Smart Network Design Methodologies

Literature review

May 2018

Contents

0. Document control

0.1. Document history

Version	Status	Issue Date	Authors
0.1	Build the structure of the document	12/03/18	A. Grissonnanche C. Higgins
1.0	Complete document ready for review	29/03/18	A. Grissonnanche C. Higgins
2.0	Updated version for review	19/04/18	A. Grissonnanche C. Higgins
2.1	Incorporate review comments	17/05/18	A. Grissonnanche C. Higgins

0.2. Document review

Name	Responsibility	Date
Francis Shillitoe	Project Manager	17/05/18
Alan Creighton	Technical Lead	20/04/18

0.3. Document sign-off

Name	Responsibility	Date
Mark Nicholson	Project Sponsor	23/05/18

1. Introduction

1.1. Background

The present design and modelling tools for LV systems are more simplistic than those used for HV & EHV planning. This was acceptable when the LV network was load centric, passive in nature and accurate monitored – SCADA or Half-Hour metering – datasets were not available. Modelling tools are either spreadsheet based solutions that consider a typical end user demand – e.g. After Diversity Maximum Demand (ADMD) scaled to match the Maximum Demand Indicator value recorded at the secondary substation if this is available and considered to be accurate – or the LV DEBUT tool that uses annual consumption figures. These tools are based on a single "worst case" scenario rather than considering the range of network loading conditions that may occur with varying customer type, seasonal effects, low carbon technology behaviour etc. All these factors combined may often lead to inaccurate and over-engineered solutions as they tend to be based on pessimistic assumptions of the LV system utilisation and operating conditions.

LV network modelling has typically been undertaken on individual LV feeders using these simplistic spreadsheet models or simplified probabilistic modelling approaches. Whilst probabilistic modelling can provide a good understanding of the impact of varying demand profiles and embedded generation rather than behaviour at peak loading, it is not based on actual power flow modelling. It also does not enable analysis of the wider LV network and the capture of any interdependencies across voltage levels from 132kV down to LV.

With the advent of SCADA and smart meter data at LV and growth of different low-carbon technologies, the methodologies/assumptions employed by the current analysis tools are rapidly becoming out-of-date. For instance, when carrying out voltage studies downstream of the final voltage-controlled busbar (i.e. primary transformer HV busbar), several uncertainties are present such as the representation of voltage variation with load within the local and wider HV and LV network. These uncertainties have led designers to use pragmatic and deterministic assumptions when assessing voltage regulation. However, on site voltage measurements show that these assumptions can sometimes lead to over-reinforcement in urban areas and under-reinforcement in some rural networks for voltage issues. Also, when assessing the holistic effects of advanced voltage control techniques such as Line Drop Compensation (LDC), existing design tools are not fit for purpose as the low voltage networks are not modelled together with the EHV and HV networks in the same model.

The 'Smart Network Design Methodologies' NIA project has therefore been launched with the aim of significantly improving design and planning assumptions through the use of smart metering data and enabling more holistic network modelling.

1.2. Document purpose

The purpose of this document is to provide a summary of current and previous Low Carbon Networks Fund project reports, academic and industry papers that provide valuable insights and learning relevant to this project. These will inform the development and trialling of improved network model methodologies and novel analysis techniques. The areas of interest for the literature review are aligned with the project workstreams: LV network model methodology, multi-voltage level network model methodology, smart meter data analytics and novel analysis techniques.

1.3. Executive Summary

The literature review undertaken has identified more than twenty relevant academic and industry papers including Low Carbon Networks Fund project reports that provides valuable insights and learning from which the project will build upon to improve the modelling, design and planning assumptions through the use of smart metering data and enable more holistic network modelling.

LV network model methodology

A number of papers were reviewed relating to LV network modelling methodologies where the LV network was modelled and analysed using smart meter, monitoring and SCADA data. In order to model the LV network, some assumptions are required to simplify the analysis however, these introduce uncertainty. The individual and cumulative impact of these assumptions should be considered, for example, granularity of customer load characterization from smart meter data, phase imbalance and power factor (which has been found to show significant variation). Clustering of customers by behavioural demand groups, across a range of timescales, can improve linking of monitored and unmonitored customers and help to better forecast future uptake of low carbon technology. The greater of use of measured data generally enhances LV network modelling beyond assumption-based models.

We will explore the development and use of LV network models using smart meter, distribution substation monitoring and SCADA data, exploring how to represent customers without smart meters. The individual and cumulative materiality of modelling assumptions will be assessed. Voltage accuracy will be an important consideration when assessing the usefulness of smart meter voltage to network modelling/network planning.

An algorithm approach to determine LV connectivity based on GIS data was also reviewed. We will consider how to efficiently extract LV connectivity data from NPg's asset management database in the development of an automated LV network build approach and may draw on this learning where relevant.

Multi-voltage level network model methodology

Increasingly, multi-voltage-level distribution network models are being considered to assess the performance of alternative design and operational strategies including voltage control. A number of voltage control technologies and techniques were successfully modelled and trialled in Smart Street that are applicable across voltage levels and in a multi-voltage context. These will be reviewed further for applicability to testing in multi-voltage level models. Smart Grid Forum Workstream 7 developed four multi-voltage Base Networks with which to undertake detailed analysis into the operation of the GB power system as projected for 2030. Findings on voltage based smart solutions tested in DS2030 will be reviewed in more detail.

Smart meter data analytics

In terms of smart meter data analytics, the review considered papers that analysed how varying levels of aggregation of smart data affect the accuracy of derived customer load profiles and data privacy issues. The papers confirmed that the aggregation of smart meter readings, the half-hourly averaging of customer readings and the inability to identify the connection phases affects significantly the modelling accuracy of power flow, technical losses and voltage levels in the LV network. In addition, the aggregation of two customer smart meter consumption profiles minimises the reduction in modelling accuracy whilst potentially meeting the requirements of the licence condition SLC10a to ensure anonymity. As part of its Smart Meter Data Analytics stream, the project will investigate suitable approaches for disaggregating load profiles based on the anticipated Level 2 aggregation – i.e. aggregating the consumption data of two households.

Regarding phase connectivity identification, the literature review provides a summary of how clustering algorithms – such as the K-means algorithm – can be used to allow phase identification on the LV network using smart meter data. However the K-means algorithm is relatively expensive to compute which may make it impractical to use. A paper[1] soon to be published and co-authored by Sheffield University and Northern Powergrid which only became available at the end of the Literature Review, gives a detailed summary of three methods of phase identification and researches one of them in more detail. We will draw on this paper later on in the project. We will also consider how the practical implementation of smart meters in GB will affect the applicability of these methods: areas of concern include voltage accuracy, patchy rollout of smart meters, and aggregation of consumption data.

When it comes to load profile, the literature review, in particular New Thames Valley Vision (NTVV), identified promising statistical methods such as bootstrapping to generate confidence data when monitoring data was not available; these are detailed in the NTVV SDRC 9 report, which will be examined later on in the project. We will define how such methods can be employed to consider load variance, spatially and temporally, for high generation or high demand conditions

Novel analysis techniques

Finally, regarding the development of novel analysis techniques, the papers reviewed demonstrated techniques that will be useful for the project and confirmed that a more probabilistic approach to network planning provides a much fuller characterisation of network behaviour, sensitivities and trends. This is particularly valuable as it enables a more appropriate techno-economic analysis of load growth compared to generalised deterministic analysis which is generally more conservative. Probabilistic methods can also be extended to include the assessment of voltage control techniques.

The Monte Carlo method can be applied to historical demand and generation data to capture stochastic effects across network voltage levels and combined with deterministic load flow for improved LV and multi-voltage level network modelling. However, there are also other efficient probabilistic techniques that could also be applicable e.g. Imperialist Competitive Algorithm. A range of approaches are available to improve algorithm accuracy and efficiency.

We will assess the suitability of various probabilistic techniques before finalising on techniques to trial, including the application to voltage control. This will also consider the enhancement of algorithm accuracy/efficiency.

In the draft Engineering Recommendation P2/7 security of supply document, emphasis is on defining the minimum level of security of supply that should be achieved rather than how that level should be achieved. Whilst the P2/7 modification is still under consultation, we will consider relevant findings where possible.

[1] A. Brint, G. Poursharif, M. Black, M. Marshall "Using grouped smart meter data in phase identification", accepted for publication in Journal of Computers and Operational Research

2. Scope

2.1. In Scope

As the project focuses on developing and testing new methodologies and techniques for network planning purposes including utilising smart meter data, the papers related to the following topics were reviewed from a network planning point of view:

- LV network model methodologies
- Multi-voltage level network model methodology
- Smart meter data and analytics
- Novel analysis techniques

2.2. Out of Scope

- Network operations

3. LV network model methodology

In order to model the LV network, some assumptions are required to simplify the analysis however, these introduce uncertainty. The individual and cumulative impact of these assumptions should be considered, for example, the effect of different levels of granularity on customer load characterization from smart meter consumption data. It has also been shown that input from smart meters and distribution substation monitoring and SCADA data can enhance an unbalanced per-phase LV model beyond assumption-based models.

An innovative LV network model connectivity approach based on GIS data is also reviewed.

Assumptions and approximations typically applied in modelling LV networks with high penetrations of low carbon technologies [L1]	
Background	Uncertainties in the assessment of LV network capacity to accommodate PV and other low-carbon technologies can lead to installation constraints or costly network reinforcements that may not be entirely necessary.
Objectives	This paper reviews the numerous assumptions often used in such assessments and highlights those relating to the time resolution of demand models, harmonics, network grounding and impedance modelling as being of particular concern. In many cases, individual assumptions may be low risk, but there is greater uncertainty when assumptions are applied in combination. Some of the assumptions typically used in LV network modelling are adopted from experience of modelling higher voltage networks. Others may stem from limitations in data available to describe the actual network configurations, and the varying characteristics of the loads and generators that are connected.
Approach/ Methodology	This paper assessed at a high level, the level of risk posed by various LV network modelling assumptions. A list of assumptions was given, including references to examples where they have been applied. The the impacts of the assumptions on modelling results was reviewed. Some of the more questionable assumptions were then reviewed in further detail and the modelling assumptions that appear to be the most critical for further evaluation were identified.
Learnings and outcomes	The following LV network modelling assumptions can affect numeric results: • The use of time-averaged demand samples for periods much longer than the typical on-time of appliances • Assuming a constant power vs. voltage model for loads. • Assuming mean demand is balanced across each phase. • Modelling the network as sinusoidal without harmonics. • Assuming one earthing scheme throughout, when many configurations and combinations may occur in practice. • Applying the Kron reduction technique when ground connections may not exist or have non-zero impedance. • The use of separate terms from Carson's equations to provide an impedance model for the earth currents. Assumptions regarding time resolution for demand, current balance and harmonics, all have impacts on models of neutral currents, losses and voltage unbalance. These assumptions are of particular concern when combined.

	The impact of approximations was shown to have minimal impact on voltage magnitudes. However, there is a greater error on estimates of voltage unbalance and losses. A formal comparative study would be needed to fully assess the impact of all of these assumptions.
Conclusion	This paper has presented a broad review of assumptions made when modelling power flow in LV networks, particularly where the impact of distributed generation is to be assessed. These are most relevant to LV networks where the demand is more subject to the stochastic variations of customer loads and as the networks are less well characterised. The appropriateness and materiality of these assumptions will be considered further alongside the LV load representation approach when developing the LV network model methodology.

Modelling and Validation of an Unbalanced LV Network Using Smart Meter and SCADA Inputs [L2]	
Background	Disruptive technologies such as PVs and EVs are connecting to LV networks, the need to understand the physical constraints and real-time system state has become crucial to designing a stable, efficient network facilitating smart grid development. This paper intends to model LV networks based on the measured smart meter demand data combined with 66kV/22kV zone substation SCADA voltage data.
Objectives	The two key components required to better understand LV networks are accurate network models and smart meter consumption data to provide real inputs into the model. This work aims to do this by modelling a three-phase, four-wire unbalanced model of an urban network in northern Melbourne consisting of 113 customers. By linking each customer's National Metering Identifier (NMI) to the smart meter consumption database, real load data per customer is integrated into the LV model.
Approach/ Methodology	The LV model was created using DigSilent PowerFactory. Conductor route lengths for the LV backbone (conductors between distribution poles) and the service cables to each customer were determined via physical onsite inspection and using GIS software cross-referenced with satellite photos of the LV Network. The model also imports the 22kV conductor and zone substation data from available HV models. Phase allocation for each customer in the model reflects the actual connection to the LV network in order to establish a true unbalanced model. Each house in the LV model is integrated with a data stream from the individual customer's smart meter. This allows the model to access actual and near real-time demand data at a granular level. Each smart meter provides voltage, current and consumption data at 30-minute intervals. The zone substation component of the model is fed with a SCADA voltage data stream from the 66kV/22kV transformers. Two GridSense PowerMonic PM45 loggers were installed at two locations on the LV network. The loggers measure key parameters such as Voltage and Current at one-minute intervals for all three phases and neutral. This data serves as a reference point for the real state of the LV backbone.
Learnings and outcomes	The simulation model presented demonstrates a strong correlation with the real network, with simulated outputs closely matching data logger reference measurements for current and voltage at different locations in the network, throughout the day. This shows that the proposed LV model is sufficiently accurate to estimate the real state of LV networks in reference to Australian Standards and the Electricity Distribution code. The input from smart meters and zone substation SCADA enhances this unbalanced per-phase LV model beyond assumption-based models often found in the literature. Using this as a baseline, the LV model can be used as an accurate, near real-time platform to perform EV and EG optimization and planning strategies going forward.

Conclusion	The modelling approach presented in the paper may be useful for this project as it shows excellent agreement with network measurements. However, the modelling is based on perfect knowledge of customer phase allocation and full smart meter uptake which may be very difficult to achieve in practice at present. Historically, customer phase connectivity has not been recorded and there is some level of uncertainty regarding phase connectivity that has been recorded.

Learning from Residential Load Data: Impacts on LV Network Planning and Operation [L3]	
Background	The deployment of various type of low carbon technologies is already taking place in many distribution networks. In order to adequately assess the impacts of these low-carbon technologies, a much better understanding of how electricity is currently consumed is required.
Objectives	The paper firstly studies the effects of load characterization on the optimal selection of the conductors from the planning perspective based on a high granularity model for UK residential consumers that mimics data that could eventually be available through smart meters. Then, from the operational point of view, the benefits of load shifting (i.e., demand-side management) to reduce peak demand are also investigated. The latter study is applied to a real LV network the North West of England.
Approach/ Methodology	LV feeders, domestic loads has been modelled in a way that their short-term variations during the day are considered (one-minute resolution models developed for UK households has been adopted, the data that could be available through smart meters). All types of consumers were randomly specified to create a pool of 1000 different load profiles to be used in the impact analysis.
Learnings and outcomes	From the planning perspective, in terms of the effects of the data granularity level on the load factor and coincidence factor, it was found that hourly 'sampling rates' produce an overestimation of those factors. On the other hand, 1 and 5 min data do not show significant differences. This is crucial in determining the right level of data to be monitored or stored for similar purposes. In terms of optimal conductor selection, it was also demonstrated that taking historical values for the load factor rather than those based on measurements could lead to suboptimal investments. From the operational perspective, it was shown through the coincidence and load factor curves that the fridge loads are above those for the total loads, making them a feasible load to be controlled. However, considering only the washing appliances, a load shifting algorithm was proposed to assess the potential peak reduction from demand-side management strategies. Results using a real LV network showed that it is possible to estimate the most likely peak reduction as well as the lowest contribution according to the number of customers per feeder. This analysis can inform operational decisions when implementing similar demand side management schemes.
Conclusion	Results clearly indicate the potential benefits of LV network planning from high granularity data, as well as the important insights that could be gained from modelling load shifting schemes using such data. The paper shows the importance of better understanding of LV demand on LV network planning and operation. Half hourly energy consumption data will be available from smart meters but this will be aggregated above individual customer level. So whilst the paper provides some useful learning, in practice, the level of smart meter data granularity available may not allow some of the benefits e.g. DSM, to be realised in the near term.

Reconstruction of low voltage distribution networks: From GIS data to power flow models [L4]	
Background	The paper proposes a systematic, practical and implementable methodology to achieve the full reconnection (connectivity) of LV feeders and, as a result, the production of suitable computer-based models. This proposed methodology can help DNOs around the world facing similar challenges. Indeed, it has already been successfully applied to create more than five hundred real residential, underground UK LV feeders.
Objectives	LV networks have no electrical modelling, however GIS systems are in place for the LV network. A methodology is proposed to create a power system model in openDSS using GIS data.
Approach/ Methodology	The paper proposes a methodology to transform GIS data into a power model through a series of steps for electrical reconnection using Breadth First Search algorithm to explore neighbouring nodes. Using geometry, the best candidate is selected and connected to the main feeder. The methodology follows 4 steps with stages within each step. Step 1: Creation of line segments. GIS uses a polyline to manage big amounts of data, the first step is to create line segments using the coordinates from GIS and identify the nodes. Step 2: Identification of connected components. Having the root on a list and using the Breadth First Search algorithm. Implementing the algorithm explores the neighbouring nodes and connects the basic structure. Step 3: Reconnection process. Using geometry, connecting one by one to reconstruct the model. Step 4: Computer-based model
Learnings and outcomes	The paper presents a systematic, practical and implementable methodology to reconstruct LV feeders from GIS data (containing connectivity issues) so computer-based network models can be produced. These models are crucial to carrying out operational and planning studies required to assess the impacts from the future adoption of low carbon technologies (LCTs). Depending on the scale and nature of the connectivity issues in the available GIS data, these reconnection techniques can be used selectively or more widely.
Conclusion	The proposed methodology can help DNOs around the world facing similar challenges. Indeed, it has already been successfully applied to 500+ residential, underground UK LV feeders. These feeders have been used to analyse the impact of LCTs and the benefits of potential solutions in several publications. Learning outcomes may be relevant to the development of an automated LV network model build approach in IPSA using LV network connectivity data from NPg's asset management database. This will be further explored in the LV network model methodology workstream.

SP Energy Networks (SPEN) – Flexible Networks [L5]	
Background	Three areas of SPEN's network with known capacity issues were identified which provide an opportunity to analyse and implement a number of alternative flexible solutions to network reinforcement. All three sites have different but representative characteristics and customer demographics, and are similar in that they have near-term constraints due to increasing demand and an uptake of low carbon technology. The rapid nature of these changes both imposes a requirement, but also provides the opportunity to trial solutions that are faster and more cost-effective to implement than traditional reinforcement.
Objectives	• Develop an enhanced network monitoring methodology and based on this network data, develop and integrate improved DNO planning and operations tools and practices that are optimised for future low carbon networks and use of the innovative techniques being trialled, • Trial novel technology measures for improved performance of the network such as dynamic thermal ratings of assets, voltage optimisation, and flexible network control, • Identify the measures by which material improvements in the cost-effectiveness of accommodation of future energy needs can best be demonstrated, • Develop an investment and future roll-out plan where appropriate cost-benefit exists.
Approach/ Methodology	The following innovative technologies were deployed and trialed: • Flexible Network Control: Use of controls to help rebalance network loading. • Real time thermal ratings (RTTR) for 33kV overhead lines • Enhanced thermal ratings for primary transformers • Voltage optimisation to reduce customer energy usage and create additional generation capacity The following analysis methodologies/tools were developed: • HV load forecasting: A more probabilistic approach to data analysis augmented by appropriate analytical tools was explored to provide a much fuller characterisation of network behaviour, sensitivities and trends. This enables a more appropriate techno-economic response to load growth compared to generalised deterministic analysis which is generally more conservative. • Characterisation of PV at LV: A model for characterising PV behaviour on network load and voltage profiles and estimating embedded generation connection capacity was developed and validated with detailed network monitoring data and power system modelling. Opportunities for voltage optimisation were also explored to facilitate increased PV connections. • Characterisation of HV and LV imbalance: A simple methodology was developed and tested to characterise LV phase thermal imbalance from large volumes of monitoring data, focusing on magnitude and persistence of phase imbalance under high loading conditions. The methodology was also applied to characterise thermal phase imbalance at HV. • Improved future network modelling: Techniques to more efficiently and accurately build HV and LV network models were investigated including increased automation and improved business database linkages. Analysis of detailed monitoring data available from secondary substations and LV feeders verified existing network modelling practices and provided recommendations for improvement. • Data Analytics: A pilot study was undertaken with IBM as part of Flexible Networks to develop a Distribution Grid Analytics tool. This utilised GIS data, NMS network configuration data, coordinates of monitoring locations and monitoring data. The current network topology was then visualised through an overlay on Google Maps and analytic tools implemented to enable identification of thermally overloaded substations, voltages outside of statutory limits, and phase imbalance, from analysis of the monitoring data.

	In terms of future monitoring strategy on the LV network, recommendations were made to the business for "smart" MDIs to be deployed to secondary substations at key locations across the LV network identified through application of the LCT Network Monitoring Strategy.
Learnings and outcomes	It was found that increased demand can be accommodated on the network through a better understanding of existing and future demand characteristics. It was also found that greater volumes of PV generation can be accommodated on the LV network through improved characterisation of PV generation and customer demand. Voltage optimisation can enable a further generation to connect. Depending on voltage profiles during times of peak demand, it may be possible to apply a permanent voltage reduction rather than a seasonal reduction. The deployment of the innovative techniques was successful, providing capacity headroom gains generally at or above the anticipated levels. The planning methodologies, design specifications, procurement, installation and commissioning approaches developed as part of this are now being adopted by the business. This enabled the successful application at the three network trial sites to defer or avoid costly traditional reinforcement as evidenced by the updated business cases.
Conclusion	Flexible Networks improved knowledge of the distribution network, the ability to detect changes, extrapolate trends and identify the appropriate response. A number of innovative techniques were trialled and proven, these can be deployed as part of a holistic toolbox of DNO-led capacity solutions to address network constraints. New and improved planning tools were developed to understand and predict network behaviour, improve investment decisions and support pipeline management. This included methodologies and tools for the trial of different approaches to more accurately assess the impact of phase imbalance and embedded generation on the LV network and voltage optimisation techniques. TNEI was closely involved in delivering Flexible Networks as a project partner so will incorporate relevant learning outcomes into developing the LV network model methodology.

Scottish and Southern Energy Networks (SSEN): New Thames Valley Vision [L6]	
Background	The New Thames Valley Vision project was executed over 5 years. The project focused on the low voltage network with the aim of gaining an insight as to how DNO's can provide a better service to the customer by understanding, anticipating and supporting future energy use in a low carbon environment.
Objectives	The NTVV project set out a number of objectives. The project aimed to apply proven data analysis from the Energy Demand Research Project (EDRP) to identify different customer types connected to the distribution network and their effect. The project also sought to understand the behaviour of different types of customer so that better investment decisions could be made. Mitigation strategies in the form of technical and commercial solutions were also investigated. Demand-side response and the use of power electronics were of particular focus to identify how these approaches could offer network flexibility and alleviate network constraints.
Approach/ Methodology	Monitoring equipment was installed in 300 substations in Bracknell. This provided voltage data at the LV bus bar as well as load current, real and reactive power, energy and voltage harmonic for each phase. The project aimed to demonstrate mathematical and statistical techniques used in other areas e.g. consumer retail, that could be useful for electricity consumers and used for network planning. Mathematical techniques were used to identify where network monitoring should be deployed through

	customer profiling. Demand response trials were carried out with large commercial and Small and Medium Enterprise (SME) customers to investigate the capability of supporting the operation of distribution networks. Power electronics and energy storage were also deployed to showcase how these technologies can manage power factor, harmonics and voltage.
Learning and outcomes	It was stated that for secondary substation monitors, a voltage resolution of +/- 0.1 V was required to provide a useful understanding of the voltage performance. Energy consumption resolution of +/- 1 Wh was preferred when used with mathematical techniques. NTVV customers with the largest peak demand are most likely to have an on-site Building Management Systems (BMS) and as a result, the average load-shed is significantly higher. It is evident there is a link between customers with a BMS and high load shedding for demand side response. Smaller non-domestic customers typically have a very limited demand that can be shed, and the additional considerations of reliability (opt-out, technical and communications issues) and costs make this approach less attractive for both the DNO and the customer. The possibility of using network-connected energy storage remains an option subject to the actual constraint parameters. For larger non-domestic customers, typically connected at HV or with a single consumer distribution substation connection, the use of LV connected storage as trialled on the project has no role, but it is much more likely that such customers would be able to participate in demand response. For customers with an air-conditioning dominated load, the use of thermal storage as demonstrated using the Ice Bear technology is possible. For a DNO to incentivise these solutions there would have to be a corresponding HV feeder or primary substation loading constraint. In any given area of the network, it may be that a combination of network management technologies provides the optimal solution for constraint management. Through smart control a DNO may be able to optimise the use of an energy storage technology by ensuring a full charge/discharge, as opposed partial usage, utilising the flexibility provided by Automated Demand Response (ADR). Customer groups could be identified based on demand during the four time periods of Breakfast time, Daytime, Evening and Overnight. Determining the volume of customers in each category connected to a feeder would allow immediate impacts to be assessed. If they show similar patterns in relation to the uptake of low carbon technologies, future demand can also be identified. Clustering of weekly behavioural demand groups improved the understanding of the dynamics and instability of behavioural groups. This resulted in clustering based on yearly characteristics. It also highlighted the weak relationship between energy demand groups and non-energy characteristics. Clustering created the basis for understanding domestic energy usage and led to the development of linking monitored and unmonitored customers. This enabled modelling of the network and customer types could be assessed.
Conclusion	This project has provided significant learning on a number of LV network modelling aspects and uncertainties. This includes the exploration of customer groupings by behavioural demand across a range of timescales which will be useful for developing the LV load representation approach, both where smart meter data is and is not available. Also, this can be apply to help forecast future uptake of low carbon technology. It is not clear whether the learning on resolution of energy consumption is useful as smart meters are unlikely to have this capability. This will be assessed further in the project.

Electricity North West Limited (ENWL) – Low Voltage Network Solutions [L7]	
Background	Voltage and current data are not regularly captured beyond the primary substation however it is the low voltage network that is expected to see thermal and voltage issues due to the uptake of LCT's before the upstream network.
Objectives	The project set out to test and develop protocols to install low voltage monitoring on 200 low voltage networks without customer interruptions and sought to expand understanding of the low voltage network performance. The project also aimed to produce detailed electrical models to determine the capability to accommodate LCTs and identify network solutions to assist with the uptake of LCTs. Refining current load estimation methods and developing a means to estimate future loads and capacity headroom across the LV and HV network was also a goal for the low voltage network solutions project.
Approach/ Methodology	An equipment specification was produced and a tendering process identified GridKey and Nortech as the supplier who would provide the required equipment. Electricity North West worked with this supplier to produce relevant installation procedures for substation and feeder monitoring(midpoint and endpoint). 200 distribution substation were chosen to have monitoring equipment installed. These substations reflect a variety of network conditions but there is a heavy focus on ground mounted transformers and areas with a high level of PV. A Live installation method, using Rogowski current coils and novel voltage connections, allowed installation of monitors without causing interruption to supply.
Learnings and outcomes	ENW have developed a method for installing monitoring equipment without causing customer interruptions and are already using these methods for business as usual and innovation projects. Specifications and procedures for installing monitoring on the LV network have been developed by ENW. Code of practice, specification and joining procedures have been published. Voltage performance at the busbars showed daily average voltage between 237V and 253V. 63% of substations were found to have daily average voltages of 241V and 248V. 93% of substations showed the difference between max and min busbar voltage was less than 11.5V. Considering all substation this voltage variation range from 5V to 18V. Nine substations were highlighted for further investigation to assess whether a temporary breach of statutory limits will cause any significant effects to customers. This is being tackled in another innovation project "Customer Voltage & power quality". The monitoring found significant variation in the average current THD per feeder which varied between 2% and 98%, although most feeders (65%) were found to have between 10% and 20% average current THD. Feeders with PV saw this average increase significantly. A review of power factor for all monitored substation showed a significant variation. Reverse power flow must be considered when interpreting some power factor results. Electricity North West does not consider the power factor results indicate any problem to be resolved. However, based on the monitored data on power factor, a change was made to the default power factor assumption from 0.95 to 0.98 in the company's existing 'Load Allocation' algorithm for estimating load across the *whole* secondary network. The future capacity headroom model, as well as the Smart Grid Forum Transform model, was used successfully in 2012 and 2013 by ENW to determine the scale of load-related interventions in the ED1 price control period.
Conclusion	ENW plan to use the findings of this project to implement a business as usual policy for deploying LV monitoring and producing a wider review of LV planning and connections. Learning from this project has also informed a number of other innovation projects such as CLASS and Smart Street.. LV network performance and modelling assumptions assessed in this project may be useful to LV network model methodology validation.

4. Multi-level network model methodology

Increasingly, multi-voltage-level distribution network models are being considered to assess the performance of alternative design and operational strategies including voltage control. A number of relevant projects have explored the build and analysis of these models.

Strategic Assessment of Alternative Design Options for Multi-Voltage-Level Distribution Networks [H1]	
Background	Many DNOs are required to reevaluate the fundamentals of their distribution system design policies considering the alternatives of various network design philosophies that have been adopted in the past. These studies are not as straightforward as they are in HV networks where detailed networks models are available.
Objectives	This paper presents a methodology for assessing the performance of alternative design strategies for multi-voltage-level distribution networks. The key feature of the proposed methodology is its ability to reproduce realistic network topologies and lengths, as calibrated against real distribution networks.
Approach/ Methodology	The paper has proposed a method of generating multi-voltage-level distribution network models. The models can assist network planners in considering the long-term strategic decision-making processes. The validity of the developed models has been demonstrated through the investigation of alternative distribution network design for a real MV network in the U.K. that includes the surrounding rural areas. It allows the rapid identification of optimal investment of alternative network design strategies by resembling a real system using a number of representative networks. The key design parameters of the representative networks are comparable with those of real distribution networks of similar topologies, particularly in terms of consumer and load density, ratings of installed conductors and transformers, as well as the associated network lengths. In order to systematically deal with the problem of determining appropriate network design and investment, the concept of economically adapted distribution networks was investigated and applied in the context of a least-cost loss-inclusive network design. The network's design is based on the minimum Life Cycle Cost (LCC) methodology, balancing annuitized capital investments and maintenance costs against the cost of losses. The model is applied to assess the performance of alternative distribution network design strategies, including consideration of an optimal number of voltage levels, voltage uprating, and comparison between peak demand network design and least-cost loss-inclusive network design. Inclusion, in the model, of further parameters for simulating load growth or energy cost increase/decrease will be the object of future investigations.
Learnings and outcomes	The paper presents a novel way to use fractal science to create generic multi-voltage distribution networks. The algorithm develops the system from bottom up starting from LV and proceeding up to HV. It consists of five major steps: LV network topology creation, LV network design, MV topology creation, MV network design, HV network modelling. Using Fractal theory network with different lengths can be produced with a same number of the connected consumer. The topology of the network can be chosen between urban, semi-urban, rural and semi-rural. Length of the generated representative LV networks is relatively similar to the real networks, across a number of distribution networks operated by various U.K. DNOs. AC load flow is performed to calculate relevant characteristics of the network such as voltage drop, losses and section currents.
Conclusion	This paper has proposed the method of generating multivoltage-level distribution network models. The models can assist network planners in considering the long-term strategic decision making processes. However, the approach is focussed on generating and analysing a generic rather than specific network

	model and is not considered relevant to this project.
ENWL – Smart Street [H2]	
Background	Traditionally there has been limited voltage regulation on distribution networks with none on the LV network. The introduction of multiple LCTs with their different operating regimes will result in complex network flow patterns making managing the real-time network voltage within statutory limits a considerable challenge. DNOs must, therefore, adopt the design and operation of their networks to facilitate efficient connection of the new LCTs, whilst maintaining the power quality and network voltage within mandated limits.
Objectives	Smart Street utilised advanced real-time optimisation software to simultaneously manage HV and LV network assets to respond to customers' changing demands. Voltage management on HV networks aimed to reduce network losses while Conservation Voltage Reduction (CVR) on the LV networks aimed to reduce energy demand. Capacitor banks on the HV network were utilised to help manage network losses by adjusting the networks power factor. On the LV network, a mix of capacitor banks and controlled meshing of networks were integrated to flatten the voltage profile and improve energy efficiency. The meshing of LV networks was also trialled with the aim to release additional network capacity.
Approach/ Methodology	The Smart Street method combined the concepts of interconnection of networks, developed within the C2C project, and elements of the voltage control technologies developed by Electricity North West under the First Tier of the LCN Fund. The project utilised advanced real-time optimisation software to simultaneously manage HV and LV network assets in real time to respond to customers' changing demands in the most efficient end-to-end manner. The three key incremental steps in the Smart Street method were the application of: • Co-ordinated voltage control, using transformers fitted with on-load tap changers and capacitors, across HV and LV networks • Interconnecting traditionally radial HV and LV circuits and assuming control of these networks within the Electricity North West control room • Real-time co-ordinated configuration and voltage optimisation of HV and LV networks. These techniques were trialled in a number of selected, representative network areas. A number of loading scenarios were also modelled using integrated HV and LV network models. An extract of network data was taken from Electricity North West's Control Room Management System (CRMS) and provided to the project's academic partners. This was used to create network models in OpenDSS, these models used Meter Point Access Number (MPAN) data to build up the customer connections per phase. These customers were assigned a load profile consistent with the ELEXON classes. Streetlight connections were also built into the model to fully capture the loadings on the trial networks. A Monte Carlo approach was used to to assess the impact of LCTs and benefits of operational actions.
Learning and outcomes	According to the simulation results, the CVR model is capable of providing energy and loss savings to LV and HV networks. On the LV network, energy consumption and energy losses can be reduced by up to 8% and 2.8% respectively. On the HV network, these reductions can be up to 7% for energy consumption and 5% for energy losses. At LV, the voltage control solutions considered were LV network capacitor banks and transformer tap positions. The OLTC transformers have 9 distinct tap positions which can be updated on a half hourly basis, while capacitors were assumed to be switchable in blocks 50 kVAr, also on a half hourly basis. The CVR objective function was defined to be the minimisation of the active power consumption of each LV network over the 24 hour winter day scenario, subject to line voltages being maintained within regulatory limits.

	In all simulations, the CVR optimised networks were compared against a base case of nominal operation where all the network devices are at nominal settings (transformer tap positions corresponding to nominal voltage and all capacitors switched off).
Conclusion	A number of voltage control technologies and techniques were successfully modelled and trialled in Smart Street that are applicable across voltage levels. These will be considered for analysis in the multi-voltage level modelling methodology, to explore where most value can be gained from this modelling approach and the voltage control solutions trialled, to generate learning for existing NPg voltage control techniques and settings. The approach to Monte Carlo modelling will also be reviewed for learning applicable to use of smart meter data and modelling votlage control actions.

Smart Grid Forum Workstream (WS) 7 (DS203) [H3]	
Background	WS7 was established by the Smart Grid Forum (SGF) to continue the 'journey' started by WS2 and continued by WS3; its purpose is to drill deeper into our understanding of what a future distribution network is and how it will operate. WS3's Transform model provided detailed information about the smart solutions that might be deployed and in what volume. However, the Transform model was not designed to validate the technical viability of the system it foresaw.
Objectives	The aim of this work was to investigate how it can be ensured that the smart grid that the Transform model has described will be technically viable and to establish how the whole system might operate most efficiently and resiliently. WS7 is a natural further progression into the detail, asking how to ensure that the smart grid that Transform has described will be technically viable and, linking with WS6, what impacts this will have on the roles and responsibilities of a DNO.
Approach/ Methodology	The WS7 consortium developed four multi-voltage level network models which are representative of many parts of the GB distribution network. Each of these models represents a single 'grid supply point' and provides a detailed depiction of the network from the transmission interface at 132 kV down to the connection of individual customers at 400 V.
Learnings and outcomes	Stage 1 consisted of clarifications on modelling approaches, data sources and deliverables and was completed in early discussions between the Consortium and the WS7 Steering Group. Stage 2 developed four Base Networks and two Scenarios to be used in the studies, along with the creation of modelling Project Delivery Use Cases (which are reported during Stage 3). A review of international developments in smart grids was conducted and reported separately. Stage 2 also included a stakeholder engagement event to gather feedback on the Base Networks, Scenarios and Project Delivery Use Cases. Stage 3 consisted of a review of specific Questions for WS7 to answer, both in light of the work done in Stage 2 and to ensure a strong agreement between the Consortium and the WS7 Steering Group prior to proceeding with subsequent Stages. Reporting on Stage 3 consisted of the conclusions of the review of Questions, including some proposed modifications to the Questions, as well as presenting the Project Delivery Use Cases, which define the approaches used to generate the outputs that form the basis of the answers to the Questions. Stage 4 and Stage 5 comprised system planning and analysis of the Base Networks. Pathfinding simulations have examined the effect of the DS2030 Scenarios and established how the Base Networks must develop to overcome the issues introduced by the uptake of Low Carbon Technologies, LCTs. Impact

	studies have examined other system parameters which are assumed to not have a significant influence on the development of the network because they can be mitigated without the application of traditional reinforcement or smart solutions. For example, it is assumed that harmonic issues can be mitigated by the application of filters, and protection problems can be overcome by altering settings or replacing protection relays with improved facilities.
Conclusion	The DS2030 project has undertaken detailed analysis into the operation of the GB power system as projected for 2030. Future needs of the distribution networks were identified with consideration of both traditional and non-traditional reinforcement, with the latter referred to as smart solutions. The modelling provides a good indication of the type of future challenges to distribution networks, understanding that the timing of these challenges may vary depending on actual LCT uptake levels. It has also demonstrated a multi-voltage level network modelling approach which will be further tested in this project.

5. Smart meter data analytics

This section includes the review of network innovation projects and academic papers on the application of smart meter data to Network Planning, in particular:

- The aggregation of smart meter data – how varying levels of aggregation affect the accuracy of derived customer load profiles and data privacy issues
- Phase connectivity identification – how smart meters data could help to identify the phases customers are connected to
- Load profiles – how customer load profiles based on Smart Meter data can be generated considering the challenges related to the aggregation of customer data and connectivity data quality

Customer-Led Network Revolution [S1]	
Background	The move to a low carbon economy, particularly the growth in low carbon technologies (LCTs), will place additional strain on electricity distribution networks, which were not designed with this change in mind. Innovative solutions could reduce the need for significant network investment and thus avoid delaying the take-up of LCTs. The network costs associated with mass uptake of LCTs could be significantly reduced, and delivery accelerated, by using a combination of: - Network technologies, such as enhanced automatic voltage control, real time thermal rating and electrical storage - Flexible customer response from both demand and generation.
Objectives	Test a range of customer-side innovations alone and in combination with network-side technology (including voltage control, real time thermal rating and storage) by: - Finding out whether customers could be flexible in the ways they use and generate electricity - Predicting future loading patterns as the country moves towards a low carbon future and to research novel network and commercial tools and techniques and to establish how they can be integrated to accommodate the growth of low carbon technologies in the most efficient manner. - Trialling new network monitoring techniques to measure power flow, voltage and harmonics, trialling alternative smarter solutions that employ active network management and customer engagement to increase network capacity and/or modify load patterns - Developing new planning and design decision support tools for engineers.
Approach/ Methodology	More than 13,000 domestic, SME, industrial & commercial customers and distributed generators took part in the project, which involved the trialling of innovative smart grid solutions on the Northern Powergrid electricity network and the trialling of novel commercial arrangements to encourage customer flexibility. The project monitored 10,006 domestic customers (9,096 general, 344 heat pumps (HP), 160 photovoltaic (PV), 14 micro-CHP, 159 electric vehicles (EVs) and 233 with electric hot water / storage heating); 1,880 small commercial customers; and 160 merchant generators and analysed the consumption data. Additionally, DNO metering data for 17,639 I&C customers was collated for analysis to support the time of use tariff signal effectiveness study. In addition, it established four test-bed networks: Urban network at Rise Carr, Darlington (County Durham); Rural network at Denwick (North Northumberland); PV cluster at Maltby (Rotherham, South Yorkshire); Heat pump cluster at Hexham (Northumberland. The project analysed the basic demand profiles of typical business and domestic customers and those with heat pumps, electric vehicles, micro-CHP and solar photo-voltaic panels using smart meter data. More detailed disaggregation of some customer load profiles was undertaken down to individual appliances using additional metering. This was done with the aim of updating the statistical analysis of the existing design standard for the design of low voltage radial networks (ACE49) to improve the planning of future LV networks and to provide a baseline against which to measure the impact of demand-side response interventions. The overall optimum solutions to resolve future network constraints which could result from the transition to a low carbon economy were developed. These solutions informed network design and were encapsulated in the prototype tool for network designers, Network Planning and Design Decision Support

	(NPADDS) tool.
Learnings and outcomes	In terms of modelling techniques, the project demonstrated that wavelet and neural net short-term forecasting techniques were beneficial to model smart grid solutions. They enable to forecast severity and duration of power systems overload, enabling more accurate planning and control of DSR storage responses so that solutions can be designed at minimum cost (storage) and lowest nuisance factor (DSR). In addition, load forecasting allows to not only use real-time thermal rating (RTTR) opportunistically but also to be able to forecast how long certain benefit from RTTR will be derived and therefore to plan network interventions much more efficiently. The project produced extensive IPSA scripting technique to automate network analysis. These automated network analysis techniques, mostly coded in python, were the focus of a number of published papers. The NPADDS software tool was also developed. It is aimed at network planners, designers and connections staff to allow the assessment of the distribution network for voltage and thermal issues and to propose solutions where constraints are identified. NPADDS accesses network data held in a separate Oracle Spatial database and considers parameters such as customer types, customer quantities, cable impedances, transformer types and spatial data. In many instances, connections can be permitted without reinforcement following a cursory assessment of the network and more complicated studies are not required. To this end, the tool contains three levels of network assessment complexity: heuristics, worst case and time-of-use. Rigorous additional academic work was undertaken to understand and benchmark how the original research methodology to produce ACE49 was undertaken back in 1981. This resulted in the documentation of the academic research methodology associated with ACE49, which is the statistical approach for calculating demand and voltage on the LV distribution network. In terms of data, for system planning purposes, half-hourly demand profiles for secondary substations, together with half hourly demand profiles for HV customers could be used in a suitable network load flow model, to provide a view of the change of loading and voltage of points on the HV and LV network that are close to design limits. This knowledge could identify circuits which will require design studies and/or additional monitoring and avoid these costs on circuits that, without this better knowledge, would have been studied. For off-line planning and design, it is recommended that in addition load profiles are measured at key points lower in the networks. Half-hourly measurements of demand at each distribution substation, together with half-hourly data at HV customer connections are sufficient for planning purposes. The benefit of the additional monitoring would be that DNOs could undertake required investments more efficiently by avoiding unnecessary spending in terms of the size and location of reinforcements, as well as in terms of the timing for the investment. Half-hourly demand profiles for individual LV customers could, in principle, be used in a network load flowmodel to provide a view of the change of loading and voltage of individual LV circuits. This would identify those circuits which, due to connection of LCTs, are close to design limits. The use of these data would depend upon data protection issues being satisfactorily resolved. Alternatively, a secondary substation monitor could measure half-hourly demand profiles of each LV feeder. The same process, if suitably designed, could compare the voltage profile derived from the half-hourly demand profiles with any voltage threshold crossing data from Smart Meters. This analysis would not only identify that an LV feeder required attention, it would also identify if the cause of the threshold crossing was known or whether higher time resolution monitoring of the feeder is required.
Conclusion	The CLNR project produced a rich body of knowledge that will be useful for the Smarter Network Design Methodologies project, in particular: - its recommendations about the data required for the network planning purposes - the statistical approach for calculating demand and voltage on the LV distribution network (ACE49) - NPADDS software tool to assessment of the distribution network for voltage and thermal issues - the IPSA scripting techniques to automate network analysis

Phase Identification in Distribution Systems by Data Mining Methods [S2]	
Background	System unbalances frequently occurs and may lead to negative consequences such as electrical losses decrease in operational efficiency or even damage the overloaded phase coils, etc. Therefore, analysing the phase identification in certain low-voltage network system is crucial to prevent such consequences. Traditionally, the phase connection layout of network systems has been determined by manual intervention or signal injection approaches. The introduction of automatic meter reading (AMR) systems, where sensors and smart-meters are embedded in a household grid coupled with a new nonintrusive and low-cost data mining approaches will allow electrical engineers to monitor the unbalanced grid in the whole network system, thus control and predict the correct demand of household usage.
Objectives	Build models using clustering techniques and smart meter data to identify the phase connectivity on the LV network.
Approach/ Methodology	The phase identification procedure developed following the following steps: 1. Model the LV network - IEEE LV Feeder in the simulation tool OpenDSS. 2. Extract simulated data from OpenDSS using Matlab and perform K-means and Gaussian Mixture Model (GMM) clustering algorithms to place the simulated data into three clusters. 3. Perform classification to identify the three clusters and label them precisely based on the a-priori information from the transformer side. 4. Verify the consistence posteriorly by comparing the labelled clusters with the correct information provided by IEEE LV test feeder manual. To build the model, time-series data of voltage magnitude at the transformer side as well as 55 end-users that have load profiles data were used.
Learnings and outcomes	Both of the clustering methods – K-means and Gaussian Mixture Model (GMM) clustering – were able to converge, and to achieve good results. However, the optimal features that both clustering algorithms needed as the input are the first 50 real-time measurements of the voltage profiles, which will be quite bloated in the case of a power network with many end-users. Since it will give rise to a matrix with a dimension of 50x N_e (N_e is the number of end-users), which is relatively expensive to compute the results when N_e becomes greater than 100.
Conclusion	The K-means and GMM clustering algorithms presented are promising candidates to enable phase identification on the LV network using smart meter data but it is too computationally extensive to be achieved in practice. Therefore, it will not be explored further in the project.

Smart Meter Data Analytics for Distribution Network Connectivity Verification [S3]	
Background	As many utilities, BC Hydro faces data quality problem with the geographical information system (GIS) records. A prominent error in GIS records is incorrect connectivity e.g. customers connected to wrong poles or wrong transformers, and transformers connected to wrong feeder phases. These errors have negative impacts on distribution system operation and planning, as well as asset maintenance. For instance, incorrect connectivity information prohibits optimal feeder and asset capacity planning, both of which are required to safely meet the growing power demand.
Objectives	Develop an algorithm that leverages smart meter data to detect and correct connectivity errors in the GIS representation of the distribution network topology.
Approach/ Methodology	Using hourly voltage and kWh data from customers' smart meters, the algorithm relies on the following two common power flow characteristics: 1. Voltage profiles of customers within short electrical distances are similar. Thus, correlation factors between the voltage profiles of customers under the same distribution transformer will be high. 2. Voltage magnitude decreases downstream along the feeder. Thus, a customer which is closest to the transformer will have a higher voltage than customers which are connected to the downstream sections of the branches stemming from the transformer. The algorithm outputs a connectivity association of a customer meter with a transformer. This could be either the transformer indicated in GIS records or a neighbouring transformer, indicating a potential topology error. The algorithm also outputs the order of customer meters along the branches stemming from the transformer, and compares with existing GIS records. That way, mistakenly recorded customer meters are repositioned to a correct location within their original transformer, or to a correct location within the network of a neighbouring transformer. Rather than considering raw voltage profiles of customer locations, the algorithm analyses the voltage profile VPC at the point of coupling (PC), which is defined as the point at which the service wire for an individual customer meets the main secondary line
Learnings and outcomes	The algorithm was tested on a range of different feeder types, and has been successful in detecting and correcting connectivity topology errors existing in the enterprise GIS within BC Hydro. The algorithm ranks the correlation factors of *V*PC profiles corresponding to meters on neighbouring transformers, and compares the *V*PC magnitudes. In this way, the algorithm was able to correctly reposition many customer meters, including 23 accounts on a 700-customer urban feeder.
Conclusion	The algorithm performs well when applied to customers attached to single phase transformers via over-head connections. Further development and tests are necessary to address underground feeders, as well as potentially developing a solution for three-phase customers and multi-dwelling unit customers with network meters.

Low Carbon London – Use of smart meter information for network planning and operation [S4]	
Background	Traditional electricity meters measured the total and cumulative energy consumed at a property and required the meters to be read manually either by the customer or by meter reading personnel on behalf of the energy supplier. Smart meters measure the energy being used at a much greater resolution, which provide an improved understanding of electricity consumption. Smart meters are able to communicate this information, in near-real-time, to industry players via a central agency when necessary and to an In-Home Display (IHD). In addition, smart meters will store data regarding customers' energy use at a Half-Hourly (HH) definition, as well as network related data such as the voltage level at the meter. The data stored on the meter, along with other metrics, will be available to various parties such as energy suppliers and Distribution Network Operators (DNOs) through the Data Communications Company (DCC). Smart meter data will provide visibility which may enable DNOs to both plan and operate the networks more efficiently. Historically, planning the network has been based on static load profiles and planners have designed the network with a conservative approach to ensure adequate security of supply. Smart meter data can also be used in a bottom up approach to provide visibility of the capacity and demand, particularly on the LV network.
Objectives	Understand how the data available from electricity smart meters will help DNOs to design, plan and operate the networks that supply electricity to customers' properties
Approach/ Methodology	The LCL Smart Meter trial was facilitated by EDF Energy who recruited customers and installed 5,533 meters. The smart meters installed as part of the trial recorded half hourly consumption data in kWh. This data allows for insights into the way that customers use energy and how this impacts the way in which a DNO must design the network accordingly.
Learnings and outcomes	• Voltage excursions are infrequent and currently not widespread The voltage level on selected areas of the London Low Voltage (LV) network was analysed and shown to generally be compliant with statutory voltage limits. 78% of the phases measured at the end of feeders had no readings at all outside of statutory limits. Only 0.35% of all the phases measured showed more than 1% of readings outside of statutory limits using 10-minute data resolution. All voltage compliance issues are being investigated • LV network voltage is more sensitive to (volt rise) than volt drop due to new loads In general, voltage on the London network is towards the higher end of the allowable limits. This means there is less headroom (margin compared to the upper limit) than legroom (margin compared to the lower limit) suggesting that the London network is more sensitive to an increase in embedded generation than increased demand from other technologies such as Electric Vehicles (EVs) and Heat Pumps (HPs). However, the lower voltage limit is responsible for more voltage excursions currently. • Smart meter data can be leveraged to avoid unnecessary reinforcement costs The project has shown that, based on the smart meter data which will be available from the mandated roll-out of smart meters, clear examples of current processes can be improved, and will benefit from such data. These include connection of new load, planning of reinforcement of existing network and voltage issue investigations. Not all of these processes will require real-time data, and indeed not all will need localised data. For example, a periodic update to the industry-standard residential load profiles may not need to happen for a further 5-10 years, and only needs to take place once nation-wide. Reinforcement issues may need to be screened annually and per licence area in response. • Customer consumption It has been determined that there are material differences between the peak energy consumption of different categories of customer. The categorisation can be based on data available to a DNO at the time of connection of new load, which allows this difference to be taken advantage of when assessing the impacts of the new connection. The effects of demand diversity were investigated and determined to be consistent across all types of customer. This leads to a single diversity factor curve which can be used to estimate the diversity that will be observed between customer groups of varying sizes.

	• Existing voltage conditions The second set of analysis carried out on data collected by the trial was regarding the existing voltage conditions of the network within the trial areas. This led to the following conclusions: - Continuous voltage supply level tends to be towards the higher acceptable limit - Voltage excursions are minimal on the trial networks, but tend to be low voltage events - Some existing or potential voltage issues could be solved by adjusting tap-changer settings at a distribution substation level. • Connections and Network Planning When assessing the impact of new connections, DNOs will be able to make better assessments of the additional load that the new connection is likely present to the network. Analysis performed in the project will be useful to provide DNOs, with better insight into customer consumption both in terms of magnitude and pattern. These findings can be used as a well-justified approach to estimate the demand of new customers, for which no historic data will be available. Connections and network planning staff will also have access to data relating to the existing customers on the network, which can be used as to assess the current loading conditions of the network. A combination of the two findings can be used to approach the connection of new load in a more consistent way, using assessments based on measured customer consumption. This will impact how additions to the network that are required to connect new load are designed cost effectively. It will also mean that the existing network load can be assessed more accurately and in-depth network studies and monitoring can be triggered when necessary. • Data privacy Based on the sections that describe how a DNO might make use of smart meter information once it is available from the national roll-out, via the Data Communications Company (DCC), an assessment of data privacy can be made. Only the consumption datasets are considered personal information and therefore network data such as supply status and alerts, and voltage data and alerts are not subject to the same requirements for data privacy. The datasets available to a DNO that are considered personal data under Electricity Distribution Licence Standard condition 10A are: active electricity energy import, reactive electricity energy import, maximum demand. This data is only considered personal if relating to an individual customer and if it relates to a period of less than one month. All uses of smart meter data in this report are able to make use of the smart meter data without referring to a single customers' data for less than one month. This can be achieved by: - Aggregating time series energy import data over a period of more than one month to produce consumption profiles - Aggregating time series consumption data to ensure that any network related parameter comprises at least 2 customers' data - Maximum demand registers are not reset more frequently than once a month.
Conclusion	The LCL Smart Meter trial has provided evidence on how customers can be categorised based on occupancy data. This can provide benefit when assessing the connection of new customers for which no data will be available for. The analysis also reveals that the network is currently more sensitive to high voltage than low voltage but simple solutions such as off-load tap changes can be used to address this problem in some cases. Finally, there is potential benefit for DNOs from the use of smart meter data. This could involve future network load/voltage studies, analysis of voltage alerts, verifying load growth and using the smart meter data for outage management. As the project focuses on Network planning and these use cases relate to Network Operations they will not be explored further in the project.

New Thames Valley Vision [S5]	
Background	Electricity demand patterns are changing as individuals, small businesses and larger companies increasingly act to reduce their carbon footprint. The options available to customers include: energy efficiency measures; the installation of solar thermal or photovoltaic (PV) panels and other small-scale renewable energy devices; an increased uptake of electric vehicles (EVs); and adoption of heat pumps (HPs). This clearly poses challenges for DNOs. To maintain and operate a reliable and cost-effective electricity distribution system, DNOs need an understanding of the expected power flows on their networks. However, at present, DNOs have no sight of the demand of the smaller individual customers, and can only make estimates based on averaging data relating to the total number of customers fed from a distribution substation. Data is already indicating issues on the LV network resulting from changing demand profiles, however traditional reinforcement of this asset across GB could cost up to £30.9 Billion. At present, LV network investment is informed by periodic measurements taken at substations. This approach is widely used, but has the disadvantage of being a relatively crude lagging indicator with no cognisance of variations over shorter timescales. With low carbon technologies now accelerating change on network, this crude monitoring leaves the network exposed to stress as load factors vary; it also hides capacity that could be otherwise utilised. Without advanced monitoring and the smart use of data, the network will require significant capital investment to support the transition to a low carbon economy, whilst ensuring security and quality of supply to customers.
Objectives	1. Apply proven data analysis from the Energy Demand Research Project (EDRP) to understand the different customer types and their effect on network demand. 2. Understand how the behaviour of different customer types allows informed network investment decisions to be made. 3. Demonstrate mitigation strategies to understand the extent to which demand side response can contribute to network flexibility, where and how power electronics can be used to manage power factor, thermal constraints and voltage to facilitate the connection of renewables on the LV network. 4. Provide front line training courses for the industry to embed real practical knowledge and skills, and keep the public informed so the intentions and benefits of the smart grid are clear
Approach/ Methodology	• Network Modelling The assessment of headroom on the LV network is dependent upon the running of power flow analysis studies. Mathematical techniques for buddying, confidence assessment and LCT clustering have been developed as described in "SDRC 9.8(c) University of Reading Smart Analytic and Forecasting Evaluation". A Network Modelling Environment (NME) was also established. It contains the complete connectivity model of the LV network being assessed, including services. This was achieved in the project by migrating the existing BaU GIS connectivity model into a version of GE's Smallworld Electric Office as described in 'SDRC 9.6 Low Voltage Network Modelling Environment Built, Installed and Commissioned.' The NME provided graphical and numerical power flow study results. The graphical results provided a sample of the GIS diagram for each LV feeder included in the study coloured Red, Amber or Green (RAG) to reflect any sections operating out of limits. • Linking Network Reinforcement to a better Understanding of Electricity Consumers Improved forecasting techniques are key to helping DNOs in operational, planning and investment activities. Agent Based Modelling was used to prepare energy usage profiles for all customers connected to selected LV feeders. This enabled short, medium and long-term forecasts. Short Term Forecasts are of primary benefit to the smart control of power electronics, energy storage, and for the management of peak demand. Medium Term Forecasts are helpful in assessing investment choices for a subsequent financial year. Three methods were simple benchmark methods including "last year as this year", "the average from the last two years", and a "linear regression model". These benchmark methods were compared to two generalised additive models (GAMs), which outperformed the benchmarks. Long Term Forecast scenarios enable a DNO to assess potential impacts from scaled up adoption of low carbon technologies (LCTs) by customers. It was recognised that LCT uptake will cluster, based on

	demographics, existing LCT adoption and human behaviour (the "Jones Effect" of copying one's neighbour). For this analysis, a clustering methodology was developed, including evaluation of the number of simulations to run to allow for uncertainty. The output of these scenario forecasts was loaded into the NME for electrical impact analysis. Confidence Bound Generation was considered to allow network modelling activities to take account of the variability of actual network loads, taking account of day of the week seasonality, weather conditions, and other social factors. For this purpose, confidence bounds were calculated from the monitoring feeder data; this allowed an additional spot load to be added into the network model, the size of which was determined by the level of confidence. A technique known as bootstrapping was also tested for generating the confidence data for when monitoring data was not available; the results were compared with results derived from the techniques used in ACE49, the UK electricity industry network planning standard which outlines a statistical method for the design of LV networks.
Learnings and outcomes	• Developed and operated Network Modelling A Network Modelling Environment (NME) was created to integrate a Geographic Information System (GIS) connectivity model with GE's Smallworld Electric Office and the Cymdist power analysis tool. The project developed mathematical techniques for applying half hourly energy profiles within power flow analysis studies to determine the capacity headroom on the selected LV Network. This incorporated methodologies for buddying similar property types, deriving a confidence measure to address uncertainty, and clustering the uptake of Low Carbon Technologies (LCT) for forecasting purposes. The detailed modelling outputs reveal the location and extent of future capacity and voltage excursions, providing a tool for a DNO to inform future network investment decisions. • Smart Metering data from Electricity Supply Companies obtained Smart meters were successfully installed with consent for the use of the half hourly power data for the project research purposes. The project worked with the customer supply team to ensure the secure transmission and management of the usage data, classed as personal information. For ease of development, three large data extracts were created and securely delivered to the project, rather than create a more complex, regular data transfer process. • Modelling outputs fed into planning systems and processes in a meaningful manner The NME was set up to run power flow studies based on energy profiles and to provide geographic and numerical outputs. To determine the criteria that represent "out-of-limits", for loading the individual cable ratings were loaded for each season, and for voltage, the statutory voltage limits at the customer's meter (230V +10% and -6%) were assigned. These ensure that any studies would reveal where and when the network was found to be out of limits in line with existing planning standards (ER P2/6, Electricity Supply, Quality and Continuity Regulations (ESQCR) and internal planning documents). RAG definitions were assigned as follows: Red Out of limits, Amber Out of limits only with confidence data assigned, Green when neither Red or Amber. For a sample of substations, real phase allocation was checked on site. This allowed a comparison study to be run where the phase allocation was corrected. This revealed that the actual phase allocation was up to 25 % more unbalanced than the assumed allocation, and this made the study results significantly worse; further, the system unbalance does not improve as the number of customers on the feeder increased. The key learning point from this was that obtaining corrected phase allocation data is justified where more detailed analysis is required.
Conclusion	The Network Modelling Environment, smart meter data collection experience as well as the forecasting techniques developed are useful for this project. They are further described in the 'Advance Modelling of Low Voltage Networks', 'Smart Analytic and Forecasting Evaluation' and 'Smart Meter Performance' reports.
Use of Smart-meter data to determine Distribution system topology [S6]	

Background	In New Zealand, smart-meters are being deployed rapidly. As of December 2014, 62.3% of the 1.75 million customer connections (called ICPs or Installation Control Points) use smart-meters. Smart-meter data presents an opportunity for utilities to improve their database records, and develop a low voltage (LV) model which may be useful for outage management and fault detection, phase balancing and network planning.
Objectives	The paper focusses on determining the topology of the LV distribution system ie identifying the transformer a particular installation control point (ICP) is connected to and the phase if that customer is single-phase.
Approach/ Methodology	The approach developed relies on: - the use of harmonic voltage data for voltage correlation - using the Fisher Z transform to determine LV connectivity and update database records in cases where much of the load is unmetered, and smart meter records were not well-synchronized - using smart-meter voltage and load data to estimate the service main and feeder impedancewithout requiring a high coverage ratio This trial was carried out on part of Vector Networks distribution network, the largest utility in New Zealand. The data samples were from 15 minute instantaneous recordings, and there were 352 samples per customer.
Learnings and outcomes	The use of voltage total harmonic distortion, or other harmonic data, when available, is likely to be much more reliable than the voltage magnitude correlation. The Fisher Z Transform Correlation Analysis algorithm developed to look for database inaccuracies was more successful than simply taking the highest correlations as in a previous study or averaging the Pearson correlation coefficients themselves. The method to estimate network impedances, based on a least-square fit to the power vs voltage relation for ICP to transformer impedance and on maximizing of correlation coefficients for branch impedances needs further work for the utility to make use of smart-meter data in this way.
Conclusion	The Fisher Z Transform correlation analysis algorithm is an effecitive algorithm to look for database inaccuracies, determine the transformer/phase to which a customer is connected and update database records accordingly. This is something that will be explored further in the project depending on the accuracy of voltage measurements and completeness of current phase connectivity records

Using smart meters to estimate low-voltage losses [S7]	
Background	Although losses on low-voltage networks represents 4% of the energy supplied to low-voltage customers in the UK, the details of when and where is poorly understood. This results from the fact that generally only the peak demands and average loads over several months have been recorded. A detailed knowledge of when and where these losses are occurring would allow better assessments of network efficiencies, assist with planning improved networks, help with operational decision making and improve identification of nontechnical losses. The advent of domestic smart meters provides an opportunity to better estimate where and when losses occur.
Objectives	The paper analyses how smart meter data can be used to improve the estimates of the low-voltage conductor losses, in particular: - How much lower the estimated losses using 30 min intervals are compared with using 1 min intervals. - How to adjust the 30 min loss calculation to get closer to the 1 min value. - The benefit for loss calculations of the smart meters reporting 10 min averages rather than 30 min averages.
Approach/ Methodology	Given that the accuracy of the loss estimate depends on the loads and the network topology being analysed, the study relied on three public smart meter datasets with a time resolution of 1 min - CLNR, UMass and UK data archive – as well as three test networks with very different topologies – a single tee with the customers split in the ratio 30:30:40 on the branches, a linear network and a high branching network with just one customer on each branch.
Learnings and outcomes	The study found the following: - *30 min estimates of losses*: The absolute percentage error (APE) of the daily estimate from using 30 min smart meter data to estimate the 1 min losses depends on the number of smart meters on each branch, with a lower APE when this number is higher. For the single tee network, the three smart meter data sets gave MAPE (Mean Absolute Percentage Error) values of 9, 14 and 24%. While these provide an indication of the order of magnitude of the underestimation of the losses when 30 min intervals are used, there will be considerable variation between different network topologies, customer types and days. - *Improving on the 30 min value*: Fitting the model the 30, 60 and 120 min readings, reduced the error from using the 30 min values to estimate the 1 min losses by around 50%. For example, the reductions for the single tee network with the CLNR, UMass and UK data archive smart meter data sets were, respectively, 41, 50 and 75%. - *Benefit of 10 min smart meter intervals*: using 10 min smart meter intervals improves the losses estimate,but the improvement in the accuracy is relatively low compared with the overall inaccuracy. For the single tee network, the improvements for the CLNR and UMass data sets were, respectively, 13 and 9%.
Conclusion	Whilst using the 30 min average currents that stem from UK smart meter results in an underestimation of the actual LV network losses, leveraging the model presented in the paper enables to reduce the error by around 50% compared to estimate using the 1 min interval data. This will be a consideration in this project for the LV network model methodology.

Analyzing the ability of Smart Meter Data to Provide Accurate Information to the UK DNOs [S8]	
Background	The introduction of smart meters in the UK has the potential to dramatically improve the visibility that DNOs have on the LV network this by providing detailed consumption/generation information from every household, at node points along the network and downstream of LV substations to the network operators. The smart meter data can lead to more accurate estimations of network losses, voltage variations, cable loading capacity, and phasing arrangements. However, the quality of smart meter data can be compromised by a number of limiting factors depending on the data recording and transmission specifications and protocols in place. In the UK, those limitations include the record and transmission to the DNOs of data at half-hourly averages, the aggregation of customer demand data to preserve customer privacy concerns and the phasing identification not being specified in the minimum specifications of the meters.
Objectives	- Investigate how the aggregation of smart meter readings, the half-hourly averaging of customer readings and the inability to identify the connection phases data can affect the estimation accuracy of technical losses and voltage levels in the LV network - Investigate how 1-minute losses and correct phasing patterns can be determined despite the limitations in smart data
Approach/ Methodology	In order to replicate a real-world LV network and considering the limited availability of real time smart meter datasets, a model three-phase LV network with balanced phasing was populated with 1-minute smart meter consumption data from 100 houses. Two versions were analysed with data from different trials, one using data collected by Loughborough University in 2008 and 2009 and using data collected by the Customer-Led Network Revolution (CLNR) project from 2011 to 2014.
Learnings and outcomes	As the time resolution of smart meter data is decreased from 1 to 120 minutes, LV network loss estimates are underestimated and voltage levels are overestimated. Crucially from the point of view of the DNOs, this is more severe at the first half-hour. In addition, the aggregation of smart meter data due to privacy reasons leads to the overestimation of losses and underestimation of voltage levels. These issues will adversely affect the accuracy levels of smart meter data in the context of various DNO applications such as network planning and design and asset management. Finally, measuring phase currents and voltages at the substation along with individual smart meter readings, can allow the phases to be identified using the sum of the currents if all the loads are metered, and comparing voltage time series if there are missing loads. For aggregated meters, if there are no missing loads and the accuracy of the recorded phases is good, it may be possible to narrow down the number of mixed groups to a reasonably small number of combinations but a few individual meter readings would then be needed to disambiguate between them and to determine the meters that are incorrectly recorded.
Conclusion	The aggregation of smart meter readings, the half-hourly averaging of customer readings and the inability to identify the connection phases affects significantly the modelling accuracy of technical losses and voltage levels in the LV network. Therefore, this needs to be taken into consideration in this project when modelling power flows and voltage levels in the LV network based on smart meter data that have those limiting factors.

<table>
<tr><th colspan="2">Smart Meter Aggregation Assessment Reports [S9]</th></tr>
<tr><td>Background</td><td>Having increased visibility of demands on the LV network via the roll-out of smart meters to all customers could be of material benefit to DNOs in assisting them manage their networks and plan reinforcement.
However, under licence condition SLC10a DNOs are unable to access raw load profile data – time series consumption data – from individual smart meters due to concerns over personal privacy issues with customers. DNOs therefore need to define an aggregation level that provides a high degree of anonymity to their customers whilst providing the highest possible network visibility for planning their investment decisions.</td></tr>
<tr><td>Objectives</td><td>- Develop an assessment of the minimum number of consumers' data sets that should be aggregated to provide a high degree of anonymity, while providing DNOs with the highest possible network visibility
- Assess the reduction in financial benefits for DNOs of not being able to make use of individual consumption profiles from individual smart meters to inform their network investment decision process</td></tr>
<tr><td>Approach/ Methodology</td><td>To determine the minimum required number of domestic smart meters that should be aggregated to ensure customers' privacy, some typical LV demand profiles representative of individual household load consumption were first required. For this purpose, the study relied on a well-established model – called the CREST model – called the CREST model. It was used to create individual household half hourly load consumption data, representative of ten real feeders with the number of customers on each feeder ranging from 9 to 124.

The modelled profiles were aggregated, at feeder level, and validated against the feeder monitoring data from the Northern Powergrid Customer Led Network Revolution project (CLNR).
Once the profiles were confirmed as being representative of real LV networks, they were subject to consecutive aggregated customer privacy studies using three different methods of analysis:
- Method 1 – Visual inspection
- Method 2 – Correlation analysis
- Method 3 – Clustering analysis

The best performing method was then assessed against the 'visibility risk' metric to evaluate the most suitable aggregation levels. Visibility risk is defined as the likelihood of an individual customer consumption profile being derived from the aggregated group load profile. In other words, if someone had access to the aggregated profile, what would be the probability of deriving one individual profile from it. Hence the lower the visibility risk the greater the customer privacy.

The study then estimated the expected benefits reduction corresponding to each aggregation level</td></tr>
<tr><td>Learnings and outcomes</td><td>The visual inspection method provided less objective results than the correlation analysis, while the clustering analysis offered less granular comparisons than the correlation analysis. Therefore, the correlation analysis is preferred.

Regarding the aggregation level required to ensure customer anonymity, the analysis indicates that moving from having individual customer profile data to data aggregated from two customers reduces the visibility risk by almost 80% while increased levels of aggregation do not greatly improve the level of anonymity.

Finally, the study concludes that the reduction in benefit has little degradation at an aggregation level of 2 but significant reduction beyond this level.</td></tr>
<tr><td>Conclusion</td><td>As a conclusion, an aggregation of two profiles, coupled with the development and implementation of DNO IT systems and/or business processes, enables to minimise the benefits reduction resulting from the aggregation whilst meeting the requirements of SLC10a to ensure anonymity.</td></tr>
</table>

6. Novel analysis techniques

The Monte Carlo method can be applied to historical demand and generation data to capture stochastic effects across network voltage levels and combined with deterministic load flow for improved LV and multi-voltage level network modelling. However, there are also other efficient probabilistic techniques that could be applicable. Probabilistic methods can be extended to include voltage control techniques.

Probabilistic techniques have been shown to more accurately characterise stochastic LV network loads and renewable generation.

Stochastic Modelling of Distribution Networks Operation [N1]	
Background	Generic load flow methods like Newton- Raphson which are widely used for deterministic analysis of HV and MV networks are not suitable for the LV network due to the level of uncertainty in the network model. Modelling of the LV distribution network should involve a combination of deterministic and stochastic methods to address the stochastic nature of these networks.
Objectives	LV network loads are highly variable and do not necessarily follow any particular pattern as well as increasing connection of distrbuted generation. Therefore deterministic and stochastic methods should be combined for distribution network analysis. This paper presents a stochastic modelling approach for distribution networks to address these uncertainties.
Approach/ Methodology	The Monte Carlo method was used to model demand and PV in LV networks probabilistically. Calculated load and PV generation output was based on data from a database and on predicted maximum load. Simulation inputs were from a database of household load profiles (load measurements of 1000 household users with 15 minute time sample) and a database of PV generation or solar irradiation. The proposed method was applied to a test network. The test network had 5 busbars and was a multi-voltage model (from 0.4kV up to 110kV). Results of this method are probabilities rather than unique values of electrical parameters (e.g. voltages, power flows) in the studied network. The load flow results including voltage profile and power flow through the network were presented as average values and their range.
Learnings and outcomes	To address the uncertainty of LV network demand and distributed generations, the Monte Carlo method can be used to produce cumulative distribution functions (CDFs) of input demand and generation profiles and then commonly used deterministic load flow methods can be applied.
Conclusion	The Monte Carlo method can be applied to historical demand and generation data and combined with deterministic load flow for improved LV network modelling. This method will be assessed further in this project.

Solving probabilistic load flow in smart distribution grids using heuristic methods [N2]	
Background	The integration of renewable energy resources (RERs) into conventional distribution networks changes the power flow characteristics of the network while its inherent characteristics such as feeder impedance remain unchanged. Conventional power flow methods may not be suitable or efficient for smart distribution networks.
Objectives	This paper proposes a heuristic optimization based Probabilistic Load Flow (PLF) method to overcome potential modelling limitations for future distribution networks.
Approach/ Methodology	Stages of the proposed algorithm are explained as follows: generating initial empire, assimilation, revolution, the exchange between the best colony and imperialist, imperialistic competition, and elimination of powerless empire. Solution steps of Imperialist Competitive Algorithm (ICA) for PLF problems can be described as follows: • All input parameters with probabilistic behaviour such as load, wind, and solar radiation are defined by a PDF. • Initially, the number of samples is set. • For each input parameter such as load, WT and PV generation, the value of parameters is determined from its PDF. • For the next step, the ICA randomly chooses the load flow unknown parameters such as bus voltages and angles within their limits as state variables. • The ICA is repeated until the load flow convergence criterion is satisfied. • All output variables such as bus voltage, angles, feeder current, and losses are calculated and saved. • A new sample is selected from the input parameters. • The above loop is repeated until all samples are selected. • The results of output parameters are presented as PDF and Cumulative Distribution Function (CDF) and histogram.
Learnings and outcomes	Results show that the ICA algorithm is very efficient and has good convergence properties for radial, weakly meshed and meshed networks with any RER penetration level. Simulation approaches such as Monte Carlo Simulation (MCS) may not apply to every grid, including more 'challenging' networks with a high rate of R/X or networks with more renewable resources.
Conclusion	An efficient probabilistic technique has been presented and shown to be applicable to a range of network types with renewable uptake. The applicability of the technique will be assessed further in the project.

Probabilistic Load flow: A review [N3]	
Background	Probabilistic load flow (PLF) techniques can be applied to different areas of power system steady-state analysis.
Objectives	The purpose of the paper is to identify different available PLF techniques and their corresponding suitable applications so that a relatively accurate and efficient PLF algorithm can be determined for the concerned system e.g. a distribution system with large integration of distributed renewable energy.
Approach/ Methodology	A a brief history of the PLF technique was presented and its rationale for application to power system analysis and network planning. PLF can be performed by using either a numerical approach or an analytical approach. The numerical approach e.g. a Monte Carlo method, substitutes a chosen number of values for the stochastic variables and parameters of the system model and performs a deterministic analysis for each value so that the same number of values are obtained in the results. An analytical approach analyzes a system and its inputs using mathematical expressions e.g. PDFs, and obtains results also in terms of mathematical expressions. The treatment of interdependence of stochastic variables such as individual loads, active and reactive power, dispatchable and non-dispatchable generation was reviewed. A number of different approaches to improve the accuracy and efficiency of the PLF algorithm were also presented.
Learning and outcomes	The statistical planning method can increase network transfer capability as compared to the traditional worst case planning principle. Different approaches were discussed to improve the accuracy and efficiency of the PLF algorithm and the application of the PLF algorithm in the power system planning and the extension of the PLF algorithm to include voltage control devices and systems integrated with DG was presented.
Conclusion	The basic PLF technique and underlying assumptions were demonstrated and a number of different approaches to improve the accuracy and efficiency of the PLF algorithm. This will be very useful in developing novel analysis techniques as part of this project.

A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts [N4]	
Background	In order to make the transition to a low carbon economy, the government published the Carbon Plan in 2011 which sets outs a strategy to achieve the decarbonisation target across sectors. A quarter of UK emissions come from the domestic transport sector which needs to substantially reduce its emissions by 2050. Electric vehicles will play a role in the reduction of these emissions.
Objectives	The paper uses a probabilistic method to combine two unique datasets of real-world electric vehicle charging profiles and residential smart meter load demand. The data was used to study the impact of the uptake of Electric Vehicles (EVs) on electricity distribution networks.

Approach/ Methodology	Peak consumption of electricity is in winter in the UK. In order to assess the additional impact of EVs during an existing peak loading event, a single peak load test day corresponding to the DNO's system peak load day in January was studied. Two real networks representing an urban and rural area, and a generic network representative of a heavily loaded UK distribution network were modelled. Monte Carlo Simulation was used to build up a distribution of possible demands on the trial networks. Data for the simulation was produced by sampling the domestic load profile and EV charging profile populations. Each of the three networks; urban, rural and generic were modelled in IPSA2. The IPSA2 load flow algorithm, based on the Fast Decoupled Newton–Raphson algorithm, was used to calculate the power flows and voltages throughout the system. The average hourly load profiles (expected values) of the households on the networks with a defined EV penetration were calculated from the 1000 runs. In addition, the 2.5% and 97.5% lower and upper bounds of the data were calculated.
Learnings and outcomes	The findings show that distribution networks are not a homogeneous group, with a variety of capabilities to accommodate EVs and there is a greater capability than previous studies have suggested. The urban network under study was able to accommodate a much higher EV penetration compared to the rural network. These results stem from the differences in EV charging profiles, network topologies and impedances between the urban and rural areas. The trial data showed that rural users relied on domestic charging more than the urban users who had access to a more extensive public charging infrastructure. The generic network gives broad and generalisable findings in comparison to more specific findings respective to a specific network (i.e. real urban network). However, the generic network is a heavily loaded network and simulating it using peak day load data at the 97.5th upper demand bound could be considered conservative.
Conclusion	This work has used a probabilistic method to combine two unique datasets of real-world EV charging profiles and residential smart meter load demand. The datasets were used to study the impact of the uptake of EVs on distribution networks. The study used real, validated networks of an urban and rural area and a generic network, representative of heavily-loaded UK distribution networks. The range of networks used demonstrated that LV networks are not a homogenous group and have different characteristics, sets of parameters and customer behaviour. Learning from this study will be valuable for the project.

7. Relevant Policy

DCRP/18/03/PC Revision to Engineering recommendation P2 – Security of supply [RP1]	
Background	EREC P2 is intended as a guide to system planning. The proposed modification of this document has been written to recognise the changes to the load and generation connected to distribution networks since ER P2/6 was published in 2006.
Objectives	The DCRP P2 Working Group who have been working on the revision are now requesting comments from Industry stakeholders on the contents of the draft EREC P2/7.
Approach/ Methodology	The proposed modification of this document has been written to recognise the changes to load and generation connected to distribution networks since ER P2/6 was published in 2006. In particular, it recognises that: • some demand customers are modifying their electricity consumption in response to market signals; this means that further consideration has to be given to establishing the true demand on the network; • in addition to providing security of supply from network assets and distributed generation, demand-side services can also contribute to the security of supplies; and • the nature and type of distributed generation connected to the network mean that their contribution to the security of supplies is different to that in ER P2/6.
Learnings and outcomes	In order to accommodate these changes, the emphasis of the new document is focused on defining the minimum level of security of supply that should be achieved rather than how that level should be achieved. The main changes proposed in this revision are: • EREC P2 is clarified as a standard defining the security of supply that is to be achieved, whilst ETR130, which is in the process of being reviewed, becomes a document describing how that security of supply should be achieved; • Formally incorporate Distributed Energy Resources (DER) into EREC P2; • Remove F-Factors and other tables associated with the security contribution from Distributed Generation which is already duplicated in ETR130; • Refresh the definition of demand to appropriately include consideration and treatment of flexible resources such as DG and DSR; and • Specifically, excluding the security of supply to Distributed Generation installations from the scope of EREC P2 as justified by the earlier work phases.
Conclusion	The Consultation is closed however the modification has not been published yet. Proposed changes will be considered in development of the design methodologies.

8. Appendices

Appendix A: References

- LV network model methodology

[L1] A.J. Urquhart, M Thomson – Loughborough University, “Assumptions and approximations typically applied in modelling LV networks with high penetrations of low carbon technologies,” Institutional repository, 2013.

[L2] D. C. Jayasuriya, J. de Hoog, D. Thomas, I. Mareels, “Modelling and validation of an unbalanced LV network using smart meter and SCADA inputs,” IEEE Telecon 2013.

[L3] A. Navarro, L. F. Ochoa, P. Mancarella, “Learning from residential load data: Impacts on LV network planning and operation,” IEEE T&D-LA, 2012.

[L4] A. Navarro, L. F. Ochoa, R. Shaw, D. Randles, “Reconstruction of low voltage distribution networks: From GIS data to power flow models,” CIRED 2015.

[L5] Flexible Networks for a Low Carbon Future – Project closedown report, December 2015, SP Energy Networks.

[L6] New Thames Valley Vision – Learning Outcome Report, Project Closedown Report, 2017, Scottish & Southern Electricity Networks.

[L7] Low Voltage network solutions – Closedown report, June 2014, Electricity North West Limited.

- Multi-voltage level network model methodology

[H1] C. Kim Gan, D. Pudjianto, p. Djapic, G. Strbac, “Strategic assessment of alternative design options for multi-voltage level distribution networks,” IEEE Transactions on Power Systems, 2014.

[H2] Smart Street – Optimisation Implementation Strategy, February 2018, Electricity North West Limited.

[H3] DS2030 Smart Grid forum workstream 7 – Stages 4 & 5: project results, March 2016, Parsons Brinckerhoff.

- Smart meter data analytics

[S1] Customer-Led Network Revolution – Project closedown report, April 2015, Northern Powergrid

[S2] F. Ni, J. Q. Liu, F. Wei, C. D. Zhu – Tellhow Sci-Tech Co., Ltd., S. X. Xie – Eindhoven University of Technology, “Phase Identification in Distribution Systems by Data Mining Methods”, IEEE 2017

[S3] Wenpeng Luan, Joshua Peng, Mirjana Maras, Joyce Lo, and Brian Harapnuk, “Smart Meter Data Analytics for Distribution Network Connectivity Verification”, IEEE Transactions On Smart Grid, 2015

[S4] Low London Carbon – Learning Report C1, Use of smart meter information for network planning and operation, September 2014, UK Power Networks

[S5] New Thames Valley Vision – Learning Outcome Report, “University of Reading Smart Analytic Evaluation”, Project Closedown Report, 2017, Scottish & Southern Electricity Networks

[S6] Jeremy D. Watson, Neville R. Watson – University of Canterbury, Christchurch, New Zealand – John Welch – Vector Network Ltd, Auckland, New Zealand – “Use of Smart-meter data to determine Distribution system topology”, The Journal of Engineering, March 2016

[S7] Goudarz Poursharif, Andrew Brint – Management School, University of Sheffield – Mary Black, Mark Marshall – Northern Powergrid UK – “Using smart meters to estimate low-voltage losses”, The Institution of Engineering and Technology, November 2017

[S8] Goudarz Pourscharif, Andrew Brint – Management School, University of Sheffield – Mary Black, Mark Marshall – Northern Powergrid UK – "Analyzing the ability of Smart Meter Data to Provide Accurate Information to the UK DNOs", CIRED, 2017

[S9] Smart Meter Aggregation Assessment Final Report, Smart Meter Aggregation Assessment Final Report – Benefits Reduction, Energy Networks Association (ENA), 2015

- Novel analysis techniques

[N1] M. Antoncic, L. Herman, I. Papič, B. Blažič, "Stochastic Modelling of Distribution Networks Operation," IEEE ISGT 2016.

[N2] N. Nikmehr, S. Najafi Ravadanegh, "Solving probabilistic load flow in smart distribution grids using heuristic methods," Journal of Renewable and sustainable energy 2015.

[N3] P. Chen, Z. Chen, B. Bak-Jensen, "Probabilistic Load Flow: A review," IEEE DRPT 2008.

[N4] M. Neaimeh, R, Wardle, A. Jenkins, J. Yi, G. Hill, P. Lyons, Y. Hübner, P. Blythe, P. Taylor, "A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts," Applied Energy Journal 2015.

- Relevant policy

[RP1] DCode, DCRP/18/03/PC Revision to Engineering recommendation P2 – Security of supply (2018).
http://www.dcode.org.uk/consultations/closed-consultations/