Proceedings Paper:

Poursharif, G., Brint, A.T. orcid.org/0000-0002-8863-407X, Black, M. et al. (1 more author) (2017) Analyzing the ability of Smart Meter Data to Provide Accurate Information to the UK DNOs. In: CIRED - Open Access Proceedings Journal. CIRED 2017, 12-15 Jun 2017, Glasgow. IET , pp. 2078-2081.

https://doi.org/10.1049/oap-cired.2017.0654

24th International Conference & Exhibition on Electricity Distribution (CIRED)

12-15 June 2017

Session 5: Planning of power distribution systems

Analysing the ability of smart meter data to provide accurate information to the UK DNOs

ISSN 2515-0855
doi: 10.1049/oap-cired.2017.0654
www.ietdl.org

Goudarz Poursharif[1] ✉, Andrew Brint[1], Mary Black[2], Mark Marshall[2]
[1]*Management School, University of Sheffield, Sheffield, UK*
[2]*Northern Powergrid, Houghton le Spring, UK*
✉ *E-mail: poursharif.goudarz@gmail.com*

Abstract: By 2020, smart meters will potentially provide the UK's distribution network operators (DNOs) with more detailed information about the real-time status of the low-voltage (LV) network. However, the smart meter data that the DNOs will receive has a number of limitations including the unavailability of some real-time smart meter data, aggregation of smart meter readings to preserve customer privacy, half-hourly averaging of customer demand/generation readings, and the inability of smart meters to identify the connection phases. This research investigates how these limitations of the smart meter data can affect the estimation accuracy of technical losses and voltage levels in the LV network and the ways in which 1 min losses and correct phasing patterns can be determined despite the limitations in smart data.

1 Introduction

Currently, the low-voltage (LV) side of the electricity distribution grid is relatively invisible to the distribution network operators (DNOs), compared to the high- and medium-voltage parts of the electricity network which have traditionally been designed to accommodate generation and various monitoring points. The introduction of smart meters in the UK has the potential to dramatically change this by providing detailed consumption/generation information from every household, at node points along the network, and downstream of LV substations to the network operators. High resolution smart meter data can enhance various DNO applications such as network planning and design, asset management, fault location and restoration, power quality management, active network management, demand side management, and distributed generation (DG) integration by providing more accurate power flow information, which in turn can lead to more accurate estimations of network losses, voltage variations, cable loading capacity, and phasing arrangements. However, the quality of smart meter data can be compromised by a number of limiting factors depending on the data recording and transmission specifications and protocols in place. In the UK, the implementation of smart meters is a gradual process and the smart meter data is proposed to be recorded and transmitted to the DNOs at half-hourly averages [1]. In addition, the minimum specifications of the meters do not take into account the need for phasing identification capabilities. Additionally, the customer demand data will be anonymised and aggregated due to privacy concerns [2]. Therefore, the impact of various time resolutions of smart meter data, from 1 to 120 min intervals and different aggregations levels, from 1 to 10 houses, on the accuracy of fundamental network information is very important to the DNOs. These issues are investigated in the following sections of this paper.

2 Methods

In order to replicate a real world LV network and considering the limited availability of real-time smart meter datasets, a model three-phase LV network with balanced phasing was populated with 1 min smart meter consumption data from 100 houses (Fig. 1). Two versions were analysed with data from different trials, one using data collected by Loughborough University in 2008 and 2009 [3] and using data collected by the customer-led network revolution (CLNR) project from 2011 to 2014.

After the network was populated with the measured 1 min data for 60 sample dates, the customer demands were averaged over 5, 10, 15, 30, 60, and 120 min intervals and the effects of varying time resolutions on the estimation of technical network losses at the end of the network and maximum voltage drops on each phase of cables B and C were observed. A previous study [4] has identified the impact of smart meter time resolutions from less than 1–30 min intervals on the estimation of network losses on a single-phase network with a limited number of houses. Additionally, the effects of various levels of aggregating meters together on the estimation of network losses and maximum voltage drops were also investigated by aggregating the half-hourly models at 2, 4, 6, 8, and 10 house levels based on similar phasing. The following sections present the results of these studies followed by solutions to determine 1 min loss estimates from lower resolutions of data in the absence of 1 min customer demands and the ways in which customer phasing patterns can be verified considering the lack of phasing information from the UK smart meters.

3 Effects of time resolution on loss and voltage estimates

The highest share of technical losses occur at the distribution levels of the electricity network and this figure is just under 6% in the UK [5]. Technical losses are a measure of the efficiency of power systems and can also highlight some of the problematic areas of the network; hence, the regulatory body in the UK, office of gas and electricity markets, have required the DNOs to reduce the losses on their network [6]. In addition, accurate voltage level information at the end of LV networks can pave the way for smoother integration DG in the system as well as pinpointing the areas of the network where the quality of power delivered to the customers is not satisfactory [7]. To this end, the loss and voltage level estimates for various time granularities of smart meter data were calculated using the LV model in Fig. 1. The total technical

CIRED, Open Access Proc. J., 2017, Vol. 2017, Iss. 1, pp. 2078–2081

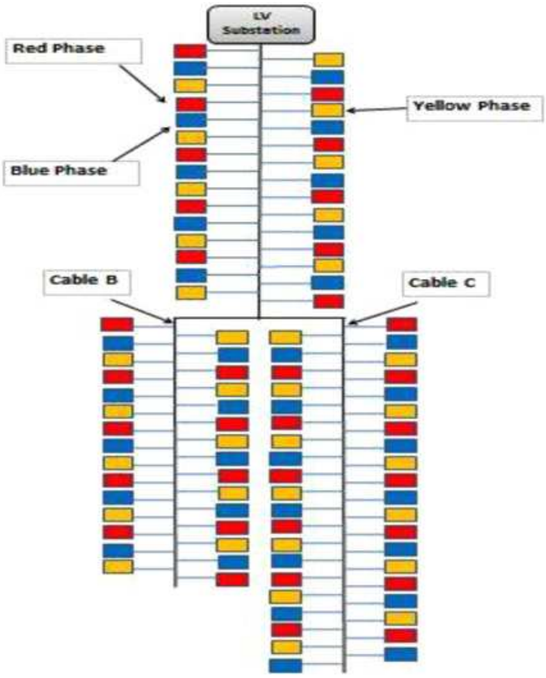

Fig. 1 *Model three-phase LV network*

losses were calculated by adding loss values at each section of the main cables (at each house). The loss values were calculated using the current measurements on each phase at every single house, which were derived from real-time customer demands, and the cable resistance information based on the cables used by Northern Powergrid. Where R, Y, B, and N represent the current on the red, yellow, blue, and neutral phases, respectively:

$$\text{Network loss at each section} = \text{main phase resistance } (R2 + Y2 + B2) + \text{neutral phase resistance } (N2)$$

Furthermore, voltage levels on each phase were calculated at the end of cables B and C (Fig. 1), where maximum voltage drops occur. This was carried out by using current and resistance measurements on the three phases at each house and adding voltage drops at each 5 m section of the network on each phase to calculate the voltage drops at the end of the network and ultimately subtracting the maximum drop from the nominal voltage level of 240 V.

3.1 Results

As mentioned above, the models were populated with various time granularities of customer demands ranging from 1 to 120 min for 60 different samples dates. Results from a representative sample of these dates are presented in Figs. 2 and 3 and Table 1, which represent the effects of varying the time resolution of smart meter data on technical network losses and voltage level estimates, respectively. The sample dates range from January 2013 to June 2013 and from January 2008 to April 2008. Fig. 2 shows that as the time resolution of smart meter data is reduced from 1 to 120 min, the loss estimate figures decrease with a dramatic fall from 1 to 15 min. Fig. 3 demonstrates that as the time resolution of smart meter data is reduced from 1 to 120 min, the voltage levels at the end of the cables rise with a sharp increase from 1 to 15 min.

As Table 1 shows, the underestimation of losses and the overestimation of voltage levels are more severe in the first half hour of the time resolution intervals, especially in the first 15 min. The voltage levels are slightly overestimated overall, but they are significant, as the DNOs are required to maintain the voltage levels in the range of 216–253 V.

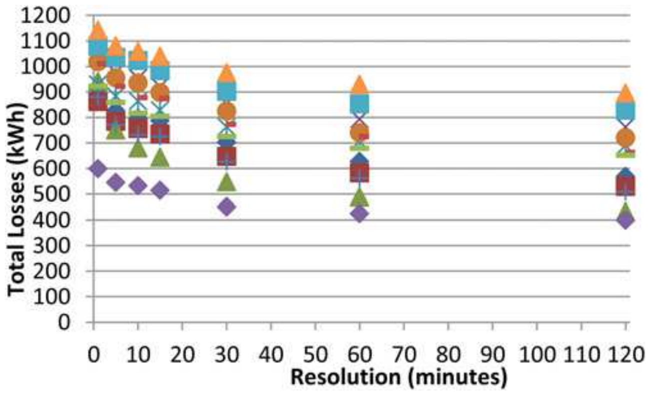

Fig. 2 *Relationship between smart data time resolution and loss estimates (markers represent different sample dates)*

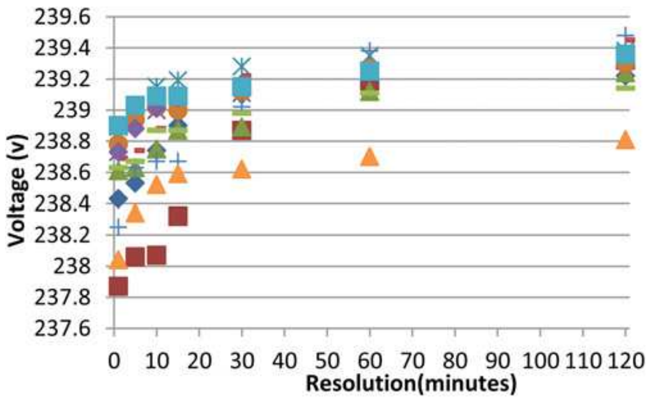

Fig. 3 *Relationship between smart data time resolution and voltage level estimates on the red phase (markers represent different sample dates)*

Table 1 Inaccuracy percentages of loss and voltage level estimates as a result of varying time resolution of smart data

Time resolution	Underestimation of losses, %	Overestimation of voltage levels, %
5	−9	0.14
10	−12	0.23
15	−15	0.38
30	−23	0.58
60	−30	0.77
120	−35	0.87

4 Effects of customer data aggregation on loss and voltage estimates

For privacy reasons, the DNOs will only be able to use readings from groups of smart meters rather than individual ones. This will reduce the benefits of the smart meter data [2]. A key problem is the placement of aggregation points on the LV network. Since the smart data that will be transmitted to the DNOs are likely to be in half-hourly average formats, it was decided to investigate various house aggregation scenarios of the half-hourly averages. In order to achieve this, the half-hourly smart meter readings used in a balanced 100-house three-phase LV model are aggregated based on five aggregation levels of 2, 4, 6, 8, and 10. The aggregation points are placed on the network and the data from houses on similar phases are aggregated based on proximity and phasing similarity (model 1). Fig. 4 shows the aggregation points on the red phase of a section of the LV network model which was used in our analyses.

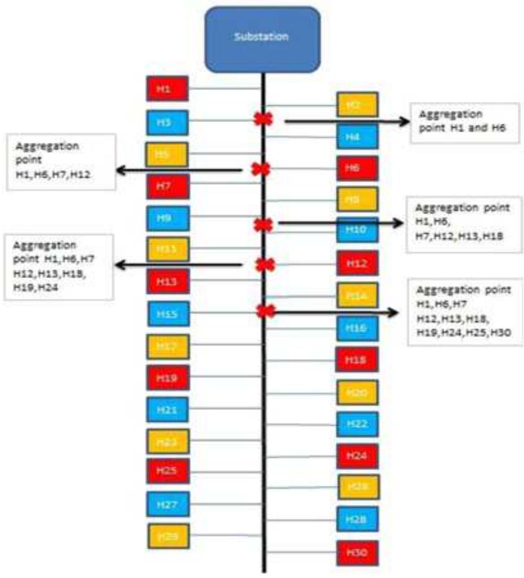

Fig. 4 *LV model with various aggregation level points*

4.1 Results

Figs. 5 and 6 demonstrate the effects of various aggregation levels on the accuracy of loss and voltage level estimates. They show that as the aggregation level increases from no aggregation (shown as 1) to 10 house aggregation, the loss estimates rise and the voltage level estimates decrease with the most significant inaccuracy occurring at 2-house aggregation level as shown in Table 2. There is another level of inaccuracy observed at the 6-house aggregation level, which occurs as a direct result of the location of the aggregation points on this particular type of network. In the 6-house aggregation scenario, some of the aggregation points which were previously placed on cable A with lower resistance are shifted to cable B which has higher resistance compared to cable A, hence this results in higher loss and lower voltage estimates compared to the 4-house aggregation scenario. This issue is rectified in Figs. 7 and 8 where all 100 customers in Fig. 4 were placed on a long cable with characteristics of cable A (model 2). This was carried out on four sample dates.

The second aggregation model shows that the major inaccuracies in terms of overestimation of losses and underestimation voltage levels occur when readings from two customers are aggregated. A comparison between the two models demonstrates the importance of the location of the aggregation points on LV networks, which requires great knowledge of the various networks operated by a DNO. Placement of the aggregation points on the LV network requires extensive knowledge of the topology of the networks and the customer phases. These two factors can introduce higher

Table 2 Inaccuracy percentages of loss and voltage level estimates as a result of varying time resolution of smart data

Aggregation	Mean overestimation of losses, %	Mean underestimation of voltage levels, %
2	44	−0.14
4	61	−0.25
6	130	−0.45
8	146	−0.68
10	167	−0.85

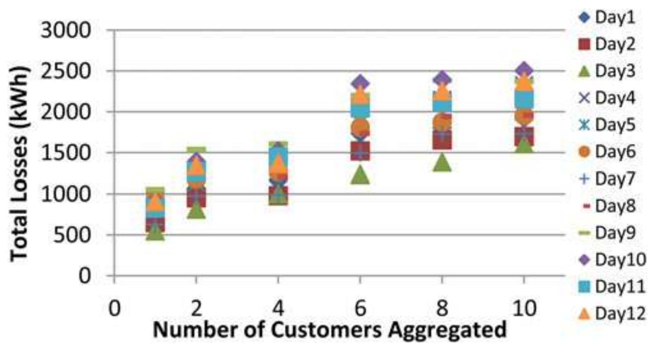

Fig. 5 *Relationship between loss estimates and customer aggregation levels (model 1)*

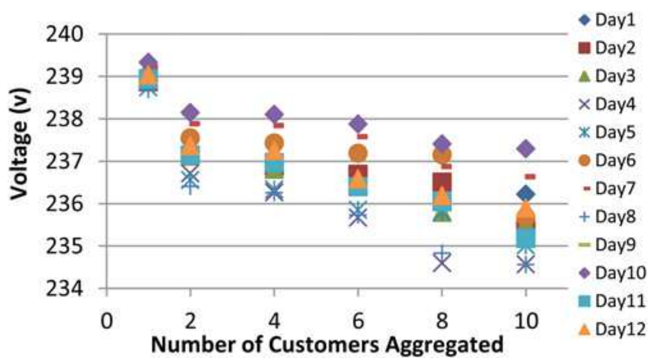

Fig. 6 *Relationship between voltage level estimates and aggregation levels on the red phase (model 1)*

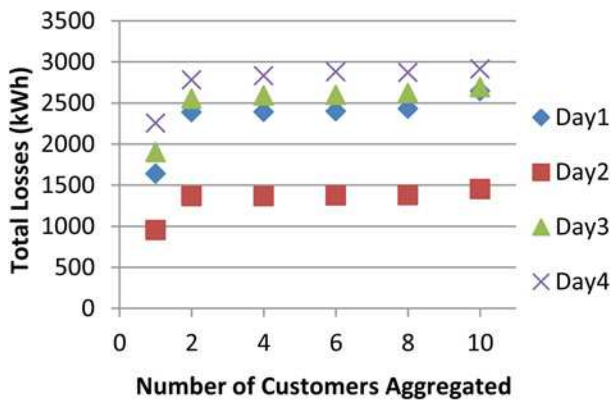

Fig. 7 *Relationship between voltage level estimates and aggregation levels (model 2)*

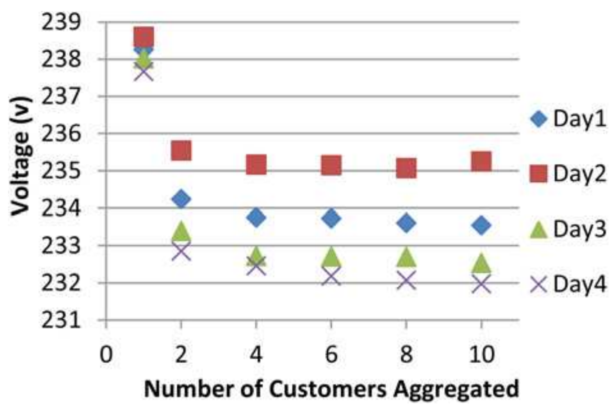

Fig. 8 *Relationship between voltage level estimates and aggregation levels (model 2)*

CIRED, Open Access Proc. J., 2017, Vol. 2017, Iss. 1, pp. 2078–2081

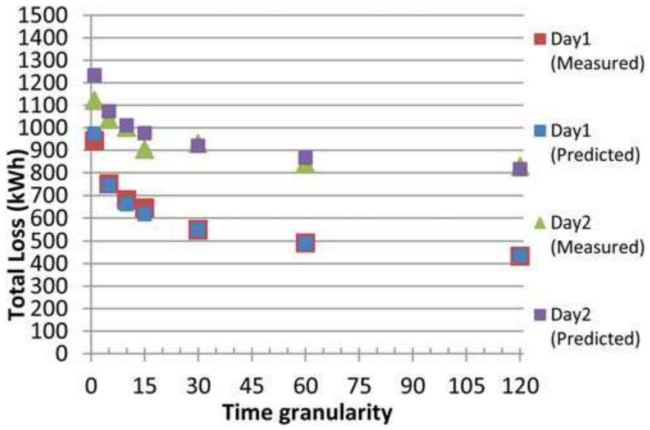

Fig. 9 *Measured 1 min losses versus predicted 1 min losses*

uncertainty levels to the accuracy of aggregated smart meter data. It is widely accepted that the knowledge of customer phases is not always reliable and the smart meters will not be providing phasing information to the operators in the UK. Therefore, in Sections 5 and 6 the limitation factors of time resolutions and the lack of phasing information and the ways in which they can be overcome are investigated in more detail.

5 Prediction of 1 min losses based on lower time resolution estimates

The demand readings supplied by the UK's smart meters will be the average (or total) demand over a 30 min period. This averaging out of the spikiness of the demand leads to the underestimation of losses as well as the overestimation of voltage levels as shown in previous sections of this work. In order to overcome this gap, the following model was devised:

$$\text{losses} = a \div t^b$$

where a and b are constants fitted to the 30, 60 and 120 min losses for each day. The average of the b values was then used to predict the expected loss for each day if the data had been available at the 1 min resolution, i.e. to extrapolate the curves to the 1 min resolution. Fig. 9 shows the results of actual 1 min loss estimates and the calculated 1 min losses based on loss estimate figures using lower resolution of smart meter data (i.e. 30, 60, and 120 min).

The results above show that loss estimates from higher resolution of smart meter data can be used to extrapolate 1 min losses with little error with the first example producing predicted 1 min loss value of 956 kWh instead of the measured 1 min loss value of 942 kWh.

6 Phasing

If measurements of the substation phase currents and voltages are made for the same periods as the smart meter data, then methods have been developed for determining the meter phases based on the voltage time series (using clustering, correlation and regression) [8] and summing the currents (using linear programming) [9]. The latter can determine the phases using relatively short time periods of data as long as all the loads are measured for each time-period. In practice, there are some discrepancies between the phases recorded and the customer phases in reality. For the summing the currents approach, these prior beliefs can be used for the linear programming's objective function, thus further reducing the number of time periods needed. Aggregating smart meters together makes identifying the phases much harder. Aggregation levels of 2, 3 and 4 m were investigated for the summing the currents approach. The prior phasing beliefs were used to form groups of meters that were believed to be all on the same phase. The designation of a few of these groups was changed to being mixed phase and for each time-period, the substation phase currents were estimated by summing the group currents with the mixed groups contribution being in line with the hypothesised phase ratio in the group. The variance over the time periods of the differences between the estimated and actual substation phase currents was calculated. This process was repeated for other combinations of mixed groups. It was found that when only a few recorded phases are incorrect, the combination correctly identifying the actual mixed groups had a variance much lower than all or nearly all of the other variances. Hence using this variance measure could be used to identify the most likely mixed groups.

7 Conclusions

Our analyses on two different datasets shows that as the time resolution of smart meter data is decreased from 1 to 120 min, LV network loss estimates are underestimated and voltage levels are overestimated. Crucially from the point of view of the DNOs, this is more severe at the first half-hour. Additional analysis also demonstrate that aggregation of smart meter data due to privacy reasons leads to the overestimation of losses and underestimation of voltage levels. These issues will adversely affect the accuracy levels of smart meter data in the context of various DNO applications such as network planning and design and asset management.

Measuring phase currents and voltages at the substation along with individual smart meter readings, can allow the phases to be identified using the sum of the currents if all the loads are metered, and comparing voltage time series if there are missing loads. For aggregated meters, if there are no missing loads and the accuracy of the recorded phases is good, it may be possible to narrow down the number of mixed groups to a reasonably small number of combinations but a few individual meter readings would then be needed to disambiguate between them and to determine the meters that are incorrectly recorded.

8 Acknowledgments

We would like to thank Northern Powergrid Ltd. for sponsoring and supporting this research project. We would also like to thank the CLNR project team for providing us with the Smart Meter datasets necessary to carry out this research. From 2011 to 2014 CLNR was carried out by British Gas, Northern Powergrid, Durham Energy Institute, the Newcastle University, EA Technology, and Low Carbon Network fund.

9 References

1 DECC: 'Smart Metering Implementation Programme: Prospectus', 2010. Available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/42718/220-smart-meteringprospectus-condoc.pdf
2 EA Technology: 'Smart meter aggregation assessment final report – executive summary. prepared for the ENA', 2015. Available at www.energynetworks.org
3 Richardson, I., Thomson, M.: 'One-minute resolution domestic electricity data', 2008–2009, SN: 6583, UK Data Archive, 2010
4 Urquhart, A.J., Thomson, M.: 'Impacts of demand data time resolution on estimates of distribution system energy losses', *IEEE Trans. Power Syst.*, 2015, **30**, (3), pp. 1483–1491
5 Sohn Associates: 'Electricity distribution systems losses', Sohn Associates, 2009. Available at https://www.ofgem.gov.uk
6 OFGEM: 'Losses incentive mechanism', OFGEM 2016, 2016, Available at https://www.ofgem.gov.uk
7 Vujošević, I., Spahic, E., Rakocevic, D.: 'One method for the estimation of voltage drop in distribution systems', *IEEE Power Eng. Soc. Summer Meeting*, 2002, **1**, pp. 566–569
8 Short, T.A.: 'Advanced metering for phase identification, transformer identification, and secondary modelling', *IEEE Trans. Smart Grid*, 2013, **4**, (2), pp. 651–658
9 Arya, V., Seetharam, D., Kalyanaraman, K., *et al.*: 'Phase identification in smart grids'. Proc. of 2nd IEEE Int. Conf. on Smart Grid Communications, 2011