

Report C1





Our extensive smart meter trial coupled with high resolution network monitoring provides new understanding of our network performance and delivers insight on how DNOs will benefit from using the smart meter roll out data.

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SDRC compliance This report is a contracted deliverable from the Low Carbon London project as set out in the Successful Delivery Reward Criteria (SDRC) section "Using Smart Meters and Substation Sensors to Facilitate Smart Grids"

Executive Summary

This learning report analyses energy consumption data collected through the Low Carbon London (LCL) Smart Meter trial and additional network monitoring to determine how smart meter data can be used to better understand the way in which customers contribute to network load. It also looks at how the data that will be available from smart meters will be useful to a Distribution Network Operator (DNO) when planning and operating electricity distribution networks.

Most up to date analysis of historic smart meter data can improve estimates of future customers' demand

Analysing the smart meter data collected as part of the LCL Smart Meter trial has shown that new customers, being connected to the network (for which no smart meter data exists) can be categorised to make better assessment of the effect of their peak demand to the network. These categories are defined by property size and demographic profile which are data that could potentially be readily acquired by the DNO for any specific connection assessment. Table 1 shows how the peak demand differs for different customer categories.

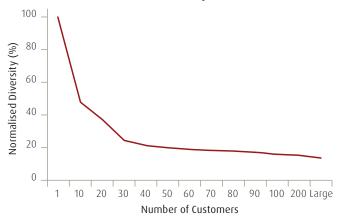
Table 1: Peak demand by customer categories

Average peak consumption (kW) of a		Number of bedrooms			
household	. , ,	Studio/1	2	3	4+
	Affluent	3.1	3.1	3.6	4.5
Demographic group (postcode derived)	Comfortable	2.6	2.8	3.1	4.0
	Adversity	2.1	2.8	3.1	4.0

Demand diversity is consistent among customers, so that a single diversity curve can be used to assess demand at different points on the network

As customer demand is aggregated, the load present on higher levels of the network shows increasing levels of diversity since customers do not use appliances at the same time. This demand diversity has been shown to be similar for all types of customer and a single view of diversity has been produced based on the 2,541 smart meter consumption datasets for which survey results were available. This analysis of demand diversity allows robust, data driven diversity factors to be identified for any customer population and asset size. While the results in this report are based on the balanced sample of London Power Networks (LPN) customer data obtained on LCL, the methodology will be able to be applied to all network areas once smart metering data is more widely available, following the national rollout.

Figure 1: General demand diversity



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 in London is more sensitive to local generation (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 integrated into current processes to improve service to customers and 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 with the inclusion of such data. These include:

- Connection of new load;
- Planning of reinforcement of existing network;
- Voltage issue investigations; and
- Supply interruption management.

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 to accelerated load growth associated with Low Carbon Technologies (LCTs).

Overall 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.

Although there are concerns that having limited visibility of voltage may be an existing problem which could be unmasked once the smart meter roll-out takes place, the analysis of the LCL Smart Meter trial data demonstrates that voltage is not currently a significant issue in the LPN network. However, with the onset of LCTs, this may become more challenging in the future. 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 in a case specific way. This could involve future network load/voltage studies, analysis of voltage alerts, verifying load growth and using the smart meter data for outage management.

Introduction

1.1 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. Manually reading the meter in this way meant gaining physical access to the property or site where the meter was located, and where there was a lack of access, this affected the results in estimated billing. Also, these meters provide very little knowledge of how energy was consumed.

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). The IHD gives the customer immediate information regarding their energy usage, both in terms of energy being consumed and the cost. Energy suppliers will have remote access to billing information on request, meaning bills can be generated accurately based on up-to-date energy consumption.

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. Smart meters can also generate alerts to energy

suppliers and network operators to indicate abnormal conditions and loss of supply.

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). Having access to this data will give DNOs an unprecedented view of conditions on LV networks which are currently not monitored. This visibility will also, to some extent, extend up to the High Voltage (HV) networks , allowing DNOs to improve practices, such as:

- Responding to faults to ensure customers' supplies are restored as soon as possible;
- Improving the design and planning to accommodate new connections:
- Responding more efficiently to abnormal voltage conditions on the network; and
- Building efficient future networks that make use of the available data to respond intelligently to network conditions.

53 million electricity and gas smart meters will be installed across Great Britain between late 2015 and the end of 2020 in a roll-out led by energy suppliers with some suppliers already installing smart meters.

1.2 Scope and Structure

This report focuses on understanding how the data available from electricity smart meters will help DNOs to design, plan and operate the networks that supply electricity to customers' properties. It analyses data from smart meters installed as part of the Low Carbon London's Smart Meter trial and uses information regarding the nature of the data that will be available to a DNO in the future. The objective is to help inform the DNOs where improvements can be made in managing networks.

The report does not cover how data concerning energy consumption can be utilised by the wider electricity industry, including suppliers and the end customers.

For further information on the potential once customers are more familiar with their energy usage please see Report C3 [Ref. 1] and Report A1 [Ref. 2]. Chapter 2 contains information on LCL's Smart Meter trial and the data it generated. This data has been analysed to draw conclusions on how customers' energy impacts loading on the distribution network in Chapter 3 and is used to make an assessment of voltage conditions on remote parts of the Low Voltage (LV) network in Chapter 4. Chapter 5 explores how the data that will be available from smart meters via the DCC will be used by DNOs in the future to improve processes. Chapter 6 looks at what technical and policy changes will be required to take advantage of the data and Chapter 7 presents the final conclusions and recommendations.

Trial Description

2.1 Smart meter customers

The LCL Smart Meter trial was facilitated by EDF Energy who recruited customers, installed 5,533 meters and later carried out a dynamic Time of Use tariff (dToU) trial. To recruit the customers for the trial EDF Energy first identified the target customers or prospects. This was initially restricted to the Mayor of London's Low Carbon Zones (LCZ) but later expanded to include all EDF Energy customers within the London Power Networks (LPN) distribution network licence area operated by UK Power Networks. Customers were excluded from the list if they met any of the following criteria:

- No longer an EDF Energy customer at the time of the trial;
- Dual Fuel customers: the trial was for electricity customers only;
- Complex meter type (i.e. not Standard or E7 meter): there was no Smart meter solution for these meter/tariff types;
- Prepayment customers: there was no smart meter solution for servicing Prepayment;
- Vulnerable: there was no smart meter solution for servicing vulnerable customers;
- Certain other restrictions: marketing opt out, debt;or
- Micro-generation installed at the property.

The majority of these constraints were driven by the desire to use the smart meters for a "first-of-a-kind ToU" tariff trial. The most significant constraints were those associated with Economy 7, vulnerable and pre-payment customers, but the LCL project has subsequently provided an up-to-date view of electricity usage in gas-heated homes and to an unprecedented level of detail.

To ensure that an even grouping of socio-economic prospects were recruited onto the trial, representative of the London-residential customer mix, analysis was undertaken to map all definitive prospects to the corresponding ACORN groups. ACORN data is generated by CACI Limited and is a customer classification that segments the UK population using demographic data, and social factors. Customers were contacted in accordance with this target.

The demographic profile is shown in Figure 2 (derived from data analysis for LCL Report A3 [ICL2]) which is consistent with the demographic profile of the LPN licence area.

and LCL trial participants (Source: LCL Report A3 [ICL2]) 35% 30% 25%

Figure 2: Comparison of demographic profile of EDF Energy customers in LPN

20% 15% 10% 5% В D Ν 0 Р 0 ■ EDF Energy customers in the LPN area LCL smart meter trial

2.2 Smart meter equipment

For the purpose of the LCL project EDF Energy explored various smart meter options. This process was running in parallel with other work to determine the specification of the launch version of SMETS, as part of the natural rollout. The work to define SMETS took longer than expected an so the project selected an existing smart meter that was known to not meet the draft SMETS 5236.

EDF Energy had previously conducted trials and knew that it was stable and performed well. Moreover, this smart meter asset was available on a mass volume scale to support the needs throughout the installation phase of LCL. An added incentive of the meter was that it was supported by CGI's Instant Energy head-end system, meaning that tariff and meter configuration could be performed prior to and after installation and that HH data could be reliably collected for analysis.

Figure 3: Landis and Gyr E470 electricity

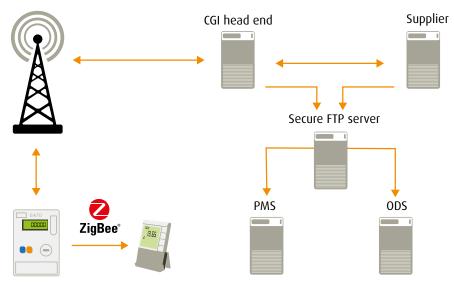




meter and ecoMeter In Home Display (IHD)

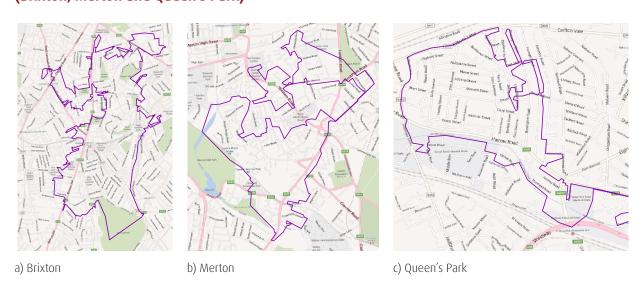
The communications infrastructure shown in Figure 4 was set up to facilitate the transfer of data to EDF Energy and UK Power Networks. In the context of the wider Smart Metering programme, the CGI head-end acted as the DCC. The 3G modems and the Vodafone network acted as the Communications Service Provider (CSP) and is/is not in fact the preferred solution for the South Region CSP. The Participant Management System (PMS), which is in effect a shared Customer Relationship Management (CRM) database shared between EDF Energy and UK Power Networks in the project, and does not normally exist between supplier and DNO. The Operational Data Store (ODS) is a database used to store the time-series data collected by the LCL's trials including the Smart Meter trials and Engineering Instrumentation Zone (EIZ) monitoring data.

Figure 4: Data architecture of Low Carbon London smart meter trial



2.3 Engineering Instrumentation Zones (EIZs)

Figure 5: Engineering Instrumentation Zones (EIZs) of the Low Carbon London trial (Brixton, Merton and Queen's Park)



2.4 Trial Data Summary

A summary of the data available from the trial and sources mentioned above is show in Table 2.

Table 2: Low Carbon London smart meter trial data summary

Data	Description
EDF Energy smart meter HH consumption data	HH electricity consumption data from 5,568 smart meters over a period of 15 months.
British Gas smart meter HH consumption data	HH electricity consumption data from 10,900 smart meters over a period of 15 months.
EIZ voltage data	10-minute average RMS voltage readings from 106 meters (318 phases) over a period of 6 months
Survey data	A comprehensive survey of customers, their premises, their behaviour and their electrical appliances was carried out at a level never collected before. This data can be matched with the energy consumption of the relevant customer.

Imperial College London provided a review and assurance of the quality of the Smart Meter data before commencing work, which provides confidence in the results shown in the reminder of this report. Their assurance statement can be read in Report C6 [Ref. 2].

Customer Contribution to Network Demand

The smart meters installed as part of the trial recorded HH 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. This Section will analyse the electrical energy demands of customers and the factors that influence the effect this has on a distribution network. This includes:

- Investigating the energy consumption of individual customers;
- The difference in electrical demand between different types of property;
- How the demand of different properties changes with season and day of week;
- The probability of peak customer demand and how this can be used to determine realistic load on the network; and
- How diversity amongst customer loads influences network peak demand.

The results of these smart meter data investigations will be brought together to help produce a practical process for distribution network planners, by which they can assess the demand contribution new connections will have at various points on the distribution network.

This is particularly relevant to new connections requiring a new distribution substation, where it is reasonable for not only the number of properties but also the type of properties to be known. Additions to an existing substation are likely to experience the benefit of diversity and require slightly less analysis. In this context the current approach using a blanket After-Diversity Maximum Demand (ADMD) is reasonable.

3.1 Categorising customers

The smart meter trial included a comprehensive survey of customers to determine how various factors influence customers' electricity consumption. By comparing the consumption data from the smart meters with the survey responses, key factors that influence energy consumption and consequent network load, can be identified.

Figure 6 shows how the demand profiles vary for different categories of customers. The customers were categorised based on two factors, the ACORN category based on their postcode and the number of people living in the property (occupancy). These factors were used to divide customers into a 3x3 matrix as detailed in Table 3 which shows the number of customers that were included in each of the 9 categories.

Table 3: Sample size of customer categories

			Оссирапсу	
		1	2	3+
	Affluent (ACORN categories ABCDE)	406	404	226
Demography	Comfortable (ACORN categories FGHIJ)	244	312	213
	Adversity (ACORN categories KLMNOPQ)	325	281	236

Figure 6: Peak demand profile of customer categories (Source: LCL Report A3 [ICL2])

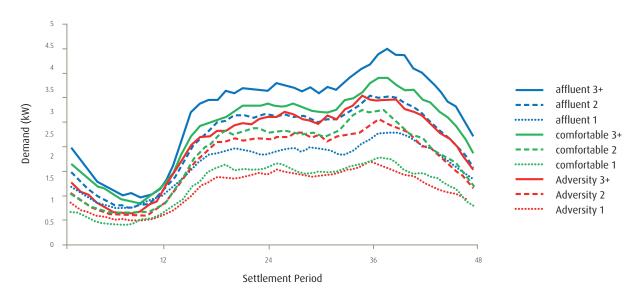


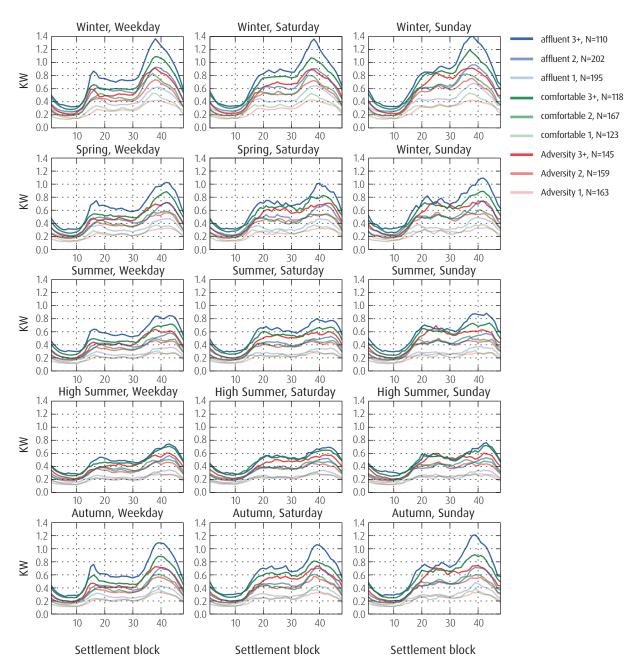
Figure 6 (from LCL Report A3 [ICL2]) shows a clear difference between the demand profiles of the customers in the different ACORN demographic categories. Although the profile shape of the demand remains fairly constant across the customer categories, both occupancy and economic factors have a clear influence on the amount of energy consumed within a day. As expected, households with more occupants consume more energy on average. It can also be observed that the customers in wealthier categories consume more energy than those in the less wealthy categories.

The difference in demand presents an opportunity for a DNO to design networks and new connections to take this into account by using relevant indicators of both occupancy and economic factors.

Season and day of week 3.2

The daily demand profile of a customer changes over time. The demand profile is influenced by the season and also by the day of the week. To investigate the nature of these changes the average peak demand profile of the each of the customer categories described in Section 3.1 were calculated (see LCL Report A3 [ICL2]) and are shown in Figure 7.

Figure 7: Peak demand profiles of customer categories for seasons (Source: LCL Report A3 [ICL2])



Elexon, the company responsible for balancing the GB wholesale electricity market, defines 5 seasons within the year:

- Winter: defined as the period from the day of the clock change from British Summer Time (BST) to Greenwich Mean Time (GMT) in October, up to and including the day preceding the clock change from GMT to BST in March;
- Spring: defined as the period from the day of clock change from GMT to BST in March, up to and including the Friday preceding the start of the Summer period;
- Summer defined as the ten-week period, preceding High Summer, starting on the sixteenth Saturday before the August Bank Holiday;
- High Summer defined as the period of six weeks and two days from the sixth Saturday before August Bank Holiday up to and including the Sunday following the August Bank Holiday; and
- Autumn defined as the period from the Monday following the August Bank Holiday, up to and including the day preceding the clock change from BST to GMT in October.

By breaking down the demand profiles by these seasons and days of week shown in Figure 7, several observations can be made.

There is significant difference between the energy consumption in different seasons. The average peak demand for a customer in the affluent 3+ category is almost twice as large in the winter as it is in the high summer season for weekday demand. There is less of a difference between weekday and weekend consumption within the same season although weekday consumption is consistently higher than weekend consumption.

The difference in energy consumption that is observed between the customer categories, described in Section 3.1 remains apparent for all seasons. Customer categories that have an average high energy demand show this consistently through the year, similar for those customers with low average energy demand.

DNOs must design networks that are capable of accommodating the maximum peak demand which is shown in Figure 7, to consistently occur on a winter weekday evening.

Probabilistic Peak demand 3.3

The load profiles presented in the previous section are averages of large numbers of customers. The process of averaging has the effect of masking the differences between the demand patterns of different customers within each category. In reality some customers within each category will have an energy demand greater than this average and this must be taken account when predicting the demand of customers being connected to the network for which no previous demand data is available. A vital underlying reason for carrying out this analysis is that another key objective for LCL has been to quantify the impacts of new Low Carbon Technologies (LCTs) such as EVs and HPs, and it is important to understand that these may be taken up by sections of the community faster than others. For example, electric vehicles may be purchased by comfortable or affluent households with proportionally higher demand in the first place.

To assess how the peak demand (the metric of most interest when designing networks) varies for customers within each group a Cumulative Probability Distribution (CPD) is shown for the 9 customer categories. It shows the minimum and maximum peak demand observed within each category and also shows what percentage of customers that do not exceed a particular peak demand.

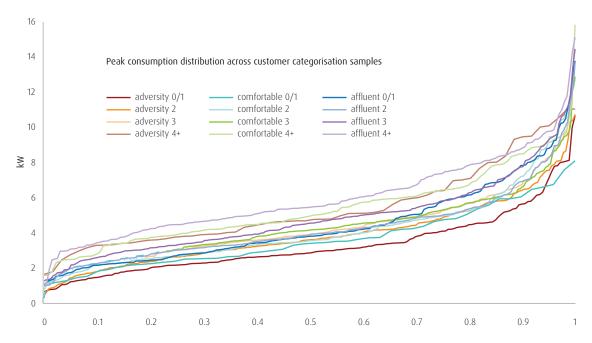


Figure 8: Probabilistic peak demand of customer categories (Source: LCL Report A3 [ICL2])

Figure 8 (derived from data analysis for LCL Report A3 [ICL2]) allows the probability or risk, that a customer within a category will exceed a specific peak demand, to be determined. The level of acceptable risk can be set and this can then be used to determine the peak demand to ensure that a customer is unlikely to exceed it.

Figure 8 also shows that the lower the level of acceptable risk, the higher the allowed peak demand must be. However, this analysis only considers the peak demand of a single customer. The majority of the network, with the exception of the service cable to an individual property, is designed to supply multiple customers. When assessing multiple customers' group demand there are other factors to consider for evaluating the demand and acceptable risk

Load Diversity 3.4

When considering the group demand of multiple customers, simply summing the expected peak demand of each customer will overestimate the peak demand of the group as a whole. There are two reasons that the demand of the group will be less than the aggregated peak loads: averaging effects and peak coincidence.

3.4.1 Averaging effects

As mentioned before, when considering a single customers' peak demand, it is not appropriate to average the demand of many similar customers because there is a reasonable probability that the customer will have a higher peak demand than the average. As more customers are considered in a group it is less likely that all the customers will have a high peak demand. For the same level of risk, a lower peak demand per customer can be assumed. As more customers are considered, the group peak demand of these customers will converge to the average of the population as a whole. This has the effect of reducing the expected peak demand of a group of customers as the number of customers within the group increases.

3.4.2 Peak coincidence

The second factor to consider is that not all of the customers will be consuming their peak demand at the same time. The peak demand figure calculated for a customer is measured over a long period of time. Although the peak demand of different customers is likely to occur at a similar time, the peak consumption will not always occur on exactly the same day or at the same time of the day. An example of this is shown in Figure 9.

Peak 1 + Peak 2 Profile 1 + Profile 2 Profile 1 Profile 2 00:00 06:00 12:00 18:00 00:00

Figure 9: Example of the effect of peak coincidence (values are indicative only)

As the demand of more customers is considered, the less likely it is that the peak demand of all customers will coincide and therefore the expected peak demand of the group will be lower.

3.4.3 Demand diversity of customer groups

The collective effect of the averaging and peak coincidence described is known as demand diversity. To evaluate how this affects group demand for increasing numbers of customers within the categories described in chapter 3, demand diversity analysis was carried out on each customer category and the results are presented in Figure 10.

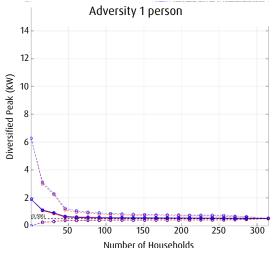
To assess the diversified peak of varying number of customers, random groups of customers were taken from within the category being assessed and the group peak was calculated. This process was repeated for each group size to ensure that enough different randomly chosen groups of the same size were selected to observe the true characteristics for a group of that size. From the group demand figures calculated for each of the repetitions the minimum, average and maximum figure observed were recorded. Each of the values for each group size were plotted in Figure 10 producing three curves per customer group.

This method of selecting random samples from customers within each category can be improved by building a representative dataset that has the same statistical properties as the original data. This modelled data has the effect of increasing the dataset which improves the resolution of the analysis beyond the limits that would be encountered with the measured data. This method, called G-Vine, also produces a minimum, average and maximum for each group size, producing a further three curves which are also plotted on the graphs making a total of six. The two methods produce very similar results, which are reflected in the similarity between the minimums, averages and maximums.

For further explanation of demand diversity and the methods used to calculate it, please refer to the demand diversity report produced by Imperial College London (see [ICL4]).

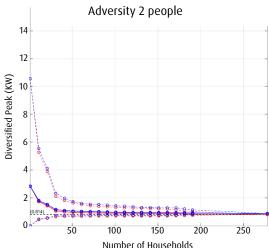
From Figure 10 (see "Quantifying demand diversity of households" [ICL4]) it can be seen that effects of demand diversity are extremely significant. When looking at the maximum curves, as more customers are considered as a group, there is a significant decrease in the contribution to peak demand of each customer. When a group of 50 customers is considered, the contribution of a single household's demand is reduced by 80% compared to the worst case scenario when considering a single customer in isolation. This effect has allowed the network to be built efficiently taking into account how many customers are fed from the network being considered.

Figure 10: Diversified demand for the customer categories (Source: Quantifying demand diversity of households [ICL4])

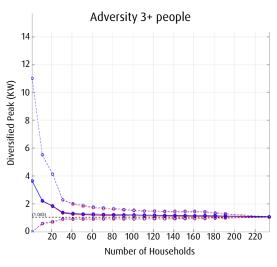


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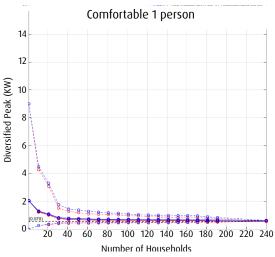
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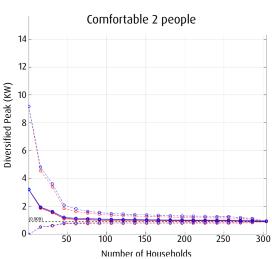
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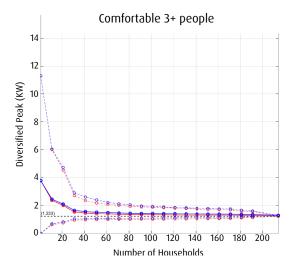
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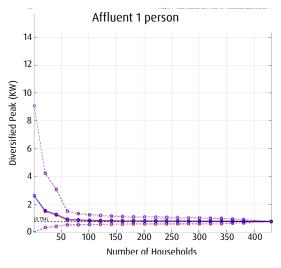
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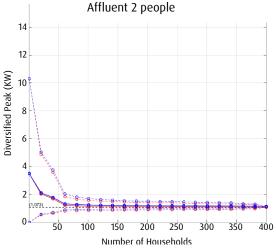
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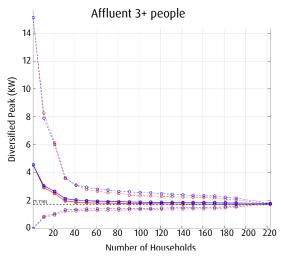
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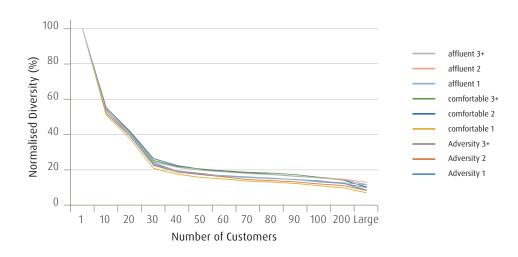


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- -O- C-Vine Samples Diversified Peak MiN

3.4.4 Normalised Demand Diversity

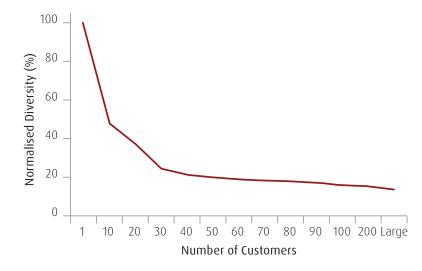
Inspection of the graphs in Section 3.4.3 shows that although the curves for different customer categories differ in magnitude as expected from the analysis in previous sections, the shape of the curves is always similar. Taking the maximum of each of the curves (representing the lowest risk approach) and normalising them based on the highest value of each curve leads to the chart in Figure 11.

Figure 11: Normalised maximum diversified demand of the customer categories



This confirms that the curves do indeed have very similar shapes with the maximum difference between the curves at any point being less than 6 percentage points. The fact that the curves are so similar allows a single shape to be derived for Demand Diversity which is shown in Figure 12 (see "Quantifying demand diversity of households" [ICL4]).

Figure 12: General demand diversity applicable to all customer categories (Source: Quantifying demand diversity of households [ICL4])



The curve in Figure 12 is generated by taking the maximum of the values at each point of the nine curves from Figure 11. The maximum figure is taken as the lowest risk method to combine the curves, ensuring that the demand is never underestimated.

This curve represents a single method, of applying demand diversity effects which applies to any customer category. To recreate any of the diversity curves for each customer category the normalised curve simply needs multiplying by the maximum peak demand expected for the customer category of interest.

The fact that this diversity curve is valid for all customer categories is used as part of a simple process for assessing the expected demand of groups of new customers being connected to the network, which is described in Section 3.6.

3.5 Property size

ACORN group classification is something a DNO can easily assign to new customers, as it can be determined using the postcode, which is something that will be known at the time of the assessment of a new connection. The occupancy, however, will not be known to a DNO and therefore cannot be used outside of a trial scenario with survey data. It is also a factor that is likely to change over time more frequently than networks are considered for load related reinforcement.

A metric more appropriate for use by a DNO is property size, measured by number of bedrooms. This is information that could realistically be obtained by a DNO at time of a new network connection request, or determined for existing customers. Figure 13 shows how the demand profile of customers differs when categorised by ACORN category and number of bedrooms of the property.

Figure 13: Peak demand profiles of customer categorised by number of bedrooms in property (Source: LCL Report A3 [ICL2])

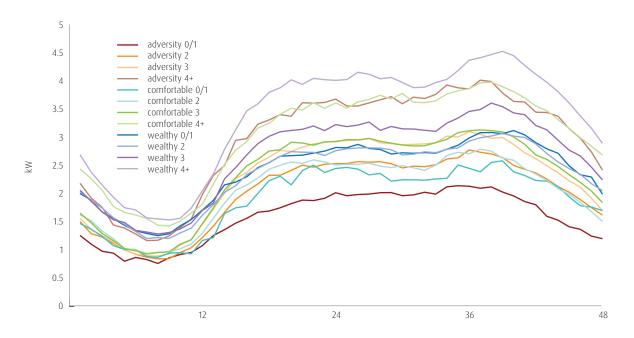


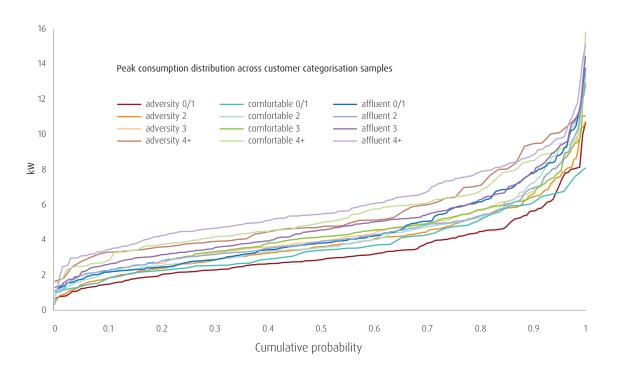
Figure 13 (derived from data analysis for LCL Report A3 [ICL2]) shows that when customers are categorised using the number of bedrooms in the property there are still distinguishing differences between the categories. This can be used by a DNO to make a more accurate assessment of the capacity required by the connection of new customers.

Table 4: Average peak consumption per customers in each category

		Number of bedrooms			
Average peak	consumption (kW)	Studio/1	2	3	4+
	Affluent (ACORN ABCDE)	3.1	3.1	3.6	4.5
ACORN group	Comfortable (ACORN FGHIJ)	2.6	2.8	3.1	4.0
	Adversity (ACORN KLMNOPQ)	2.2	2.8	3.1	4.0

As before, these profiles are generated by averaging the demand of the large numbers of customers within each category. To assess the likely maximum peak demand of a single customer within each category a CPD, as described in Section 3.3, was generated from data analysis for (LCL Report A3 [ICL2]) for each of the 12 categories and they are presented in Figure 14.

Figure 14: Probabilistic peak demand of customers categorised by number of bedrooms in property (Source: LCL Report A3 [ICL2])



As observed before, as the probability increases (risk decreases), the required demand value increases. Taking a low risk approach and obtaining a peak demand value for each category from the high probability end of the scale, the summary table of maximum peak demand of single customers in each category is shown in Table 5.

Table 5: Peak consumption per customer categorised by number of bedrooms in a property

		Number of bedrooms			
Peak consump	tion (kW)	Studio/1	2	3	4+
	Affluent (ACORN ABCDE)	13.8	13.7	14.5	15.1
ACORN group	Comfortable (ACORN FGHIJ)	8.1	12.7	12.9	15.9
	Adversity (ACORN KLMNOPQ)	10.7	10.8	12.8	11.1

The values in Table 5 prove to be inconsistent with the properties seen between the averages of the customer categories. This suggests that when working at the extreme end of probability, the difference between customer peak demands are not reliable and are dominated by anomalous customer behaviour. This means that categorisation is not reliable until enough customers are included in the group that averaging effects are strong enough to produce reliable differences between customer groups. By studying the CPD in Figure 14 and the data behind it, the point at which customer categorisation becomes reliable can be determined as the 75th percentile. Based on the average group size this means that the group size must be greater than 50 to achieve a reliable distinction between customer categories. A summary of the results for the 75th percentile peak demand are shown in Table 6.

To remove the averaging effects, see Section 3.4.1 inherent in the 75th percentile data the numbers in Table 6 have been scaled back up to be equivalent to undiversified peak demand of a single customer and rounded up to the nearest 1kW. This is to allow the load calculated by these peak demands to be diversified in the same way as the general diversity described in

Table 6: Scaled and rounded 75th percentile peak demand per customer

Scaled and rounded 75th percentile peak		Number of bedrooms			
consumption ((kW) of each household	Studio/1	2	3	4+
	Affluent (ACORN ABCDE)	13	11	13	16
ACORN group	Comfortable (ACORN FGHIJ)	11	11	12	14
	Adversity (ACORN KLMNOPQ)	9	11	12	14

The numbers presented in Table 6 are consistent with the results obtained previously, with larger properties having a higher peak demand and wealthier customers also having a higher peak. The only figure not consistent with this pattern is the peak demand calculated for 2 bedroom properties in the affluent band; which is lower than that of studio/1 bed properties. This result seems to be anomalous and may be a feature of the dataset this used for the analysis, and could be the subject of further analysis with additional future datasets.

Based on the average sample size in the customer categories, the 75th percentile relates to groups of customers greater than 50. For groups of customers less than 50, the worst case peak demand of 16kW per customer should be used as an undiversified peak demand of an individual customer in all categories.

These values can be used as the starting point for assessing the group demand of new connections to the network, as described in the process presented in Section 3.6.

Assessing new connections 3.6

The previous sections have introduced and analysed an up-to-date and demographically balanced data set gathered from smart meters. This represents a significant update to assumptions about load profile and diversity, which were last reviewed and published in 1986.

Analysis in the previous sections, have shown that customers can be categorised using available information into groups that show significant differences in peak demand. It has also been shown that as the demand of more customers is aggregated, the average contribution of each to the total peak demand decreases due to diversity effects and this decrease is consistent across all customer groups. These two findings can be used together in a simple process for making more accurate assessments of the peak demand of new connections to the network using customer information that is available to a DNO. The process involves two steps which are described below.

• Step 1: Sum customer peak loads.

When customer numbers are below 50, a single figure of 16kW should be used. Table 6 can be used to assess load.

Table 7. Scaled and rounded 75th percentile peak demand per customer

Scaled and rounded 75th percentile peak		Number of bedrooms			
	kW) of each household	Studio/1	2	3	4+
	Affluent (ACORN ABCDE)	13	11	13	16
ACORN group	Comfortable (ACORN FGHIJ)	11	11	12	14
	Adversity (ACORN KLMNOPQ)	9	11	12	14

Example A: A new development of 6 one-bedroom flats and 4 three-bedroom houses has a total number of less than 50 new properties. In this case the table cannot be used reliably and the worst case figure of 16kW is used.

10 x 16kW = 160kW

This value represents the undiversified maximum demand; the next step is to diversify this load based on the number of customers.

Example B: A larger development of 40 new 1 bedroom flats, 20 new 2 bedroom flats and 10 new 3-bedroom houses in an area that falls within the ACORN categories designated as comfortable. Since the total number of new properties is greater than 50, the peak demands in Table 7 can be used to calculate the maximum demand based on the customer categories.

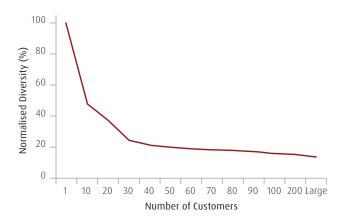
$$(40 \times 11kW) + (20 \times 11kW) + (10 \times 12kW) = 780kW$$

This value represents the undiversified Maximum Demand (MD), the next step is to diversify this load based on the number of customers.

• Step 2: Diversify based on total number of customers.

The combined peak demand must now be diversified using the diversity curve in Figure 15.

Figure 15: General demand diversity curve applicable to all customer categories



Continuing **Example A** for a total of 10 properties the diversity factor is 55%. Applying this to the combined peak demand calculated:

160kW x 55% = 88kW (average 8.8kW per customer)

This value represents the maximum expected peak demand of the new connection.

Continuing **Example B** from above, for a total of 70 properties the diversity factor is 19%. Applying this to the combined peak demand calculated:

780kW x 19% = 148kW (average 2.1kW per customer)

This value represents the maximum expected peak demand of the new connection.

As can be seen from the examples above, when assessing larger groups of customers a lower average peak demand per customer can be allowed due to the effects of diversity. It can also be seen from the values in Table 7 that customers in different categories can have significantly different peak demands. These factors can be used to ensure that the network designed to accommodate the new connection can be as cost-effective as possible for the expected demand.

Assessment of network voltage

The voltage level of the LV network is an important parameter, as it determines the supply voltage to domestic customers' properties. Equipment that a customer connects to the power supply in their property is designed to operate within certain voltage limits. If the voltage supplied is outside of these limits it can lead to damage or incorrect operation of a customer's electrical equipment. All voltage excursions identified by the trial have been referred to the supply quality team within UK Power Networks for further investigation and remedial action where necessary.

All DNOs must comply with the Electricity Safety, Quality and Continuity Regulations (ESQCR) [Ref. 3] which state that:

•• the voltage declared in respect of a low voltage supply shall be 230 volts between the phase and neutral conductors at the supply terminals and in the case of a low voltage supply, a variation not exceeding 10 per cent above or 6 per cent below the declared voltage at the declared frequency

In summary, the ESQC Regulations state that the voltage on the LV network must be 230V +10% -6% which in absolute terms is:

Table 8: UK Statutory voltage limits

Limit	Value
Maximum	253V
Nominal	230V
Minimum	216.2V

To measure the voltage conditions of the extremities of the low voltage network, smart meters were installed in street cabinets close to the feeder end-points of the network, furthest from the feeding secondary substation. These smart meters were connected to the network to provide 3-phase voltage measurements. The meters were installed in areas of the network which also had comprehensive monitoring installed in the secondary substations as part of the Engineering Instrumentation Zones (EIZ) .The combination of these two data sources allows a more complete view of the voltage levels across these selected networks. The meters were configured to measure the voltage as 10-minute RMS averages as described in Table 8.

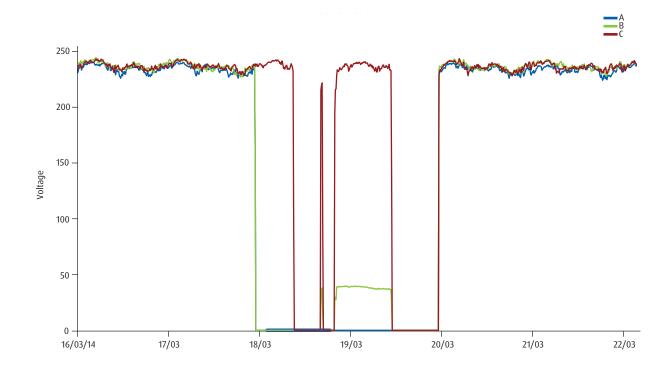
4.1 Data cleansing LPN

The analysis carried out in the following sections is concerned with determining the continuous supply voltage level of various parts of the London network. For this reason, certain anomalous events were removed from the data where they were identified as being due to either technical issues with the meter, or generated by abnormal network conditions, such as, supply outage or fault conditions.

To identify these events, a minimum voltage threshold was set out as 150V and values below this level were excluded from the analysis. Voltages at this level can be attributed to extraordinary events on the network or instances where the meter failed to record voltage readings.

A typical example of such an event is shown in Figure 16 where it can be seen that such readings do not relate to demanddriven network voltage conditions.

Figure 16: Example of voltage variations caused by anomalous network event. Each line represents the voltage of one phase of an installed meter.



These events were not excluded from the analysis carried out in Chapter 4 relating to voltage alerts, as these events would still trigger voltage alerts and are therefore of interest for the voltage alert analysis.

4.2 **Voltage profiles**

To gain an overall view of the voltage level on the network that was monitored, 5 metrics were calculated for each of the feeder end-point meters installed. The metrics are described in Table 9.

Table 9: Voltage metrics

Metric	Description
Maximum	The maximum 10-minute average RMS voltage measured.
99th Percentile	99% of voltage readings were below this value.
Mean	The average of all voltage readings.
1st Percentile	99% of voltage readings were above this value.
Minimum	The minimum 10-minute average RMS voltage measured.

Once the metrics were calculated for each individual meter they were separately sorted in decreasing order and plotted on In Figure 17.

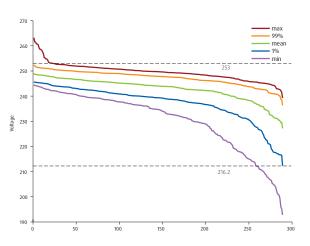
The nominal voltage and statutory voltage limits are also plotted on Figure 17 to provide context to the metrics. This gives a general view of the continuous supply voltage on the LV networks that were monitored and allows some observations to be made.

In general the voltage on the monitored networks tends to be closer to the higher end of the voltage limits than the lower end. This can be seen by the fact that the average voltage (green) is closer to the higher limit for the vast majority of the phases. However, there are more phases which show readings above the lower voltage limit than above the upper voltage limit.

Although there are readings outside of the statutory voltage limits, the majority of phases (77%), have no readings outside of the limits and only very few have more than 1% of readings outside of the limits. This can be observed from the fact that the 1st and 99th percentile lines (blue and

orange respectively) stay within the limits, except in a few extreme cases. This observation is supported by section 3.4, which investigates the voltage measured by the meters with respect to time duration.

Figure 17: Voltage levels of smart meters installed on remote feeder-ends



Voltage bandwidth 4.3

Voltage bandwidth is defined as the difference between the maximum measured voltage and the minimum measured voltage. The voltage bandwidth is of interest as it describes not only what voltage level the network is operating at, but how much of the allowable bandwidth (the difference between the upper and lower statutory voltage limits), is being occupied. In general, a narrower bandwidth is preferable, as it means there is more scope for movement in the voltage, whether that is through the addition of load/ generation or an intervention to solve a voltage related issue.

Since most solutions to voltage related problems would be implemented at the substation level or above, the secondary substation voltage data has been included in this analysis. The smart meters installed on feeders associated with each secondary substation have been identified and grouped with the substations. The bandwidth of each group of substation and smart meters is then shown alongside each other to determine the total voltage bandwidth for the network fed by the substation.

This is shown in a summary chart on Figure 18 which, gives a good overall view of the bandwidth of the substations within the monitored parts of the network. Representative examples are then shown in more detail in the next section.

4.3.1 Broad bandwidth

Figure 18 shows an example of a network that utilises almost the entire allowable bandwidth with some extreme values, (less than 1%), going below the minimum voltage limit or above the maximum voltage limit.

The graph shows the voltage at the substation on each of the three phases of the LV transformer tails, with a light blue shaded background. The three transformer tail phases demonstrate slightly different voltage ranges when plotted side-by-side, indicating an imbalance of load on the three phases on the wider LV network being fed by the substation. For each phase, the maximum and minimum extremes are shown along with the range within which the vast majority fall (defined as the 1% percentile to the 99% percentile).

A total of 12 LV feeder points were then monitored using instruments at the end of the LV feeder, and these are plotted (in no particular order) to the right of the substation results. Apart from occasions in which the data quality checks discussed earlier excluded the results, each of the three phases is plotted for each end of feeder.

This means that a general rise in voltage (for example, due to connection of generation) or a decrease (for example, due to connection of significant new loads) is likely to lead to voltage excursions.

It also means that any voltage excursions that do arise, cannot be solved by a simple shift in voltage by, (for example, by repositioning the off-load tap-changer at the secondary substation), as there is no room for movement within the allowable bandwidth. A more complex solution would have to be considered that can either adjust voltage on a time basis or localised on particular parts of the network.

260 250 240 **Voltage** 530 210 200 190 Voltage banding by substation/feeder Minimum Substation Maximum ■ 1% - 99%

Figure 18: Voltage bandwidth chart for example Sections of network

In Figure 19, substation voltage bandwidths are indicated by blue shading with the associated feeder end-point meters in the white space that follows. Dashed lines indicate groups of meters on the same LV feeder. The red of the bandwidth bars represents the voltage observed for 98% of readings of the individual phases; between the 1st and 98th percentiles. The orange shows the maximum 10-minute average RMS reading observed for the phase and the light blue shows the minimum.

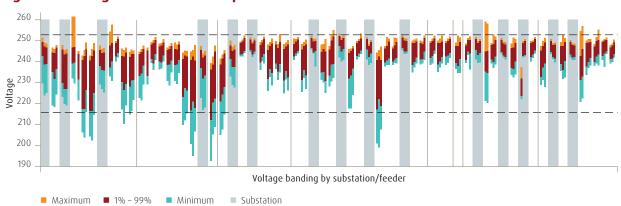


Figure 19: Voltage bandwidth example of a network Section with wide bandwidth

Figure 20, shows part of the network that, although close to the upper voltage limit, has a narrow bandwidth. It is very clear that a general reduction in voltage would have to be very large before any voltage excursions were caused.

If the voltage were to be increased, (for example, the connection of new generation to the network), it would be likely to cause high voltage issues, these could easily be mitigated by repositioning the off-load tap-changer at the secondary substation.

250 - 240 - 240 - 220 - 210 - 200 - 190 - Narrow Bandwidth

Maximum 1% - 99% Minimum Substation

Figure 20: Voltage bandwidth chart for an example of network Section with narrow bandwidth

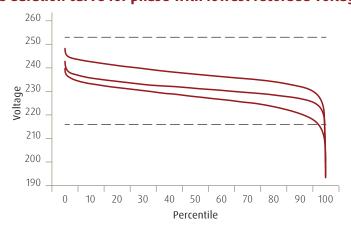
4.4 Voltage duration curves

To investigate locations on the network where the voltage was measured as being towards the limits of highest and lowest recorded voltages recorded, voltage duration curves were produced for selected examples. For the phases chosen as examples, all three phases of the associated meter have been plotted. The voltage duration curves show what percentage of time a phase was measured as being above or below a particular value.

4.4.1 Lowest minimum voltage

This example was selected as having the lowest recorded voltage.

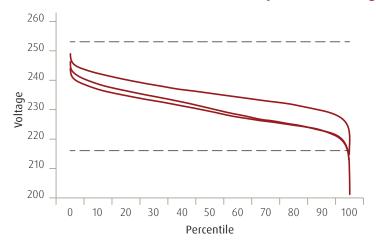
Figure 21: Voltage duration curve for phase with lowest recorded voltage



It can be seen that only one of the phases spends a significant time outside of voltage limits but even in this case only \sim 4% of readings are below the statutory limit.

This example was chosen as having the lowest voltage reading above the 1st percentile.

Figure 22: Voltage duration curve for meter with lowest 1st percentile voltage reading



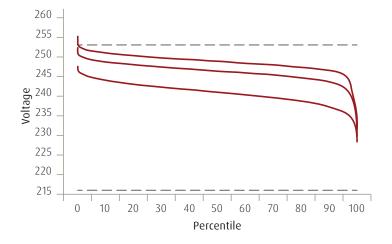
One of the phases of this meter shows only an extremely small amount of time below the statutory limit. The remaining two have a very low percentage below; less than 2%. It can also be seen that although some readings are already below the limit, the general voltage level at this point of the network would have to reduce by ~5V before 5% of readings were below the limit, which would be an indication of a more serious voltage problem.

4.4.3 Highest 99th percentile voltage

This example was chosen as having the highest voltage reading below the 99th percentile.

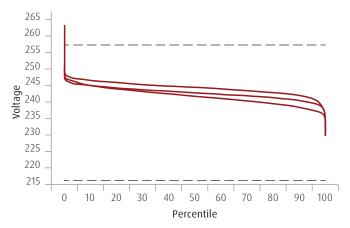
Figure 23: Voltage duration curve for meter with highest 99th percentile voltage reading

It can be seen that only one phase of this meter went above the upper voltage limit and only for an extremely small amount of time. However, in contrast to the lower voltage example above, this phase is more sensitive to a general rise in voltage. An increase of only ~2V would cause 10% of readings on this phase to be above the voltage limit, which would be an indication of a severe voltage issue.



This example was chosen as having the highest voltage reading.

Figure 24: Voltage duration curve for meter with highest voltage reading recorded



Although having the highest single voltage reading, this high voltage was only recorded for a very small amount of time. Otherwise this meter has an overall lower voltage than the previous example, although it does also show a "flatter tail" at the higher end, which indicates sensitivity to rising voltage; if the voltage did start exceeding the maximum limit, it would quickly exceed it for a high percentage of time.

4.5 Conclusions

The analysis shown in this section gives a good indication of the state of the voltage level on the networks that were monitored as part of the trial.

In general, the voltage level measured on the monitored networks is closer to the higher voltage limit, meaning there is less voltage headroom on the networks than legroom. This suggests that adding load to the networks will be less likely to cause voltage issues since higher load tend to reduce the voltage down a feeder. On the other hand, connection of generation is more likely to cause voltage level issues, since generation can increase the voltage on a network. If the voltage on the network is already close to the upper allowable limit, it may exceed this limit when the generation is connected.

The conclusion is compounded by the fact that the overall profile, both in terms of number of phases and time, is more sensitive to increases in voltage. This means that a general increase in voltage on the network could cause a larger number of phases to exceed the upper limit for a longer time than is observed at the lower end of the voltage limits. Therefore increases in voltage are more likely to cause a larger volume of more serious voltage issues.

However, the current state of voltage on the network is generally within acceptable limits with only very few meters showing voltage consistently outside of statutory voltage limits. Of those that are, very little time is spent outside of the limits, no more than 5% of readings were observed outside of limits for any single phase. Voltage limit excursions tend to be at the lower end of the voltage limit, despite the general trend for voltage to be towards the higher end.

The occupied voltage bandwidth varies significantly across the network. However, some areas of network that are fed from the same secondary substation show a narrow bandwidth. This means that adjustments could be made to the general voltage of this area of network to shift the voltage away from either of the voltage limits if any potential issues are identified. The off-load tap changer at the secondary substation could be adjusted, which could be used as a simple low cost alternative to traditional reinforcement or smart technologies to free up headroom or legroom, to avoid voltage issues

Finally, it is interesting to note that a relatively stable design policy over the last 20-30 years (since the area has been a single Regional Electricity Board or Licence Area throughout) has nevertheless led to a variety of broad and narrow bandwith sites

Using smart meter data

The preceding sections have analysed the data that was produced by the Low Carbon London smart meter trial to draw conclusions that are relevant to network design and planning. This section will explore:

- What smart meter data will be available in the future when smart meters are installed in the majority of GB households;
- How that data will further inform and/or enable the opportunities described in the preceding sections; and
- Some of the further opportunities that smart meter data presents to the DNO.

Whereas the previous analysis has informed general insights into potential customer contribution to network loading, as more data becomes available it can be used to assess current network loading in specific circumstances. It can also be used to accurately measure the voltage on any part of the network that feeds a customer with a smart meter installed and can detect potentially problematic load growth before issues occur.

5.1 Data summary

Table 10 summarises the data and alerts generated by SMETS 2 compliant smart meters that are available to a DNO. This is not an exhaustive list of smart meter data and functionality, but only a summary of information relevant to a DNO. The use and opportunities of the data and functionality are detailed later in this chapter.

Table 10: Summary of data and alerts generated by SMETS 2 compliant smart meters

Data	Description	
	13 months of half-hourly active energy consumption data stored on the meter and available on request.	
Consumption profile data	months each of half-hourly: Reactive energy import;	
	Active energy export; and	
	Reactive energy export.	
Daily consumption log	2 years of total daily active energy consumption data stored on the meter and available on request.	
Voltage profile data	4,320 average RMS voltage readings stored on the meter available on request. Period over which RMS voltage is averaged is configurable by the DNO. If set to 10-minute averages 30 days of readings will be available.	
Maximum demand	Maximum active energy import in any half hour period since the last reset with time stamp of occurrence. Only the DNO can reset the register.	
Time limited maximum demand	me limited maximum demand Maximum active energy import in a half hour period within a time period configurable by the DNO. Only the DNO can reset the register.	

Alert/Poll	Description	
Average RMS above/below limit	Average RMS voltage above or below the DNO configurable maximum and minimum limits. The averaging period is shared with the voltage profile described the above and is configured by the DNO.	
Extreme over/under voltage	RMS voltage above or below the extreme maximum and minimum voltage limits for a set time period. All parameters configurable by the DNO.	
Voltage sag/swell	RMS voltage above or below the swell and sag voltage limits for a set time period. All parameters configurable by the DNO.	
Voltage event log	The three alerts above also record events to a circular buffer capable of holding 100 entries.	
Energisation check	The DNO will be able to "poll" the smart meter to determine if the meter is energised. This is an indication of the status of the power supply to the property from the distribution network.	
Outage start/finish	The start and finish time of an interruption to the electrical supply to the meter. This alert is sent following the restoration of the supply.	
Last gasp	An alert will be sent if the communications hub in a property loses electrical suland does not send a notification of restoration within 3 minutes.	

5.2 Demand and voltage time-series data in planning

Table 11: Schedule of time series data

Data	Description	
	13 months of half-hourly active energy consumption data stored on the meter and available on request.	
Consumption profile data	3 months each of half-hourly:	
	Reactive energy import	
	Active energy export	
	Reactive energy export	
Daily consumption Log	2 years of total daily active energy consumption data stored on the meter and available on request.	
Voltage profile data	4,320 average RMS voltage readings stored on the meter available on request. Period over which RMS voltage is averaged is configurable by the DNO. If set to 10-minute averages 30 days of readings will be available.	

Chapter 3 discusses how the analysis of smart meter data can be used to improve the assessment of the maximum demand of a new connection. To assess whether reinforcement will be required to accommodate this new demand on the network, the existing loading conditions must be determined. A typical, current process is described in Figure 25 along with an explanation of where smart meter consumption and voltage data can be used to improve the process of assessing existing load and voltage conditions.

Figure 25: Example high level diagram of network planning process

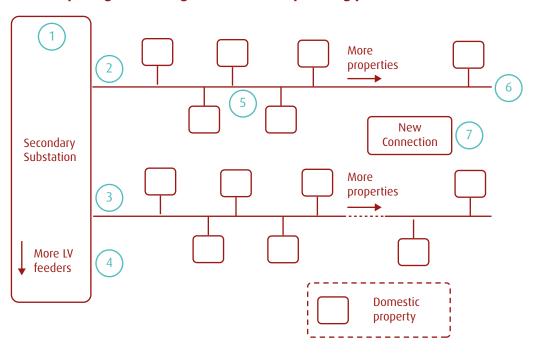


Table 12 describes the process shown in figure 25

Table 12: Schedule of planning process steps

Step	Description	
1	The maximum demand of the secondary substation is assessed either using Maximum Demand Indicator (MDI) readings which are read periodically and recorded in the asset register or using the data from a Remote Terminal Unit (RTU) with LV monitoring where one is installed.	
2, 3, 4	The substation demand is attributed to the LV feeders using either instantaneous readings taken at the substation or in less demanding situations the load flow mode attributes the load based on network and customer topology.	
5	The load of the LV feeder in question is then distributed along the feeder by the load flow tool based on customer and point load positioning.	
6	This load is then modelled on the network using a load flow tool and in conjunction with network asset parameters such as cable ratings and impedances and thermal or voltage constraints are identified.	
7	The new expected load of the connection request is added (with an 80% diversity allowance if the network already feeds a large number of customers) and step 6 is repeated to identify any possible thermal or voltage constraints that will be caused by the addition of the new demand.	

Smart meter data has the potential to improve a number of the steps in the process which would improve the accuracy of the load estimate which, depending on the situation, could allow more load to be connected to the network, or alternatively avoid overloading the network which can reduce asset life and cause failures.

As the smart meter roll-out proceeds and more smart meter consumption data is available, it may be possible to attribute substation load to the LV feeders, in lieu of instantaneous readings taken on-site as in steps 2, 3 and 4. This process also allows load to be assessed at time of network peak, which isn't always possible when taking instantaneous readings. Using the smart meter data in this way will have limitations to the accuracy due to various factors such as: the completeness of the data, phase imbalance and the presence of unmetered loads on the network. An alternative approach which could be considered if required, is additional per-feeder monitoring in the substation.

As data from smart meters becomes available for numerous customers on the feeder, step 5 can be improved by using the measured consumption of the customers to determine the distribution of the load along a feeder. Again, this process will improve as more smart meters are installed by customers on the part of the network being studied. This data must be aggregated in a way that satisfies the data privacy requirements of HH consumption data, as detailed in Section 6.3.

An area where smart meter data will be able to vastly improve on the current process is the evaluation of the voltage level on remote parts of the network; step 6 in the process. This is an area which is currently hard to physically measure, typically requiring a visit to a customer's premise. It is recommended that any new network design policies are tested against a sample of the data collected here, in order to test their impact on existing networks which have been demonstrated to have broad and narrow voltage ranges, and voltage ranges towards the upper end and lower end of the permitted range. These studies are likely to be carried out per licence area, i.e. policies tested against representative networks in that licence area, such as those measured here.

Ways in which smart meter data will improve step 7 are covered in Section 3.6.

Assessment of the smart meter data will also be able to improve assumptions in the network load flow model regarding power factor, which can be determined by assessing the active and reactive energy consumption profiles. Also problematic phase imbalance may be detectable, using smart meter consumption data in conjunction with phase association as this improves.

Maximum Demand

5.3

Table 13: Schedule of maximum demand registers

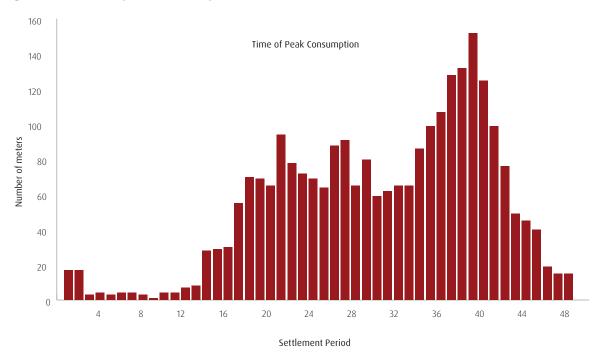
Data	Description
Maximum demand	Maximum active energy import in any half hour period since the last reset with time stamp of occurrence. Only the DNO can reset the register.
Time limited maximum demand	Maximum active energy import in a half hour period within a time period configurable by the DNO. Only the DNO can reset the register.

To assess the difference that can be seen between the two types of Maximum Demand (MD) register described in Table 13. The consumption data collected as part of the trial was analysed, to determine what the reading of each meter would have been in both cases. The time period used to assess time limited MD was the 3 hour period from 1700 to 2000, which was the observed band that aggregated peaks accounted the customer categories described in chapter 3.

The results found that the MD for individual customers only occurred within this band (network peak) for 29% of customers; the remaining 71% had their MD at another time in the day. The customers who had a peak outside of the network peak time, showed an average 0.91kW (21.5%) lower consumption during the network peak period than their unconstrained MD. The overall difference between constrained MD and unconstrained MD was 15.3%. Figure 26 shows when individual customers' peak load occurred. Despite a bias to the time of network peak loading (evening), there is a clear spread throughout the day.

Figure 26 shows that there is clearly a material difference between the two types of MD register, and the constrained peak may be more useful to assess network peak loading. The constrained time band can be set to suit local conditions and be used to detect accelerated/problematic network peak load growth, which can be considered for further monitoring.

Figure 26: Time of peak consumption observed for smart meters



5.4 Voltage alerts

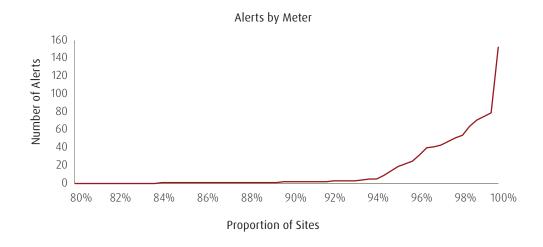
Table 14: Schedule of available voltage alert registers

Alert	Description	
Average RMS above/below limit	Average RMS voltage above or below the DNO configurable maximum and minimum limits. The averaging period is shared with the voltage profile described in Section 5 above and is configured by the DNO.	
Extreme over/under voltage	RMS voltage above or below the extreme maximum and minimum voltage limits for a set time period. All parameters configurable by the DNO.	
Voltage sag/swell	RMS voltage above or below the swell and sag voltage limits for a set time period. All parameters configurable by the DNO.	
Voltage event log	The three alerts above also record events to a circular buffer capable of holding 100 entries.	

The voltage measurements obtained from the feeder end-point smart meters installed on the network were analysed to determine an estimate for how often they would have generated voltage alerts based on the Average RMS above/below limit alert as described. Using limits equal to the statutory voltage limits of 253V and 216V (described further in chapter 5), the amount of times the 10-minute average RMS voltage was above or below the limit was counted for each phase individually. An alert is only generated on the first reading of a voltage excursion i.e. a reading outside of the voltage limits will only generate an alert if the previous measurement was within the limits. The results of this analysis are shown in Figure 27 for data measured in the 6 month period between 1st February 2014 and 1st August 2014.

A practical application of this is likely to be that DNOs set a threshold of alerts at which manual intervention takes place; and a lower threshold at which network areas are prioritised for inclusion in an annual review, or "sweep", intended to catch future issues.

Figure 27: Number of voltage alert events observed for feeder end-point smart meter phases



From Figure 27 it can be seen that ~84% of phases did not generate any voltage alerts. Of the 16% of phases that generated alerts, approximately 65% generated low voltage alerts and the remaining 35% generated high voltage alerts. No phase showed both high and low alerts.

Alert Type	None generated	At least one low voltage alert	oltage At least one high voltage alert	
Percentage (number) of phases	84% (248)	10% (31)	6% (17)	

With regard to the voltage event log which is capable of holding 100 entries, only 2% of phases generated more than 50 alerts in the 6 month period analysed. It should be noted that seasonal affects may affect how many voltage alerts are generated, and also that the voltage event log is shared between all three voltage alert types described in Table 15. All voltage excursions identified by the trial have been referred to the supply quality team within UK Power Networks for further investigation and remedial action where necessary.

Based on the findings in Table 15, it could be suggested that the voltage alerts are used to trigger the collection of voltage profile data from the meter at regular intervals. Collection of 10-minute average RMS voltage readings would require a significant amount of data retrieval and storage, the alerts could be used to determine when this is needed and avoid unnecessary collection of large amounts of data. In this case, it would only be necessary to collect data from a small amount of meters and store it locally, to produce a longer term view of the voltage profile than would be possible using the buffer on the smart meter.

5.5 Outage management

Table 16: Schedule of energisation states

Alert	Description	
Energisation check	The DNO will be able to "poll" the smart meter to determine if the meter is energised. This is an indication of the status of the power supply to the property from the distribution network.	
Outage start/finish	The start and finish time of an interruption to the electrical supply to the meter. This alert is sent following the restoration of the supply.	
Last gasp	An alert will be sent if the communications hub in a property loses electrical supp and does not send a notification of restoration within 3 minutes.	

The "last gasp" functionality of the meter will send an alert to the DNO via the DCC, informing them that the communications hub associated with a property has lost its energy supply. This is an indication that the power supply to the property has been interrupted. These alerts associated with power outages can be assessed by the smart meter system operated by a DNO, and reported to control engineers as faults on the network. Having this knowledge of an outage will mean that the DNO does not need to rely on interrupted customers to report the loss of supply, which can lead to a faster response.

DNOs will be able to remotely determine the energisation status of a smart meter when a customer calls to report a problem. If there is not a known fault on the area of network in question, the energisation check can be carried out while the customer is on the phone, which avoids the need for an operative to unnecessarily visit the property which can cause inconvenience to the customer who must be present. If the meter is determined to be energised this will be explained to the customer with advice as to the possible nature of the problem and how to address it.

The energisation check will also be useful following faults, particularly in storm situations where a fault upstream on the network may be rectified, but the customer is still affected by a "masked" fault at the lower voltage levels. Energisation checks can be carried out following restoration of faults to detect this situation, or any other remaining issues and ensure it is dealt with appropriately.

Having better visibility of faults as they occur, and the extent to which customers are affected, will help DNOs to ensure that faults are responded to as quickly as possible, and by the most appropriate team for the job. Better data regarding faults will improve a DNOs capability to accurately measure and report on customer interruptions.

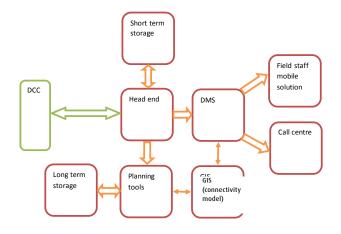
Requirements to utilise

Given the analysis in this report and the data from the LCL trials, this chapter explains what the DNO might do differently in order to achieve benefits based on the new opportunities presented by smart meters.

6.1 IT and Technical requirements

To take advantage of the smart meter information available from the Data Communications Company (DCC) a DNO must have access to the data. Figure 28 shows how this data will be integrated into UK Power Network's current IT architecture and shows how this will impact existing systems.

Figure 28: Example high level data structure for smart meter system



6.1.1 Data Retrieval

The system will be capable of retrieving both instantaneous readings from the meter. For example, energisation status, and historic data stored on the meter such as consumption profile data. The data retrieval will be automated to allow the collection of data from groups of meters identified either by network area or a particular subset of customers. The collection of data from meters on particular parts of the network will be assisted by the integration of the LV connectivity model which will identify where meters are connected to the LV network. This connectivity will also allow geospatial presentation of processed data and will be shared with the distribution management system for inferring faults from outage alerts.

In the case of voltage and consumption data, end users within the DNO will collect the information through a network planning tool which will help identify the meters that are of interest for the particular study. This will also allow the data to be aggregated and processed into useful network parameters which will also ensure compliance with data protection policies as described in Section 5.3

6.1.2 Alert Handling

The system will be capable of receiving the unsolicited alerts that are generated by meters and delivered via the Data Communications Company (DCC). Single events may cause large numbers of alerts, so the system will be capable of analysing the incoming alerts with respect to the LV connectivity model, to infer network events from multiple alerts and alert users in the appropriate way.

In the case of supply outage alerts, an event will be inferred and communicated to control engineers highlighting the suspected area of the network affected. This may be supplemented by energisation checks to further confirm the extent of the loss of supply. Following restoration, the detail contained in the outage alerts can be used to accurately report on the extent and duration of the outage. This event information will also be available to field staff and call handlers, to ensure supplies are restored as quickly as possible and customers can be given accurate information regarding the supply status.

In the case of voltage alerts, the system will be able to highlight areas of network that are producing alerts and indicate where further investigation is necessary. Users will then be able to use a combination of the voltage alert log and the voltage profile data from the meters identified to determine the correct response. This will avoid the need for users to respond to a large number of individual alerts.

6.1.3 Data storage

The system head end that connects to the DCC will have short/medium term data storage, to deal with incoming data either from data requests or unsolicited alerts. Long term data storage will be used in conjunction with the associated planning tool to store network data for analysis

6.2 DNO Activities

To make best use of the new information that will be available when smart meters are installed in a substantial number of customer homes, some DNO activities may change.

6.2.1 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 such as that in Chapter 4 of this report 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 estimating 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 suggested in Chapter 4 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.

6.2.2 Voltage investigation

The process of dealing with voltage issues on the network will be improved by the availability of smart meter data. Customer inquiries regarding voltage level can be addressed far more efficiently by having access to the alert history and historic voltage data as measured at the premises. Not only will this help the DNO with their investigation, it will also avoid the need for visits to customer properties in many cases and the associated inconvenience.

The availability of smart meter data will allow DNOs to provide more useful information to customers in a more timely and accurate fashion. To achieve this, smart metering systems will allow call handlers to access the appropriate data to answer customer queries regarding the state of their electricity supply while on a call.

Further to this, the improvements to DNOs processes, such as the voltage investigations described and an improved fault response and restoration process, will ultimately lead to better service to customers. Being able to provide customers with better estimates of restoration times based on the type of fault identified will also improve the customer's experience during a power outage.

6.2.4 Field staff

The smart meter data system will be able to identify the nature of faults more accurately and quickly than is achievable through customer calls alone. This will allow appropriate teams to be dispatched to faults in the first instance, which will lead to more efficient resolution.

The functionality to check the supply status of meters without having to enter the customer's property could be used to avoid unnecessary customer visits, particularly in situations when access is difficult. This will also help to ensure all customers' power supplies are restored following work, to avoid situations where customers experiencing longer than necessary outages.

6.3 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; and
- 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; and
- Maximum demand registers are not reset more frequently than once a month.

These processes can be implemented in the tools described, which will ensure that the information provided is relevant to the user and their activities and also that personal data is not exposed to end users within the DNO.

The data will necessarily have to be extracted on an individual basis and may have to be stored this way either temporarily before processing or longer term for future processing and analysis. This storage should be secure to prevent unauthorised access and use of personal data.

The analysis presented in Chapter 3 of this report regarding customer consumption would require customer consent for their personal data to be used in such a trial and subsequent analysis. In this case the consent of the customer will have to be obtained before undertaking such analysis.

Conclusions and recommendations

The findings of this report fall broadly into two categories. Firstly, the analysis of the smart meter data collected as part of the trial has drawn conclusions that are useful to assess the energy demand of similar future customers, who will exhibit similar behaviour, but for which no data will exist at time of connection to the network. Also, the associated in addition voltage was analysed to draw conclusions of the existing voltage level on the monitored networks. Secondly, the future uses of smart meter, data that will be available from the national roll-out of smart meters were investigated using findings from the LCL trial to inform the possible use of the data by DNOs in the future.

7.1 Customer consumption

From analysis of the LCL smart meter trial data 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.

Similar analysis to that shown in this report could be carried out on further data sets more regularly, when they become available through the national smart meter roll-out. This analysis could be achieved without the need to expose individual customer consumption, which would avoid the need for customer consent under data privacy regulations, meaning that a large number of customers' profiles could be included. This would update the results and also enable them to be extended beyond the urban customer focus of LCL trial. This may also allow the categorisation of customers to be used when assessing smaller groups of customers, which is only currently reliable for groups greater than 50 customers.

The effects of demand diversity were also investigated thoroughly 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.

7.2 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 conclusions summarised, which are further described in chapter5:

- Continuous voltage supply level tends to be towards the higher acceptable limit for the trial networks;
- Voltage excursions are minimal on the trial networks, but tend to be low voltage events; and
- Some existing or potential voltage issues could be solved by adjusting tap-changer settings at a distribution substation level.

In addition to this, the analysis developed practical ways of assessing the severity of any network voltage issues, such as voltage duration curves, which could be constructed from smart meter voltage data in the future. It also developed a way to assess the voltage over a wider area of network to determine if changing off-load tap-changer settings can be used to release headroom or legroom on a network as required.

Given the capabilities and costs identified this section will provide recommendations for cost effective use of smart meter data.

7.3 Use of smart meter data in network planning

In addition to the findings regarding the contribution of new customers' consumption to network load, smart meter data that will be available through the national roll-out can be used to assess the current network load conditions. This process is described in Section 6.2 and would be used in conjunction with the assessment of new demand, to determine the most cost effective way to connect the new load to the network. The availability of voltage data from remote parts of the network will also replace the need to rely on predictions from load flow models. This process will improve over time, as more customers install smart meters and a greater coverage of data is achieved.

The process would be achievable using the data that is stored remotely on the smart meter itself. This would mean that the analysis could be carried out without the need to build up a dataset in advance, which would not be practical in the timescales of a new connection. The data required for the process would be available by sending requests via the DCC as and when required.

Voltage data 7.4

Smart meters have two ways of communicating network voltage to a DNO: voltage alerts and historic data. An assessment was made of the amount of alerts that could be expected based on the trial networks. The results of this are presented in Section 6.3 and show that few meters will generate alerts based on voltage and only very few will generate a significant amount. These alerts could be used to automatically trigger the collection of more detailed historic voltage data, for use when assessing any identified voltage issue.

The period over which the RMS voltage is averaged and stored by the meter is configurable by a DNO. It is suggested that this could be set to a 10-minute average to reflect the guidance provided in BS-EN 60150 regarding supply voltages. This would allow 30 days of data to be collected retrospectively, and more to be collected and stored by a DNO if necessary.

Supply status 7.5

As with voltage, the supply status of the meter will be communicated in two ways: alerts and on-demand polling of meters. This data will allow a DNO to better understand the nature of network events, allowing them to provide better information to customers and to restore supplies as quickly and efficiently as possible.

The alerts received will need to be aggregated using knowledge of where the meters are installed on the network. This will then be presented to the user as a network event rather than individual alarms, the volume of which would likely be too large to deal with individually.

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Glossary

ACORN	Categorisation of customers from postcode	HV	High Voltage (Network)
ADMD	After Diversity Maximum Demand	ICL	Imperial College London
BS-EN 60150	Product quality standard for Low and medium voltage networks	ICT	Information and Communications Technology
BST	British Summer Time	IHD	In Home Display, to view data from smart meter
CACI Limited	Company, creator of Acorn categorisation	LB	London Borough
CPD	Cumulative Probability Distribution	LCL	Low Carbon London
CRM	Customer Relationship Management system	LCT	Low Carbon Technologies
CSP	Communication Service Provider	LPN	London Power Networks
DCC	Data Communications Company	LV	Low Voltage (Network)
DMS	Data Management System	MD	Maximum Demand
DNO	Distribution Network Operator	MDI	Maximum Demand Indicator
E7	Economy 7 (multi-meter configuration for domestic supply)	Occupancy	Number of people living in a property
EIZ	Engineering Instrumentation Zone	ODS	Operational Data Store
ENA	Energy Networks Association	PMS	Participant Management System
ESQCR	Electricity Safety, Quality and Continuity Regulations	RMS	Root Mean Square
GIS	Geographic Information System	RTU	Remote Terminal Unit
GMT	Greenwich Mean Time	SMETS	Smart Metering Technical Specification
HEUS	Household Electricity Usage Study	Zigbee	Smart meter communications protocol



Instrumenting a Smart Grid



Electrification of heat



ANM/network operation



Electrification of transport



Dynamic Time of Use tariff



Energy efficiency



Demand Side Response – demand



Demand Side Response – generation



Smart meter



Network planning



Distributed Generation

Project Overview

Low Carbon London, UK Power Networks' pioneering learning programme funded by Ofgem's Low Carbon Networks Fund, has used London as a test bed to develop a smarter electricity network that can manage the demands of a low carbon economy and deliver reliable, sustainable electricity to businesses, residents and communities.

The trials undertaken as part of LCL comprise a set of separate but inter-related activities, approaches and experiments. They have explored how best to deliver and manage a sustainable, cost-effective electricity network as we move towards a low carbon future. The project established a learning laboratory, based at Imperial College London, to analyse the data from the trials which has informed a comprehensive portfolio of learning reports that integrate LCL's findings.

The structure of these learning reports is shown below:

Summary

SR DNO Guide to Future Smart Management of Distribution Networks

Distributed Generation and Demand Side Response

- A1 Residential Demand Side Response for outage management and as an alternative to network reinforcement
- A2 Residential consumer attitudes to time varying pricing
- A3 Residential consumer responsiveness to time varying pricing
- A4 Industrial and Commercial Demand Side Response for outage management and as an alternative to network reinforcement
- A5 Conflicts and synergies of Demand Side Response
- A6 Network impacts of supply-following Demand Side Response report
- A7 Distributed Generation and Demand Side Response services for smart Distribution Networks
- A8 Distributed Generation addressing security of supply and network reinforcement requirements
- A9 Facilitating Distributed Generation connections
- A10 Smart appliances for residential demand response

Electrification of Heat and Transport

- Impact and opportunities for wide-scale Electric Vehicle deployment
- **B2** Impact of Electric Vehicles and Heat Pump loads on network demand profiles
- B3 Impact of Low Voltage connected low carbon technologies on Power Quality
- **B4** Impact of Low Voltage connected low carbon technologies on network utilisation
- **B5** Opportunities for smart optimisation of new heat and transport loads

Network Planning and Operation

- C1 Use of smart meter information for network planning and operation
- C2 Impact of energy efficient appliances on network utilisation
- **C3** Network impacts of energy efficiency at scale
- C4 Network state estimation and optimal sensor placement
- **C5** Accessibility and validity of smart meter data

Future Distribution System Operator

- **D1** Development of new network design and operation practices
- DNO Tools and Systems Learning
- Dasign and real-time control of smart distribution networks
- **D4** Resilience performance of smart distribution networks
- **D5** Novel commercial arrangements for smart distribution networks
- **D6** Carbon impact of smart distribution networks











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