A FRAMEWORK FOR LOW VOLTAGE NETWORK PLANNING IN THE ERA OF LOW CARBON TECHNOLOGY AND ACTIVE CONSUMERS

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

The increased deployment of low-carbon technology and the anticipated impact on low voltage (LV) networks has led to a requirement for more detailed analysis and new planning methods for LV networks. This paper discusses the likely functionality required by a probabilistic LV planning framework that incorporates the stochastic characteristics of customer load. This facilitates the development and assessment of DNO led Demand Side Management schemes.

INTRODUCTION

Low voltage network design and planning in the UK is primarily concerned with providing a secure, good quality supply and relies on the techniques of After Diversity Maximum Demand (ADMD) and the 'statistical method' for estimating load demand.

Planning and operating distribution networks with increased levels of low-carbon technology and customer participation requires detailed distribution system analysis that allows the effects of distributed energy resources and proposed control methodologies to be investigated at all levels of the network [1]. For example, identifying the time and size of peak load on an LV feeder containing Electric Vehicles (EV), Heat Pumps, solar photovoltaic (PV) generation, combined heat and power generation (CHP) and thermal storage could be a considerable challenge. A planning approach that allows detailed analysis of phase unbalance and voltage/thermal constraints will be required. In addition, should there be varying degrees of control that could dispatch these Distributed Energy Resources (DER) in response to local or system events or market signals, additional uncertainty is added to the planning problem if anything but the most conservative, risk-averse approach was taken.

Instead of a worst case scenarios analysis, probabilistic and long period times-series load flow techniques are being increasingly used to capture the stochastic nature of customer load profiles and DER behavior.

DEVELOPING AN LV PLANNING FRAMEWORK

When considering long-term planning of LV networks, new approaches need to be found to simulate the likely operating conditions. Scenario analysis provides a method of analyzing possible future operating conditions and assessing the ability of an LV network area to cope in those conditions. A planning framework that allows stochastic/probabilistic analysis (with a well understood degree of accuracy) of an LV network under any proposed scenario of EV, electric thermal loads, flexible tariffs and load control by 3rd parties, for example, would provide a spatial and temporal probabilistic view of the network operating conditions and allow weaknesses to be identified.

The following sections outline some key components of such a planning framework.

Synthetic load profiles

With the advent of smart metering, vastly improved load data is expected to become available over time. Access to detailed historical data will facilitate forecasting of expected customer load profiles, however timescales for smart meter delivery and hence the availability and granularity of this data is currently unclear in the UK. At present when considering studies of LV, transformer load profiles or averaged customer annual profiles are generally available. Various methods of creating synthetic individual profiles from these aggregated profiles have been utilized [2], [3], [4], [5]. An alternative approach is to derive individual profiles from assumptions on occupancy and appliance use [6]. It is logical that the load data will significantly affect the results of a study and a level of confidence would be required in the predicted customer load profiles.

Network Model

Underlying any load flow study 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. These single phase connections could also be unbalanced across the phases.

The most accurate method of modeling distribution lines is via Carson's equations using the basic physical characteristics of the cables and the separation distances [7]. Commonly, such detailed network information is not available, however it has been demonstrated that deriving an approximate phase impedance matrix from positive and zero sequence impedance values will introduce negligible error as long as further assumptions on balanced load or mutual coupling are not made [8], [9].

Load Flow Engine

The standard Newton and Gauss methods perform poorly when applied to LV networks as they do not exploit any radial nature of the network and require the solution of a set of equations to the order of the number of buses [10]. Specific distribution system load flow algorithms have been developed to address these issues and to allow three phase analysis [11]. There is an extensive prior art in this area ranging from applications of the ladder technique to modified Newton Raphson methods. For weakly meshed systems, methods based on the ladder technique perform well, however for larger, strongly meshed systems, modified Newton Raphson methods have been shown to be more suitable [12].

An alternative to implementing a load flow within a planning framework would be the use of an existing package. Commercial packages with unbalanced solvers and scripting capability could be integrated, however the lack of access to the source code may be an issue. Alternatively, EPRI's openDSS provides an open source engine with a COM interface [13].

Integrating Control

Demand Side Management (DSM) is an area of significant research and many methods of controlling customer point of connection load have been presented in the literature [14], [15]. These include price arrangements, optimizing charging of electric vehicles and frequency response of white goods. Any proposed scheme that does not fully consider LV network constraints in its scheduling or optimization algorithms must be evaluated in terms of its impact on the network. A planning framework must be able to incorporate any proposed control that will influence the behavior of load and provide an understanding of how this will affect the state of the network.

From a DNO perspective, based on a probabilistic analysis, the likely need for intervention can be established. When unacceptable operating conditions are predicted, solutions can then be assessed. The probable spatial and temporal weak points can be identified and will form the minimum requirements that any DNO led DSM action must address.

CASE STUDY ANALYSIS

A case study is presented to inform the discussion areas outlined above. A simulation tool has been developed in Matlab that forms the three-phase network model from positive and zero sequence network data, creates individual customer stochastic load profiles and computes the load flow solution for each time step. A three-phase unbalanced load flow algorithm based on [16] is used for steady state power flow analysis. The load flow accuracy was verified by comparison against a commercial package and EPRI's OpenDSS.

Network Model

A generic urban UK LV network is used as the case study network (shown in Fig. 1.). As is commonly the case, the data available provided positive sequence impedance values only. In the absence of zero sequence data, approximations are often used where the positive sequence impedance is multiplied by a factor of between three and five to estimate the zero sequence impedances [17]. Initially a factor of three has been assumed for the case study network.

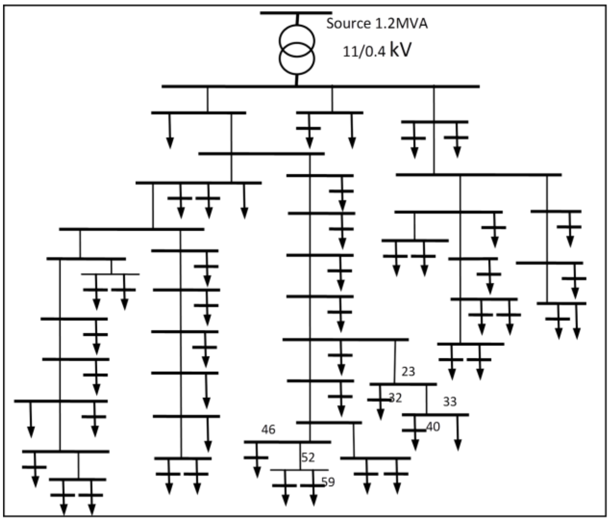

Fig. 1. Case Study LV Network

The network has 83 nodes, and a 1.2 MVA 11/0.4 kV transformer. Fifty nodes have connected load. Forty four nodes connect a total of 396 domestic customers. Six nodes connect commercial loads. The simulation records any over/under voltage or excess phase imbalance at each node in the network for each half-hour. All branch currents are monitored for thermal violations.

Creating synthetic load profiles

Three sources of customer load profile data have been considered, CREST [6], UKERC [18] and UKGDS [19] and two methods of creating synthetic data compared. Individual customer profiles are created from an average profile to reflect differing occupancy and appliance use. A probability distribution of the likely load value for that customer is created for each time step. At each time step of the power flow simulation each load's pdf for that time step is sampled.

EV load profiles were simulated using the technique in [20]. 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.

To capture the probabilistic nature of the load profiles and cover a sufficient range of the possible load values at each node at each time step, a base case simulation comprised 100 runs of annual analysis.

Understanding the assumptions

In [21] the authors discuss the underlying assumptions of a probabilistic LV analysis and the need to represent these in the results of such analysis. Various scenarios of network data and load profile assumptions are analysed and it is noted that assumptions on zero sequence impedance have a minimal effect on the base case scenario but as EV penetration increases, the probabilities of voltage constraint violations increase considerably. As would be expected, the synthetic load data has a significant effect on the results. Despite disparity in overall probabilities between synthetic load data sources, specific nodes on one radial branch consistently experienced higher probabilities of voltage constraint violations due to EV charging.

Integrating control

In order to investigate the impact of demand control, a simple heuristic algorithm has been applied that delays EV charging in response to network constraints. The base case probabilistic analysis indicates likely constraints occurring in response to EV charging behavior. In response, at any time step where a constraint is predicted, the algorithm searches the radial branches of the network and identifies the EV affecting the constrained nodes. The algorithm then steps through each of those EV in turn; delaying their charging by one time step until the constraints are resolved or all EV charging has been delayed. The results in Fig.2. show at least a 50% reduction in predicted overall probability of voltage constraints per node.

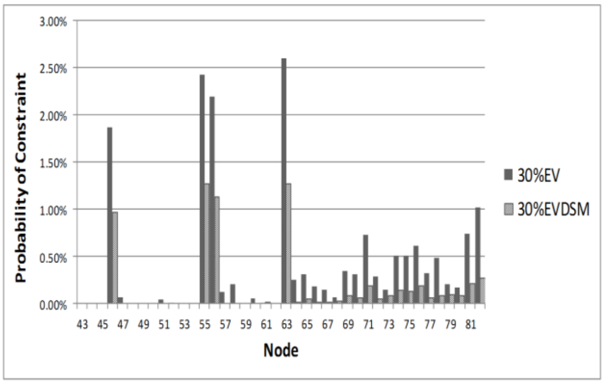

Fig. 2. Comparison of overall voltage constraint probabilities for 30%EV penetration with and without demand control.

A view of when constraints will occur at particular nodes provides an extra level of granularity. Fig.3 shows the results at 18:30 on a Winter Monday. The majority of nodes have their probability of constraint reduced by the shift in EV charging, however the high probability for nodes 46, 55, 56 and 63 are unaffected.

This fairly simple example demonstrates the way in which a proposed control scheme can be evaluated. This could be applied to either direct control or price response schemes. The anticipated change in behavior can be simulated and the ability of the LV network to facilitate this could be predicted.

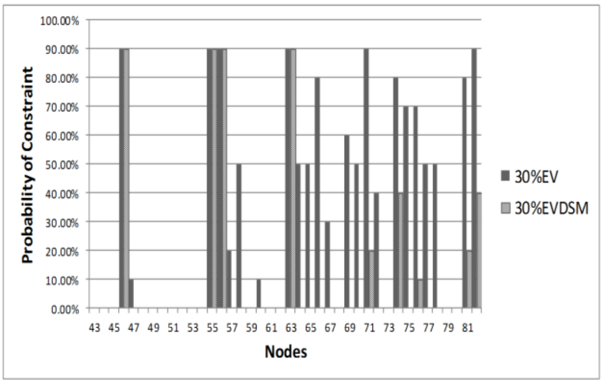

Fig. 3. Comparison of one half hour's voltage constraint probabilities for 30%EV penetration with and without demand control.

Assessing demand control resource

By integrating an assessment of demand control into the framework, the ability to assess potential demand control resource within an LV area is enabled. For wider network management applications such as Active Network Management or frequency response schemes, this would provide a probabilistic view of the potential level of resource available at particular times and provide a view of non-DNO demand management able to be accommodated within network constraints.

In the case study, this idea is explored by analyzing the scope of delaying EV charging without incurring network constraints. An algorithm has been implemented to assess the network in terms of the potential EV charging demand that could be delayed per half hourly time step. The results for a Winter Friday are shown in Fig 4.

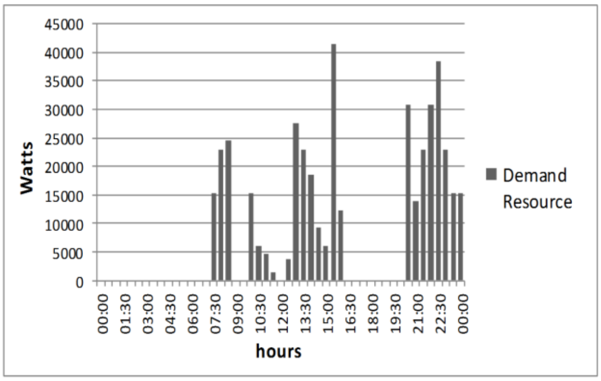

Fig. 4. Average predicted demand resource for a 30%EV penetration scenario on a Winter Friday.

The algorithm operates by assessing the system wide EV charging state for each time step. All EV charging is shifted by one time step and the potential constraints calculated. If this action is found to cause constraints, the demand control heuristic described above is used to reduce the number of EV shifted until no constraints are observed. This allows the maximum possible demand control action for that time step to be identified. Using the probabilistic approach over 100 iterations of analysis, an average predicted demand resource is found. Clusters of potential demand resource up to 40kW can be seen in the morning, afternoon and the late evening. It is noticeable that no demand resource is predicted during peak hours.

CONCLUSIONS AND FUTURE WORK

LV modeling techniques have been reviewed and the requirements of an LV planning framework examined. The probabilistic case study analysis has highlighted the need for thorough sensitivity analysis around network modeling and load assumptions. The results indicate that, working within an understanding of these assumptions, some general conclusions can be drawn on the likely weak areas of a network. The need to integrate potential control actions into the planning analysis has been demonstrated. The case study results indicate that relatively simple demand control actions that operate within network constraints can significantly reduce probabilities of voltage constraints and that the probabilistic approach can be used to assess the potential demand management resource available within an LV network area.

The planning framework will be developed further to include electric space and water heating, more granular time step analysis, and supplier-led DSM schemes in order to further explore the application and value of probabilistic analysis to LV networks. Advanced load control techniques will be developed to analyse the need for, operation of, and value provided by DNO led Demand Side Management.

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. Arritt, 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] 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.

[3] A. Maitra, K.S. Kook, J. Taylor, A. Giumento, "Grid Impacts of Plug-in Electric Vehicles on Hydro Quebec's Distribution System", Proceedings of the Transmission and Distribution Conference and Exposition, April 2010.

[4] P. Papadopoulos, S. Skarvelis-Kazakos, I. Grau, L. M. Cipcigan, N. Jenkins, "Predicting Electric Vehicle Impacts on Residential Distribution Networks with Distributed Generation", Vehicle Power and Propulsion Conference (VPPC), 2010.

[5] 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.

[6] 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

[7] W.H. Kersting, "The Whys of Distribution Analysis", IEEE Industry Applications Magazine, Vol. 17, Issue 5, pp 59–65, Sept-Oct 2010.

[8] W.H. Kersting, "Distribution System Modeling and Analysis" in *Electric Power Generation Transmission and Distribution*, CRC Press, 2007, pp**21**-3.

[9] W.H. Kersting, W.H. Phillips, "Distribution Feeder Line Models", IEEE Transactions on Industry Applications, Vol. 31, No. 4, July-August 1995.

[10] D. Shirmohammadi, H.W. Hong, A. Semlyen, G.X. Luo, "A Compensation-Based Power Flow Method For Weakly Meshed Distribution And Transmission Networks", IEEE Transactions on Power Systems, Vol. 3, No. 2, May 1988.

[11] M.S. Srinivas, "Distribution load flows: a brief review", Proceedings of the IEEE Power Engineering Society Winter Meeting, Jan 2000.

[12] 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

[13] OpenDSS (Distribution System Simulator). http://sourceforge.net/projects/electricdss/, accessed November 2011.

[14] 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.

[15] A. Santandreu-Corretgé, M.R. Mora-Marin, I. Cairó-Molins, A. Sumper, A. Sudrià-Andreu, "Demand Side Management and Electric Vehicle Integration (Verde)", 21st International Conference on Electricity Distribution (CIRED), June 2011.

[16] E. Bompard, E. Carpaneto, G. Chicco, R. Napoli, "Convergence of the Backward/Forward Sweep Method for the Load-Flow Analysis of Radial Distribution Systems", International Journal of Electrical Power & Energy Systems, Volume 22, Issue 7, pp 521-530, Oct 2000.

[17] G.F. Moore, "Electric Cables Handbook", Wiley-Blackwell, 1997.

[18] 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.

[19] UK Generic Distribution System. http://www.sedg.ac.uk/ukgds.htm, accessed November 2011.

[20] S. Huang, D. Infield, "The Impact of Domestic Plug-in Hybrid Electric Vehicles on Power Distribution System Loads", Proceedings of the Int. Conf. on Power System Technology, Zhejiang, China , 2010.

[21] D. Frame, G. Ault, "Exploring the Uncertainties of Probabilistic LV Analysis", 22nd International Conference on Electricity Distribution (CIRED), May 2012. (In submission at the time of writing).