A MONTE CARLO ASSESSMENT OF CUSTOMER VOLTAGE CONSTRAINTS IN THE CONTEXT OF CVR SCHEMES

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ABSTRACT

Conservation Voltage Reduction (CVR) schemes are seen as promising techniques to deliver ancillary services, defer investments and provide energy savings. However, the benefits that might be unlocked are limited by the voltage variations that can be introduced without negatively affecting LV customers. This paper statistically quantifies this limit adopting a Monte Carlo approach on 57 UK LV feeders during winter. For this purpose, the percentage of BS EN 50160 non-compliant customers for different voltage levels on the primary side of the LV transformer is quantified. Results show that to maintain this figure below 1% the voltage on the primary side of every LV transformer should be maintained between 0.94 and 1 pu. Finally, the limitations imposed by these constraints are shown on a real UK MV network where the maximum voltage reduction for a specific day is also quantified.

INTRODUCTION

The possibility to manage customer demand represents an opportunity for Distribution Network Operators (DNOs) to provide peak demand reduction and ancillary services. However, especially at residential level, scalability and customer acceptance might hinder the success of a demand response scheme in which the customer involvement is required.

A non-invasive approach to overcome this limitation is to leverage the known positive correlation between voltage and demand [1]. Indeed a reduction of the supplied customer's voltage will reduce its drawn demand. This technique, also known as Conservation Voltage Reduction (CVR), is typically applied for energy savings purposes but can also be adopted to achieve power reduction during specific periods.

Although secondary substations (11/0.4 or 6.6/0.4 kV in the UK) might be considered as the best locations to control voltages [2] given their proximity to residential customers, these typically use off-load tap changers, i.e., are in reality not controllable. Consequently, the most practical alternative is to remotely control the existing on-load tap changer (OLTC)-fitted transformers in primary substations (33/11 or 33/6.6 kV).

To quantify the benefits that a CVR scheme might unlock it is necessary to assess the extent to which the voltage at the primary substation could be changed without negatively affecting the customers' voltage. This analysis should involve medium voltage (MV) and associated low voltage (LV) networks simultaneously as the control actions influence both voltage levels. One of the major barriers for such an analysis, however, is the large number of LV networks supplied by a given primary substation (from dozens to hundreds). In addition, most DNOs typically lack the corresponding LV data for power flow studies [3]. Due to these limitations, recent works have carried out simplistic analyses considering synthetic LV networks [4] or only a few real ones [2], or did not even consider the LV constraints [5]. Neglecting the LV constraints or adopting simplistic approaches lead to results that cannot be generalised and therefore cannot be used to quantify the true benefits of CVR schemes.

This work, part of the ongoing UK Low Carbon Networks Fund Project (LCNF) CLASS [6] that considers CVR for power purposes, seeks to adequately incorporate LV constraints by analysing a set of 57 real LV residential feeders. Time-series synthetic residential winter load profiles and different voltage levels on the primary side of the LV transformer (the interface with the MV network) are considered. To cater for the uncertainties due to demand variability and size, a Monte Carlo approach is adopted.

The main outcome of this study is the probability of having LV customers non-compliant with the standard BS EN 50160 [4], [5] as a function of the LV transformer primary side voltage. Once the DNO determines the acceptable level of risk (i.e., maximum percentage of non-compliant customers), the corresponding LV primary side voltage becomes the constraint needed to determine the lowest voltage target at the primary substation.

This work is structured as follows: section II introduces the load and network modelling used in this study. The methodology is presented in section III while section IV introduces the main results. In section V the application of the LV constraints is illustrated using a real UK MV network. Finally, conclusions are drawn in section VI.

LOAD AND NETWORK MODELLING

In this section the load profiles and LV networks adopted in this study are described.

Load Profiles

Realistic 10-min resolution residential load profiles are produced using the CREST tool [7] for a winter weekday. To cater for the diversity seen in real LV networks, a pool of 5000 randomly generated profiles is created considering number of residents according to UK statistics [8].

Figure 1 Four of the 57 real UK LV feeders

Real UK LV Feeders

To take into account the potential constraints imposed by a variety of LV residential customers, 57 real LV feeders from "Low Voltage Network Solution" project [9] are considered in this study. These urban and mainly cable networks are located in the North West of England and are own and operated by Electricity North West (ENWL). They have been fully modelled from GIS data considering real customer location, conductor characteristics and phase connectivity. Examples are shown in Figure 1.

Typical UK secondary substations are equipped with one LV transformer with a transformer ratio of 11/0.433 kV or 6.6/0.433 kV, i.e., a normal boost of 8.2% (compared to the nominal 400V phase to phase voltage). As mentioned previously, the transformer is fitted with an off-load tap changer (tap position commonly set at nominal). All these aspects have been considered in this study.

METHODOLOGY

This section proposes the methodology to statistically assess the LV network constraints in the context of CVR schemes. For illustration purposes, a deterministic approach is firstly introduced. This is then incorporated into a more complex Monte Carlo methodology. For simplicity, both methodologies are here described considering one feeder only.

When adopting CVR schemes, where voltages are lowered (permanently or for a short period of time), it is important to assess whether any customer voltage (thereafter indicated as V_{LV}) violates the statutory limits. In the case of the UK, the standard BS EN 50160 [10] and the Electricity Safety, Quality and Continuity Regulations [11] have been adopted. They indicate that the nominal customer phase to neutral voltage is 230V (1

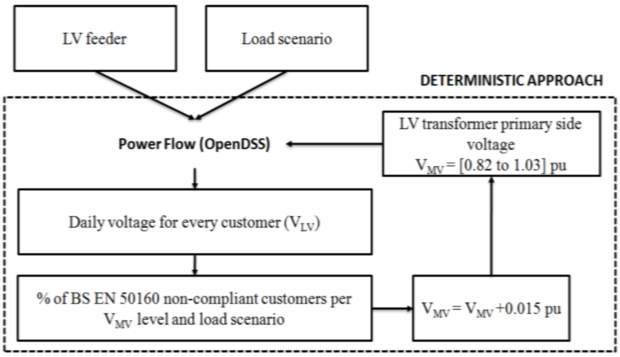

Figure 2 Deterministic voltage constraint assessment approach

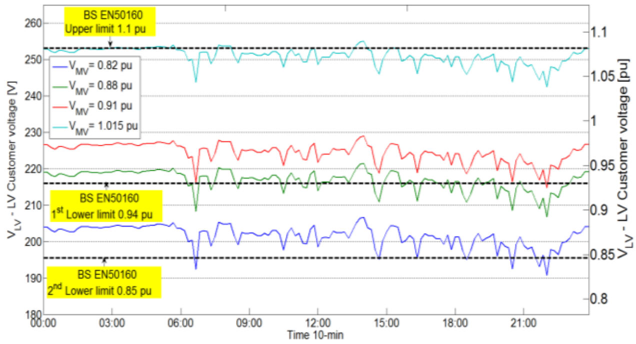

Figure 3 Daily supplied voltage profile (V_{LV}) of a single customer with four different LV transformer primary side voltages (V_{MV}) in one feeder

pu) and that in normal operating conditions the 10 min average customers' voltage should respect the following limits:

- Be maintained within 0.85 and 1.1 pu during 100% of the time (on a weekly basis).
- Be maintained within 0.94 and 1.1 pu during 95% of the time (on a weekly basis).

In case any of the two above limits is violated the corresponding customer is flagged as non-compliant. For simplicity, the limits are considered here on a daily basis.

Deterministic Approach

Figure 2 illustrates the key steps of the deterministic approach for one LV feeder. Firstly, a daily demand profile, randomly extracted from the pool previously introduced, is allocated to each customer. This generates a hereafter called "load scenario" (Figure 2).

In order to study the effects of voltage changes in the MV network different voltage values at the primary side of the LV transformers (V_{MV} from 0.82 to 1.03 pu, Figure 2) are investigated. For simplicity, these voltages are kept constant throughout the day.

For the above considerations, a daily power flow analysis is carried out using OpenDSS [12]. Finally, the percentage of customers non-compliant with BS EN

Table I Percentage of BS EN 50160 non-compliant customers per V_{MV} level and adopted load scenario

V_{MV} (pu)	0.82	0.88	0.91	1.015	1.03
% of non-compliant customers for the adopted load scenario	100	85.71	14.29	100	100

50160 (applied on a daily basis) is assessed for every V_{MV} level.

An example is shown in Figure 3 where the voltage for one customer (V_{LV}) at the far end is illustrated for four different V_{MV} values. In addition, the voltage level of 0.85, 0.94 and 1.1 pu are highlighted (black horizontal lines) as key limits for the UK. With a V_{MV} of 0.82, 1.015 and 1.03 pu the customer voltage V_{LV} is not compliant as it does not lay within the 0.85 and 1.1 pu range all the time. Similarly, with V_{MV}=0.88 pu the customer voltage lays for more than 5% of the time below 0.94 pu. Only for the voltage level V_{MV}=0.91 pu this customer can be defined as compliant to the standard.

Following the same procedure the total number of non-compliant customers per V_{MV} level has been calculated for this particular feeder and load scenario. The results are reported in Table I.

Given the deterministic nature of this particular case, it is difficult to capture the real effects of demand location and variability. Therefore, the actual number of non-compliant customers could in practice be higher or lower. To overcome this, a Monte Carlo approach is adopted.

Monte Carlo Approach

A Monte Carlo approach has been applied to the selected 57 LV feeders considering 200 randomly generated winter load scenarios for each of the 15 studied LV transformer primary side voltages (V_{MV}). The approach is illustrated in Figure 4 considering a single feeder.

The percentage of non-compliant customers per V_{MV} is obtained for each one of the 200 simulations. However, to extract the most representative percentage of non-compliant customers per V_{MV} the average of the 95th percentile of those 200 results has been considered. Consequently, a single value of non-compliant customers is obtained per V_{MV} level and feeder.

RESULTS

The Monte Carlo approach has generated a total of 855 values (15 V_{MV} values and 57 feeders) that for convenience are represented with coloured cells in Figure 5. Each cell corresponds to the average percentage of non-compliant customers per feeder (rows) and the investigated primary side voltage V_{MV} (column).

It is worth noticing that the number of customers with

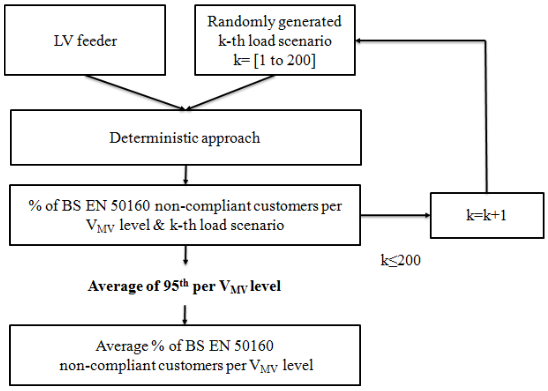

Figure 4 Monte Carlo voltage constraint assessment approach

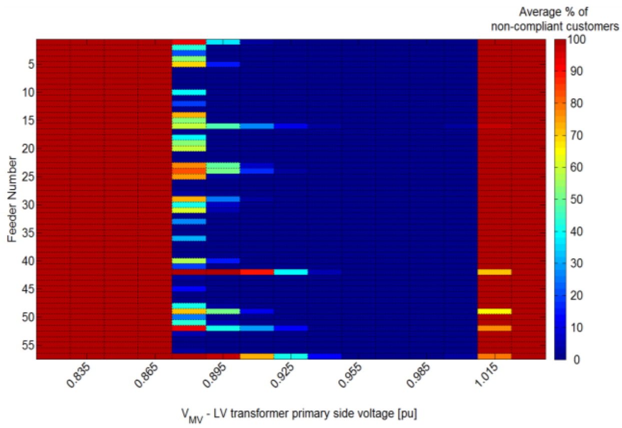

Figure 5 Average percentage of non-compliant customer per feeder and LV transformer primary side voltage V_{MV}

problems varies more from feeder to feeder for lower V_{MV}. For instance, feeder number 57 (the longest and with more than 180 of customers) starts experiencing voltage issues at 0.94 pu, whilst this occurs to feeder number 1 (with only 70 customers) only at 0.91 pu. This highlights the importance of considering different types of feeders as their characteristics (i.e., topology and number of customers) will limit lower values of V_{MV}.

The results in Figure 5 are further summarised in Figure 6 and Table II. This is done by averaging, for the same primary side voltage V_{MV}, the percentage of non-compliant customers for all the feeders (from Figure 5). Table II suggests that for a given V_{MV} between 0.94 and 1 pu the average percentage of customers with problems is below 1%. This can be defined as a “low risk scenario”. However, if the DNO adopt a less conservative figure of 5% of non-compliant customers, a wider voltage range from 0.91 to 1 pu could be considered.

It is important to highlight that the voltage range defined above (i.e., 0.94 to 1 pu with 1% of non-compliant customers) is obtained by two “averaging” processes. Indeed every percentage of non-compliant customers associated per V_{MV} shown in Table II is the summary of 11,400 simulations (57 feeders, 200 load scenarios each).

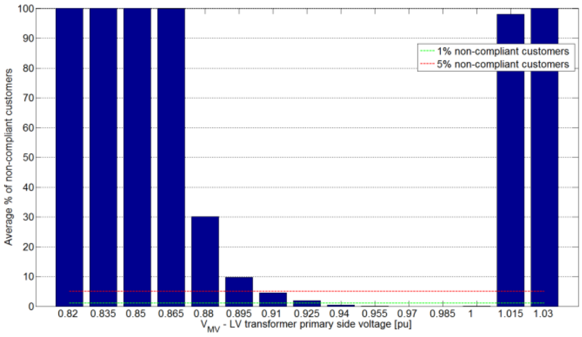

Figure 6 Average % of customers non-compliant per primary side voltage at LV transformers

Table II Average % of customer with problems per primary side voltage range (“Low Risk Scenario” in green)

LV transformer primary side voltage in V_{MV} pu	0.820-0.895	0.910-0.925	0.94-1.00	1.015-1.030
% of non-compliant customers	>10%	1-5%	<1%	>10

Hence, caution should be taken when reading these initial results. For instance, a V_{MV} 0.94 pu does not expose in average more than 1% of customers to voltage issues (Figure 6 and Table II). Nonetheless, feeder 57, characterised by a higher than average cable extension, experiences an average of 13.22% (last row, 9th column from the left side in Figure 5) of non-compliant customer with a V_{MV} of 0.94 pu.

APPLICATION: VOLTAGE CAPABILITY OF A REAL UK MV NETWORK

This section provides an illustrative example on how the LV customer constraints shown in Table II can be integrated in MV network studies where the LV feeder cannot explicitly be modelled (because of the extent of LV networks and lack of data). For this purpose, a real urban MV network from the North West of England is adopted. A daily time-series analysis is carried out for a winter weekday day.

From the knowledge of the total number of customer per class type (e.g., residential, commercial, industrial) per secondary substation it is possible to generate an aggregate demand profile for every LV transformer. For this purpose, diversified half-hourly profiles per customer type based on ELEXON profile classes [13] have been adopted for the 12th January 2012.

Once the load profiles and the MV network topology are known, power flow studies in OpenDSS are carried out. The resulting voltage profiles at the primary side of every LV transformer (V_{MV}) are shown in Figure 7. A voltage snapshot for one instant (at around 18:30, peak) is also depicted in Figure 8. For simplicity, the primary side voltage of the MV transformers (i.e., 33kV) has been assumed constant at 1 pu throughout the day.

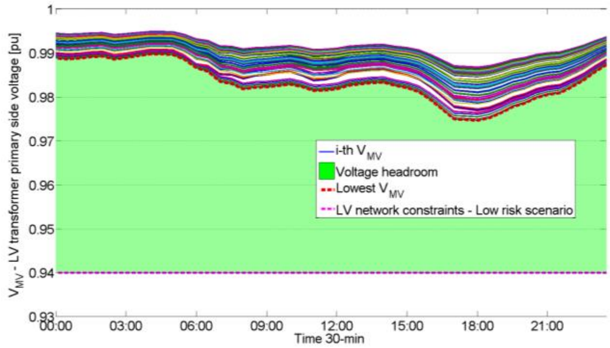

Figure 7 Daily voltage profile of every LV transformer and headroom for voltage reduction purpose for the analysed MV network

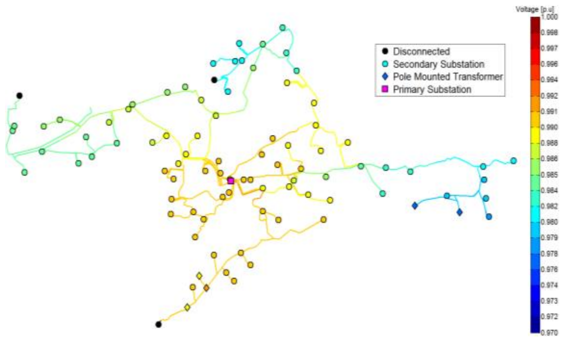

Figure 8 Voltage heat map of the analysed MV network at peak

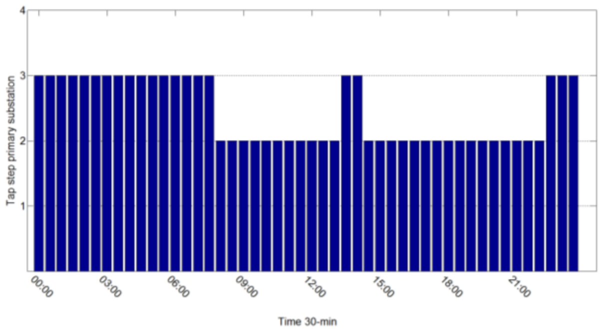

Figure 9 Highest number of tap changes that can be introduced at primary substation considering the LV network constraints

Assuming that the average percentage of customers with problems should be maintained below 1% (i.e., a “low risk scenario”), the voltage on the primary side of every LV transformer (V_{MV}) should be kept within 0.94 and 1 pu (Figure 6 and Table II). For simplicity, a linear relationship between voltage at the primary substation and voltage along the MV network can be assumed (i.e., 1% voltage reduction at primary substation causes 1% voltage reduction in every point of the downstream MV network). Thus, the voltage headroom in terms of voltage reduction at the primary substation is illustrated in Figure 7 by the green area. The allowable voltage range is limited by the LV transformer with the lowest primary side voltage (in dark blue in the right hand side of Figure 8).

Finally, dividing the voltage headroom over the voltage amplitude of one tap step (i.e., 1.46% for typical UK primary substations) the time-varying voltage capability in term of tap changes (for voltage reduction purposes) is illustrated in Figure 9. It can be concluded that, for this case study, the voltage can be permanently reduced up to 3% (i.e., 2 taps) without exceeding 1% of BS EN 50160 non-compliant customers. A voltage reduction of up to 3 taps could be carried out for most of the day.

Nonetheless, care should be taken when reading these results as only one example of a specific UK MV network during one winter weekday has been considered. Other MV networks and different periods of the year might provide different outcomes.

Ultimately, it is the time-varying availability of taps that will determine the extent to which the DNO can trigger the CVR scheme. Hence, from the operational perspective, this availability assessment increases confidence in the technique as it considers the potential impacts on LV customers. This assessment overcomes the limitations from quantifying those impacts considering only peak demand, hence resulting in a much better exploitation throughout the day.

CONCLUSIONS

This paper has presented and discussed the methodology to integrate LV network constraints in the assessment of the time-varying voltage capabilities of primary substations for the deployment of Conservation Voltage Reduction (CVR) schemes.

In particular, a Monte Carlo approach has been applied to 57 real residential, underground UK LV feeders considering 200 simulations, each of them representing a winter weekday. To study the effects of voltage changes in the MV network different voltage values at the primary sides of the LV transformers were investigated. The result is a percentage of non-compliant customers for every LV transformer primary side voltage. To maintain this percentage below 1% it was found that the voltage on the MV side of every LV transformer should be maintained between 0.94 and 1 pu. However, if a less conservative figure of 5% of non-compliant customers is adopted, a wider voltage range from 0.91 to 1 pu could be considered.

The application of these LV constraints was demonstrated using a real MV network considering a daily time-series analysis. It was found that a voltage reduction of up to 3 taps can be introduced under a “low risk scenario” in terms of non-compliant customers (i.e., less than 1%). Ultimately, these results, due to their time-varying nature and associated risk, will increase operational confidence in triggering the CVR scheme to different extents throughout the day.

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