LOW VOLTAGE NETWORK MODELLING

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Abstract:

With the increasing uptake of new technologies (such as PV, wind, EVs and LED lighting) there is a need to study their effect on the low voltage (LV) network, and this is one part of the Green Grid project's objectives. Although detailed modelling of an LV network will provide a more accurate assessment of their impact for a given scenario and network, to develop guidelines this type of impact assessment can be performed on representative networks. These studies will identify the penetration level, for example of PV, that a typical system can withstand without adverse effects. This will be a function of the characteristics of the PV inverter and its controls and the benefit of different control schemes can be evaluated. It allows quick evaluation and can identify which scenarios need further evaluation with more particular details.

The generation of representative LV networks that are truly representative is not a trivial task and is the focus of this paper. The k-means clustering technique is applied to cluster LV networks supplied by 10558 MV/LV transformers on the Orion distribution network. The extent and largely high quality Orion data has enabled the silhouette method to be used to evaluate how good the cluster fit is. The clusters identified from the data are:

- City centre
- Urban
- Industrial
- Rural

The technique gives the median and two extremes for each cluster. Several examples of using these representative networks for evaluating the impact of PV on the LV network are also provided.

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With the increasing uptake of new technologies (such as PV, wind, EVs and LED lighting) there is a need to study their effect on the low voltage (LV) network, and this is one part of the Green Grid project's objectives. Although detailed modelling of an LV network will provide a more accurate assessment of their impact for a given scenario and network, to develop guidelines this type of impact assessment can be performed on representative networks. These studies will identify the penetration level, for example of PV, that a typical system can withstand without adverse effects. This will be a function of the characteristics of the PV inverter and its controls and the benefit of different control schemes can be evaluated. It allows quick evaluation and can identify which scenarios need further evaluation with more particular details.

The generation of representative LV networks that are truly representative is not a trivial task and is the focus of this paper. The k-means clustering technique is applied to cluster LV networks supplied by 10558 MV/LV transformers on the Orion distribution network. The extent and largely high quality Orion data has enabled the silhouette method to be used to evaluate how good the cluster fit is. The clusters identified from the data are:

City centre
Urban
Industrial
Rural

The technique gives the median and two extremes for each cluster. Several examples of using these representative networks for evaluating the impact of PV on the LV network are also provided.

1. Introduction

In order for power quality, protection and other studies to be performed at the Low Voltage (LV) level, an investigation of the typical parameters of the LV network needs to be undertaken.

This paper presents the results of clustering the LV feeders associated with 10558 distribution transformers from the Orion owned Christchurch and central Canterbury distribution network. The objective was to:

- determine the distribution of parameters for the LV network within each cluster.
- find a statistically sound way of choosing representative networks.

This approach was done at a much smaller scale by Li [1-2] and similar parameters for classification were used by Gonzalez et al [3]. It is also widely used in HV and MV analysis [4].

Figure 1 shows a schematic of the master plan for LV modelling with regards to power quality.

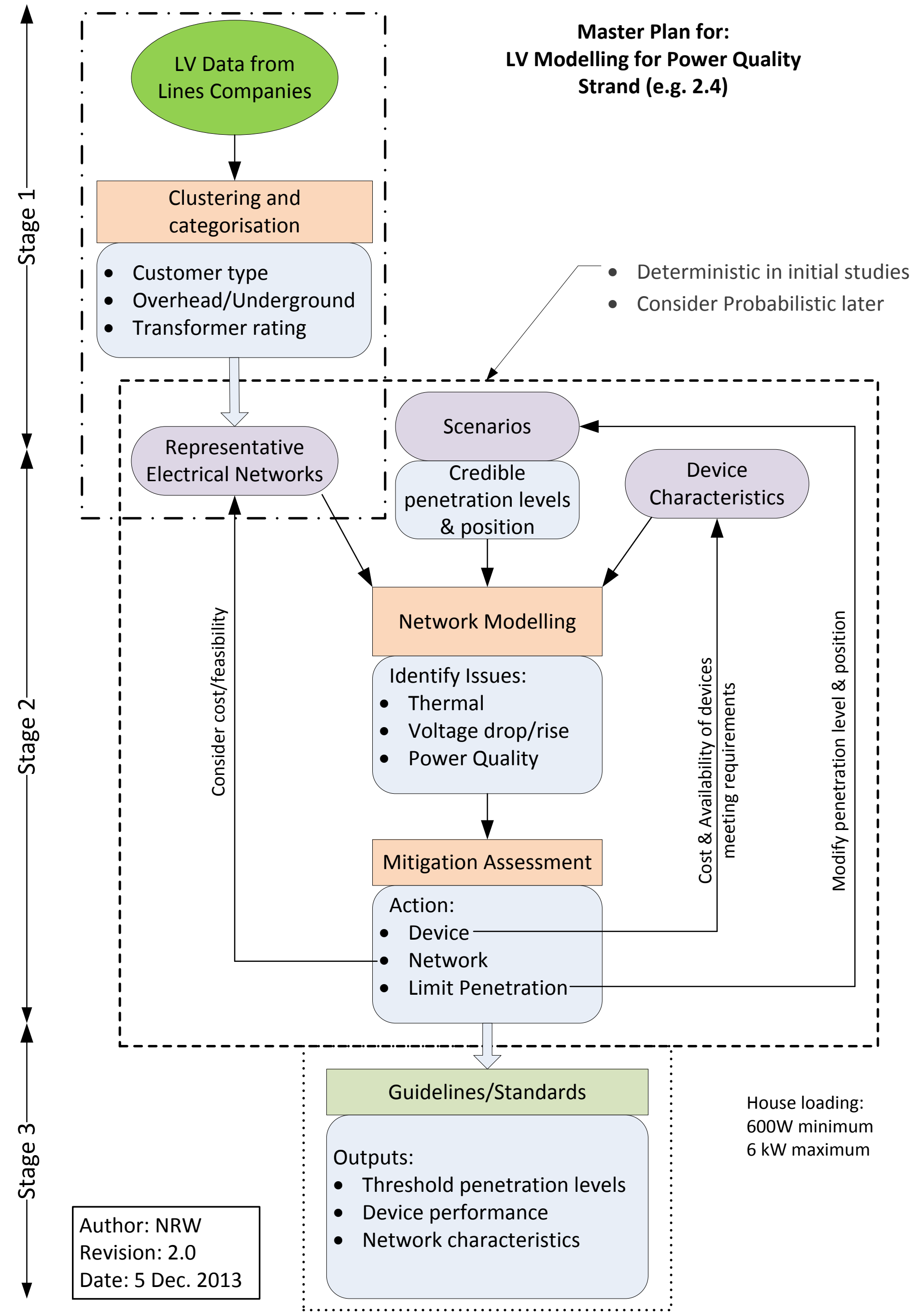

Figure 1. Master plan of LV modelling for power quality

2. Methodology

2.1 Weighted k-means clustering

K-means clustering is a well-known and well-established clustering technique. The basic method is quite simple. The method used was a variant of this:

1. k cluster centres are spawned in the n-variable space
2. Each point is assigned to the nearest cluster (Euclidean distance / 2-norm is usually used). This may be a weighted process.
3. The new mean of each cluster is then computed by averaging all its data points. If a centre has no data points it is reassigned randomly.

4. Iterate steps 2 and 3 until convergence to a given tolerance. The algorithm usually converges quickly.

The addition of empty cluster reassignment in step 3 appears to be undocumented. Previous approaches have either: deleted the empty cluster, ignored the empty cluster, used modified k-means clustering, etc. Note that the final result depends on the initial cluster centres. Many different sets of parameters were used to come up with realistic clustering. Figure 3 shows the concept of clustering with two cluster variables. For each cluster 3 representative LV networks have been chosen. More could be selected using different extremities of the cluster but limited to 3 at this stage. The first is the centroid (Centre) of the cluster and called the typical representative LV network for the cluster. The second is median (half way between centre and boundary of the cluster), and finally the extreme LV network siting on the extremity of the cluster.

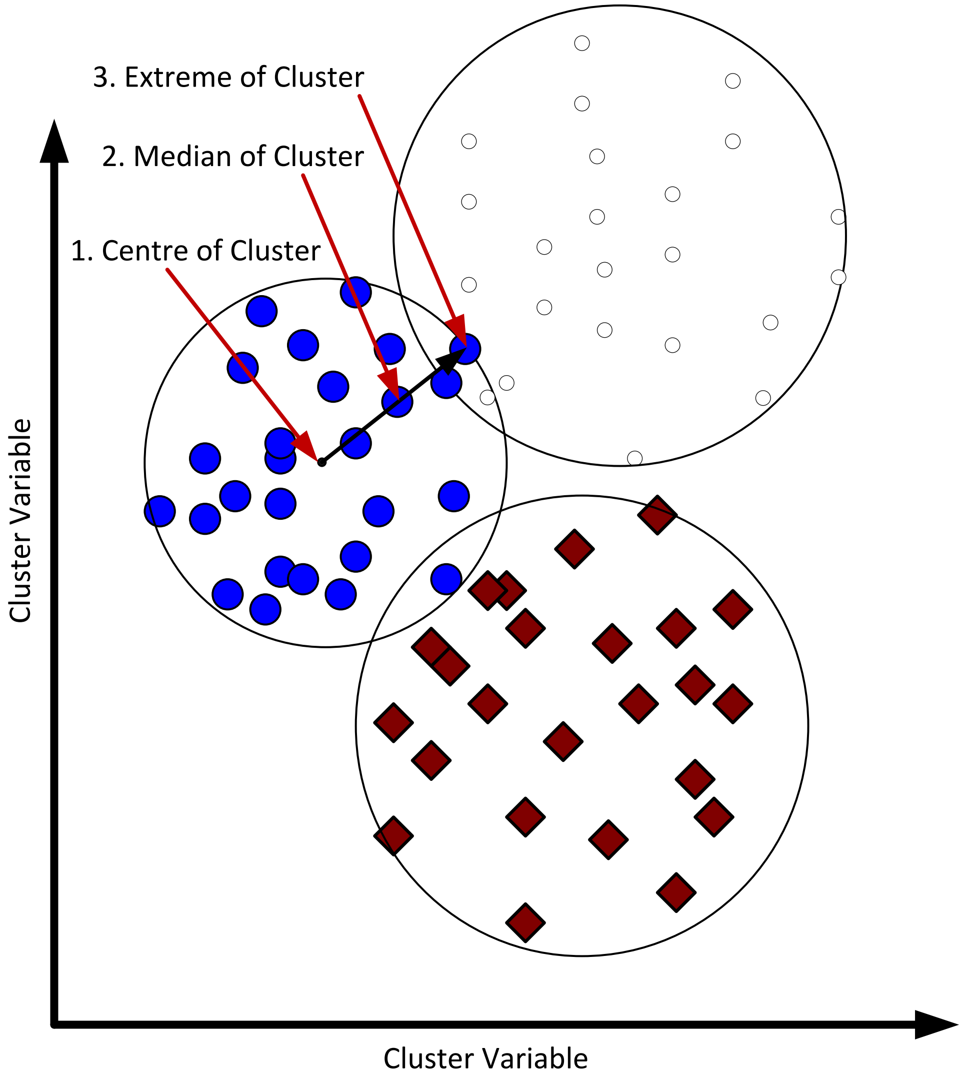

Figure 2. Clustering with two cluster variables

2.2 Evaluation

The silhouette method was chosen. It evaluates how good a cluster fit is by comparing:

b(I) - the average distance from one point in a cluster to all the others in the same cluster; to

a(I) - the average distance from one point in a cluster to all the others in the nearest cluster.

Then the silhouette statistic is calculated by:

$$s(I) = \frac{b(I) - a(I)}{\max(a(I), b(I))}$$

This is averaged over all data points; the metric lies between -1 and 1 by definition. It is commonly accepted that a statistic < 0.2 represents poor clustering, whereas a value above 0.5 represents a good fit.

With large data sets, this is computationally expensive. It has therefore become standard to use a modified form for speed. This modified method evaluates how close each point is to its centre b(I), compared to the nearest other centre a(I). The silhouette statistic is still

$$\frac{b(I) - a(I)}{\max(a(I), b(I))}$$

2.3 Clustering centres

The number of cluster centres is particularly important. This is usually chosen from physical characteristics and/or statistical analysis. The number of cluster variables was varied and the results are shown in Table 1.

Table 1. Silhouette experimental derivation of optimum no of clusters

No of clustering centres	Silhouette statistic
3	0.68
4	0.71
5	0.69
6	0.68
10	0.57

This shows that the data naturally falls into clusters, four being the optimum. By inspection of their composition, these may be classified into the categories of “City”, “Urban”, “Rural” and “Industrial”.

Since the silhouette statistic is close to 1, we can conclude that the data contains clear evidence of clustering.

2.4 Cluster variables

Likewise, the number and choice of cluster variables is equally important. At present best results are obtained by the use of 4 cluster variables: “no of residential ICPs”, “no of non-residential ICPs, “average distance between loads” and “kW rating. The choice of parameters is reasonably similar to that in previous studies [2-3].

“Residential loads” naturally includes houses, but also some farms; whereas “non-residential loads” include schools, shops, factories, etc. This terminology is borrowed from Orion [5].

2.5 Verification

A program which picked out transformers and their connected feeders was developed in order to:

1. Generate basic statistics and an overview of the Orion LV network
2. Find any feeder of interest effortlessly, esp. for modelling purposes.
3. Filter the 10000+ feeders easily.

This was used to verify the results. For example, consider a simple model of a residential LV feeder with the following parameters:

Load < 5.00 kW per ICP: 21.91% of transformers

No of ICPs from 20-350: 25.61% of transformers
Average distance between ICPs <= 30m: 53.99% of transformers

With a uniform distribution (i.e. no correlation between parameters), one would expect 3.03% of the feeders to fall into this category. However, 15.22% of the feeders fall into this category which is clear evidence of clustering.

A summary of the statistics for the clusters is given in the Appendices.

3. Representative feeders

In order to choose representative feeders in an unbiased manner, each feeder is classified in terms of distance to centre. The closest feeder is then chosen, as is the furthest and the median. This seems to produce a reasonably diverse selection of feeders with varied parameters. All diagrams have R and X per km.

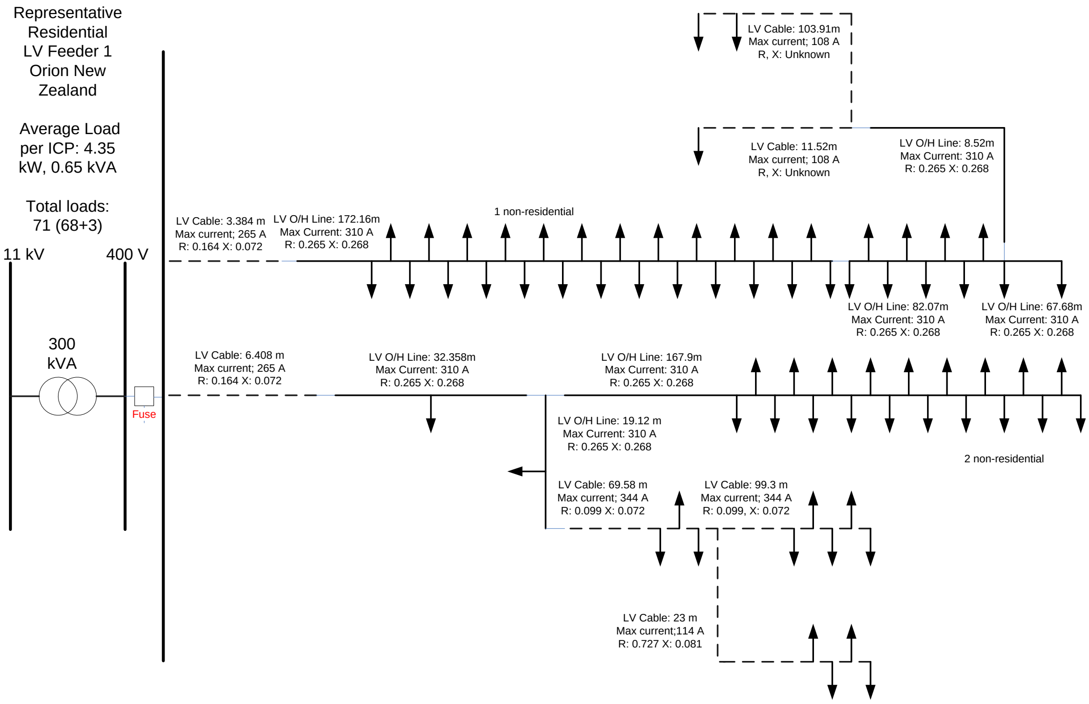

Figure 3. Schematic of first representative LV feeder (Urban 1 or Centre of cluster).

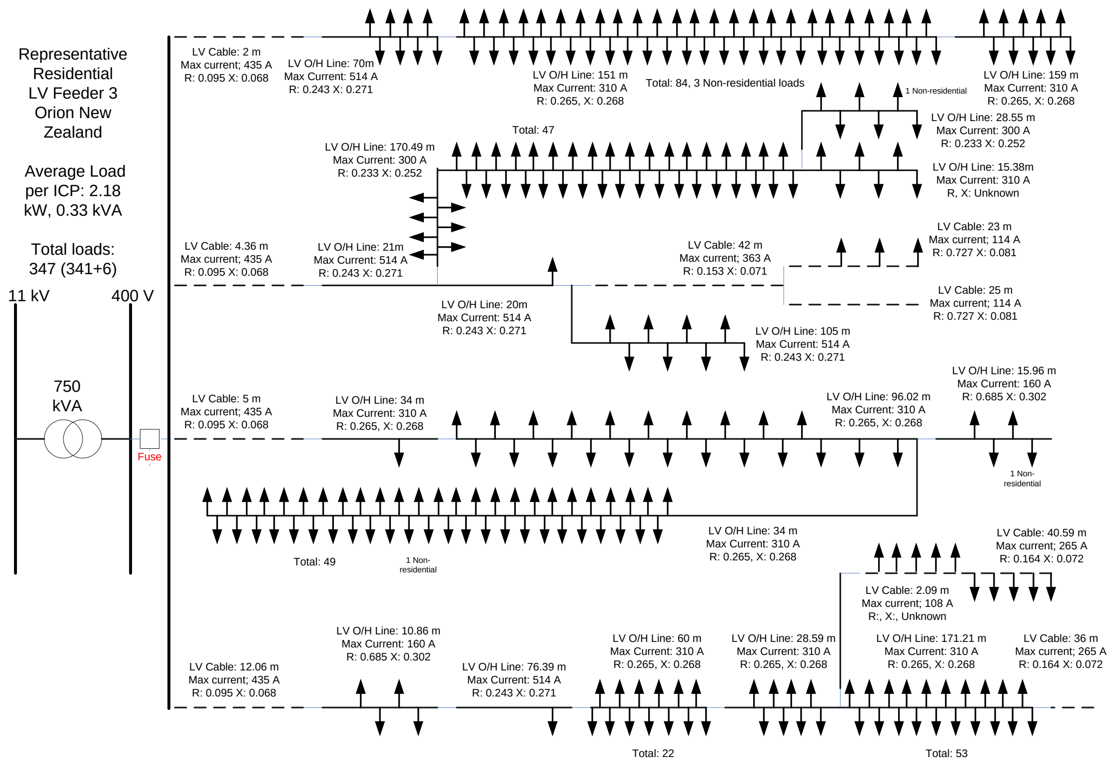

Figure 4. Schematic of third representative LV feeder (Urban 3 orextremity of cluster).

3. Simulations

3.1 PV with no power-factor control

Figure 5 shows the steps required to perform a study. A power-flow using an iterative admittance matrix method was used in a MATLAB environment. A SinCal model was developed of the typical Urban network and used to verify the MATLAB power-flow algorithm.

MATLAB was chosen for the simulation platform for the following reasons:

- Ease with which different scenarios can be simulated. Even the typical Urban LV network was too large to manually change each load for each different scenario. There are 71 ICPs that need editing every time a different loading scenario is simulated.
- Ease of integration to the LV data (both the full and clustered data).
- Ability to graphically present the results.
- Ability to perform statistical studies.

To illustrate the use of the modelling tool developed the impact of PV on the LV network will be investigated. A minimum household load of 600W (typical residential area after diversity demand between midday and 3pm on a summer day over the Xmas holidays) is assumed (mid-day). Actual measurement data from a 5kW EnaSolar PV inverter is used to represent the PV. At the measurement time current was approximately 16 Amps giving 3.7 kW of PV generation per unit. The phase angle of the PV inverter injection is manipulated to give the correct angle between the terminal voltage and current injected at each PV site.

More details of the simulation procedure is given in Fig. 6. A particular penetration level of PV is selected. The PV sites are randomly selected to give this penetration and a simulation performed to check for over-voltages and overloads of conductors. Then another case is run with the same penetration level and another randomly distributed site selection. This is continued until enough cases have been run to provide a meaningful spread of results. A new penetration level is then selected. This methodology of randomly placing PV sites is performed as any guess on distribution is likely to be wrong, but taking many cases gives a spread of likely scenarios. As the distribution of PV units is unknown, and likely to be clumpy, by running lots of scenarios it is likely to capture some of the clumpy cases.

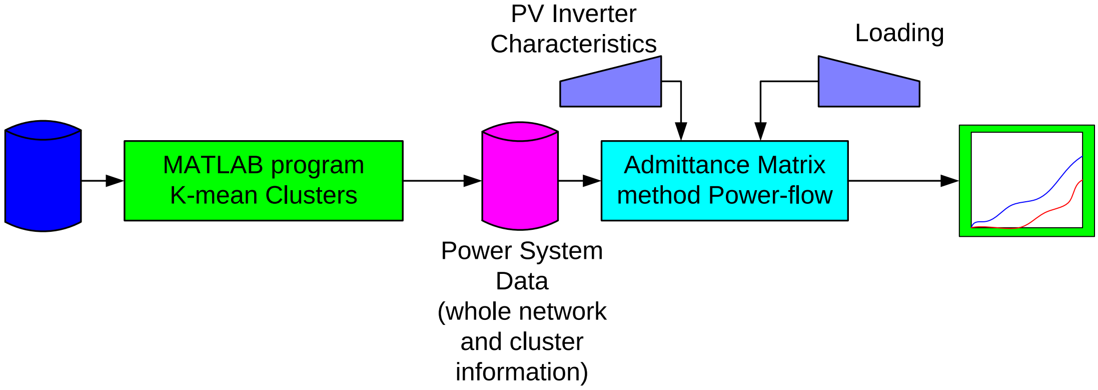

Figure 5. Simulation procedure

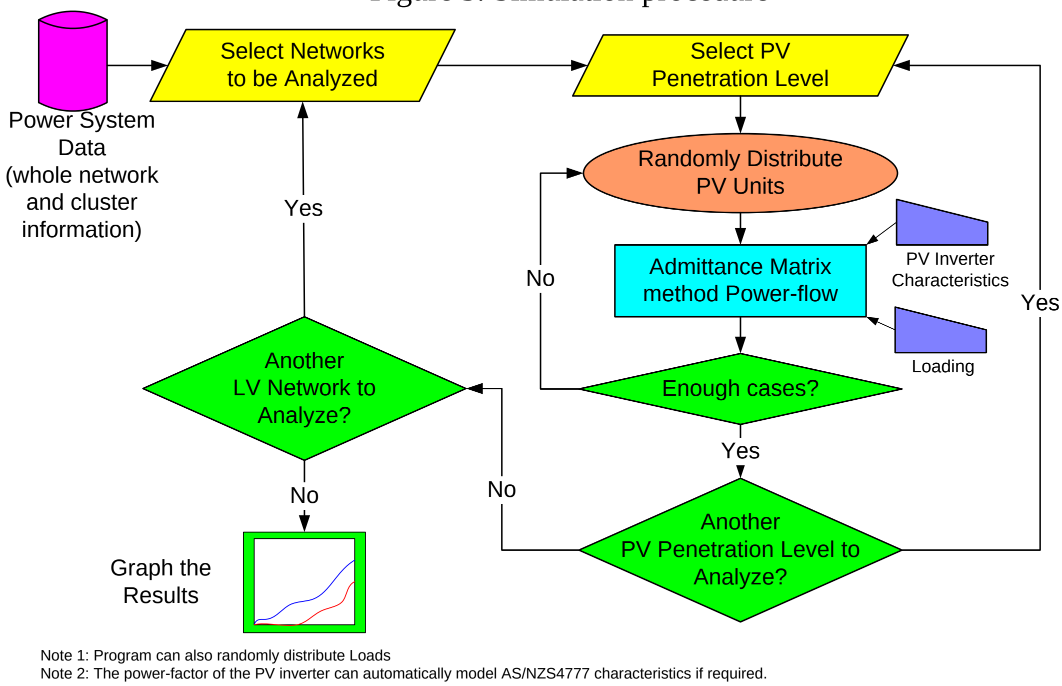

Figure 6. Flow-Chart of the Simulation Process

Figure 7 shows the raw results for over-voltages for the urban representative networks. When these are averaged, and plotted with other representative LV networks, then one gets the curves in Fig. 8. From this it can be seen that at a penetration level of 0.2 (that is 1 house in 5) the weak Urban areas will have approximately 17% of nodes with over-voltages while the typical Urban network will not. The City representative networks show that the hosting capacity is greater for these networks.

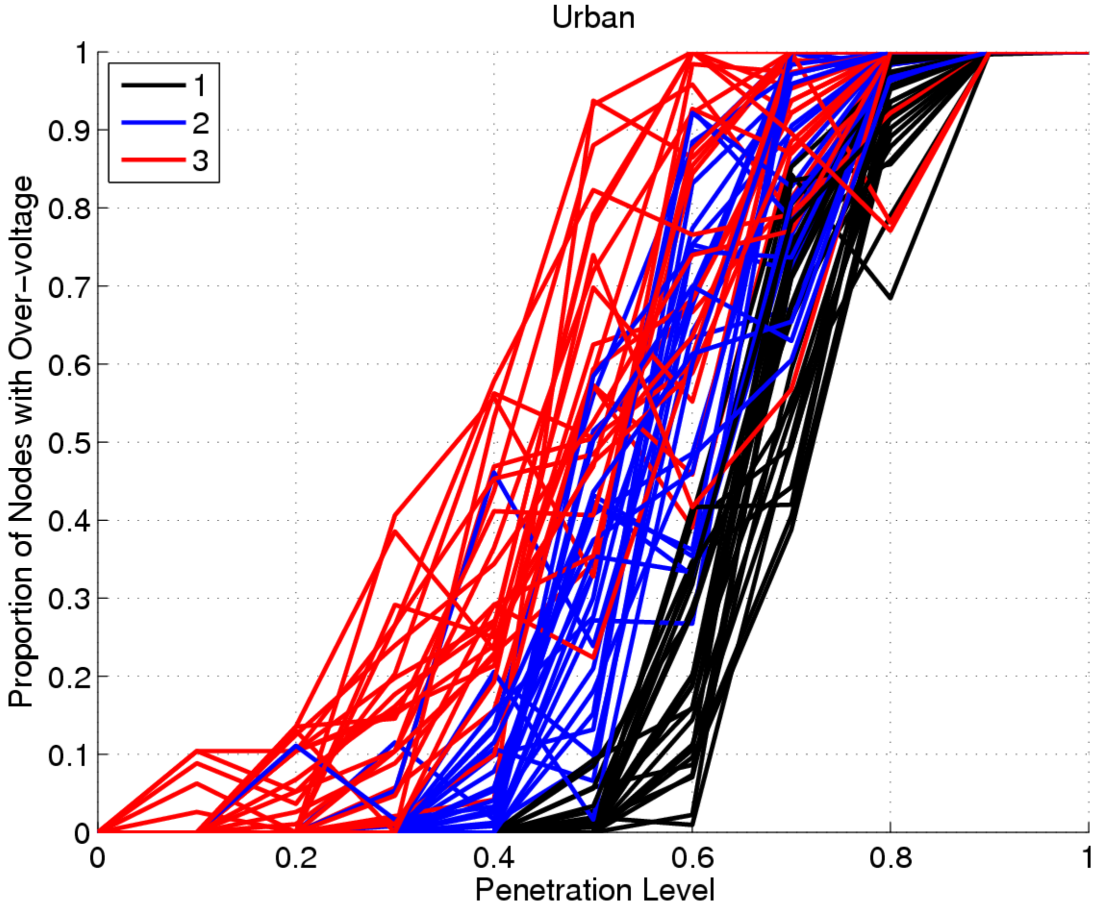

Figure 7. Urban networks

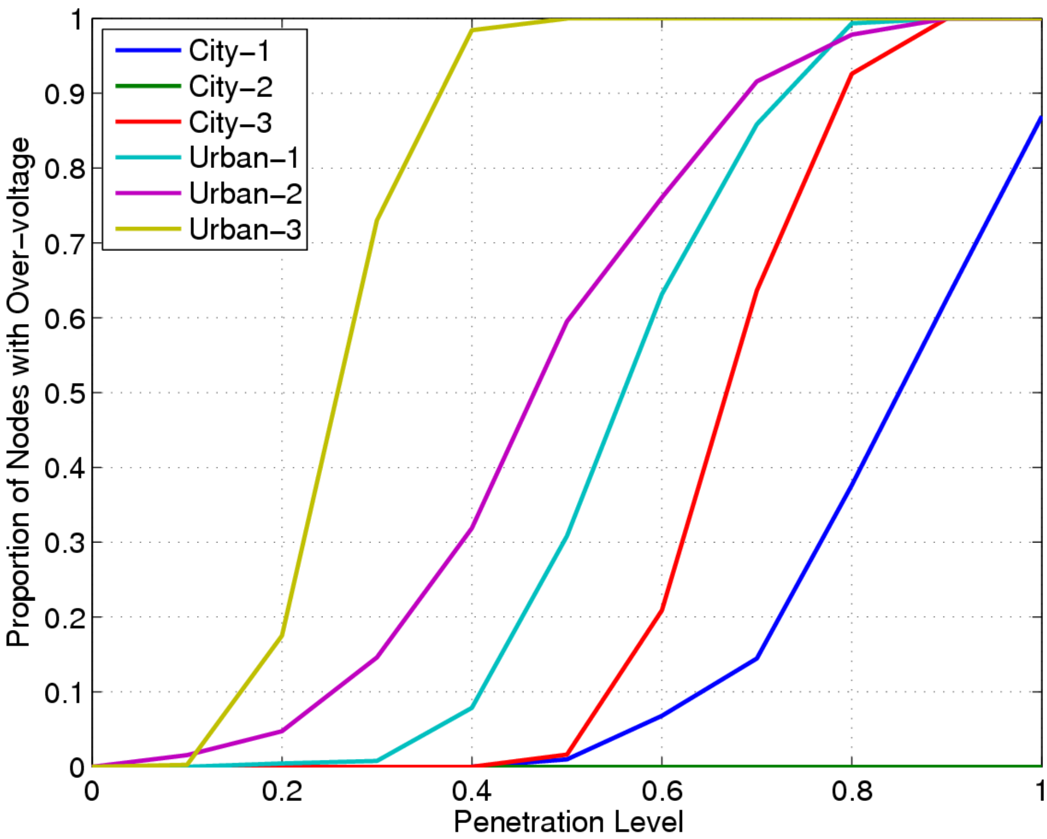

Figure 8. Proportion of PV versus PV Penetration level

3.2 PV with control

The draft AS/NZS4777.2 standard has information on power-factor control that may be desirable for PV inverters so as help regulate the voltage. This wording is "may" and is definitely not required for PV inverters below 5 kW. The proposed control action is summarised in Tables I & II and Fig. 9. The simulation tool was used to evaluate the effectiveness of this and resulting increase in hosting capacity it will bring. The initial simulation with these values showed no difference as the cut-in voltage is too high for New Zealand conditions (it must be remembered that Australia has a high voltage range, i.e. +10% rather than 6%). The cut-in voltage was lowered by 10V to 240 V and simulations performed with 0.95 and 0.80 power-factor limits (both allowed in the standard). The PV inverter model changed the power-factor and kept the current constant (i.e. assumed constant apparent power). The results of this simulation with power-factor control up to 0.8 enabled are displayed in Fig. 10. It is clear that this has significantly increased the hosting capacity of the network. A penetration level of 0.2 can now be accommodated in Urban networks with practically no over-voltages. The choice of 240 V as cut-in voltage was arbitrary and more studies are needed to find the optimum cut-in voltage.

Table 2. Volt-VAr Response Set Point Values for Reference Voltages

Reference	Default Value	Range
V_1	0.95 Leading	0.8 Leading to 1
V_2	1	1
V_3	1	1
V_4	0.95 Lagging	0.8 Lagging to 1

Table 3: Volt Response Reference Values (Table 7 of [6])

Reference	Default Value	Range
V_1	207 V	Not applicable
V_2	220 V	216 to 226 V
V_3	250 V	244 to 258 V
V_4	265 V	Not applicable

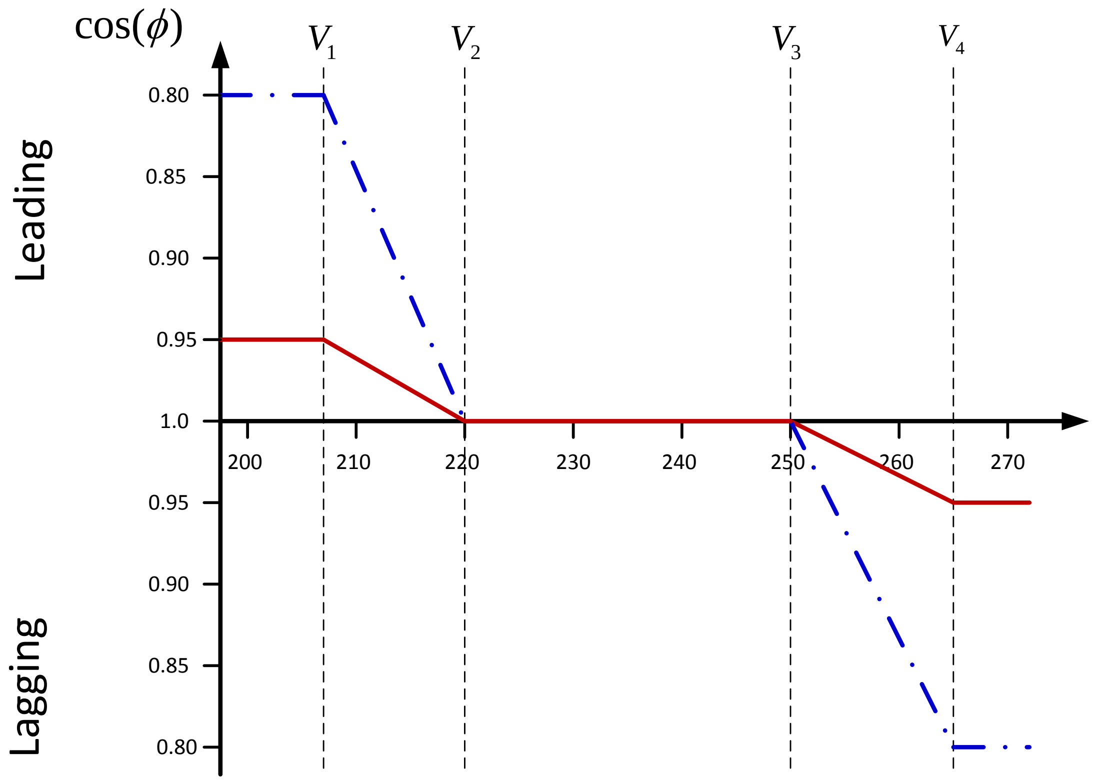

Figure 9. Power-factor control characteristics [6]

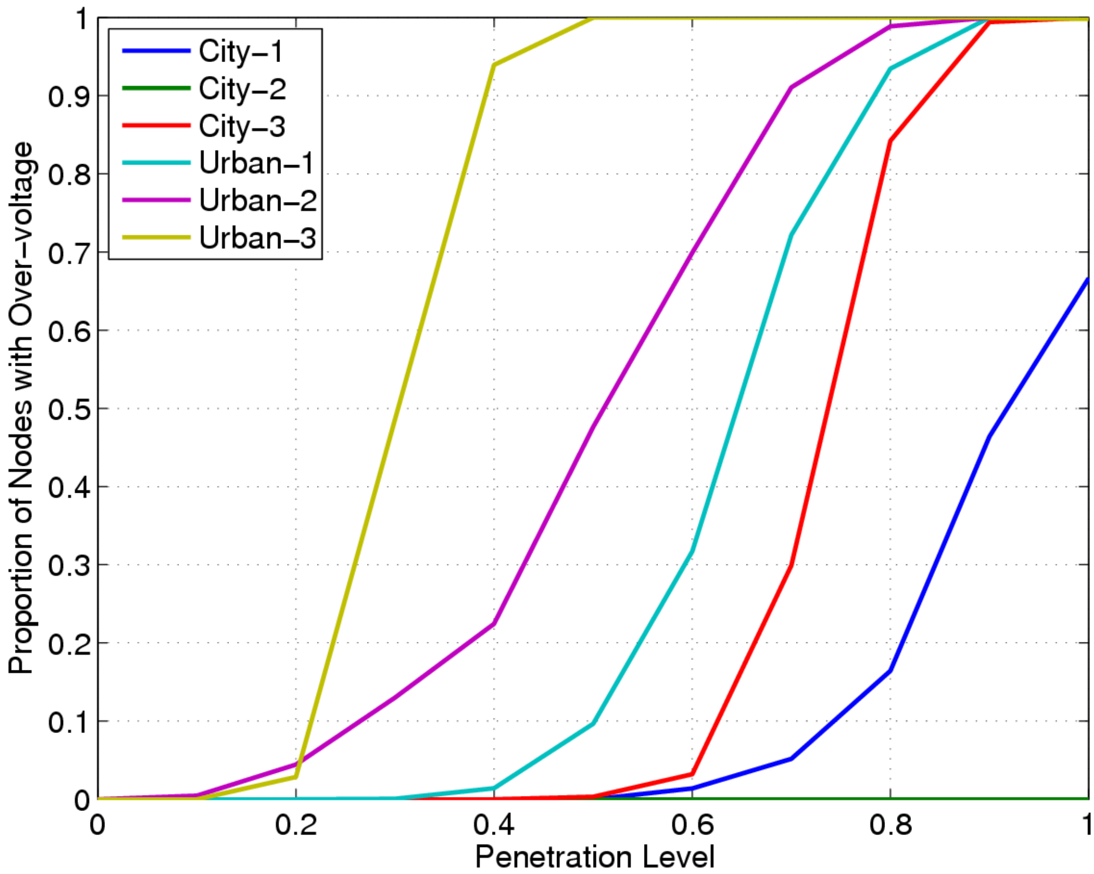

Figure 10. Proportion of PV versus PV Penetration level with PV inverter power-factor control

3.3 Complete LV Network

Lastly to demonstrate the capability of this technique the complete LV network, with 10,550 11kV/415V transformers and their associated LV network, was modelled and the impact of PV investigated. Fig. 11 shows the results of this case.

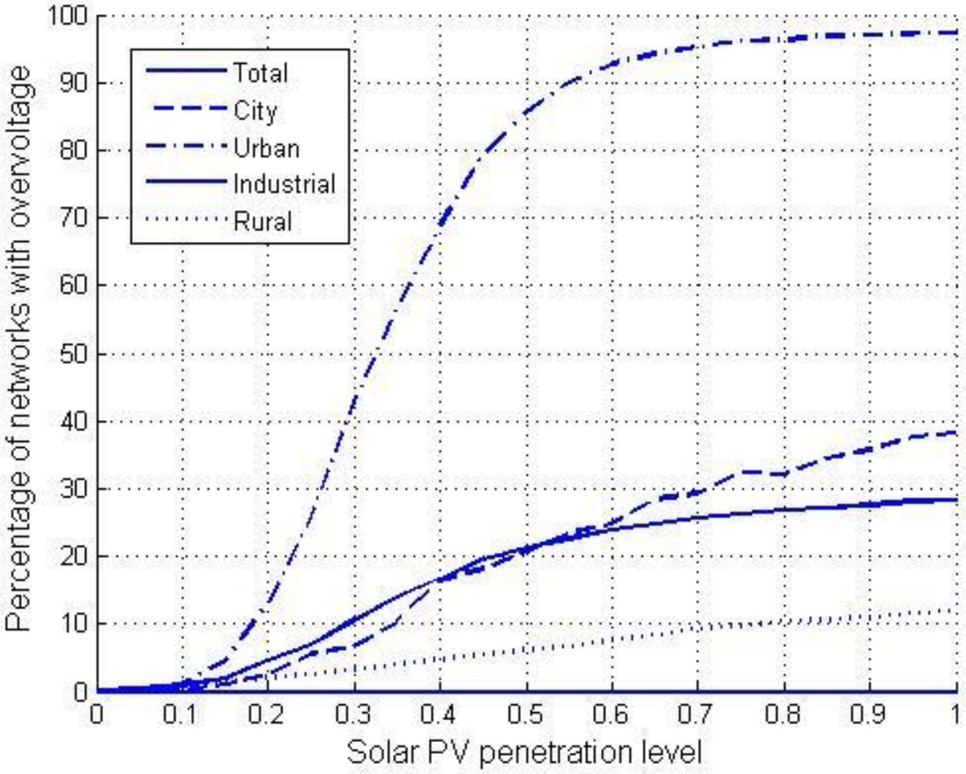

Fig. 11. Percentage of networks with overvoltage problems by classified categories

7. Conclusion

Weighted k-means clustering has been used to divide the Orion LV network into four categories. These have been labelled appropriately and related to physical characteristics. Analysis of suitable cluster variables, no of cluster centres, and appropriate metrics of evaluation has been conducted.

For each cluster, the key statistics have been presented. The statistics and clustering data could be used to determine representative networks, as well as to derive a fitted probability density function for each cluster variable and other variables of interest.

8. FUTURE WORK

Representative feeders will be constructed from the clustering analysis, as in references [1] and [4], and these may be used for various types of analysis – e.g. power quality, protection, etc. It is likely that for each cluster a "mean" network close to the cluster centre will be chosen, as well as more extreme cases.

It is hoped to receive further information from other NZ electricity distribution businesses, in order to compare these results between networks and get a clearer New Zealand picture.

Possible future work to improve the cluster algorithm are:

- using a different metric to evaluate the nearest cluster

- using a more advanced form of k-means clustering
- using a different clustering technique
- optimizing the choice of cluster variables (e.g. use of the impedance as a cluster variable).

However, the results presented in this report represent a good start: a fairly simple model with an excellent fit. This may be sufficient, given that uncertainties in the supplied data are likely to have more effect than any small optimizations to clustering. A fitted probability density function for certain variables (e.g. impedance, cluster variables) within each cluster may also be derived. Further modeling of distribution of PV uptake, underway at present, may also be incorporated.

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[4] K. P. Schneider, Y. Chen, D. Engle, and D. Chassin, "A taxonomy of North American radial distribution feeders," in Power & Energy Society General Meeting PES '09, IEEE, 2009, pp. 1-6.
[5] A Mulligan, Orion LV Report, 2011 (confidential).
[6] Draft AS/NZS4777.2 standard

Appendix

A.1 City/Commercial

Table 4 gives the cluster parameters for the city/commercial cluster. The above table summarizes the records of 358 MV/LV transformers and their associated LV networks, or 3.4% of the network transformers. The statistics for the three representative City LV networks is shown in Table 5.

Table 4. City clustering results.

	No of residential ICPs	No of non-residential ICPs	Density (average distance (m) between ICPs)	kW per ICP
Cluster Centre	15.26	27.31	18.48	9.13

5% level	0.00	15.00	5.27	2.74
Median	2.50	23.50	16.22	7.50
95% level	67.00	47.00	39.32	19.73
Standard deviation	24.05	14.08	12.16	9.76
Maximum	129.0	132.0	117.63	160.0
Minimum	0.00	14.00	0.20	1.30

Table 5. City Centre Cluster

	1 (centre)	2 (median)	3 (extreme)
residential ICPs	19	0	58
non-residential ICPs	27	18	132
average distance between ICPs (m)	8.42	0.95	7.27
kW per ICP	5.67	11.94	4.16

A.2 Urban

Table 6 gives the cluster parameters for the urban cluster. The above table summarizes the records of 1962 MV/LV transformers and their associated LV networks, or 18.6% of the network transformers. Note that this cluster constitutes a large proportion of the network as there are many lines/loads on these LV networks. The statistics for the three representative Urban LV networks is shown in Table 7.

Table 6. Urban clustering results.

	No of residential ICPs	**No of non-residential ICPs**	**Density (average distance (m) between ICPs)**	**kW per ICP**
Cluster Centre	68.48	3.12	15.20	5.58
5% level	39.00	0.00	6.36	2.10
Median	62.00	2.00	13.89	3.22
95% level	118.00	10.00	27.76	5.45
Standard deviation	28.02	3.48	6.78	18.11
Maximum	341.00	24.00	46.95	240.00
Minimum	30.00	0.00	0.35	0.65

Table 7. Urban Representative Network statistics

	1 (centre)	2 (median)	3 (extreme)
residential ICPs	68	50	341
non-residential ICPs	3	1	6
average distance between ICPs (m)	12.23	22.05	4.61
kW per ICP	4.35	3.65	2.18

A.3 Rural

Table 8 gives the cluster parameters for the urban cluster. The above table summarizes the records of 7937 MV/LV transformers and their associated LV networks, or 75% of the network transformers. The statistics for the three representative Rural LV networks is shown in Table 9.

Table 8. Rural clustering results.

	No of residential ICPs	No of non-residential ICPs	Density (average distance (m) between ICPs)	kW per ICP
Cluster Centre	3.09	1.24	33.37	39.68
5% level	0.00	0.00	1.33	5.10
Median	1.00	1.00	19.43	24.00
95% level	19.00	5.00	106.90	160.00
Standard deviation	6.44	2.01	43.72	46.39
Maximum	39.00	14.00	614.81	291.00
Minimum	0.00	0.00	0.00	0.00

Table 9. Rural Representative Network statistics

	1 (centre)	2 (median)	3 (extreme)
residential ICPs	3	2	0
non-residential ICPs	1	3	1
average distance between ICPs (m)	57.56	103.37	0.55
kW per ICP	40	40	51

A.4 Industrial

Table 6 gives the cluster parameters for the urban cluster. The above table summarizes the records of 327 MV/LV transformers and their associated LV networks, or 3.1% of the network transformers.

Table 10. Industrial clustering results.

	No of residential ICPs	No of non-residential ICPs	Density (average distance (m) between ICPs)	kW per ICP
Cluster Centre	0.01	0.86	12.85	544.96
5% level	0.00	0.00	N/A	315.00
Median	0.00	1.00	8.13	525.00
95% level	0.00	1.00	36.00	800.00
Standard deviation	0.10	0.44	18.70	185.07
Maximum	1.00	2.00	199.00	1200.00
Minimum	0.00	0.00	0.00	294.00