IMPACT OF PROSUMER GROWTH ON FLEXIBLE DER THROUGH CURTAILMENT ASSESSMENT

Rachael TALJAARD
Smarter Grid Solutions – UK
rtaljaard@smartergridsolutions.com

Finlay MCNICOL
Smarter Grid Solutions – UK
fmcnicol@smartergridsolutions.com

Robert MACDONALD
Smarter Grid Solutions – UK
rmacdonald@smartergridsolutions.com

Kjersti BERG
SINTEF – Norway
kjersti.berg@sintef.no

Hanne SÆLE
SINTEF – Norway
hanne.saele@sintef.no

ABSTRACT

Across Europe Distribution System Operators (DSOs) are increasingly looking to harness network flexibility and provide more efficient network investments, lowering network costs for consumers. DSOs require a robust method of evaluating the benefit of flexibility actions, and the time-varying impact of prosumer growth is a critical input to this process. This paper presents the outputs of a collaborative study that explores the impact of growth in domestic Low Carbon Technology (LCT) in terms of network constraint emergence and harnessing flexibility.

Through the application of the curtailment assessment methodology to network development scenarios (reflecting different growth rates and forms of LCT), the studies present the impact of domestic LCT growth on the frequency and magnitude of network constraint events, ultimately reflecting the scale of flexibility required to manage constraints.

Comparative evaluation of the study outputs highlights the importance of modelling developments on the low voltage (LV) network, even where studies are focused on medium voltage (MV) or high voltage (HV) constraints. The two presented methods: time-series prosumer growth modelling and constraint analysis are of great relevance for DSOs. The value presented by the methods reflects a required development in network planning and design processes as DSOs look to respond to, and harness, greater levels of flexibility on networks and accommodate greater volumes of low-carbon technology. This can result in the more efficient utilisation of existing network capacity and deferral or avoidance of expensive grid reinforcement.

INTRODUCTION

Over the last few decades the shape of the energy landscape has changed drastically. There has been a marked change in the nature of new generation connecting to the grid. This has shifted from large, transmission connected power plants to increasing volumes of smaller distribution connected generation.

The introduction of renewable generation at distribution level, particularly those that are intermittent and variable, creates a new requirement for flexibility in distribution networks. Traditionally networks have followed a worst-case planning process and have been designed in a “fit and forget” manner. Given that generation output cannot always be accurately forecast or planned for, there is a new requirement for flexibility to allow for the continued balancing of the grid. Electricity networks are becoming more intelligent with the roll-out of smart grid technologies and Active Network Management (ANM), and the increased visibility provided by these technologies is incredibly valuable. The popularity in distribution-connected generation has now resulted in constraints at the lower voltage levels, driving innovation in connection processes. Flexible connections at distribution provide generators with a non-firm connection, with their export managed against specific network constraints, allowing cheaper and faster connections when compared with traditional grid reinforcement.

Active networks and flexible connections also provide DSOs with a greater awareness of how their network is being operated within an “operation-scale” time frame. This awareness enables DSOs to determine which autonomous solutions are best suited to maximise utilisation of network assets. The need for automation is clear – the flows on the network change too quickly for a human in the loop to always be able to adequately determine the appropriate control action and issue the command.

The change in the energy landscape does not stop at distribution level. Changes are permeating down to the consumer level, both residential and non-residential. Consumers are becoming energy aware, and in addition to taking advantage of various incentives, have embraced roof-top PV. Electric vehicles and heat pumps are two low carbon technologies for which system operators are expecting a significant consumer uptake over the next decade and beyond. By adopting energy efficient technologies, and installing generation at home, the consumer profiles that were once fairly static and predictable, become less predictable and more changeable.

There is still a requirement for network operators to plan networks for continued, safe, reliable operation, even more so given the variability introduced by renewables and changing consumer habits. This paper investigates new methods for developing consumer profiles, accounting for different low carbon technologies and aggregation, and their application in analysis methods designed for flexible networks.

USE CASE DESCRIPTION

An anonymised section of the UK distribution network has been chosen for analysis. The section of network represents a typical rural network. The flexible generators and constraints are located at the end of a 33 kV radial feeder; this area is shown in Figure 1. Equivalent lumped profiles are used to represent primary substation and Bulk Supply Point (BSP) loads. The key parameters in the network are:

- 6 flexible PV generators connected at 33 kV;
- 14 primary substation loads and 1 BSP load connected at 33 kV;
- 2 BSP loads connected at 132 kV;
- 3 overhead line thermal constraints at 33 kV.

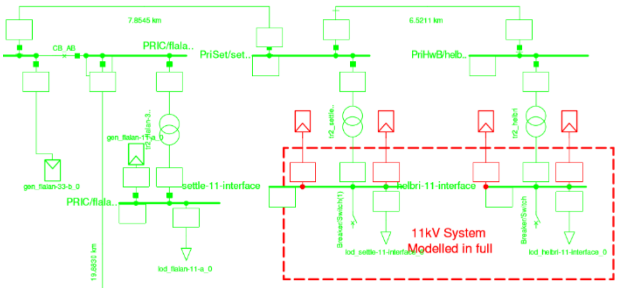

Figure 1: Network diagram

CUSTOMER PROFILE DERIVATION

Within the SmartGuide project SINTEF Energy Research has developed a tool which can develop typical profiles for different types of customers with different low carbon technologies (EV charging, PV production or demand response). With this tool new profiles for customers with different types of installed low carbon technologies can be developed based on hourly data for a year (8760 values) of the base consumption. The hourly data can be smart meter data from a specific customer or as in this case, profiles for different types of customers (domestic, commercial and industrial).

With use of the tool, profiles are made from linear regression on consumption data versus temperature data for each hour. The analysis gives a temperature dependent and a constant value. Before performing the regression, the data is classified after hour, day type (weekday or weekend) and season types (winter/spring/summer/ autumn). A more detailed description of the tool is presented in [1].

The input data in this case was UK representative demand profiles, for three customer types (provided by ELEXON [2]):

- Domestic – Domestic Unrestricted Customers (Profile Class 1)
- Commercial – Non-Domestic Unrestricted Customers (Profile Class 3)
- Industrial – Non-Domestic Maximum Demand Customers with a Peak Load Factor of less than 20% (Profile Class 5)

It is assumed that within a Profile Class (PC), there is a certain share of customers with PV production, EV charging and heat pumps (HPs) for space heating. The resulting load profile is then found as:

$$P_S = \sum_{PC} n_{PC,S}\, P_{PC,S} \qquad (1)$$

Here, $n_{PC,S}$ is the share of customers in profile class *PC* in scenario *S*. $P_{PC,S}$ is the load profile for profile class *PC* in scenario *S*, and is found as in (2):

$$\begin{aligned} P_{PC,S} = n_{reg,S}P_{PC,reg} + n_{HP,S}P_{HP} + n_{PV,S}\left(P_{PC,reg} - P_{PV}\right) \\ + n_{EVslow,S}\left(P_{PC,reg} + P_{EVslow}\right) \\ + n_{EVfast,S}\left(P_{PC,reg} + P_{EVfast}\right) \end{aligned} \qquad (2)$$

Here, $n_{reg,S}$, $n_{HP,S}$, $n_{PV,S}$, $n_{EVslow,S}$ and $n_{EVfast,S}$ are, respectively, the shares of "regular customers", customers with heat pumps, customers with PV panels, customers with EV slow charging and customers with EV fast charging. $P_{PC,reg}$, P_{HP}, P_{EVslow} and P_{EVfast} are, respectively, the load profiles of a "regular" PC1 customer, a customer with heat pump, the load profile of EV slow charging and EV fast charging.

$P_{PC,reg}$ is found from linear regression on the different load profiles (PCs) vs temperature data (hourly values for one year). The temperature data used is found from the Met Office Integrated Data Archive System [3], for Valley weather station, 2017. P_{HP} is also made from linear regression, however a yearly heat pump profile from [3] is added to the yearly load profile (PC) before the linear regression is performed. The temperature data is again used to obtain the hourly values for a whole year.

P_{PV} is the production profile of a Mitsubishi Electric PV_MLU255HC PV panel, with modules of 255 Wp. In addition to the specs given in [4], it is assumed that the inverter efficiency, n_{inv}, is 0.9. The production per hour is calculated from the irradiation and temperature data given as input, as done in [4]:

$$P_{PV} = C_{FF} N_m n_{inv} \frac{G ln(10^6 G)}{T_{mod}} \qquad (3)$$

N_m is the number of modules, T_{mod} is the temperature of the PV module, C_{FF} is a fill factor model constant and G is the solar radiation. Hourly values for the solar radiation used as input are found for 2017 from Valley weather station [5], along with the already mentioned hourly temperature values from the same weather station.

The profiles for EV charging are from [3].

The different profiles developed are the basis for three different scenarios for 2030 and 2040. The profiles for each scenario and year are developed based on different combinations of the profile class 1 – 5 and for different types of low carbon technologies (PV/EV/HP), as presented in Table 1.

Given the rural location of the study network, the demands in the network are mostly residential, with a very low level of commercial and industrial demand. This is reflected in the 98%/1%/1% split applied to the profile classes. To determine the PV, heat pump and EV percentages included in the profile classes, the standard growths were applied, as forecast in the previous industry 'DS2030' study for 2030 [3], and the UK National Grid Future Energy Scenarios (FES) were used to scale these 2030 projections for a 2020 base case, and a 2040 future scenario [6]. The FES Community Renewables scenario is used for determining PV growth, and the Consumer Evolution scenario is used for determining heat pump and EV growth.

Table 1: Scenario description – including aggregation level

Scenario	Profile Class/ Share	2030	2040
Base Case	PC1/ 98%	PV: 2%, 6kWp/ EV: 1%, 7kW/ HP: 1%	
	PC3/ 1%	PV: 2%, 12kWp/ EV: 0%/ HP: 0%	
	PC5/ 1%	PV: 2%, 50kWp/ EV: 0%/ HP: 0%	
High PV Growth	PC1/ 98%	PV: 4.4%, 6kWp EV: 1%, 7kW EV: 1%, 24 kW HP: 2%	PV: 7.8% EV: 4% EV: 4% HP: 4%
	PC3/ 1%	PV: 4%, 12kWp EV: 2%, 24kW HP: 0%	PV: 10% EV: 4% HP: 0%
	PC5/ 1%	PV: 4%, 50kWp EV: 2%, 24kW HP: 0%	PV: 10% EV: 4% HP: 0%
High Load Growth	PC1/ 98%	PV: 3%, 6kWp EV: 4%, 7kW EV: 4%, 24kW HP: 9%	PV: 6% EV: 12.8% EV: 12.8% HP: 16.5%
	PC3/ 1%	PV: 3%, 12kWp EV: 20%, 24kW HP: 0%	PV: 6% EV: 30% HP: 0%
	PC5/ 1%	PV: 3%, 50kWp EV: 20%, 24kW HP: 0%	PV: 6% EV: 30% HP: 0%

CURTAILMENT ASSESSMENT

The introduction of flexible connections creates a requirement for new analysis techniques. When applying flexibility in network planning it is important to approximate the volumes of energy curtailment required when assessing the economic feasibility of Active Network Management. Forecasting curtailment for flexible connections can be a complex matter that is based upon variation in network operation, which is influenced by environmental, technical, and sociological factors including renewable resource availability, network outages and faults, and demand customer behaviour patterns. In the UK the standard method has been to apply a Last In First Off (LIFO) principle of access for network capacity, where the last generator to connect is the first to be curtailed [7]. This approach to principles of access is applied in the analysis.

The methods employed use time-series analysis, simulating network power flows and generator output over the course of a year and typically at half hourly time intervals. It is possible to estimate how frequently particular network constraints will be triggered, and subsequently calculate the expected impact on generator output. Previous papers on curtailment assessment have investigated the different analysis methodologies that can be applied [8] [9].

Analysis Results

The results for the Base Case and High PV Growth scenarios are shown in Table 2. The curtailment for each generator is presented as a percentage reduction of total export. It can be seen that PV curtailment increases from 2020 to 2040 following growth in rooftop PV installations. The volume of curtailment for each generator is shown in Figure 2.

Table 2: High PV Results

	MVA Rating	Curtailment as % reduction of export		
		2020	2030	2040
Generator 1	19.7	0.00%	0.00%	0.00%
Generator 2	7.25	0.00%	0.00%	0.00%
Generator 3	12	0.04%	0.05%	0.06%
Generator 4	14	0.71%	1.04%	2.05%
Generator 5	0.5	4.69%	5.73%	8.17%
Generator 6	2	7.09%	8.20%	11.17%

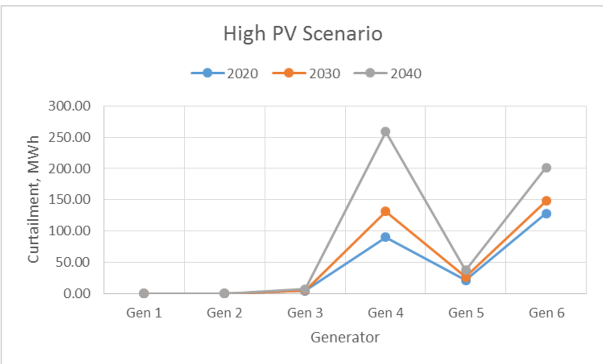

Figure 2: High PV scenario curtailment

The tabulated results illustrate the LIFO nature of curtailment, with the last generator in the priority stack experiencing the highest percentage curtailment. Figure 2 shows that the volume of curtailment can be larger for generators higher in the priority stack, but it is dependent on the sensitivity factor to the constraint, and the size of generators [8] [9].

The results for the Base Case and High Load Growth scenarios are shown in Table 3. The curtailment again increases from 2020 to 2040, however the volume of curtailment is lower. This scenario still includes PV growth, though lower than that in the high PV scenarios. Even with demand increases there are still network constraints which require mitigating action. The volume of curtailment is shown in Figure 3.

Table 3: High Load Results

	MVA Rating	Curtailment as % reduction of export		
		2020	2030	2040
Generator 1	19.7	0.00%	0.00%	0.00%
Generator 2	7.25	0.00%	0.00%	0.00%
Generator 3	12	0.04%	0.04%	0.05%
Generator 4	14	0.71%	0.75%	1.11%
Generator 5	0.5	4.69%	4.94%	5.57%
Generator 6	2	7.09%	7.10%	8.09%

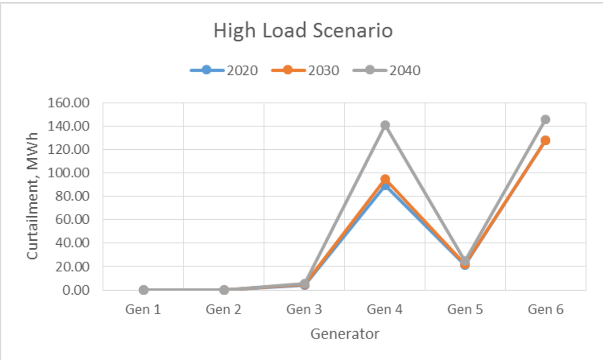

Figure 3: High Load scenario curtailment

The overall results are shown graphically in Figure 4 and Figure 5. Figure 4 shows the total curtailment (summed for all generators) in the High PV and High Load scenarios. By 2040 there is almost 200 MWh of difference between the two scenarios, showing that increasing generation has a greater impact on network constraints.

Figure 5 shows the total number of hourly constraint events (summed for all constraint locations) between the two scenarios. There is a higher number of constraint limit exceedances in the High PV scenario, showing again that increasing generation has more of an adverse effect on network constraints.

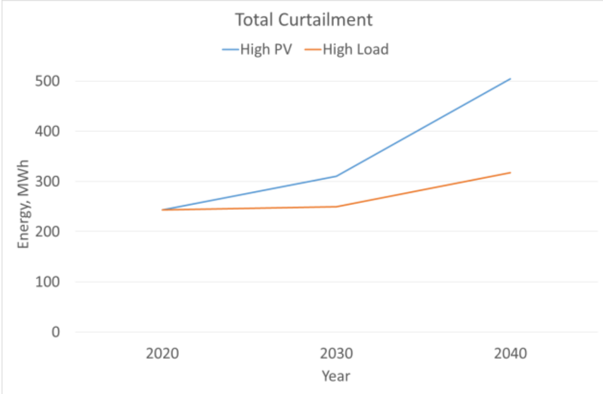

Figure 4: Total curtailment

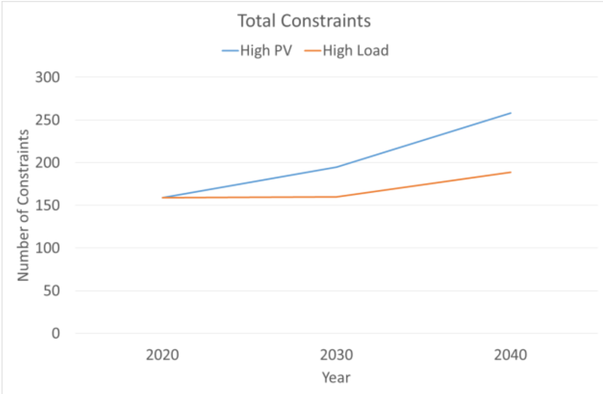

Figure 5: Total constraints

RESULTS DISCUSSION/CONCLUSION

The results show that as the level of embedded LV-connected generation increases in the network, the number of constraints and the volume of curtailment will also increase. In the High Load scenario, while there is significant projected load-growth in 2030 and 2040, it is not sufficient to remove the requirement for curtailment as a result of the growth in PV.

As new constraints emerge in a network it is not customary for existing generators to be managed against them. In this analysis known constraints are modelled, and it is possible new constraints will emerge in the study network with the increase in load and generation up to 2040. The generators under study were not controlled against any new constraints that emerge.

The growth in PV was modelled in rooftop PV which is typically considered as uncontrollable given the small scale and distributed nature. The more growth there is in small scale generation, the larger the impact will be on larger, controllable generators. Diversity is key here. Rooftop PV is modelled and the controllable generation in the network is PV. These are modelled with correlated PV profiles, giving conservative results. In reality there would not be the same level of correlation between PV site exports, although coincidence in a neighbourhood would be high, and it is likely there would be diversity in the generation mix. The introduction of different generating technologies with different profiles is likely to reduce the severity of constraints given that it is unlikely different technologies will experiences peaks coincidentally. This is likely to contribute to the continued increase in curtailment levels in the high demand growth study case.

The derivation of prosumer profiles, based on the different profile classes, has shown one way in which the changes in end user behavior can be captured and modelled. The characteristics applied can be updated for different growth rates in the different technologies to be in line with new forecasts as they become available. This is extremely useful given the expected uptake in EVs, heat pumps and the continued growth anticipated in rooftop PV.

The time-series analysis of network constraints given these customer profiles allows for an understanding of how the growth in low carbon technologies and changes in end user behavior can be analysed for network planning and control purposes. As growth in distributed generation continues, this type of analysis will become more necessary in order to have a greater understanding of what power flows in the network are likely to be given the variation in demand and generation through the day, and year.

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