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Assessment of Conservation Voltage Reduction in Distribution Networks with Voltage Regulating Distribution Transformers

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Abstract: The application of voltage reduction in medium and low voltage grids to reduce peak power demand or energy consumption has been implemented since the 1980s using several approaches. Conservation Voltage Reduction (CVR), as one such approach, uses a voltage control device to reduce or increase the voltage setpoint on a busbar, thereby reducing or increasing the amount of active and reactive power supply in the network. Voltage regulation for CVR is always implemented according to established network planning standards in each country. Research in this field has proven that a CVR factor (CVR_f) of 0.7–1.5 for peak demand reduction can be achieved. This is an evaluation metric of CVR. The aim of this research is to determine and validate CVR_f for peak demand reduction by comparing actual results obtained during regular tap changes with other randomly distributed periods outside tap change operations, using a set of measurement data. It is important to understand CVR deployment capability by evaluating CVR potentials from historical random tap operations before a robust network-wide deployment is introduced. This research provides such guidance. It also provides a novel approach to determining tap changes from voltage measurements using a time-based algorithm. A CVR_f ranging from 0.95 to 1.61 was estimated using a measurement dataset from a test field. The result of the entire evaluation shows that the CVR_f are smaller during peak PV production and greater during peak demand periods. Further evaluation using statistical hypotheses testing and a control chart was used to validate the evaluation.

Keywords: conservation voltage reduction; peak power; tap change; voltage regulating distribution transformers

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1. Introduction

The increase in power demand due to the rise of electric mobility, heat pumps, distributed generation, and overall economic development has stretched the current German electricity distribution network to its maximum capacity [1]. Network expansion is considered to be an inherent challenge as a result of increasing electricity demand from current and future building construction in the distribution network [1]. Although the infrastructure cost of expansion can be curbed by implementing new grid optimization technologies, a few challenges remain. These challenges include a limited regulatory framework for wide adoption of the new technologies, additional equipment upgrades to improve grid compatibility, and implementation of Supervisory Control and Data Acquisition (SCADA) or advanced measurement devices for proper monitoring and measurement [2,3].

Demand is met with an increasing generation (at the distribution level) from Renewable Energy Sources (RES) such as photovoltaic (PV) or wind power. Integrating RES into the grid requires a proper evaluation of voltage stability and other factors that can negatively influence the power supply. Consequently, optimizing power supply by deploying Demand Response (DR) and Volt/Var Optimization (VVO) can save huge infrastructure costs in additional generation and expansion while achieving set emission reduction targets for 2050 [4–6]. DR relies on demand-side collaboration in establishing a load control protocol. Such a protocol can be initiated through an advanced distribution management system (ADMS). VVO concepts apply voltage regulation techniques in power flow control and assessment. It also makes use of CVR application techniques such as capacitor banks, voltage regulators, or tap changers [7].

CVR factor evaluation techniques define a systematic methodology for determining the ratio between voltage and power reduction. Its results help the grid operator to plan and understand the periods where CVR deployment will be most beneficial [8]. From a bottom-up approach, load models are analyzed for each feeder connection on the secondary substation using several methods categorized as static, dynamic [9], and composite load models [10,11]. The most used model is the ZIP model for static load modeling [12]. It represents constant impedance, constant current, and constant power loads on the consumer side from which active and reactive power responses can be computed [11]. A simplified method for obtaining CVR factors from the reactive and active power responses in a ZIP model has been researched [8]. A composite load model was developed in [13] by combining individual load profiles of representative loads from domestic appliances for each load class of the ZIP model. In [12], a ZIP model was developed for nationwide CVR evaluation. Top-down CVR evaluation techniques make use of a reduced voltage setpoint to achieve load demand reduction from residential and industrial consumers in a distribution grid. It determines the amount of load demand reduction during peak and total energy savings achieved for a specific duration. By carrying out this operation regularly or based on a scheme, the utility can channel the excess energy toward critical demand areas or new expansion. In this context, the CVR factor (CVR_f) is the ratio between a percentage change in power or energy corresponding to a percentage change in the voltage.

$$CVR_f = \frac{\%\Delta P}{\%\Delta U} \tag{1}$$

U and P represent voltage and power, respectively [5]. A similar equation can be used to express CVR_f for energy by replacing $\%\Delta P$ with $\%\Delta E$. In the recent past, the application of CVR has resulted in noticeable savings in energy based on the results of the research conducted so far. In such an application, the voltage can be lowered to a specific limit that will not affect the end-user appliances. These limits are usually around $\pm 10\%$ which is always sustained in the medium voltage (MV) and till the end of the line on the low voltage (LV) level [14].

Many North American and a few European utilities have carried out CVR assessments in several test sites. In their research, the CVR_f results range from 0.71 to 1.34 [7,15–18]. The Smart Street project by Electricity Northwest (ENWL) in the United Kingdom achieved energy savings of 5–8% in rural, urban, and dense urban LV networks [19]. In North America, the CVR project for peak demand reduction of the Snohomish County in Washington achieved 0.59–0.89 CVR_f [20]. Current research in this field with influence from RES, with the implementation of DR, shows that more savings can be achieved by improving and automating voltage reduction during peak demand.

In Figure 1, the voltage regulating distribution transformer (VRDT) equipped with an on-load tap changer (OLTC) which can be used to deploy CVR, is becoming prevalent in distribution substations in Germany. The economic benefits of peak power reduction have inspired this research. The OLTC components perform the tap operations that reset the voltage to a desired level. This device can consist of a simple or complex mechanism depending on size and manufacturer. One such mechanism is the high-speed-resistor-type technology combined with vacuum tubes [21]. Therefore, the component price relative to the VRDT can range from 20% to 40% [1]. Using measurement data from test fields, statistical evaluations can be carried out to find out (1) how much power can be saved by implementing CVR through VRDTs, (2) does PV integration in the network impact the daily variation of CVR_f, and (3) what effect does the estimation of mean power for each tap operation have on CVR_f. Several statistical and programming tools have been deployed during this evaluation. This research applied Big Data analytic processes in determining and validating CVR.

Figure 1. A VRDT with an OLTC [22].

1.1. Literature Review

1.1.1. Operating Principles of VRDTs

Distribution transformers are electrical devices used to regulate voltage within a distribution network. Distribution transformers operated at the secondary substations can regulate the voltage at the desired setpoint. Voltage regulation can be deployed manually or automatically in response to power demand. This kind of transformer is the last power asset where such control can be deployed before reaching the end users. The demand for VRDTs is determined based on terminal voltage limit deviation. According to EN 50160, VRDTs can be installed selectively within the network [14]. The decoupling between the MV and LV is necessary to create a voltage transition from the VRDTs [14]. Voltage limit violations are set at ±10% of nominal voltage, such as the IEV 601-25-25 specification. A 230 V nominal voltage will reach its upper and lower thresholds at 253 V and 207 V, respectively. However, a voltage setpoint is required in order to trigger a tap change. A permitted bandwidth of ±2.5% is applied during the VRDT operation configuration.

1.1.2. Data-Driven CVR Evaluation

The estimation of CVR using measurement data from test fields has proven to be an efficient top-down approach. Datasets recorded by SCADA systems in a digitized distribution network can easily be transmitted to a central data center and retrieved in batches for CVR evaluation, network monitoring, and other performance management implementations. The methodology presented in this research supports the need for a rapid and automated evaluation of CVR in a distribution network. Network operators can simply host CVR evaluation algorithms natively within their network planning infrastructure and supply it with data. Feeder data were collected from test fields for this research. Characteristic test fields are selected based on the defining factors that can influence DR [5,12,23–25]. A comprehensive report on extensive field testing of CVR across substations in the USA showed that for a 5% reduction in voltage, a corresponding 1–3% reduction in peak power demand was observed [26].

The methodologies identified for computing CVR_f are comparison-based, regression-based, synthesis-based, and simulation-based [27]. The two-feeder approach implemented in two studies [20,24] is a typical comparison-based method where two similar feeders are used for testing. The first feeder is used for measuring voltage (U), active power (P), and reactive power (Q) during normal operating (CVR-off) conditions. The second feeder is used for measuring U, Q, and P at a reduced voltage setpoint (CVR-on). However, using one feeder, the CVR on/off test can be carried out at different times but under similar weather and load conditions. In two investigations [28,29], a regression-based model was used for estimating the load for CVR off during testing. Using a linear regression model [29], CVR_f ranging from 0.5–0.9 were obtained. Other researchers applied the synthetic approach to individual load types based on their voltage sensitivity function and used it to estimate energy consumption for industrial, commercial, and residential consumers [30]. This estimation method does not consider weather dependency on energy demand. The common approach of estimating load during normal operations for the testing period has been applied in multiple investigations [27,31,32] using various forms of statistical modeling. These methods emphasize understanding the load composition and the relationship between voltage changes and changes in load composition. In terms of error handling and uncertainty mitigation, their approaches vary from one another. A load uncertainty prediction from the normal distribution of the time series of response loads was applied by Hossan and Chowdhury [31]. The magnitude of the uncertainty was directly determined by the 95% confidence limits of the standard deviation of the load. Approaching CVR_f estimation by modeling load changes analytically; the emphasis should be placed on the accuracy of the estimated load. This is the center of methodology verification adopted in this study—the difference in estimated CVR_f and that of an expected CVR_f. This approach was tested using nine months of data from five feeders during peak demand.

Another methodology to consider is the one developed in the KEPCO pilot testing project [5]. CVR_f was computed using P, Q, and U measurements from the various feeders, using the Mean Absolute Deviation (MAD) direct method. This method applies various filtering measures to the U and P, Q changes based on their magnitude, causality, and direction of the initiating tap change. Percentage changes are determined at the point of switching on the VRDT from measurement points on the feeders. Changes in power are calculated directly from the corresponding datasets without estimating CVR-off power using regression models, hence the direct method. To account for uncertainties and variations in load, MAD considers the maximum and minimum load in the dataset. Applying these to the KEPCO pilot project, CVR_f for active power obtained was in the range of 0.72–0.78. For reactive power, the range was 7.36–18.73. One key observation is that voltage changes of 0.5–1.5% that was used to evaluate CVR_f are below the magnitude of noise and measurement uncertainties found in our dataset. Therefore, tap changes of $\pm$1.5% cannot be used to compute CVR_f due to the uncertainties in the measurement data.

This research provides a novel approach for identifying tap changes associated with CVR using a measurement-based algorithm. It also provides a statistical approach for validating CVR_f results. Energy digitalization and the resulting power system data help to feed the measurement-based algorithms and strengthen the knowledge of system behavior to apply CVR techniques. In Section 2, this paper presents the methodology for identifying tap changes, and in Section 3, the method is applied to a dataset to compute CVR_f and validated with respect to the obtained results. In Section 4, the conclusions of the research work are given, and further research potential is provided.

2. Materials and Methods

Power demand reduction from CVR can be computed using known tap positions from the VRDT. A well-planned measurement campaign takes measurements of U, P, Q, and tap positions at a particular time and known intervals. It ensures that the measurement interval is set at an adequate granularity so that enough CVR events are recorded in order to improve the statistical accuracy of the computation. In the literature, sample size can influence the error magnitude of a derived function or key performance indicator (KPI), such as CVR_f. To achieve higher accuracy in this research, the duration of the evaluation was extended to include all tap changes in 2020.

2.1. CVR Factor Evaluation Methodology

The best CVR_f computation methodology accounts for natural variations in voltage and power by applying several filters for maximum and minimum limits of power and voltage changes resulting from sudden events such as outages and natural distortions. In order to ensure that voltage response magnitudes are significantly higher than the noise magnitudes of the natural variations in the given voltage measurement, tap operations were carried out within a percentage voltage change interval of 2.1–5.5%. This range falls approximately within the common execution intervals of CVRs which is 2–5% [4]. In this research, the averaging interval (t_m) was used to determine the average voltage change before and after a tap change. A time-step resolution t_i found in the interval for evaluation constitutes the number of samples in t_m. The interval of t_i is 10 s. This interval represents the delay time before a tap change and the OLTC switching operation time. An accurate interval for t_m is affected by the standard deviation of voltage variations before and after a tap change.

CVR_f estimation by the direct method is defined as the ratio of the percentage change in power to the percentage change in voltage. The number of samples that will be adequate for estimating an accurate CVR_f was determined from the number of tap changes detected during the testing period. A complete tap operation consists of a tap down and tap up or vice versa. For each CVR_f estimate, the magnitude of variation in load affects its accuracy. The distribution of ΔP_m should be Gaussian. This results from the nature of the measurement data as independent and identically distributed within a short duration of the measurement. Sample data with a 20% change in P have lesser variation than another with a 50% change. Let the number of samples for the t_m interval be n_m. As shown in Figure 2, P_{mi} is defined as the mean value of active power before a tap change (*h*–*i*) while P_{mj} is defined as the mean value of active power after a tap change (*j*–*k*). The CVR_f for P and Q can be defined using the equations below. The tap change was measured from the changes in U—similar to Figure 2.

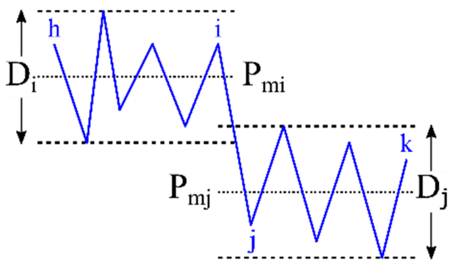

Figure 2. Estimating CVR by the direct method.

$$P_{mi} = \frac{1}{n_m}\sum_{i=t_i}^{n_m} P_i, \quad P_{mj} = \frac{1}{n_m}\sum_{j=t_i}^{n_m} P_j \tag{2}$$

$$\%\Delta P = \frac{P_{mi} - P_{mj}}{P_{mi}} \times 100 \tag{3}$$

$$\%\Delta Q = \frac{Q_{mi} - Q_{mj}}{Q_{mi}} \times 100 \tag{4}$$

$$CVR_{f\_P} = \frac{\%\Delta P}{\%\Delta U}, \quad CVR_{f\_Q} = \frac{\%\Delta Q}{\%\Delta U} \tag{5}$$

If the magnitude of deviation (D_i, D_j) approaches zero, the degree of uncertainty in the estimated mean power reduces. High uncertainty in Q affects the accuracy of CVR_{f_Q}. This tendency was often encountered when Q is stationary around zero.

2.2. Dataset

The dataset for this evaluation was obtained from a test field in eastern Bavaria, Germany. It consists of a continuous 10 s measurement of U, P, and Q in the three phases during random tap operations. It is an LV grid with PV (98 kWp) integration supplying 85 residential consumers. According to the annual profile, the PV output is low or zero (on some days) during the winter months and at night times. The period of testing was 12 months in 2020. The monthly datasets were compiled into CSV file format and were provided for evaluation. After data processing and cleaning, the monthly U measurements in three phases were individually evaluated for tap change detection. Tap change was detected across all phases at the same time. Based on the expected output of the PV system, four time groups (TG) were specified. 16:00–22:00, 22:00–04:00, 04:00–10:00, and 10:00–16:00 are TG_1, TG_2, TG_3 and TG_4 respectively. In TG_2, zero yields are expected from the PV system. Our targeted time group for evaluating the CVR_f results without PV influence was TG_2. PV influence was isolated because it impacts the power demand from the grid.

2.3. Tap Change Detection

The entire duration of a tap change operation was captured in two data points across the whole measurement dataset.

$$d_{(t+2)} = |U_{t+2} - U_t| \geq U_m \tag{6}$$

$$d_{(t+3)} = |U_{t+3} - U_{t+1}| \geq U_m \tag{7}$$

$$if \begin{cases} d_{(t+2)} > d_{(t+3)} : & t \\ d_{(t+3)} > d_{(t+2)} : & t+1 \end{cases}$$

U_m is the magnitude of voltage noise in volts. This was calculated using the value of 2.0% tap change from the nominal voltage setpoint. In this case, it was 4.0 V. The voltage differencing functions $d_{(t+2)}$ and $d_{(t+3)}$ defines the change in voltage from U_t to U_{t+2} and from U_{t+1} to U_{t+3}. At some point, the value of $d_{(t+3)}$ is known to be greater than $d_{(t+2)}$. When $d_{(t+2)}$ is greater than $d_{(t+3)}$, the point of origin of the tap change is t. When $d_{(t+3)}$ is greater than $d_{(t+2)}$, the point of origin of the tap change is $t+1$ (c.f. Figures 3 and 4). A list of potential tap change timestamps is recorded for the individual voltage phases (U_1, U_2, U_3) according to the daily sample sizes (c.f. Figure 5).

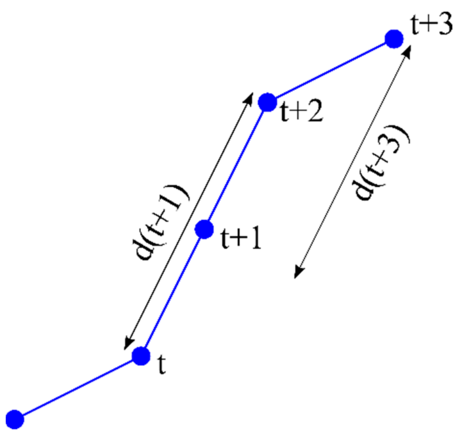

Figure 3. Line plot of voltage rise.

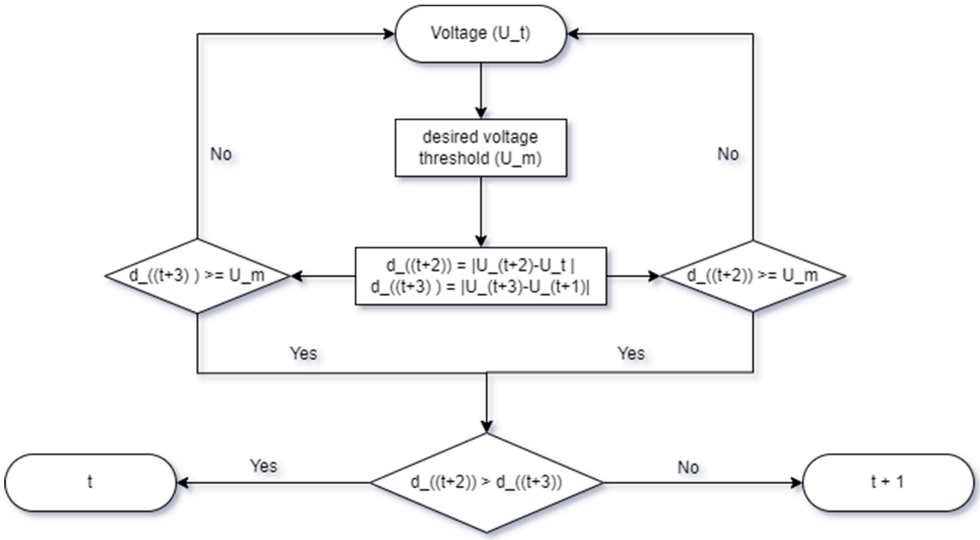

Figure 4. Flow chart of the algorithm used for this study.

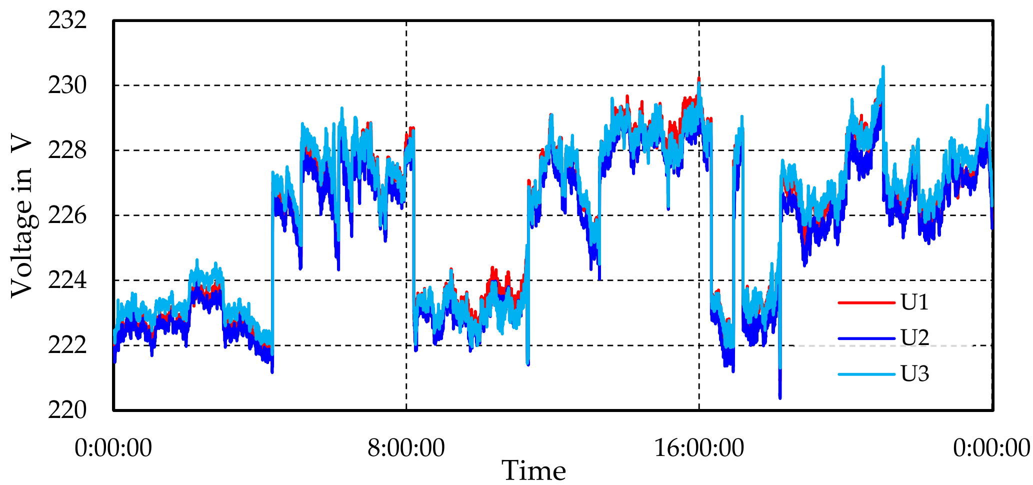

Figure 5. Voltage profiles on 20 January 2020.

The averaging interval (t_m) value is 1 min; a resolution of 10 s implies that $n_m = 6$. If the same timestamps are found across the three phases simultaneously, then a tap change is recorded. With spacing greater than t_m, the timestamp was recorded as the starting point of a new tap change. When there was a detection of two tap changes within the interval t_m, the second timestamp was rejected—physically not possible. In the voltage profile of 20 January 2020, there were seven tap changes that were detected by the algorithm. This process was repeated iteratively on the individual daily profiles of complete days in the season, and their corresponding timestamps were determined.

The voltage patterns observed across the lines were identical at the point of tap change, such that the number of tap operations on each line on the same day was the same. TG_1 and TG_2 contains 969 and 603 values, respectively. The CVR_f evaluation was initially focused on the overnight time group (TG_2 = 22:00–04:00) and evening time (TG_1 = 16:00–22:00). They both contained 524 tap operations during three months of measurement (c.f. Figure 6).

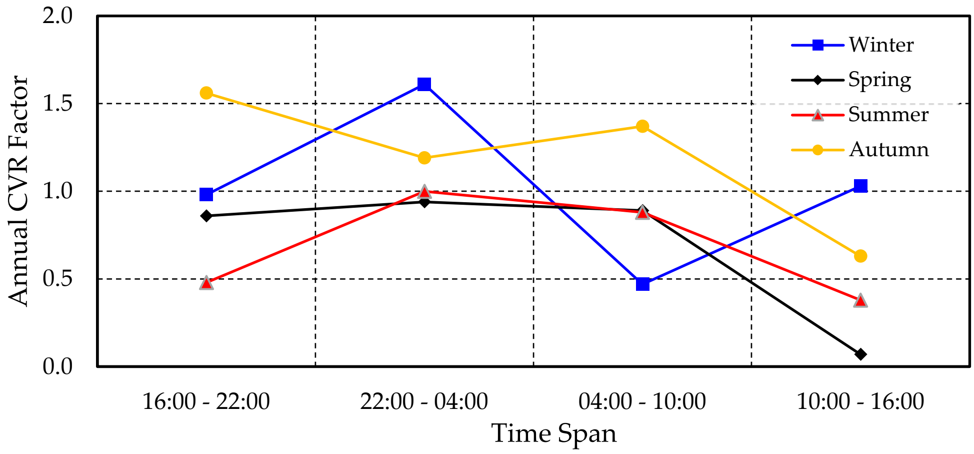

Figure 6. Annual CVR factors for active power.

Daily timestamps without tap changes were recorded; it served as a benchmark for comparing the results of the CVR factors with tap change and without tap change.

3. Results and Discussion

3.1. CVR Factor Computation

At the end of the CVR_f evaluation according to Equation (1), the CVR_f for P and Q are collected separately. Threshold values of outlier filtering conditions were applied to CVR_{f_P} and CVR_{f_Q}, respectively. By filtering, extreme conditions of voltage reduction because of natural changes in consumption patterns were eliminated. For the given dataset, the yearly average CVR factor values for active and reactive power are 1.30 and 4.96, respectively. This means that the CVR effect of a 1% change in the voltage could result in a 1.30% change in the active power and a corresponding 4.96% change in the reactive power. During the summer months, the CVR factors are the lowest. In the winter months, there was a higher result of the CVR factor at night. The CVR factor is generally lower during the day. This could also be a result of higher generation from PV systems on domestic rooftops. Spring months have the lowest CVR factors, as shown in Figure 6. The CVR_f with known tap changes were benchmarked against the CVR_f without tap changes.

These observations vary according to geographical region and climate. Climate and geographical impacts on CVR factor consist of external environmental factors such as temperature and humidity. Temperate climates require additional constant power loads, such as heat pumps and radiant flow heating systems that do not respond to CVR. Regions with a higher percentage of such load types will not experience higher savings from CVR. In tropical climates, however, CVR can produce extensive power savings resulting from higher demand for space cooling and increased load density.

The overall range of active power CVR_f as shown in Figure 6, was 0.70 to 1.61. The reduction in power using a voltage reduction setpoint of 2.5% will be 1.75% to 4.03%. Assuming a peak power demand of 52.5 kW, CVR can yield a 0.92 kW to 2.11. Similarly, the average CVR factor during the peak period (TG_1) was 0.97. Therefore, a peak demand reduction of 2.4% can be achieved using the current setup. This reduction has an economic impact on the overall tariff cost for the consumers. Studies [5,15,33] have shown that a CVR factor estimation of 0.70 to 1.61 is realistic. Our research has advanced further to implement CVR with VRDT in Germany and classify time periods where it is more prominent.

3.2. Result Validation

The hypothesis testing and control chart for CVR_f validation is described subsequently.

3.2.1. Evaluation of Outliers

Distribution transformers operated at the secondary substations can regulate the voltage at the desired setpoint.

From Equation (1), CVR_f is the ratio of percentage change in P and U. The observed range of $+\%\Delta U$ is 1.70–4.03 in December. Therefore, the outlier can be said to originate from load changes across the three phases. According to Figure 7, the sample interval of ΔP contains both actual and outlier values. Using known filtering criteria [5], the outlier values from real changes in P were demarcated. With an average CVR factor of 0.94, the average $\%\Delta P$ is always between 1.60–3.80.

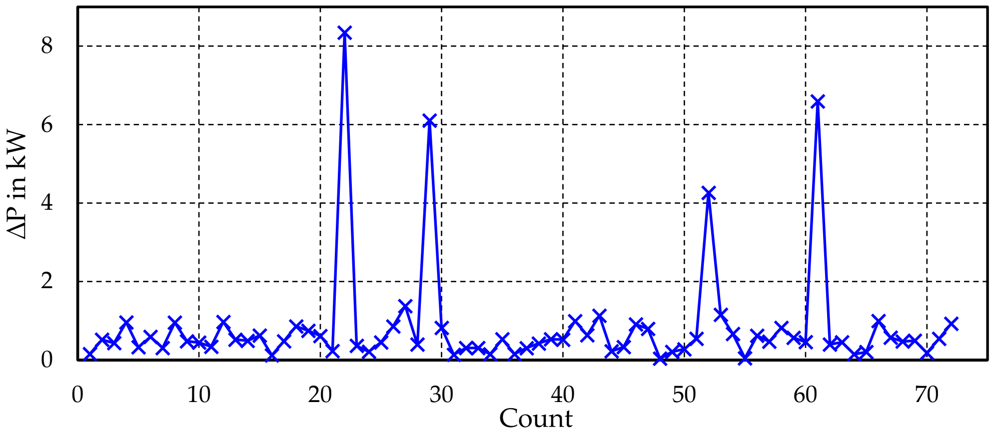

Figure 7. Line plot of outliers.

The four outliers that can be seen from these images show that they have a different magnitude from the rest of the changes in power. They occur randomly throughout the dataset and time sample groups, but they are more common in TG_1 and TG_4.

These outliers can introduce a higher magnitude of standard deviation and variance to the average CVR_f. Such deviation can result in an inaccurate estimation of CVR_f. Therefore, the higher the number of samples, the higher the accuracy of the mean CVR_f value estimation. Using 1000 samples of CVR_f sufficiently produced a z-score of 1.96 at a 95% confidence level. The outliers considered for evaluation in this research were natural variations in the voltage signal and estimation errors. Estimation errors are errors associated with CVR factor computation. This error is encountered when a narrow range of voltage and power change is applied as filtering conditions during CVR_f computation. It reduces estimation accuracy by reducing the number of samples used in mean estimation. However, the voltage and power measurements contain some magnitude of signal noise that did not affect the accuracy of the estimation.

3.2.2. Stationarity of CVR-Off Control Group

Let us consider the randomized control group. The average values of ΔU and ΔP are 0. This is the null hypothesis (H_0) that is to be proven. A rejected null hypothesis (H_a) disproves that the mean of ΔU and ΔP is zero. This is expressed in Equation (11). The stationarity originates from an equal distribution of $\Delta\overline{U}$ and $\Delta\overline{P}$ on the positive and negative real axis $\pm\mathbb{R}$. Alternatively, there is an equal probability of obtaining a positive or negative value from changes in voltage and power.

$$H_0 : \overline{X_i}(t) = 0, \forall i \in \{1, \ldots, n\} \tag{8}$$

$$H_0 : \overline{X_k}(t) = 0, \forall k \in \{1, \ldots, m\} \tag{9}$$

$$H_0 : \overline{X}_i(t) = \overline{X_k}(t), \;\; with\ p_{value} < 0.05 \tag{10}$$

$$H_a : \overline{X}_i(t) = \overline{X_k}(t), \;\; with \; p_{value} > 0.05 \tag{11}$$

Let X_i and X_k be data points from two different sample groups of n and m. The values of X_i and X_k can be positive or negative, while n and m are the sample sizes drawn from a Gaussian normal distribution of independently and identically distributed (iid) random samples. According to Equations (8) and (9), the null hypothesis implies that the mean of the n and m samples should be zero. Equation (10) compares the similarity of the mean values $\overline{X}_i(t)$ and $X_k(t)$, and ensures that it falls within an acceptable statistical significance. The p-value (degree of statistical significance) is the test statistic that describes the error tolerance of the average value $X_i(t)$. A test for stationarity on both sample groups was performed before proceeding to evaluate the null hypothesis. When Equations (8) and (9) pass with a p-value lesser than 0.05, then Equation (10) is tested. Figures 8 and 9 show the depth of the changes in the random sample groups for voltage and power. One can observe that the average value is around zero.

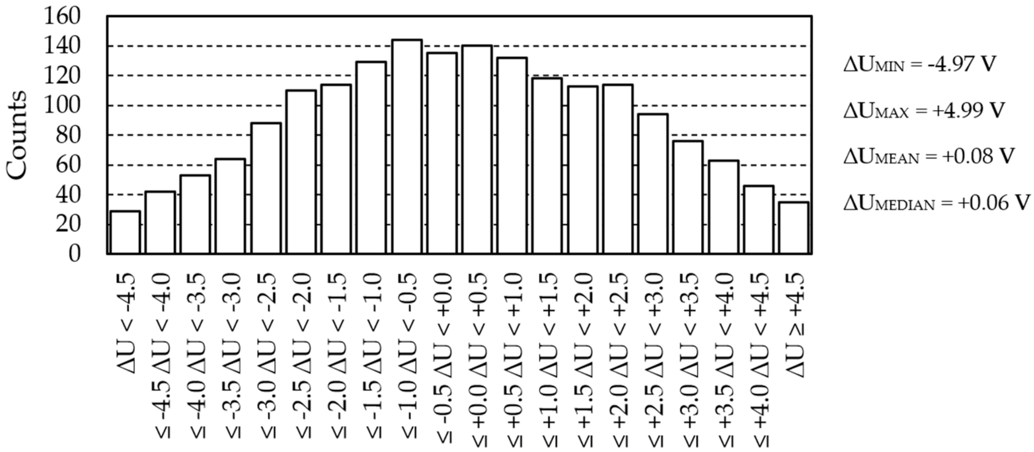

Figure 8. Voltage changes in the random group.

The stationarity test using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests produced a p-value of 0.047 for ΔU samples and 0.100 for ΔP samples. The p-value of ΔU was less than 0.05 according to Equation (10). Conversely, the p-value of ΔP was above the defined limit of Equation (11).

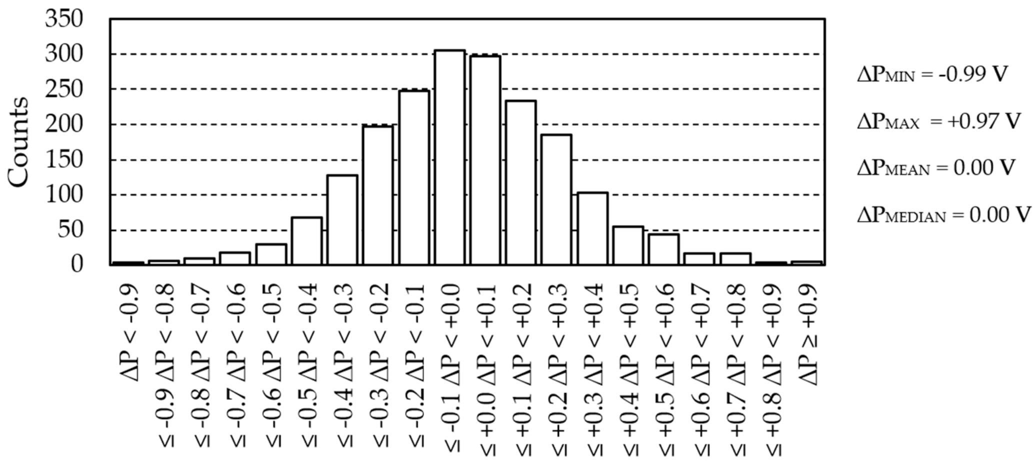

Figure 9. Load changes in the random group.

Therefore, ΔU was stationary while ΔP was non-stationary. Non-stationary data always have a trend. Using the *z*-test [34], *p*-values for Equations (8) and (9) were evaluated. $\Delta\overline{U}$ *p*-value was 0.0497, therefore the hypothesis of H_0 was accepted. $\Delta\overline{P}$ *p*-value was 0.0276, the hypothesis H_0 was accepted. Using the same *z*-test, Equation (10) was evaluated. For ΔU_i and ΔU_k, the *p*-value was 0.0362—null hypothesis H_0 was accepted, and for ΔP_i and ΔP_k, the *p*-value was 0.0249—null hypothesis H_0 was accepted. This evaluation shows that a random sample group of voltage and power changes produces zero effects of CVR.

3.2.3. Sensitivity to Averaging Intervals

The averaging interval for estimating $\Delta\overline{U}$, $\Delta\overline{P}$ and $\Delta\overline{Q}$ was determined to be 1 min. In this section, the target was to study what effect an interval adjustment (halving and doubling) would have on the CVR_f. Increasing the number of data points used in determining the averages has a significant statistical role to play in the final value of the CVR_f and its accuracy. By extending the interval, there could be an improvement in the accuracy of the average values of voltage and power if the noise level, degree of randomness, or trend is insignificant.

The lower the number of CVR_f outliers for a particular averaging interval, the more accurate the estimated mean factor is. Such observation can be seen in the reactive power profile in Figure 10, which is why this evaluation focused on the active power profile. However, if the interval were extended to introduce a trend, then natural variations in voltage and power would begin to influence the results. This was not a problem for a near-stationary profile such as the reactive power profile. The averaging intervals and corresponding results can be seen in Figure 10.

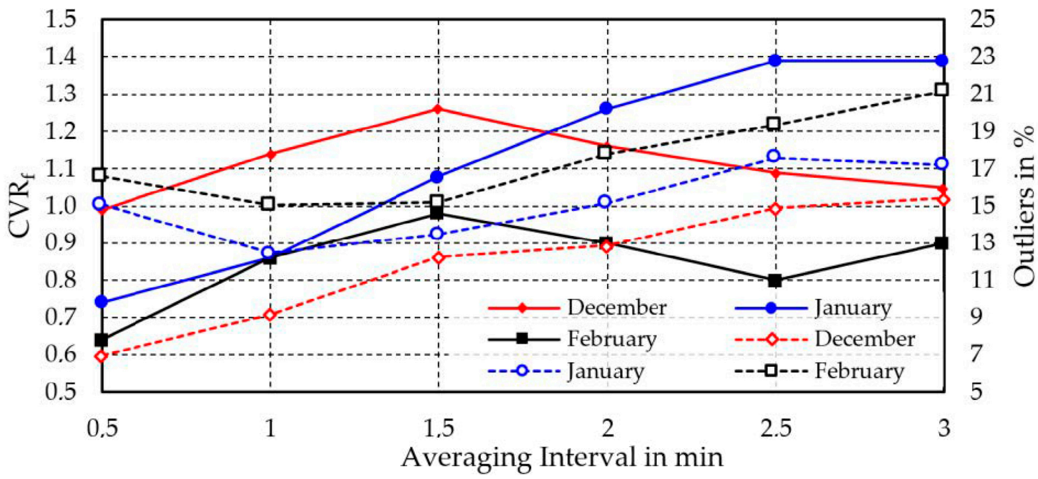

Figure 10. Averaging interval effect on CVR factors.

This figure shows that a rise in the interval size increases the percentage of outliers in the total CVR_f evaluated. This means that such averaging interval includes natural variations in the power consumption that is not just attributed to a tap change. Thus, it can be concluded that a 1.0–1.5-min interval is adequate for estimating the most accurate CVR_f because the average CVR_f in the table above can be found between these intervals. This observation may be peculiar to this dataset.

4. Conclusions

In this project, the goal of validating CVR_f for peak demand reduction using a set of measurement data from representative substations was achieved. CVR was introduced as a method of reducing power demand during peak periods in other to achieve lesser energy consumption and improve the potential for network expansion. The direct method of CVR_f computation with result validation was implemented in this work. This involved the use of statistical significance and hypothesis testing. Our evaluation of average CVR_f for active and reactive power gave 1.30 and 4.96, respectively. The result of the entire evaluation shows that the CVR_f are smaller during peak PV production and greater during peak demand periods. During peak power demand, a reduction of 2.4% was achieved, corresponding to a 2.5% reduction in voltage. These results show that CVR can induce power demand reduction, and its benefits are significant for both utilities and consumers. Voltage optimization and reduction using CVR are excellent and reliable approaches to achieving peak shaving.

The new frontiers of research in CVR and VVO from an evaluation and technology perspective involve integrating digital solutions based on machine learning. Machine learning and AI solutions allow DNOs to evaluate large datasets with all forms of variables that represent the network configuration, consumer behavior, and weather changes. Research in this field should also include demand response management systems. The tools and processes of estimating energy savings from test field datasets have evolved through the years from simple mathematical evaluations and curve fittings to advance statistical and machine learning solutions. Therefore, CVR evaluation methodologies that implement all features of machine learning should be further studied.

Moreover, the sensitivity of reactive power to voltage changes needs to be studied further. It was discovered that changes in reactive power produced CVR_f values that are significantly different from the active power CVR_f. No research project has clearly defined the reason for this. Therefore, further research into this observation is required.

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