ENHANCING THE UNDERSTANDING OF DISTRIBUTION NETWORK LOSSES

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ABSTRACT

Distribution network losses are an unavoidable result of transporting electricity from the transmission system and distributed generation to consumers. Due to the size and complexity of distribution networks, a variety of estimation methods are used to calculate network losses; these are used to inform network decision making and settlement of customer bills. Network losses are affected by many factors, including the network topology, the voltage, asset ratings, and variation in demand and generation within the network. The goal of this project is to enhance the understanding of these losses, and the methods used for estimation, in the context of changing electricity demand.

INTRODUCTION

Electrical loss within the distribution system can be defined as the difference between the energy entering the system and the energy which reaches consumers [1]. Losses are an inherent by-product of the distribution of electricity and can be sub-divided into two main categories; technical and non-technical [1]; technical losses typically account for the greatest proportion of overall distribution system losses in Great Britain.

Increased losses indicate a higher level of network utilisation – which is a consequence of certain smart technologies such as real-time thermal ratings [2]. It is therefore not necessarily desirable to reduce losses in all cases, given that the increased losses could be as a result of deferring the construction of new assets. Another factor is the cost or carbon intensity of the energy – losses could be considered more problematic when the generation is more expensive and carbon intense than when the generation is low cost and dominated by renewables – this can also be applied on the demand side, introducing the concept of whole system losses.

It is vital for Distribution System Operators (DSOs) to understand the losses within their networks; where they occur, and whether there are appropriate actions that can be taken to manage them in the context of whole system losses. The work described in this paper is part of a project developing new tools and techniques to enable this understanding.

THE STATE OF THE ART

Technical losses

Technical losses result from the physical properties of electricity distribution through the network [1], and can be sub-divided further to fixed losses and variable losses.

Fixed losses

Fixed losses are the losses experienced when a network component is energised but without any real power flowing for servicing customer energy needs. There are typically three main sources of fixed losses: Corona discharge in overhead lines, dielectric losses in underground cables; and losses from the energising of transformers, which are often referred to as 'no-load losses' or 'iron losses' [3].

Variable losses

Variable losses occur as a result of power transfer through a network component for servicing user energy needs. The conductor heats up when carrying an electrical current due to its electrical resistance, and the loss is proportional to the current squared [2] hence why variable losses are often referred to as I^2R losses.

As conductor cross sectional area increases, resistance decreases, thus providing a reduction in losses for a given current flow. As a result of this characteristics a common method for loss reduction is the installation of a replacement conductor with an increased cross sectional area. The profile of the power transfer is also of significant importance when considering losses, as a more variable load profile will result in significantly greater losses than one for which the same amount of energy is delivered at a lower constant power value.

Historically, the majority of loads connected to the distribution network had linear characteristics. However, there is now an increasing number of non-linear loads characterised by higher order current harmonics due to the wide-scale use of power electronic devices [4]. The voltage and current harmonics introduced by these devices, and those already present on the network, can lead to an increase in losses due to the additional current flows of higher harmonic order.

Load imbalance – in which the loading is not equally distributed across the three phases of the network – is common within distribution networks supplying single phase loads. As a result of the I^2R relationship between current and losses, an unbalanced system will lead to greater losses than a balanced one for the same demand. Furthermore, the current flow in the neutral can lead to a further increase in losses arising from the imbalance, but this is not always explicitly modelled, which could lead to these losses being neglected [4, 5].

Loss Estimation

Overview of Loss Estimation Methods

Losses can be estimated by measuring the power entering the system and the power leaving the system, and taking the difference. Any error in the measurement equipment would be reflected in the estimated losses, and in some cases the percentage measurement error can be greater than the actual level of losses. An alternative method to estimating technical fixed and variable losses is through a load flow calculation, which estimates the losses based on a snapshot of the load profile and the network impedances.

Impact of Demand Variability and Data Granularity

Loss estimation presents a number of challenges: because technical losses are non-linear, it is not appropriate to use an average value for the load. Instead, various approaches have been used to develop Loss Load Factors, Load Factors, or Equivalent hours (defined in Table I) to allow the use of a single value for the load on the network to calculate the total losses for a year [5]. The relationship between Loss Load Factor and Load Factor is explored by both [6] and [5] by considering two extreme cases, and thereby providing a credible range in which the relationship exists. This then enables estimation of the Loss Load Factor based on the Load Factor, allowing estimation of the losses within a range of ±10% of an estimate made using an observed Loss Load Factor. Further to this, the resolution of data used to calculate losses has a substantial impact on the accuracy of the calculation: research by Northern Powergrid (NPg) and Sheffield university suggested that using half hourly data resulted in an under-estimate of between 24% and 9% compared with using one-minute data from smart meters [7].

Term	Definition
Loss Load Factor	The actual losses over a period, T, divided by the maximum observed losses within the period multiplied by T [6].
Equivalent Hours (Heq)	The number of hours at maximum load which gives the same total energy loss as the actual system with the varying load [6] – can be calculated by T × Loss Load Factor
Load Factor (LF)	Ratio of the average load to the maximum load [6].

Table I: Commonly used terms in loss estimation

Many authors have presented methods for breaking the demand down into peak, average, and minimum demand periods, and using a weighted sum of these to calculate the total energy loss [8]. However, in many cases the averaging method used for the periods is not appropriate, due to the non-linear relationship between load and losses, and therefore these methods will systematically underestimate network losses. The authors of [9] present a simplified approach to calculating line losses based on the Loss Load Factor of each feeder within a network and a weighting based on the proportion of the overall system energy transferred by each feeder. However, the method is not adequately validated – instead it is merely claimed that the answer provided is credible – and a limited sensitivity analysis is provided to show the influence of power factor on the result.

Impact of Low Carbon Technologies

As part of the low carbon transition, an increasing amount of heating and transportation load is expected to be served by electricity distribution networks [10]. Furthermore, there are already significant levels of generation present throughout the distribution network. All of these changes can materially impact distribution network losses through increased energy demand, changes in the load shape, and introduction of harmonic currents. The existing penetration levels have had a minimal impact on overall network losses, but studies suggest that LV network losses can increase in a quadratic form with the penetration of heat pumps [11] – although this can be mitigated through the use of more efficient heat pumps and better insulation – and that even with smart charging of EVs, off-peak losses could increase by as much as 40% with an EV penetration level of 60% [12].

Distributed generation – particularly variable renewables – can lead to an increase or decrease in losses, depending on the power output of the generator relative to the local demand, and how the generator and load vary with respect to time. How this variability is accounted for can also have a significant impact on the accuracy of any loss estimation technique [13]. Understanding and quantifying the impact of this generation on losses is particularly challenging for DSOs when carrying out the cost-benefit analysis of design options in the connection process.

In estimating the losses of future distribution systems, the ability to make informed forecasts about the likely uptake and usage of low-carbon technology – and how they will impact on the underlying energy demand – is therefore an essential requirement.

Important Factors Affecting Losses

Based on the existing literature, the following factors have been identified for investigation within the project:

Present and future network scenarios including temporal and spatial variation of demand, demand growth, and uptake of emerging technology.

Smart and non-Smart Technology, including demand, generation, and network technology, in both controlled and uncontrolled deployments.

Measurement accuracy when estimating network losses. An understanding of the uncertainty inherent in loss estimation and ways to mitigate measurement uncertainty can lead to better understanding of losses.

Data aggregation and time resolution can have a material impact on the estimated losses within a network; this should be accounted for when selecting data sources and performing calculations.

FUTURE LOAD SCENARIO DATA

The future load scenario datasets for this study are obtained from NPg's Element Energy Load Growth (EELG) forecasting model, which takes outputs from National Grid's Future Energy Scenarios (NGSO FES 2018): 'Two degrees' and interprets how they are distributed across NPg's substations (with and without customer flexibility). The load profile of a representative load point – in 2017 and 2050 – is shown in Figure 1 as an illustrative example.

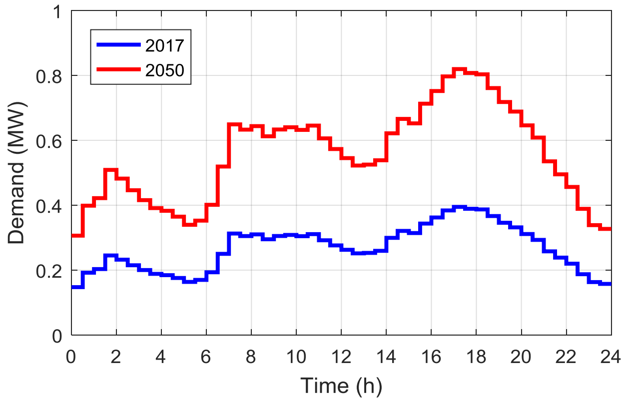

Figure 1: Modelled Demand Profile of a Typical Load Point in 2017 and 2050 (illustrative example).

CASE STUDY NETWORK

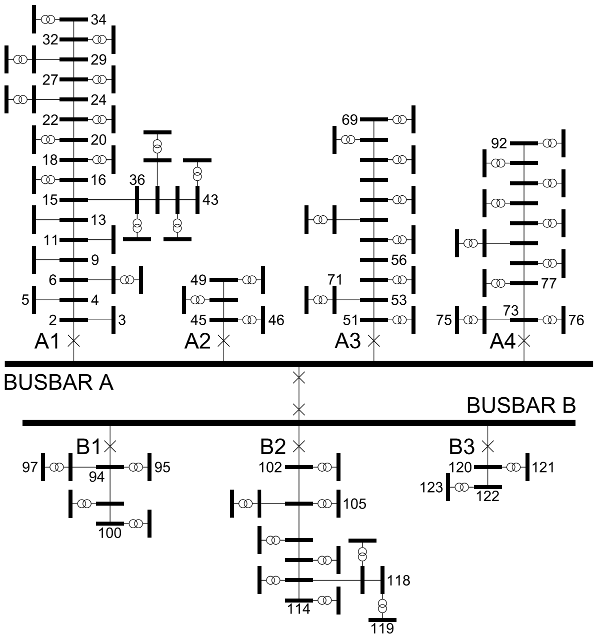

Figure 2: Case Study Network

A case study has been carried out using a real distribution network from NPg's North East England distribution license area, utilising the EELG-modelled loading data. The network is an 11 kV distribution network, supplied by a single primary substation with two transformers and a split-busbar arrangement. The network comprises seven feeders, and has a peak load of 11.59 MVA. The loading of each feeder within the network is shown in Table II. All load flows were carried out using MATPOWER [14].

Primary Feeder	Number of Load Points	Modelled Feeder Peak Demand (MW)
A1	19	2.30
A2	3	0.51
A3	9	1.84
A4	10	2.02
B1	4	0.70
B2	9	3.41
B3	2	0.81
Total	56	11.59

Table II: Feeder loading for the case study network; feeder names indicate feeders supplied by Busbar A and B

RESULTS AND ANALYSIS

Base Case (Modelled Demand Data 2017/2018)

Using the modelled peak demand data for 2017/2018 (constant load model), a power flow analysis was performed, which yielded the following results.

Feeder Losses	0.125 MW	43.1%
Dist. Transformer Losses	0.165 MW	56.9%
Total	0.29 MW	100%

Table III: Power Flow Results for Modelled Peak Demand Data 2017/2018 (Constant Load)

Power losses were then calculated for each time step, using the modelled half-hourly demand profile data for each load point; the results are illustrated in Figure 3. Table IV presents the corresponding energy losses.

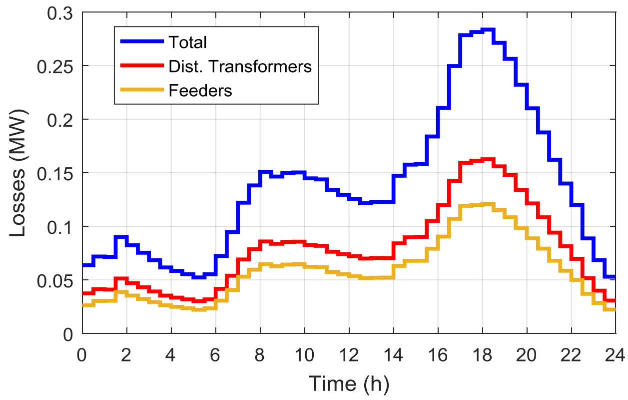

Figure 3: Hourly Variation of Losses.

Distribution transformers account for a significant fraction of total network losses; low loss transformers could be an option for reducing these losses (e.g. Amorphous core and Ecodesign Tier 2 compliant transformers [15]).

Feeder Losses	1.41 MWh	42.6%
Dist. Transformer Losses	1.90 MWh	57.4%
Total	3.31 MWh	100%

Table IV: Overall Energy Losses

So far, energy losses have been calculated using half-hourly demand data; this value will be compared to energy losses computed using a loss load factor. The loss load factor (LLF) is defined as:

$$LLF = k \cdot LF + (1-k) \cdot LF^2 \qquad (1)$$

where LF is the load factor, and k is a constant coefficient. A value of 0.3 for k is recommended by *Buller* and *Woodrow* [16], whereas a value of 0.08 is suggested by *Gustafson et al.* [17]. Both of these will be used to compare the energy losses for a day with the value derived using the half-hourly demand data. Using the loss load factor method, the energy losses are calculated as follows:

$$E_L = P_L \cdot N_{hours} \cdot LLF \qquad (2)$$

where E_L are the energy losses for a given time period, P_L is the power loss calculated at the peak demand for the same period of time, and N_{hours} is the number of hours of the given time interval.

A value of 0.68 was used for the load factor, which was calculated as the weighted mean of the individual load factors of the load points, using their corresponding modelled demands as weights (either average or peak). N_{hours} was equal to 24, as the energy losses were calculated for a day. The results of the comparison are presented in Table V. Both LLF methods overestimated energy losses; however the second LLF method (k = 0.08) produced an estimate, which is very close to the value derived using the modelled half-hourly demand data. This means that while the LLF method can deliver accurate estimation of losses, the factors involved need to be carefully selected based on the loading and topology of the network.

Losses Calculation Method	Energy Losses (MWh)	Error (%)
Modelled half-hourly demand data	3.31	0
LLF method (k = 0.3)	3.67	11.05
LLF method (k = 0.08)	3.34	0.98

Table V: Comparison of Energy Losses Calculation Methods

Load Growth

Demand data between 2017 and 2050 were used in this section. The modelled load profiles for each load point were not available; only (modelled) peak demand was available in the given dataset. Therefore, the 2017 load profiles were scaled in proportion with the peak demand increase for each load point. The energy losses for each year from 2017-2050 are shown in Figure 4.

Customer Flexibility

EELG Customer Flexibility models the impact of domestic time of use tariff, EV smart charging and demand-side response (DSR) for industrial and commercial customers on future load growth. Customer flexibility has the potential to substantially decrease overall network losses by reducing the peak demand. Data were available for the demand peak including customer flexibility; therefore, power losses at peak demand were calculated for each year and compared with the corresponding values without customer flexibility.

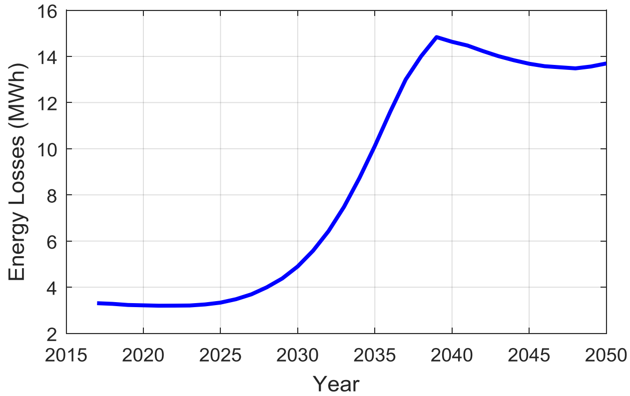

Figure 4: Energy Losses from 2017-2050.

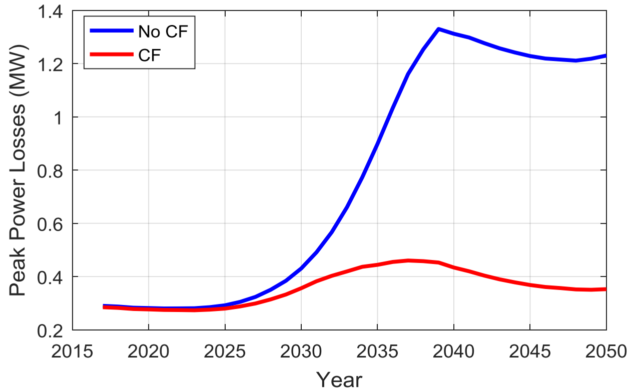

Figure 5: Power Losses Calculated at Peak Demand with and without Customer Flexibility (CF) for each year between 2017 and 2050.

As the demand peak grows, particularly between 2025 and 2035, the peak losses increase by around 400%, while with flexibility, the losses only increase by 50%. However, the overall impact of customer flexibility is likely to be less significant than this, since the demand profile will be flatter; therefore leading to higher losses during the non-peak periods (this corresponds to a higher load factor). Some of these losses could be offset by network reinforcement and asset replacement, which will result in a network with greater capacity and more efficient assets.

Discussion and future work

This paper illustrates the potential for using a flexible simulation tool with predictions of future demand growth for enhancing the understanding of network losses; however, only two parameters – demand growth and customer flexibility – have been examined in detail. Future work will seek to quantify the impact of many other factors affecting network losses, including uptake and usage of specific technologies. The proposed approach uses four phases for understanding of losses:

1. The impact of demand growth.
2. The impact of specific, uncontrolled low-carbon technologies.
3. The impact of DSO actions which are not taken specifically to address losses (e.g. procurement of flexibility for security of supply, constraint management, voltage regulation).
4. The impact of DSO actions taken specifically to reduce losses.

CONCLUSION

Distribution network losses present a significant cost to network customers. Future networks, with higher utilisation and increased peak demand, could have higher losses than those experienced today. It is therefore vital that DSOs understand how and where these losses occur, how they will evolve with changing demand and increased use of low carbon technology, and where and when it is appropriate to take actions to reduce losses. This paper provides initial investigation into how demand growth and customer flexibility will affect losses, and proposes a broader methodology for further investigation, with the ultimate goal of enabling accurate load estimation without the need for computationally intensive studies.

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