

EXPLORING THE UNCERTAINTIES OF PROBABILISTIC LV NETWORK ANALYSIS

Damien Frame
University of Strathclyde – United Kingdom
damien.frame@eee.strath.ac.uk

Graham Ault
University of Strathclyde – United Kingdom
g.ault@eee.strath.ac.uk

ABSTRACT

Increased interest in the analysis of low voltage (LV) power distribution networks using probabilistic and long period time-series techniques has arisen due to the anticipated growth of low-carbon technology and the advent of the Smart Grid. Recent approaches are reviewed and the uncertainty introduced by the underlying assumptions explored. A specific case study analysis of electric vehicle (EV) penetration on a generic UK distribution network is used to investigate the effect of key assumptions on the results of a probabilistic analysis.

INTRODUCTION

In response to the predicted increase of low carbon technology that will primarily interact with the low voltage (LV) network, techniques for detailed analysis of LV networks are receiving increased attention. Scenarios of high penetrations of micro-generation, plug-in electric vehicles and electric space and water heating, possibly with a flexible price response or even direct control, would create a situation requiring new approaches to LV planning [1].

The stochastic nature of LV customer load profiles and DER behavior has driven increased interest in probabilistic and long period time-series load flow techniques. Rather than a worst case scenario analysis this approach provides information on the probabilities of attributes such as network constraints and system losses that would then form the basis of planning decisions.

In this paper, approaches to probabilistic LV network analysis are considered and a case study of varying penetrations of EV on a generic UK network used to explore the effect of key assumptions.

LV ANALYSIS

The starting point for any power system analysis is the network model. For low voltage distribution networks, the general assumptions do not apply; lines are rarely transposed and the effects of diversity and aggregation have yet to influence the inherently unbalanced load profiles of individual consumers with single phase connections. In addition to this, connections may not be evenly balanced across the phases, exacerbating the unbalanced load problem.

Although a fully accurate model can only be derived using Carson's equations [2], where detailed network

information is not available it has been demonstrated that deriving an approximate phase impedance matrix from positive and zero sequence impedance values will introduce negligible error providing further simplifications of assumed balance or neglecting mutual coupling are not made [3].

With an appropriate network model in place, an unbalanced load flow engine is required. The extensive prior art in this area describes a variety of methodologies including the Backward Forward Sweep (BFS) approach [4] and specific formulations of the Newton Raphson method [5]. The BFS technique provides an easy to implement, fast and accurate solution for weakly-meshed systems. However, for larger, strongly meshed systems a Newton Raphson formulation such as the Current Injection Method has been shown to perform well [6].

A probabilistic analysis also requires time-series load information which, when described at an individual customer level in highly granular time steps, is highly stochastic. The literature provides multiple examples of the different approaches that can be taken to creating synthetic load profiles for a probabilistic analysis [7], [8], [9], [10]. The methods vary between studies, however the majority are similar in that an existing data set (historical substation data or typical, averaged annual customer profiles) was used with a probabilistic method to randomly assign individual customer profiles. In a few cases high resolution load profiles are built directly from occupancy and appliance use probabilities per dwelling.

Underlying all of these studies is some level of assumption or simplification regarding one or all of: network parameters, balanced conditions and customer load profile through time. In the majority of cases it is not clear how an alternative set of assumptions on the network model, or method of generating synthetic load profiles, would affect the results of the study.

CASE STUDY

A case study network has been modeled to allow an analysis of a typical probabilistic approach to LV analysis that explores the underlying assumptions involved.

The network is modeled in Matlab and a three-phase unbalanced load flow algorithm based on [4] is used for steady state power flow analysis. The simulation records any over/under voltage or excess phase imbalance at each node in the network for each half-hourly load flow solution. All branch currents are monitored for thermal violations. The load flow accuracy was verified by comparison against a commercial package and EPRI's OpenDSS [11].

Network Model

A generic urban UK LV network is used as the case study network (shown in Fig. 1.). The network is fed by a 1.2 MVA 11/0.4 kV transformer and has 83 nodes with 44 of those connecting domestic load. The model is full three phase however the single phase service connections are not modeled and are aggregated at each load node. Six nodes connect commercial loads. As is often the case, the data available provides positive sequence impedance values only. For underground three-core cables, a common approach is to multiply positive sequence impedance by a factor of between three and five to estimate the zero sequence impedances [12]. Initially a factor of three has been assumed and the positive and zero sequence data used to form approximate phase impedance matrices.

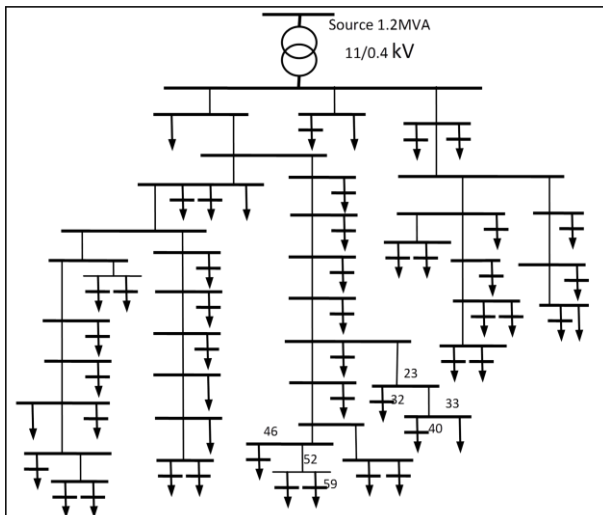


Fig. 1. Case Study LV Network

Synthetic Load Profiles

Three sources of customer load profiles have been considered: UKERC [13], UKGDS [14] and CREST [15]. The first two provide half hourly averaged profiles for typical customer classes over the course of a year. Open source software developed by CREST builds individual profiles directly from assumptions on occupancy and appliance use. Each source was used to create a base set of random node load profiles reflecting differing occupancy and appliance use. For each node, at each half hourly sample point, a normal probability distribution is created around the sample value with σ chosen so that 99.7% of the distribution is within 15% of the original value. At each half hour of the power flow simulation each load's pdf for that half hour is sampled. This process results in appropriately stochastic, 'spiky' individual, single-phase customer profiles that aggregate to the

expected smooth profile and peak values at the transformer. The profiles vary randomly through each iteration and by their stochastic single phase nature, introduce random unbalance across the phases.

Electric Vehicle profiles were generated using a Monte Carlo Simulation model of domestic Electric Vehicle use and availability based on probabilistic characterizations obtained from the 2003 UK Time of Use Survey [16]. Simulations for 20%, 30% and 50% penetration of EV for the case study customer base were undertaken and the resulting charging profiles randomly assigned to domestic customer nodes. The EV type simulated was assumed to have a constant charging rate of 7.68kW.

Methodology

The base case simulation utilized the UKERC load profiles and assumed zero sequence impedances equal to three times positive sequence impedances. Multiple scenarios were analysed with the zero sequence impedance varied to four and then five times the positive sequence impedance and alternative load profile sources used to create synthetic profiles. Each simulation consisted of 100 runs of annual analysis. Each of these simulations was then repeated for 20%, 30% and 50% EV penetration levels.

Results

The simulation results return a likelihood of the load flow solution at any time step identifying voltage, thermal or unbalance constraint violations at all nodes. A selection of results for all EV penetration scenarios are shown in Table 1. The data is displayed as Voltage (% of periods in year with voltage threshold violated), Unbalance (% of periods in year with unbalance threshold violated), Max Thermal (maximum % of current rating occurring at any branch over all periods) and Min Voltage (minimum per unit voltage occurring at any node over all periods). The maximum thermal loading for all simulations occurred at the transformer. The assumptions on zero sequence impedance have a clear impact on the probability of over/under voltage and unbalance threshold violations. The alternative load profiles have varying impact. Using UKGDS load data significantly changes the predicted constraints and maximum thermal loading observed whilst the profiles created from CREST and UKERC data (base scenario) track quite closely.

System wide probabilities of constraint violations provide a useful high level view of network performance under various scenarios, however a more detailed understanding of the network's weak points may be required. The probabilities of voltage threshold violations for individual nodes for 50% EV penetration are shown in Fig. 2. for both UKERC and CREST load profile sources.

TABLE I
PROBABILITIES OF CONSTRAINT VIOLATIONS FOR VARYING
ASSUMPTIONS AND EV PENETRATIONS

STANDARD LOAD	BASE	Z0 x5	UKGDS	CREST
VOLTAGE	0.01%	0.02%	2.30%	0.01%
UNBALANCE	0.69%	3.24%	2.98%	0.73%
MAX THERMAL	88.3%	91.2%	102.2%	84.43%
MIN VOLTAGE	0.9369	0.9317	0.9267	0.939
20% EV	BASE	Z0 x5	UKGDS	CREST
VOLTAGE	1.45%	6.54%	10.09%	0.68%
UNBALANCE	13.7%	33.6%	17.65%	12.42%
MAX THERMAL	90.1%	89.7%	102.5%	83.89%
MIN VOLTAGE	0.9237	0.8899	0.901	0.928
30% EV	BASE	Z0 x5	UKGDS	CREST
VOLTAGE	2.86%	7.99%	12.30%	1.52%
UNBALANCE	19.1%	42.8%	23.31%	20.05%
MAX THERMAL	90.8%	90.0%	103.9%	84.53%
MIN VOLTAGE	0.9084	0.887	0.900	0.924
50% EV	BASE	Z0 x5	UKGDS	CREST
VOLTAGE	8.75%	18.9%	20.07%	6.98%
UNBALANCE	33.1%	53.9%	34.64%	31.23%
MAX THERMAL	91.2%	93.3%	101.4%	88.37%
MIN VOLTAGE	0.897	0.8738	0.8894	0.9

A full analysis of results indicates a pattern that is consistent in across all scenarios. It can be seen that assumptions on zero sequence impedance and load profiling change the magnitude of the probability of voltage violations but not the specific nodes where violations take place. In all scenarios, nodes 23, 32, 33, 40, 46, 52 and 59 experience the most constraint violations. Fig. 2 provides an example of this pattern for UKERC and CREST 50% EV scenarios.

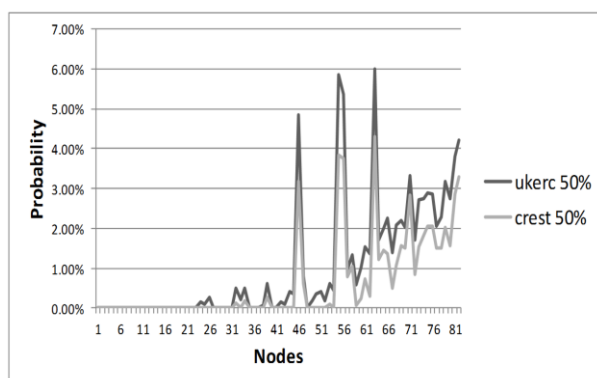


Fig. 2. Probability of voltage violations per node for varying load assumptions and 50% EV penetration

An understanding of the overall probabilities of various constraints provides an indication of weak areas of the network, however an understanding of when these

constraints are most likely to occur provides additional value. In Fig. 3. the probabilities of voltage constraint violations occurring at peak hours in different seasons are compared for 30% and 50% EV penetration and UKERC and CREST sourced synthetic load data. As would be expected, winter peak hours dominate the periods when constraints occur, however this is not exclusive and the load profile assumptions affect the level of dominance.

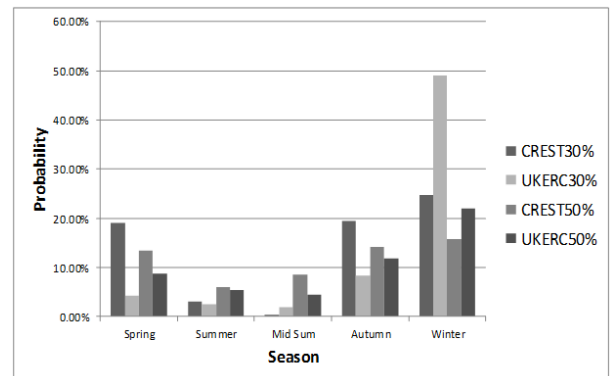


Fig. 3. Probability of voltage violations at seasonal peak hours for varying load assumptions and EV penetrations

The half hourly comparison indicates that although winter peak times see a majority of constraint violations, this trend is stronger for the UKERC synthetic data (with violations ranging from 50% to 22%) as CREST results only range from 24% to 21%. For both synthetic data sources, the proportion of constraint violations occurring during winter peak hours decreases for higher penetrations of EV (although overall the probability of voltage constraint violations increases) indicating that winter peak hours may not continue to be the worst case scenario. Despite this common trend, and although the UKERC and CREST results track closely for a system level analysis, a significant difference can be seen in the detailed predicted times of constraint violations.

CONCLUSIONS AND FUTURE WORK

The probabilistic approach to LV analysis relies heavily on assumptions relating to the network model and the predicted customer load profiles. The analysis presented here indicates that key assumptions significantly affect the predicted probabilities of constraints throughout the case study network.

Taking the underlying assumptions into account, the results in the presented case study still appear to provide a level of confidence in some general conclusions on EV penetration. Weak points in the network were identified due to the increased load of EV charging with specific nodes on one radial branch consistently experiencing higher probabilities of voltage constraint violations. These violations frequently occurred during peak hours, however the source of base customer load profile data significantly affected the concentration.

It is noted that, regardless of the customer load profile source, with increasing EV penetration constraint violations become less concentrated in traditional peak hours. These results imply that characteristic vehicle ownership and driving behavior will naturally incur significant levels of charging outside traditional peak hours. With typical price response schemes often designed to shift demand from traditional peak times or to incentivize increased demand during times of high renewable generation output [17], this study indicates that it cannot be assumed a network with high EV penetration would have the capacity to cope with such a shift in demand. In the case study presented here, the result would be increased EV charging during non-peak periods that already experience high probabilities of voltage constraint violations.

These general conclusions provide a useful insight to a particular scenario of EV penetration on the case study network, however the large disparity in the predicted probabilities of constraints between scenarios prevents specific detailed conclusions being drawn. For planning questions that require a reliable prediction of nodal constraint violations at specific times a thorough sensitivity analysis is required to understand the uncertainty introduced by these assumptions. The level of assumptions may vary for particular applications and the data available (or work required to obtain that data) may dictate how appropriate a probabilistic planning approach may be.

The anticipated availability of smart meter data is expected to allow highly accurate forecasting of customer load profiles, however timescales for the availability, and the arrangements for access to, this data are unclear. In the absence of smart meter data, a probabilistic, stochastic approach to LV analysis using typical averaged profiles, or indeed relevant transformer profiles, provides a powerful method of understanding likely future operating conditions; however, as demonstrated here, the choice of source profile will significantly affect the results and needs careful verification.

Future work will study these issues on other generic and real distribution networks, comparing various methods of generating synthetic load profiles and considering methods of identifying appropriate levels of assumption for particular planning applications.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the support of Scottish Hydro Electric Power Distribution Ltd for this research, Mr Sikai Huang of University of Strathclyde Glasgow for assisting with EV charging profiles and also Dr D. Pudjianto of Imperial College London for the supply of a generic LV network case study through the work of the Engineering and Physical Science Research Council Highly Distributed Energy Futures (HiDEF) consortium

(Grant reference: EP/G031681/1)

REFERENCES

- [1] R. C. Dugan, R. F. Artritt, T. E. McDermott, S. M. Brahma, K. Schneider, Distribution System Analysis to Support the Smart Grid", Proceedings of the IEEE PES General Meeting, Minneapolis, July 2010.
- [2] W.H. Kersting, "Distribution System Modeling and Analysis" in *Electric Power Generation Transmission and Distribution*, CRC Press, 2007, pp21-3.
- [3] W.H. Kersting, W.H. Phillips, "Distribution Feeder Line Models", IEEE Transactions on Industry Applications, Vol. 31, No. 4, July-August 1995.
- [4] C.S. Cheng, D. Shirmohammadi, "A Three-Phase Power Flow Method for Real-Time Distribution System Analysis", IEEE Transactions on Power Systems, Vol. 10, No. 2, May 1995.
- [5] P.A.N. Garcia, J.L.R. Pereira, S. Carneiro Jr, V. M. Da Costa, N. Martins, "Three-Phase Power Flow Calculations Using the Current Injection Method", IEEE Transactions on Power Systems, Vol. 15, No. 2, May 2000.
- [6] L. R. Araujo, D. R. R. Penido, S. Carneiro Jr, J. L. R. Pereira, P. A. N. Garcia, "A Comparative Study on the Performance of TCIM Full Newton versus Backward-Forward Power Flow Methods for Large Distribution Systems", Proceedings of the IEEE Power Systems Conference and Exposition, November 2006
- [7] F.A. Viawan, F. Vuinovich, A. Sannino, "Probabilistic Approach to the Design of Photovoltaic Distributed Generation in Low Voltage Feeder", 9th International Conference on Probabilistic Methods Applied to Power Systems, Stockholm, June 2006.
- [8] I. Richardson, M. Thomson, D.G. Infield, A. Delahunty, "A Modelling Framework for the Study of Highly Distributed Power Systems and Demand Side Management", International Conference on Sustainable Power Generation and Supply, Nanjing , 2009.
- [9] J. Taylor, A. Maitra, M. Alexander, D. Brooks, M. Duvall , "Evaluation of the Impact of Plug-in Electric Vehicle Loading on Distribution System Operations", Proceedings of the IEEE PES General Meeting, Calgary, July 2009.
- [10] P. Richardson, D. Flynn, A. Keane, "Impact Assessment of Varying Penetrations of Electric Vehicles on Low Voltage Distribution Systems", Proceedings of the 2010 IEEE PES General Meeting, Minneapolis, July 2010.
- [11] OpenDSS (Distribution System Simulator). <http://sourceforge.net/projects/electricdss/>, accessed November 2011.
- [12] G.F. Moore, "Electric Cables Handbook", Wiley-Blackwell, 1997.
- [13] Electricity user load profiles by profile class, UK Energy Research Centre, <http://data.ukedc.rl.ac.uk/browse/edc/Electricity/LoadProfile/data>, accessed November 2011.
- [14] UK Generic Distribution System. <http://www.sedg.ac.uk/ukgds.htm>, accessed November 2011.
- [15] I. Richardson, M. Thomson, D. Infield, C. Clifford, "Domestic electricity use: A high-resolution energy demand model2. Energy and Buildings 2010, Volume: 42, Issue: 10, Pages: 1878-1887
- [16] S. Huang, D. Infield, "The Impact of Domestic Plug-in Hybrid Electric Vehicles on Power Distribution System Loads", Proceedings of the International Conference on Power System Technology, Zhejiang, China , 2010.
- [17] A.J. Roscoe, G.W. Ault, "Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response", IET Renew. Power Gener., vol. 4(4), 369-382.