FUTURE LOW CARBON TECHNOLOGIES, IMPACTS AND ENERGY STORAGE SOLUTIONS ON UK DISTRIBUTION NETWORKS

Oghenetejiri ANUTA
Newcastle University – UK
o.anuta@newcastle.ac.uk

Christian BARTECZKO-HIBBERT
Durham University – UK
christian.barteczko-hibbert@durham.ac.uk

Neal WADE
Newcastle University – UK
Neal.wade@newcastle.ac.uk

ABSTRACT

Investment and uptake of low carbon technologies is increasing due to government policies that are set to decarbonise the electricity grid in the UK Understanding future demand and generation in distribution networks where these low carbon technologies will prevail is important in planning and managing the networks. This paper assesses the impacts of future demand and generation in the form of heat pumps and solar photovoltaics, which could be evenly dispersed or locally concentrated on a medium voltage distribution network. The effectiveness of using energy storage to manage the resulting issues arising from such networks is investigated.

INTRODUCTION

Low carbon technologies (LCT) are projected to grow in the UK based on government targets and policies to enable 15% of demand to be produced from renewable sources by 2020 and to decarbonize the grid [1]. A report by UKERC discusses issues with the evolving UK power sector and different scenarios to handle such issues between now and 2050 [2]. Among the issues are problems in the distribution network caused by LCTs such as heat pumps (HPs) and solar photovoltaics (PV). Furthermore, Ref. [2] discusses the change in the mind-set of Distribution Network Operators (DNOs) in the UK towards the assumptions that LCTs would be evenly distributed. As DNOs do not have control over the distribution of LCTs, it is conceivable that high concentrations would be installed in areas that are already overstretched, thus leading to bottlenecks in the distribution networks. Such developments would require a more active mode of managing the networks as demand and generation becomes more variable and bidirectional power flows occur. LCTs provide benefits such as reduced losses and increased reliability in the transmission and distribution network discussed in Ref. [3]. However, they could also lead to issues locally on the network which can limit LCT uptake, such as voltage rise, thermal overloading, and reverse power flows [3-5].

DNOs will have to move from a passive, demand driven control and investment approach which was suitable in the past, to a more active and innovative approach involving new technologies other than the traditional investment in wires and transformers. Technologies such as demand side response and energy storage are seen as possible solutions to the future challenges caused by LCTs [6].

LOW CARBON TECHNOLOGIES AND ENERGY STORAGE

Assessing low carbon technology impacts on the distribution network

It was discussed in [2] that network operators of transmission and distribution systems in the UK lack an understanding of the changes they would need to implement beyond the year 2025. Future planning and operation will be demand and generation driven. The variable locations and operating patterns of demand and generation LCTs brings about uncertainty. For example solar PV generation output is dictated by the vagaries of the weather. Solar PV is expected to make up 2% of the 15% target for renewables and HPs are expected to be installed in 25% of domestic households by 2030 [7, 8].

DNOs currently employ deterministic load flow methods in evaluating, planning and operating their networks. This however disregards the uncertainties or stochastic deviations that customers with LCTs would present on the networks. To enable a more accurate representation of the issues that may occur on a distribution network, the authors employ a probabilistic load flow (PLF) approach. Furthermore, an assessment is carried out on the effect of varying concentrations of these LCT customers on the network to understand the issues and severity as concentrations vary.

Energy storage solutions

Energy storage systems (ESS) implemented in the distribution networks can be used to manage and alleviate the impacts of LCTs. The applications of ESS include, voltage control, to manage overvoltage and undervoltage; power flow management to reduce losses, reverse power flows and thermal overloading of overhead lines, cables and transformers [9]. This paper implements ESS to mitigate LCT impacts on a representative medium voltage (MV) distribution network.

SIMULATION METHODOLOGY

The load and generation profiles used in this study comprise domestic customers, HP loads and PV generation. The simulated profiles were created from anonymised data gathered and processed under the Customer Led Network Revolution (CLNR)project in the UK [10]. CLNR is conducting a series of monitoring trials using over 9000 smart meters in residential, industrial and commercial locations within the UK to understand current and emerging load and generation profiles. The CLNR smart meter dataset is classified by different categorical variables from household income to rurality.

Demand and generation profiles

CLNR domestic metered data

Winter and summer data was considered due to the extremes both seasons provide for generation with PV and demand with HPs. A clustering approach was used to determine the number of natural customer groups that exist in the CLNR dataset. K-means is an unsupervised learning algorithm that partitions data into *k*-clusters. Clustering was performed on over 7200 domestic customers. In the winter month of January, 3 clusters identifying distinct demand groups were shown to exist based on their magnitude of energy usage. This clustering approach was repeated for the summer month of July based on the assumption that customer types would not differ. Each cluster in effect assigned probabilities to a given customer type. For January, the proportion of customers with the highest demand was attributable to 7% of the total sample, 36% to the medium cluster and 57% to lower demand customers. All domestic customers on a particular LV network were considered to be of the same type and thus homogeneous.

The domestic customer base for each LV network was derived through a weighted approach based on the aforementioned customer types and the available number of customers on that LV network.

SOLAR and HP

As part of the CLNR database two distinct LCT groups of HPs and PV exist. For both HP and PV, data is converted to half hourly real power readings. Because no information of the property type and HP characteristics are known a Monte Carlo method was used with the customer's 48 half hourly profile. This analysis uses weekday data as the random variable. To increase the sample selection, all customers in the database for that month with a full weekday demand profile were added to the sample set. This was deemed appropriate as HP operation on a day by day basis were considered as independent events.

To enrich the sample set of PV generation each customer's monthly maximum power consumption was computed. Taken over a 4 month period from May to September there was sufficient data for a representative sample set considering the different latitudes and PV inclinations.

Test network description

The test network used was obtained from [11]. A single line representation of the IEEE 33 bus radial distribution test network is shown in Figure 1. It was adapted to represent a UK MV distribution network based on the following assumptions:

- Following reliability requirements on MV networks, the MV transformer power rating was selected so 50% of its capacity meets peak demand while the line ratings were chosen so 75% meets peak demand on the network.
- The network was assumed to have only residential customers and an after Diversity Maximum Demand (ADMD) of 1.5 kW for residential households was used to determine the number of customers on each busbar [12].

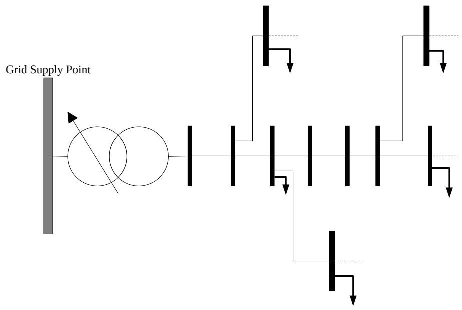

Figure 1: IEEE 33 bus test network

Monte-Carlo application

To deal with uncertainty a Monte Carlo approach was applied to demonstrate the feasible types of load and generation a network could experience over a 24 hour period. 1000 network realisations were deemed sufficient to encapsulate voltage variations across the network as in Ref. [13]. When considering LCTs, the minimum number of customers allowable on the first randomly selected LV network was the specified penetration level on the network, this was necessary as a base to start populating the network with the required LCT. Afterwards to ensure good accounting on successive realisations, the minimum penetration was updated to reflect the networks status in terms of customer type added to the quantity still required. The random number selected was given by $P_i^t = [P_i^{min,t},1]$ where P_i^t is the penetration over bus i with technology t $P_i^{min,t}$ indicates the minimum required for that part of the LV network and unity is the maximum possible. The simulation procedure is described in Figure 3.

Once the network is populated with the customer types a load flow analysis was performed and the condition of the network assessed. The network constraints that were monitored during the random load flow simulations were the voltage at ±6% of nominal voltage, reverse power flow at 10% of the on-load tap changer (OLTC) rating, and MV transformer and line thermal capacity at a threshold of 50% and 75% of thermal rating . A base case simulation was carried out to establish the default conditions on the network. The case study was carried out using half hourly winter and summer demand and generation data, which represents the two extremes for the operation of HPs and PV, with HPs being used more frequently in the winter for heating and PV reaching its full generation potential in the summer. Figure 2 depicts a representative HP demand on five of the busbars on the IEEE test network.

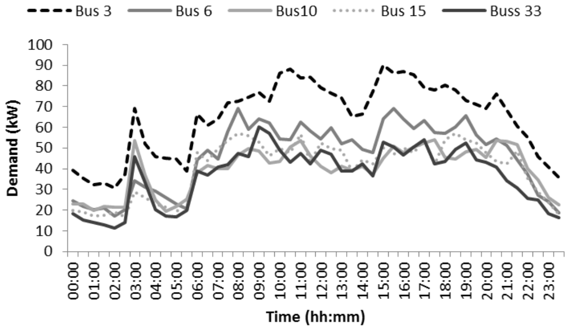

Figure 2: Representative busbar loadings for accumulated heat pump demand

The following steps were taken for populating the busbars with the required PV, domestic and HP profiles:

- Random population of varying penetrations for all customer types across the network using penetration limits of 25 and 50%;
- Using the same penetration limits outlined above a line sensitivity approach was explored to populate the network with HPs and PV. Line sensitivity was determined based on demand of LV network demand at each MV network node to produce the worst scenario. For HP technology this resulted in the line with the highest demand and for PV the line with the lowest demand was selected.

Energy storage planning and operation

Two locations were explored for the ESS, with one location chosen at the network midpoint and another at the location of the busbar with the highest voltage excursions. The maximum power rating of the ESS, which was connected to the MV side at the secondary LV substation, was constrained based on line capacity.

The ESS was used on the worst case demand and generation scenarios. This was considered based on the simulation with the maximum amount of losses and highest magnitude and number of excursions outside of the network limits. Thresholds were set for ESS to be invoked to resolve any power flow issues and maintain the voltage within constraints. The ESS is operated to resolve or reduce overvoltage and undervoltage excursions by providing a combination of real and reactive power; this is required because of the low X/R ratios in distribution networks. However, preference in the control option is given to reactive power compensation and when the limits of the ESS are reached (i.e. based on the converter ratings), real power is then applied.

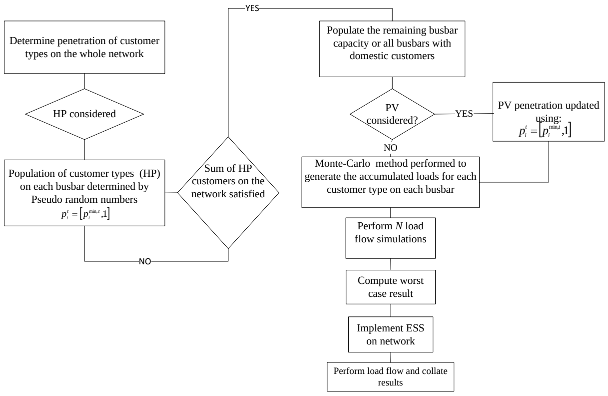

Figure 3: Load flow simulation process

Power flows were managed by sourcing real power during overpower and peak periods, or by sinking real power during periods of high generation that lead to reverse power flow in order to reduce thermal overloading on the transformer and lines on the network. Managing voltage and thermal constraints will in turn lead to a reduction in real power losses.

RESULTS AND DISCUSSION

Over all the simulations, there were only issues with voltage and reverse power flow as the network was robust enough to handle the increase in demand and generation caused by HPs and PV. The most severe case in which over voltage and under voltage occurred was at 50% penetration levels in terms of customer numbers. Figure 4 depicts the voltage extremes and system losses for HPs and PV respectively compared to the base case. 25% penetration of both HP and PV does not cause any voltage or thermal excursions. However, at a 50% penetration issues occurred on the network. Maximum overvoltage for both PV cases occurred at 1pm. For HPs the period with the lowest voltage was consistent at 5pm. For the case of HPs with line sensitivity, there were four undervoltage events and the network was operating close to the lower voltage limit over the 1000 simulations for both cases. Likewise, at 50% PV penetration there was a higher reverse power flow event for all simulations and there were 5 cases of overvoltage for the case with line sensitivity and 48 overvoltage events for the case without line sensitivity, this is illustrated in Figure 4. The higher density of overvoltages for the PV case with line sensitivity is as a result of the room for wider installation of PV at all remote ends of the network. On the contrary, for HPs the frequency of undervoltage for the scenario with line sensitivity showed a higher frequency with lower magnitudes of undervoltage compared to that of the system with no line sensitivity.

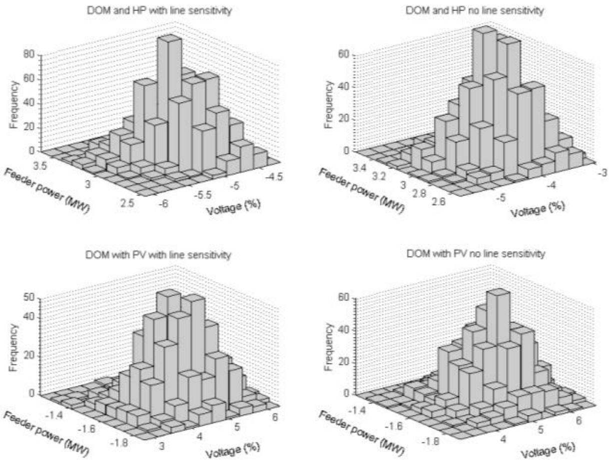

Figure 4: Density plots of voltage percentage as a function of nominal voltage vs. real power of the network at 50% penetration of HP (above) and PV (below).

From the worst case results that were selected, there were 14 reverse power flow events reported for both cases of 50% PV penetration with and without line sensitivity. But the overvoltage deviations were extreme in the case without line sensitivity. For HPs, although there was one undervoltage event, there was a higher amount of real power loss as the amount of HP was increased as shown in Figure 6. The ESS was implemented at two locations in turn, one at the midpoint of the network and at the end of the feeder, i.e. the most problematic busbar. The ESS operated at the end of the feeder was better at reducing the losses on the network. Results of loss reduction using ESS are shown in Figure 5 and Figure 6.

Figure 5 and Figure 6 shows the base case results (only domestic customers) alongside the respective PV and HP and domestic customer results for the two sensitivity cases (25% and 50% penetration levels). In each case the voltage and losses are computed for comparison purposes of the extreme events. The result from implementing ESS to resolve network constraints on the different cases is also depicted. The real power losses were reduced for the 25% cases when compared to the basecase but increasing the penetration levels to 50% increased the losses. This is expected because of the high amounts of reverse power flow on the network. To curb the voltage excursions and maintain the network voltage within limits, the ESS was used cooperatively with the OLTC. The operating limits for the ESS were thus set at 5% above and below the nominal network voltage. In addition, the ESS was charged up during periods of reverse power flow over a defined threshold of 0.75 MW. As a result of sinking reverse power on the network, losses were reduced below base case levels by 40% for the PV case with line sensitivity and 32% for the case without line sensitivity as shown in Figure 5.

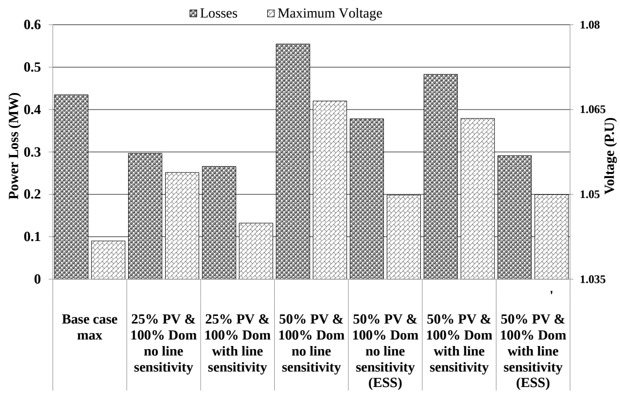

Figure 5: Maximum voltage and losses for PV base case, sensitivity study cases and EES implementation

Figure 6 illustrates the increase in losses as the penetration of HPs increases on the network. The losses increase even more with line sensitivity as expected due to the feeder having a higher demand than respective feeders on the network. The ESS was implemented for the 50% HP case with line sensitivity where there was a voltage excursion.

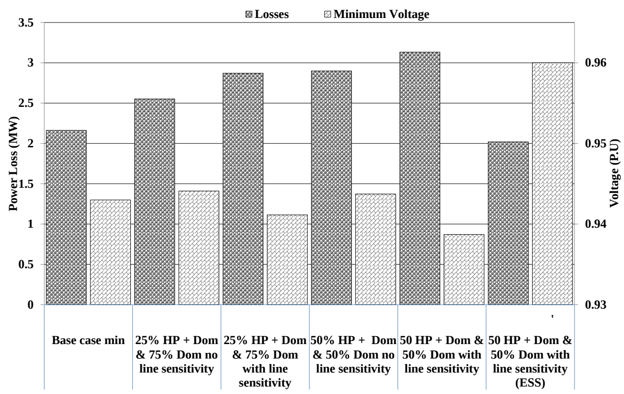

Figure 6: Maximum voltage and losses for HP base case, sensitivity study cases and EES implementation

The ESS was also discharged to reduce peak power flows on the feeder with high concentration of HPs with a threshold set at 40% of the line capacity rating, this reduced the amount of losses on the network by 36%. However, with ESS efficiency losses considered assuming a round trip efficiency of 90%, there was a net increase in losses of 5.5%. This negates the loss reduction benefits provided on the network.

Figure 7 shows the operation of the ESS and the resulting drop in capacity utilisation of the feeder with the highest utilisation. A summary of the ESS power rating and energy capacity used is shown in Table 1.

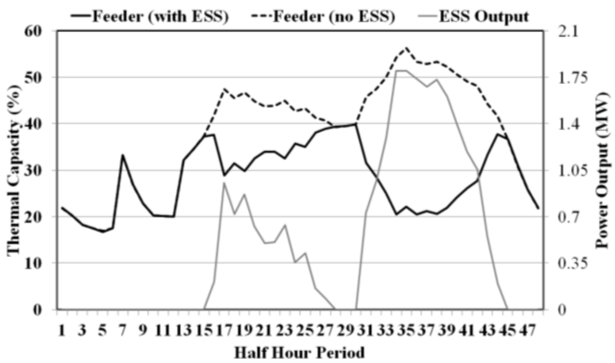

Figure 7: Peak power reduction on feeder with highest PV concentration

Table 1: Energy storage power rating and energy capacity for cases

Case	*Power Rating / Energy capacity*	*Actions*
50% PV with line sensitivity	1.2 MW/ 6 MWh	Reverse power flow and overvoltage
50% PV without line sensitivity	1.1 MW / 5.1 MWh	Reverse power flow and overvoltage
50% HP with line sensitivity	1.8 MW/ 11.9 MWh	Overpower and undervoltage

CONCLUSION

Higher penetration of HPs and PV can lead to voltage excursions, increased losses and reverse power flow. The authors have shown the impacts of variable levels of penetration and concentrations of HPs and PV on a network whilst demonstrating that the effective use of ESS can be used in resolving voltage issues and reverse power flows that would be caused by these LCTs. Furthermore PV and HPs on the network lead to increase in losses, this was worse for the cases with high HP concentrations. Losses were reduced by reducing the peak power flows on the network using ESS. When using ESS, the net losses on a network could potentially increase because of the storage efficiency losses, hence ESS operation will need to be optimised to minimise system losses during daily ESS operation.

With large amounts of HPs and PV on the distribution network, ESS could be a possible solution outside of traditional planning methods to manage the problems that will occur.

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