Voltage Reduction Field Trials on Distributions Circuits

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***Abstract*—This paper describes field trials of voltage reduction on nine distribution circuits. The median CVR factor was 0.6 on these circuits. Results were normalized using measurements from nearby comparable circuits. Advanced metering infrastructure data on some circuits allowed comparison by customer type. On one circuit, commercial customers had lower CVR factors than residential customers. For residential customers, CVR factors were lower for customers with higher winter loads.**

***Index Terms*—Power distribution, efficiency, conservation voltage reduction.**

I. Introduction

VOLTAGE reduction or conservation-voltage reduction (CVR) as a means of improving end-use efficiency has been studied for many years, with significant interest in the 1980's. Many loads operate more efficiently at lower voltage. With voltage optimization, we are optimizing voltages to loads, so that they operate as efficiently as possible with minimum disruptions.

During this study, we evaluated the energy reduction on nine circuits monitored over a period of at least one year. Circuis in the field trial experiments were operated at normal voltage and reduced voltage on alternate days.

II. Background

The impact of voltage on loads is often quantified as a CVR factor, the percent change in load for a 1% change in voltage. Kirshner and Giorsetto [1] analyzed trials of voltage reduction at several utilities. While results varied significantly, most test circuits had energy savings of between 0.5 and 1% for each 1% voltage reduction at the substation. Their regression analysis of the feeders found that residential energy savings were 0.76% for each 1% reduction in voltage, while commercial and industrial loads had reductions of 0.99% and 0.41% (but, the correlations between load class and energy reduction were fairly small).

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More recently, the Northwest Energy Efficiency Alliance (NEEA) and their contractor RW Beck and several utilities evaluated voltage reduction in the US pacific northwest [2]. They evaluated changes at the circuit level and also changes directly to residential customers. In their evaluation of voltage changes at the circuit level, using temperature adjusted regressions, they found an average CVR factor of 0.69 based on an average substation voltage change of 2.5%.

In NEEA's evaluation of 395 residential customer evaluations, they estimated a CVR factor of 0.57 based on an average voltage change of 4.3% at the customer. The NEEA study found seasonal differences. In the customer evaluation, they found a CVR factor in the winter of 0.5 compared to a summer CVR factor of 0.78.

The NEEA study found even more dramatic changes with reactive power. In their feeder monitoring study, they found that CVR_{var} factors between 3.0 and 3.5 (vars drop by 3% for every 1% drop in voltage at the substation).

Lefebvre et al. [3] reported on tests of voltage reduction at Hydro Quebec. They found a strongly temperature-dependent CVR factor. At 20°C, they estimated a CVR factor of 0.55, and at -10°C, the CVR factor dropped to 0.15. Overall, for their mix of loads, they estimated a summer CVR factor of 0.67 and a winter CVR factor of 0.20 and an overall CVR factor of 0.4.

The evaluation of voltage optimization or voltage reduction is performed following the approach set out by the NEEA study. Voltage is controlled on alternate days as follows:

Normal mode – typical voltage control strategy

Reduced-voltage mode – voltages are lowered using voltage regulators and/or LTC controls

After enough time operating in alternating modes, the variations due to weather and load usage will even out, and we should see the impact of the difference in voltage.

Primary metering from the substation was available to monitor voltages, real power, and reactive power usually at 15-min intervals. Several of the circuits had wide advanced metering infrastructure (AMI).

There are a number of different ways to implement a reduced-voltage mode. For this study, all voltage control was implemented by local regulator or LTC controls. The reduced-voltage mode was implemented as a change in the voltage setpoint or a change in the voltage setpoint along with the addition of line-drop compensation. On some circuits, line-drop compensation was needed to prevent voltages from going too low under peak load. No significant measures were taken to adjust voltage profiles to accommodate reduced voltages; neither capacitors nor voltage regulators were added to flatten voltage profiles.

III. Regression Approach for Normalization

Because we are dealing with energy consumption changes on the order of one to three percent, and loading is highly variable, it takes many months of data to be confident in results. Using a regression model to normalize the voltage effect helps reduce the amount of data needed to get a statistically significant estimate of the voltage effect.

In the NEEA pilot feeder study, feeder-level energy consumption data was temperature normalized using heating-degree hours and cooling-degree hours.

For the voltage optimization trials in this project, we attempted temperature correction along the lines of the NEEA method, but we found that using a regression approach using measurements from a similar circuit resulted in a better regression model. Compare the two regression models in Fig. 1 and Fig. 2. Each graph includes plots of daily average power consumption, one plotted against average daily temperature and another plotted versus the average power consumption of another circuit with a similar load composition. Each point represents the average results for one day. Other than a few outliers, the model based on the comparable circuit has a higher coefficient of determination (R^2) and a higher degree of statistical significance based on the term related to the voltage control mode.

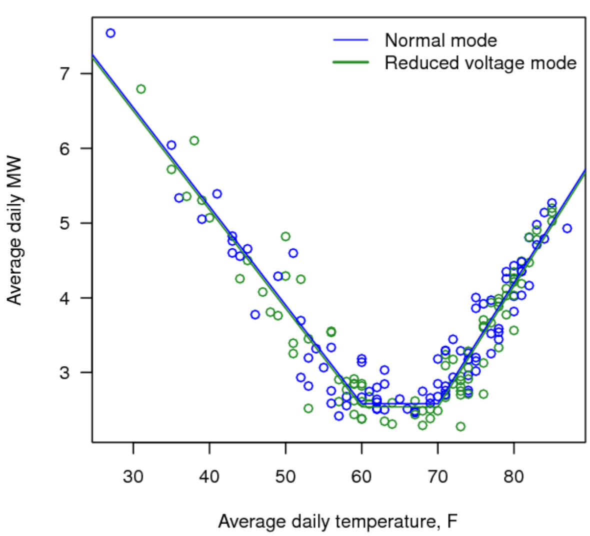

Fig. 1. Temperature normalization.

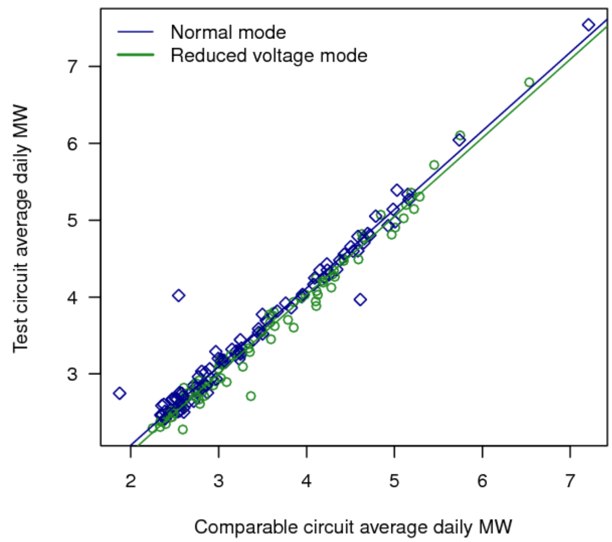

Fig. 2. Comparable-circuit normalization.

The most straightforward comparable-circuit linear regression model is as follows:

$$MW = k_1 \cdot MW_{comparable} + k_2 \cdot V_{state} + k_0$$

where

MW = average power of the test circuit

$MW_{comparable}$ = average power measured at a comparable circuit

V_{state} = 1 for normal voltage, 0 for reduced voltage

k_0, k_1, k_2 = regression coefficients

Especially for determining prediction intervals, we used the following adjustments to improve the results from the linear regression models:

Outlier removal – Outliers can significantly skew results. Outliers can occur because of unusual load patterns (holidays, possibly) or from circuit changes (outages or other feeder switching on either circuit). We excluded days manually based on the regression residuals (days with large errors between predicted and measured).

Autocorrelation adjustment – Time series data has autocorrelation, meaning that the data is correlated with itself. One day tends to look like the next. In linear modeling, we need to account for this, especially for determining confidence intervals.

Analyzing daily data proved to be sufficient for the normalization. Using hourly data did not improve confidence intervals on regression estimates for circuits in which we tried this.

IV. Overall Results

See TABLE I for characteristics of the nine test circuits. Most of them were in the Southeast United States. Most had mainly residential load. TABLE II summarizes the results from the normalized regression model used to estimate the energy reduced along with the confidence interval. The CVR factors ranged from 0.5 to 0.9.

TABLE I
CIRCUIT CHARACTERISTICS

	Voltage kV	Number of customers	Circuit miles	Location	Percent residential
A	34.5	3597	105	SE US	75
B	34.5	800	8	SE US	80
C	12.5	1545	73	SE US	97
D	20.0	1515	90	Europe	N/A
E	20.0	903	5	Europe	N/A
F	12.5	1379	48	SE US	96
G	12.5	721	38	SE US	97
H	23.9	2867	48	SE US	94
I	23.9	2088	37	SE US	94

TABLE II
VOLTAGE OPTIMIZATION RESULTS FROM FIELD TRIALS

Circuit	Monitor Days	Voltage Reduction	Energy Reduction [95% Confidence Interval]	CVR Factor
A	729	3.28%	2.01% [1.65, 2.37]	0.613
B	729	3.29%	0.23% [-0.42, 0.89]	0.071
C	664	2.50%	2.14% [1.77, 2.52]	0.858
D	379	2.98%	2.09% [0.86, 3.32]	0.701
E	379	2.98%	1.66% [0.95, 2.36]	0.556
F	345	3.57%	2.38% [1.93, 2.82]	0.665
G	519	3.95%	2.40% [2.03, 2.77]	0.608
H	430	2.00%	1.17% [0.97, 1.37]	0.584
I	430	2.00%	1.51% [1.27, 1.75]	0.756

Fig. 3 shows the energy reduction compared with the voltage reduction based on the results in TABLE II. The confidence intervals were relatively tight. The two European circuits had the widest confidence limits. Note that the voltage changes given were based on substation measurements. The percentage changes in customer voltages were likely to differ from the substation values. Fig. 4 shows the same data with CVR factors on the Y axis. The CVR factors stayed approximately the same or declined slightly with a deeper voltage reduction.

The one data point that stands out is Circuit B, which did not have a statistically significant energy reduction. Circuit A—a circuit fed from the same bus as Circuit B—had energy savings that were statistically significant. The load characteristics seem similar. Circuit B had less loading than its sister circuit, and the instrumentation may not have been as accurate as a result. Circuit B had some office park commercial load, and Circuit A had more restaurant type commercial load, but both were still composed of more than 75% residential load. Overall, the difference between the two circuits remains a mystery.

Voltage reduction was typically less effective in the winter as shown by Fig. 5. "Summer" is defined as June through August; "winter" is December through February; and the remaining months are "shoulder" months. The median circuit CVR factor in the winter was 0.33. The median CVR factor during the summer was 0.77.

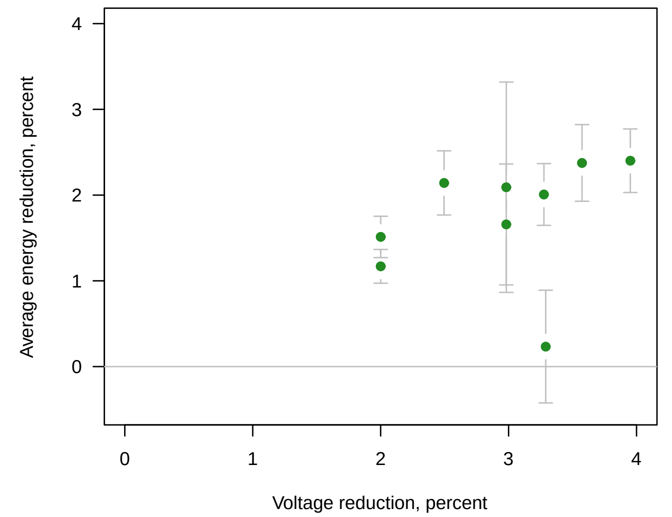

Fig. 3. Comparison of energy reduction and confidence intervals.

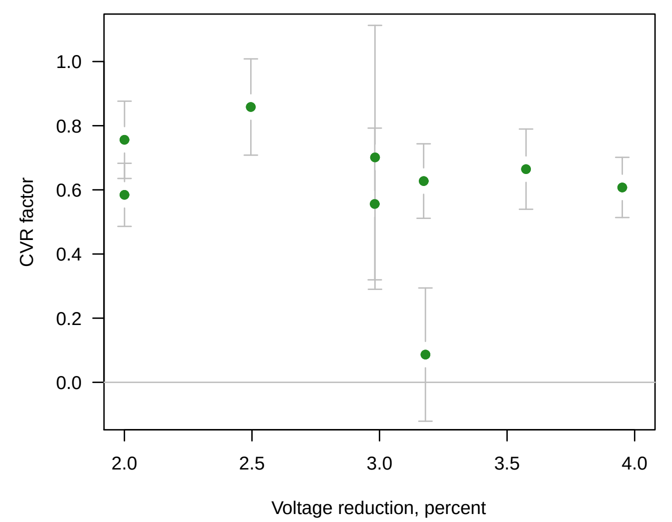

Fig. 4. Comparison of CVR factor and confidence intervals.

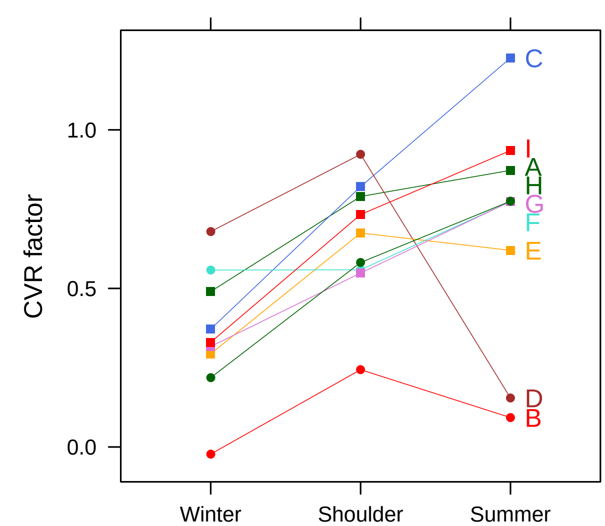

Fig. 5. CVR factors by season.

V. Analysis of Metering Data

Four of the circuits in the voltage-reduction field trials had advanced meters on some customers for parts of the field trial. Advanced metering infrastructure (AMI) data can help an investigator better determine the response by customer type and find out which customers see more benefit from voltage reduction. Fig. 6 shows statistical distributions of measured voltages on the circuits with AMI when operating in normal mode. This set of circuits had significant room for voltage reduction without additional feeder voltage flattening. The median customer meter voltage on these five circuits ranged from 122 to 123 V. Ninety-nine percent of customer voltage readings were above 117.5 V on these five circuits.

For Circuit A, an AMI dataset of 3744 meters covered 23 months of day-on/day-off operation. On this circuit, hourly watt measurements were recorded. Voltage was also recorded, but it was a spotty measurement without much precision. Both residential and commercial customers were monitored. Reactive power was not measured by the meters.

The analysis approach for the AMI data was similar to that for feeder-level analysis. The meter data was grouped together, and then the energy reduction was estimated based on a regression of average daily watt readings for the grouping. As with the feeder-level estimates, the customer-group estimates were based on regressions based on comparable circuits. The same regression model was used for the complete circuit as was used for the customer subsets. One difference is that outliers were excluded automatically rather than by hand.

Circuit A had considerable commercial load. One of the main questions about voltage reduction is how effective it is on commercial loads. Fig. 7 shows a breakdown for four load classifications for the metered customers on Circuit A. Fig. 7 shows clear differences by customer type. Not surprisingly, lighting loads had the largest reduction in energy. The commercial load on this circuit was mainly shopping, bars, and restaurants. This type of commercial load appears to have had less reduction in energy than residential load.

In Fig. 7, the right-most column of graph panels shows the energy reduction for that set of customers. The red dot marks the estimate of the energy savings with voltage reduction, and the gray line marks the 95% confidence intervals around the estimate. The left two columns of graph panels show yearly and hourly customer usage profiles for each grouping of customers.

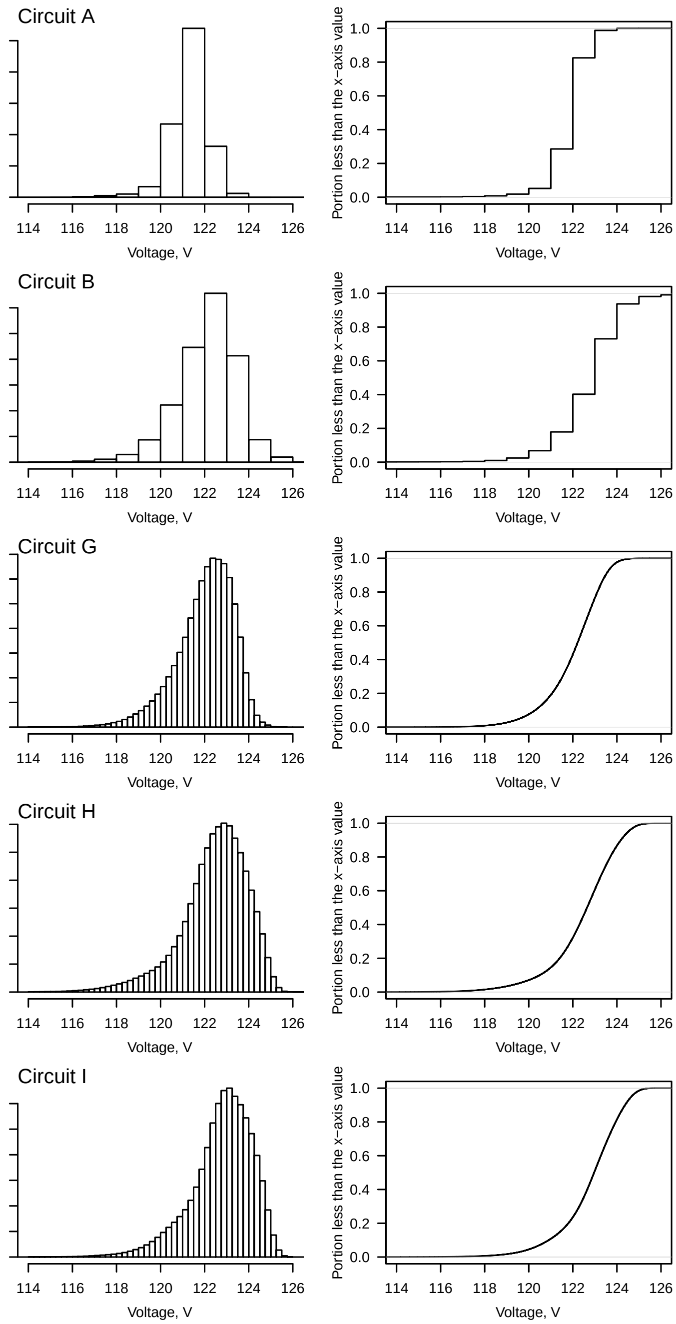

Fig. 6. Statistical distribution of customer voltages by circuit.

On Circuit A, the average voltage reduction at the substation was 3.28%. Because this was a relatively short 34.5-kV circuit with little voltage drop, the customer voltage reduction was likely to be similar to the feeder-level voltage reduction. Based on a 3.28% voltage reduction, the CVR factors for the each category are shown in TABLE III.

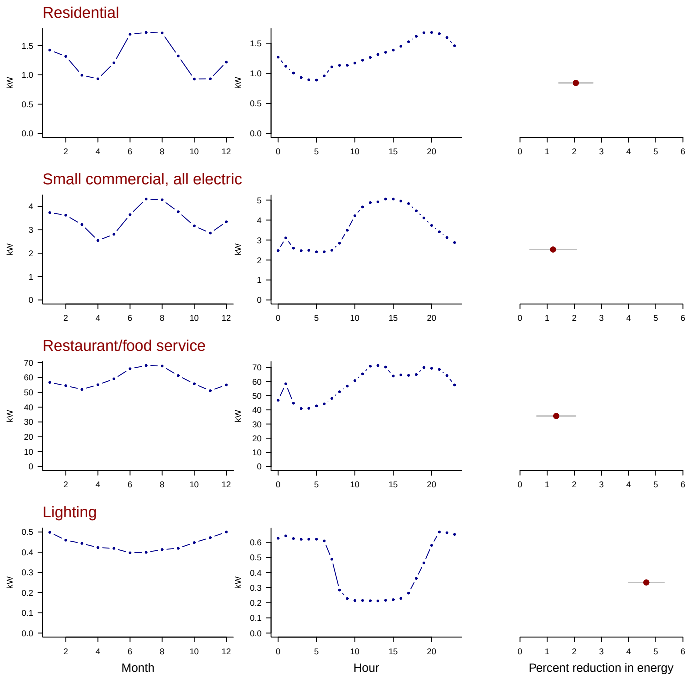

Fig. 7. Energy usage profiles by customer class with energy reduction from voltage reduction for circuit A.

TABLE III
CIRCUIT A CVR FACTORS BY CUSTOMER TYPE

Customer Type	Energy Reduction in Percent	CVR Factor (ΔW / ΔV)
Residential	2.06	0.63
Small Commercial	1.22	0.37
Restaurant	1.33	0.41
Lighting	4.65	1.42

Annual load profiles showed significant difference between customers by season. Fig. 8 compares groups of customers clustered by normalized monthly usage profiles. Clustering was done with the widely used K-means algorithm. In Fig. 8, "summer" is defined as June, July, and August; "winter" is defined as December, January, and February; and "shoulder" is defined as April, October, and November. All five customer categories had similar energy reductions of about 2% in the summer. The summer-peaking groupings in the top graph panels had more energy reduction than did the winter-peaking groupings in the bottom panels. Low gains in the winter for winter-peaking loads were likely from thermostatically controlled resistive heat loads, which have constant energy usage despite voltage reductions. Heat pumps were common in this service territory, and these often had resistive heating elements to boost heating on colder days. Shoulder months tended to have a higher percentage savings, possibly because there was relatively more lighting load during that time.

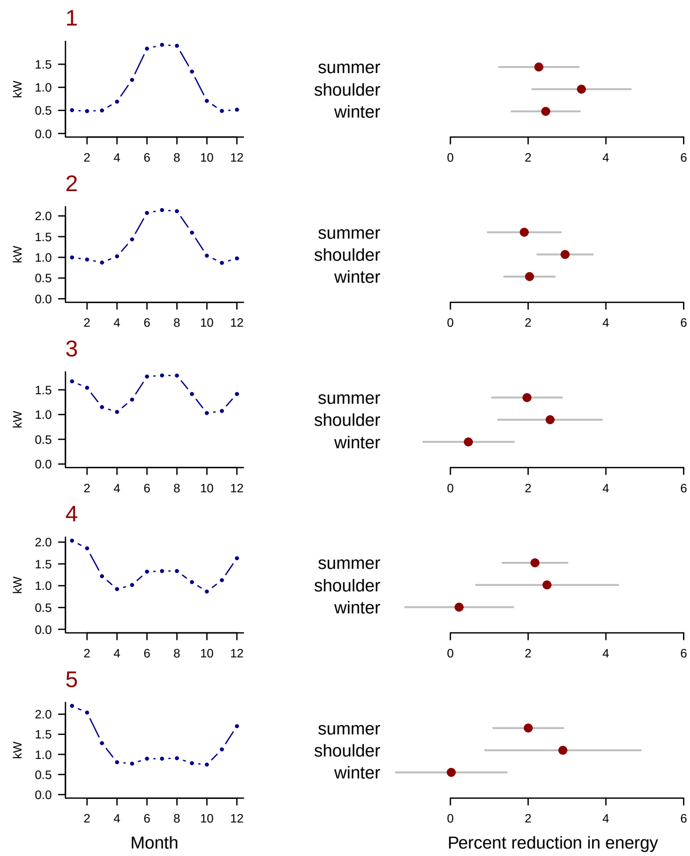

Fig. 8. Daily profile grouping with energy reduction from voltage reduction by season for residential customers on circuit A.

VI. REACTIVE POWER IMPACTS MEASURED BY AMI

Reactive power impacts of voltage reduction were significant. The reactive-power measurements from the AMI meters on Circuits G and H allowed us to better evaluate the impact of voltage reduction on reactive power. This was especially helpful because estimating load reactive power at the substation would be difficult because of the presence of switched capacitor banks.

TABLE IV shows reactive-power CVR factors for two circuits with quite different levels of voltage reduction. These CVR factors were based on the voltage change at the customer. The CVR var factors for both were above 4.

TABLE IV
CVR VAR FACTORS FOR CIRCUITS G AND H

Circuit	Voltage Reduction in Percent	Reduction in Reactive Power in Percent	CVR var Factor (Δvar / ΔV)
G	4.0	17.0	4.3
H	1.9	9.9	5.3

Fig. 9 shows CVR var factors for customers on Circuit G as split out by residential rate category. Differences by rate category were not dramatic.

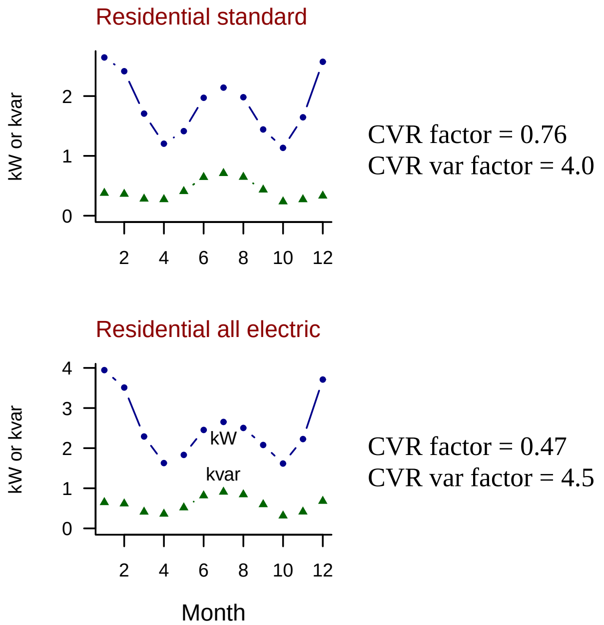

Fig. 9. CVR factors by customer billing class for AMI subset G.

VII. Customer Complaints From Voltage Reduction

For the most part, there were no complaints on circuits operating at reduced voltage. On Circuits D and E, which were fed by the same LTC, there were complaints after the field trial was initiated. The utility reduced the level of voltage reduction, and no additional complaints were received. Properly tuning the voltage reduction is an important component of voltage optimization, possibly requiring modeling and analysis of voltage profiles, responsiveness to customer complaints, and field measurements.

VIII. Summary and Conclusions

This set of field trials, mainly in the Southeast United States, confirmed energy use reductions from reducing voltage. Energy reductions were comparable to those found in the Northwest United States by NEEA. The median CVR factor of the set of nine circuits studied was 0.61, meaning that for every 1% drop in voltage, the average energy dropped by 0.61%. Analysis of AMI data from some circuits showed the most energy savings from summer-peaking residential customers. Winter heating load showed the least energy savings. While the test circuits were mainly dominated by residential customers, where commercial data was available, these commercial customers had less energy reduction than residential customers.

Reactive power reduced even more dramatically than real power. CVR factors for reactive power were over four in two circuits with AMI data.

Customer complaints or problems associated with reducing voltage were minimal. On one circuit, the site utility received complaints after the field trial was first started, but these were remedied by reducing the level of voltage reduction. No other significant complaints or operational issues were reported by utilities running the field trials. Based on monitoring on the primary and on the secondary for those utilities with AMI, this set of circuits had significant room to lower voltage and still be above the 114-V ANSI C84 range-A lower limit at the service entrance during most of the year.

These field trials have identified the energy savings of voltage reduction on several trial feeders. More research in this area would be beneficial, especially work aimed at the following:

Develop a method to predict CVR factors based on load composition. This would allow better confidence for energy conservation groups or regulators to award funding for voltage-optimization programs.

Quantify energy reductions on different types of commercial and industrial customers. These test circuits had mostly residential loads.

Predict future changes to CVR factors based on changes in load composition. As load compositions change from incandescent to LED lighting and as plug-in electric vehicles gain traction, these may change the effectiveness of voltage reduction.

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