 30% at 100% EV penetration. Further analysis is recommended to determine whether branch impedances are realistically modelled for winter temperatures. Approximately 8% of branches are expected to be current constrained at 100% EV penetration using the 2HH threshold.

8. **References**

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