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Anomalous Voltage Data Detection: Utility Experience from Large Scale CVR Deployment

M.S. HOSSAN, W. FAN A. COOK, S.A. FARD, E.A. PAASO
Commonwealth Edison Company
USA

A. KHODAEI
PLUG LLC
USA

SUMMARY

Electric utilities deploy Conservation Voltage Reduction in distribution systems driven by the benefits of energy savings and peak demand reduction. The objective is to reduce the energy or demand consumption by operating the circuits in a relatively lower voltage of the regulatory band and make the system more energy efficient. The complexity arises when voltage data due to system operational issues is utilized in benefits evaluation, such as energy savings calculation or CVR factor estimation. To conclude with precise results on benefits evaluation, these operational issues associated data need to be eliminated. In many cases, voltage data due to operational issues are not easily detectable without having detailed knowledge on the system or having other variables checked in parallel to the voltage data. This paper investigates practical algorithms on how data issues related to operation can be detected and eliminated. These algorithms are dependent on system conditions in different CVR states. The algorithms are tested using SCADA voltage data collected from many substation transformers where CVR is being deployed at a utility level.

KEYWORDS

Benefit Analysis, CVR, CVR Status, SCADA, Voltage Anomaly.

mdshakawat.hossan@comed.com

1. INTRODUCTION

Utility companies are relying on the energy efficiency techniques to minimize the gap between generation and end user consumption. In addition, implementation of these techniques can minimize the environmental impacts and operate the system effectively by reducing the consumption [1], [2]. Conservation Voltage Reduction (CVR) is an energy efficiency approach that constantly appeals the utilities for deployment. CVR is a concept within Volt-Var optimization (VVO) that relies on reducing the operating voltage at the substation transformer. Lower operating voltage reduces the energy consumption at the customer end due to load to voltage (LTV) sensitivity [3]. Besides, the reduction of voltage in the substation must be optimal in a way that end users' voltage do not go beyond the threshold of the regulatory limit [4]. As per American National Standards Institute (ANSI) C84.1, voltages at the end user must lie within 114V to 126V in a base of 120V [5]. Thus, in principal, while CVR is deployed the range should be within 114V to 120V or 0.95 p.u. to 1.0 p.u throughout the distribution feeder [1]. With the advent of technology in the smart grid arena, deployment of CVR has been very dependent on the closed-loop control of the SCADA system using the real-time communication [6]- [8]. The voltage can be controlled in an adaptive way depending on the condition (i.e., loading, network configuration) of the system.

It is reported by Pacific Northwest National Lab (PNNL) that around 3.04% annual energy consumption may be saved if CVR is deployed throughout the distribution feeders in USA [9]. In a recent benchmark, it has been reported that several utilities have already deployed or currently deploying CVR in small or large scale program which includes, just to name a few, American Electric Power (AEP), Ameren Illinois Company(AIC), Commonwealth Edison (ComEd), Portland General Electric (PGE), Duke Energy, Xcel Energy [10]. Thus, it is apparent that the utilities those are investing on deploying CVR would like to be able to accurately measure the benefits. Benefits from CVR deployment are captured by an index named CVR factor (CVRf) which is the ratio of change in consumption to the change in voltage. It can be presented as below [9], [11]:

$$CVR_f = \frac{\%\Delta E}{\%\Delta V} \tag{1}$$

Where $\%\Delta E$ and $\%\Delta V$ represent the change in energy and change in voltage, respectively. Consequently, energy savings for an individual feeder is calculated from the derivation of (1) which can be written as below [12]:

$$E_{savings} = E_{baseline} \times \Delta V \times CVR_f \tag{2}$$

Where $E_{savings}$ and $E_{baseline}$ refer to the energy savings and baseline energy consumption. It is evident from (1) and (2) that ΔV plays a significant role in determining the CVR factor and the energy savings. Since the time-series data are utilized for the estimation of %ΔV, any anomalous voltage data can impact the estimate. In general, data quality check is conducted before utilizing these sorts of data in any analytical approach. In most common practices, several quality checks are required for SCADA data which include outlier, repetitive, interpolation, non-numeric/missing etc. [12]. However, no research or any utility report has reported on the data anomalies due to the real-world operational issues of the system based on the actual scenarios. For instance, there may be scenarios like CVR status is showing that CVR is ON, however the voltage level doesn't support the claim or phase imbalance is extremely high if CVR is deployed in individual phases, separately. Addition of such scenarios using actual utility data makes this work unique. Therefore, this paper discusses several data issues that need to be identified and eliminated for estimating %ΔV using time-series voltage data, precisely. Several algorithms are developed to address the challenges with data related to operational issues. These algorithms will drive the identification and elimination of data due to the operational issues and have been tested on more than 200 transformers with the SCADA data. The algorithms are flexible enough for any utility engineer to modify based on the engineering judgement and system operation unlike any sophisticated classification or regression type data-driven algorithm. Moreover, the algorithms can also be utilized with AMI data if deemed appropriate by a utility engineer.

The rest of the paper is organized as follows: Section II provides an overview of the terminologies the utility engineer may utilize for the identification of data associated with operational issues while CVR is deployed, section III describes the algorithms on how the data related to operational issues are identified and eliminated, section IV demonstrates the effectiveness of the algorithms with examples, and section V concludes the paper with remarks.

2. OVERVIEW OF THE MEASUREMENT TERMINOLOGIES

This section discusses the overview of the measurement terminologies that are utilized in the anomaly detection. Besides the SCADA/AMI voltage data, CVR status and low limit (LOLM) alarm signals are also required to determine the anomalies. In the following sub-section, a summary of CVR status detection along with the associated attributes is discussed.

A. CVR Status

Once the command is sent to activate CVR on any distribution station/transformer from Distribution Management System (DMS) or Advanced Distribution Management System (ADMS) software platform, it is not guaranteed that CVR will be activated immediately. There are multiple checks which need to be conducted to ensure that CVR can be turned ON. At first, two things are insured after the activation command is sent: a) Approval of Control Center (CC); b) Substation Condition status. CC status refers to the controllability of the transformer. It checks if any construction, equipment upgrade, or maintenance work is on-going in the associated stations/transformers. On the other hand, substation status resembles if the substation has any network connectivity issue or any outage at that moment. If both statuses return affirmative confirmation, CVR scheduler can be activated.

Next, if CVR scheduler is activated, to check the status of the transformer LTC ensuring ability to receive setpoints (SP), a periodic scanning timer (ST) needs to be sent from the software. ST is a communication signal that is assigned with a default value to detect any misoperation resulting in deactivation of CVR. Thus, the scanning will continue as long as the ST is above a certain threshold. During the time of CVR schedule, the timer receives an automatic reset when it’s about to go below the threshold. Besides, the option to manually reset the timer is also available by any operator. This is visually demonstrated in Fig.1 below with further explanation on different relevant terminologies. If the scanning is properly occurred, a SP will be calculated from the network model and measurements utilized from the field at the backend of the software. The SP defines the LTC operating voltage during the CVR activated period and is calculated with the conditions analyzed by the analog (i.e., power, voltage) and status (i.e., switching) measurements from different locations of the field. Then, SP is compared with secondary load voltage (SLV) and default bandcenter (DB). SLV refers to the load voltage from the secondary side of the transformer and DB refers to the LTC operating voltage that is utilized when CVR is OFF. If the SP is not able to drive the secondary load voltage (SLV) below the default bandcenter (DB) and associated bandwidth, the CVR is not effectively turned ON. At the same time, the SLV needs to be within bandwidth of the SP to follow the typical LTC bandwidth. In a nutshell, the following sequential steps are needed to be confirmed to consider that CVR status is ON:

1) Command is sent to turn the CVR scheduler ON
2) Approval of the Control Center and Substation Conditions are affirmative
3) ST is ON and above a defined threshold
4) SP is calculated and sent lower than DB
5) SLV < DB-bandwidth and SP-bandwidth < SLV < SP+bandwidth

In Fig.1, the timestamps in the highlighted rectangle areas meet the criteria above and confirms that CVR is ON whereas the arrow pointed area doesn't meet the criteria. The saw tooth and/or oscillation nature of the ST is due to the automatic or manual reset of ST. Different corner cases of CVR status detection is discussed in detail with examples demonstrated in [13].

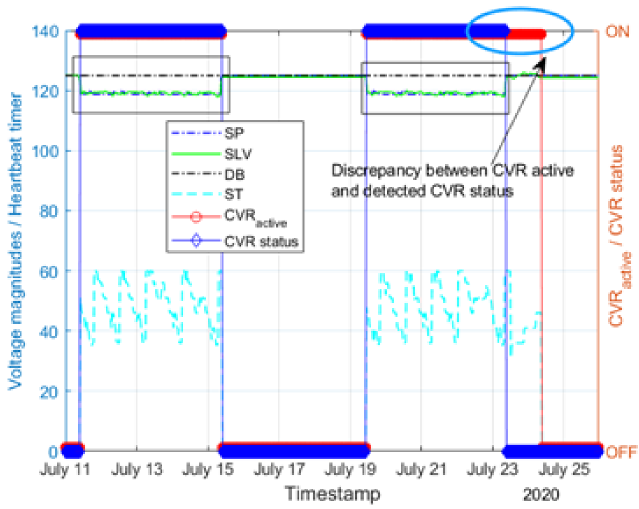

Fig.1. CVR status depending on different factors.

B. LOLM Alarm

There are instances when CVR is deployed and LTC SP hits the lowest possible tap position. At those times, operating voltage is not able to go any lower than the associated DB and bandwidth depending on the loading scenario, and SCADA receives a signal of low-limit (LOLM) alarm. Fig.2. shows an example of how LOLM is displayed. In the next section, this signal will also be utilized to detect some instants where operational issues occurred.

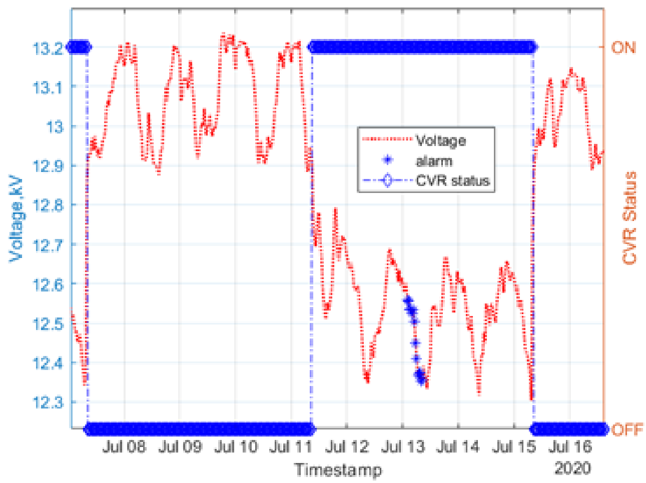

Fig. 2. LOLM alarm during CVR is ON.

3. DETECTION OF DATA ASSOCIATED WITH OPERATIONAL ISSUES

In this section, the anomalous data detection due to system operational issue is discussed based on different scenarios. The scenarios are presented and described in detail with an algorithmic structure.

A. Phase Imbalance

In some certain cases, it is required for CVR to be activated on individual phases. This could cause a scenario where one phase won't operate at the correct SP due to backend calculation or communication issue. This issue leads to a highly imbalanced situation in the LTC SP. If proper reactive power control is not present, imbalance may happen in different nodes of the distribution network due to extreme imbalance in loading. However, SP is adjusted in the LTC, the initial node, where the voltage should remain balanced. Moreover, utilities take pre-emptive measures and control the reactive power to eliminate high imbalance in downstream nodes through the software platform that dictates CVR using different objective functions. Finally, proper activation of CVR should provide certain reduction in voltages. Hence, voltage difference between phases are calculated and checked if any phase has any pre-determined deviation compared to the other two phases based on the CVR status. For example, if CVR is ON and only one phase is reducing the voltage compared to the other two phases, it refers that SP is not adjusted to other two phases due to any operational issue. In this scenario, the phases which are not following the CVR activation are assumed as anomalous data. The complete algorithmic structure is provided in algorithm 1.

Algorithm 1: Detection of Phase Imbalance

Define the time range of data cleaning as T_{Range};

Extract the three phase voltage data within T_{Range} **and store as** $V_{T_{Range,A}}$,$V_{T_{Range,B}}$, **and** $V_{T_{Range,C}}$ **for phases A,B, and C, respectively;**

Estimate the phase to phase difference as
$$Diff_{Ph_1,Ph_2} \rightarrow \frac{\left[V_{T_{Range,Ph_1}} - V_{T_{Range,Ph_2}}\right]}{V_{T_{Range,Ph_1}}},\ Ph_1, Ph_2 = A, B, C;$$

Accumulate the differences together as $Diff_{Total} = [Diff_{AtoB}, Diff_{AtoC}, Diff_{BtoC}]$;

Find the global indices of time instants where two of the differences are greater than a pre-determined value $\ddot{k}$ **in percentage and store in** T_{diff} **as** $T_{diff} = any[Diff_{Total} > \ddot{k}, 2]$;

Find the flags per phase based on the global indices, CVR status, and boundary of the voltage as $T_{flag,Ph}$ **in** $T_{flag,Ph}(CVR_{status} == 0) = [V_{T_{Range,Ph}} < \ddot{z}\ \&\ V_{T_{Range,Ph}} > 0.9 * nominalV\ \&\ T_{diff} == 1]$**; and** $T_{flag,Ph}(CVR_{status} == 1) = [V_{T_{Range,Ph}} > \ddot{z}\ \&\ V_{T_{Range,Ph}} > 1.1 * nominalV\ \&\ T_{diff} == 1]$**, Where** $Ph = A, B, C$;

Accumulate the flags for both CVR OFF and ON instants as $T_{anom_{imb,Ph}} = [T_{flag,Ph}(CVR_{status} == 0), T_{flag,Ph}(CVR_{status} == 1)]$ **Where** $Ph = A, B, C$;

Declare phase imbalance related time instants, $T_{anom_{imb,Ph}}$ **as NaN** $V_{T_{Range}}[T_{anom_{imb,Ph}}] = NaN$;

B. Invalid CVR data

It is mentioned in section II that when CVR status is ON, LTC setpoint may not able to lower voltage if LOLM alarm is ON. However, there may be contrary scenarios, such as LOLM alarm is active when CVR is OFF. This is theoretically not possible since operating voltage should remain near the DB during CVR OFF period or If CVR status is OFF, operating voltage cannot go below the DB and the associated LTC bandwidth. This scenario can happen if CVR ON/OFF test is ongoing. After the testing schedule is OFF, the SP is not able to go back to the DB due to any software, communication, or equipment anomaly that disables the LTC to restore to DB. This detection scheme works as shown in algorithm 2.

Algorithm 2: Detection of anomalous instants due to LOLM

1. **Define the time range of data cleaning as** T_{Range};
2. **Extract the voltage data within** T_{Range} **and store as** $V_{T_{Range}}$;
3. **Find the CVR OFF time instants within** T_{Range} **and store as** $T_{CVR_{OFF}}$;
4. **Find the time instants within** T_{Range} **where LOLM alarm is active and store as** T_{LOLM};
5. **Find the time instants where CVR OFF operating voltage is lower than a pre-deterimined value** $\ddot{z}$ **and store as** T_{Low};
6. **Find the common time instants and store as** T_{bad} **where** $T_{anom_{lolm}} = T_{range} \bigcap T_{CVR_{OFF}} \bigcap T_{LOLM} \bigcap T_{Low}$;
7. **Declare lolm related time instants,** $T_{anom_{lolm}}$ **as NaN;** $V_{T_{Range}}[T_{anom_{lolm}}] = NaN$;

C. Primary and Secondary Measurement lagging

On a CVR activated network, many measurement devices are installed. Data from these devices are being scanned and stored frequently with a certain interval. However, collection of these measurements may have certain lag due to issues related to settings of communication channels and their frequency. This may provide some discrepancies on how these data can be interpreted. For example, if CVR is ON, both transformer primary and secondary side measurements should reflect that by reducing the voltage in same ratio. However, if they don't reflect the same, then, the discrepancy points out to some lagging between the timestamp and their data collection. To accurately perform a study, these anomalous data should be eliminated from the data pool. Detection of these suspicious timestamps depend on the moving or rolling mean calculated based on CVR status, average CVR ON/OFF data, and the particular time instant data. If the data don't have any discrepancy, the moving mean and timestamped data should have very minimal absolute difference and it should be lower than the absolute difference between the timestamped data and average counterfactual (i.e., if timestamped data corresponds to CVR ON, counterfactual refers to CVR OFF and vice versa) data. This detection algorithm is shown in algorithm 3 with algorithmic view.

Algorithm 3: Anomalous data detection due to time lag between Secondary and Primary Voltage

1. **Define the time range of data cleaning as** T_{Range};
2. **Extract the voltage data within** T_{Range} **and store as** $V_{T_{Range}}$;
3. **Find the moving mean and standard deviation based on the CVR status:**
4. **CVR OFF and ON moving mean are calculated over** K **time horizon as, respectively** $V_{MM}(CVR_{status} == 0) = Movemean(V_{T_{Range}(CVR_{status}==0)}, k)$ **and** $V_{MM}(CVR_{status} == 1) = Movemean(V_{T_{Range}(CVR_{status}==1)}, k)$;
5. **Find the indices of time instants where secondary and primary voltage are not aligned based on moving mean, CVR OFF status, and ANSI bounday** $T_{anom_{secdiff}}(CVR_{status} == 0)) = abs(V_{T_{Range}}(CVR_{status} == 0) - V_{MM}(CVR_{status} == 0)) > abs(V_{T_{Range}}(CVR_{status} == 0) - mean(V_{T_{Range}}(CVR_{status} == 1)))\&(V_{T_{Range}} < 1.1 * nominalV | V_{T_{Range}} > 0.9 * nominalV)$;
6. **Find the indices of time instants where secondary and primary voltage are not aligned based on moving mean, CVR ON status, and ANSI bounday** $T_{anom_{secdiff}}(CVR_{status} == 1)) = abs(V_{T_{Range}}(CVR_{status} == 1) - V_{MM}(CVR_{status} == 1)) > abs(V_{T_{Range}}(CVR_{status} == 1) - mean(V_{T_{Range}}(CVR_{status} == 0)))\&(V_{T_{Range}} < 1.1 * nominalV | V_{T_{Range}} > 0.9 * nominalV)$;
7. **Declare associated time instants where voltage difference between primary and secondary are observed,** $T_{anom_{secdiff}}$ **as NaN** $V_{T_{Range}}[T_{anom_{secdiff}}] = NaN$;

D. Voltage Spike

It is very common to see voltage spikes in SCADA data and it is also not very straight forward to pinpoint if they are true outliers. Therefore, these data are assumed suspicious and should not be utilized in any calculation. It is seen in experimental estimation that voltage data follows gaussian distribution [14]. Thus, any data beyond 3 standard deviation should be considered as an outlier. However, voltage spikes are usually not that extreme similar to outliers. Instead, they are sudden upward or downwards change. Therefore, if the mean and standard deviation are utilized with a rolling horizon, these spikes are easily detectable. Algorithm 4 shows the details of voltage spike detection. In this algorithm, the time horizon is utilized as three hours prior and after each data point. Therefore, in the estimation process total 12 data points were utilized considering 30 minutes interval measurement. Simultaneously, voltage data is also tested if they are within the defined regulatory boundary according to ANSI range (0.9 p.u. < V < 1.1 p.u.). If they are outside the boundary, then they are not handled by this algorithm since they are considered separately as an outlier.

Algorithm 4: Detection of Voltage Spike

1. **Define the time range of data cleaning as** T_{Range}**;**
2. **Extract the voltage data within** T_{Range} **and store as** $V_{T_{Range}}$**;**
3. **Find the moving mean and standard deviation based on the CVR status:**
4. **CVR OFF and ON moving mean are calculated over** K **time horizon as, respectively** $V_{MM}(CVR_{status} == 0) = Movemean[V_{T_{Range}(CVR_{status}==0)}, k]$ **and** $V_{MM}(CVR_{status} == 1) = Movemean[V_{T_{Range}(CVR_{status}==1)}, k]$**;**
5. **CVR OFF and ON moving std deviation are calculated over** K **time horizon as, respectively** $V_{MStd}(CVR_{status} == 0) = Movestd[V_{T_{Range}(CVR_{status}==0)}, k]$ **and** $V_{MStd}(CVR_{status} == 1) = Movestd[V_{T_{Range}(CVR_{status}==1)}, k]$**;**
6. **Find the indices of time instants where voltage spike occured based on moving mean, standard deviation, CVR status, and ANSI bounday** $T_{anom_{spike}} = [V_{T_{Range}} > V_{MM} + 3 * V_{MStd}] \mid [V_{T_{Range}} < V_{MM} - 3 * V_{MStd}] \mid [V_{T_{Range}} > 1.1 * V_{MM}] \mid [V_{T_{Range}} < 0.9 * V_{MM}] \mid [V_{T_{Range}} < 1.1 * nominalV \mid V_{T_{Range}} > 0.9 * nominalV]$**;**
7. **Declare voltage spike associated time instants,** $T_{anom_{spike}}$ **as NaN** $V_{T_{Range}}[T_{anom_{spike}}] = NaN$**;**

4. Case Studies

This section discusses the case studies using the actual utility data to demonstrate the effectiveness of the algorithms presented in section III. For the purpose of privacy, the timestamps have been manipulated. While testing the algorithms, 30 minutes interval data are utilized. Calculation of any rolling or moving mean and standard deviation are considered with K=24 consecutive intervals based on CVR status. The suspicious data detected by the algorithms should be eliminated from any study related to voltage reduction and CVR factor. If these are not properly considered, any CVR related studies may be jeopardized since CVR studies depend on the data of counterfactual states (i.e., CVR OFF data if CVR is ON and vice versa) and several confounding factors (i.e., season, temperature, day type).

In algorithm 1, $\ddot{z}$ refers to the system-wide lowest DB. Therefore, while CVR is ON, voltage needs to be lower than $\ddot{z}$. $\ddot{k}$ corresponds to the maximum imbalance in the system. $\ddot{z}$ and $\ddot{k}$ values are pre-determined as 1.02 p.u. and 2 % based on the experience of the system performance. However, these values are flexible, and utilities can change them based on the overall system condition. In Fig.3, detection of phase imbalance is shown within a highlighted zone. It is clear that within the region CVR is ON and only Phase A is able to lower the voltage than 1.02 p.u. Other two phases are not able to lower the voltage and they demonstrate 2% imbalance with Phase A. Therefore, Phase B and C data within that period are detected as anomalous data.

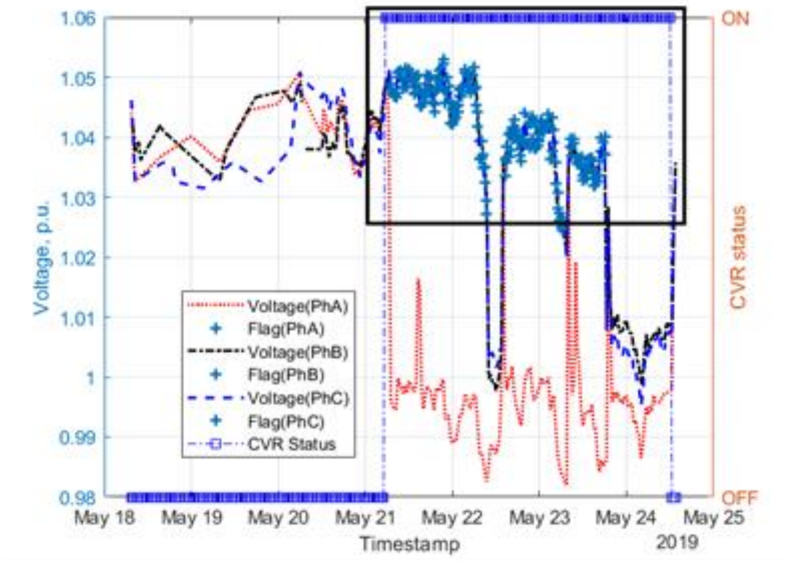

Fig. 3. Detection of phase imbalance.

In algorithm 2, it is discussed that LOLM is only justified if voltage is not able to go any lower when CVR is active. If CVR is OFF, by default, operating voltage stays in the upper range of the band. Therefore, activation of LOLM alarm alerts that there may be some operational issues occurring that disables the precise LTC operation. Similar to algorithm 1, lowest DB, $\ddot{z}$, is pre-determined as 1.02 p.u. In Fig.4, the highlighted area shows that CVR is OFF, voltage is below, and LOLM is active which clearly defines some anomaly and ensures that these data are opposite to the natural operation.

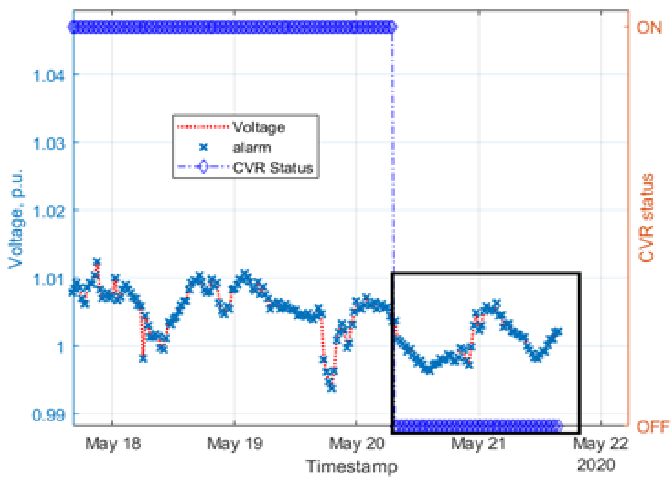

Fig. 4. Detection of invalid CVR data.

Algorithm 3 determines if there is any lag in data collection from different sources. CVR status is determined based on the SLV and SP data collected from the secondary side since those are only available when the system is scanning. On the other hand, the feeder-head LTC data is collected from the primary side and used for voltage reduction calculation. Although the data is intended to be collected and historized with the same timestamp, it is not guaranteed that the data pull happened exactly at the same time due to the communication lagging. Therefore, one data source may have slight lagging with others. This may be very apparent during the time of transition from CVR OFF to ON and vice versa. Detection of these data points are dependent on the comparison among the individual time instant data, rolling mean, and simple mean based on the CVR status. In Fig.5, a data point is highlighted which senses the primary and secondary measurement difference. In Fig.5, the voltage starts to go lower which is clearly visible at 12:00, presumably when CVR command is sent.

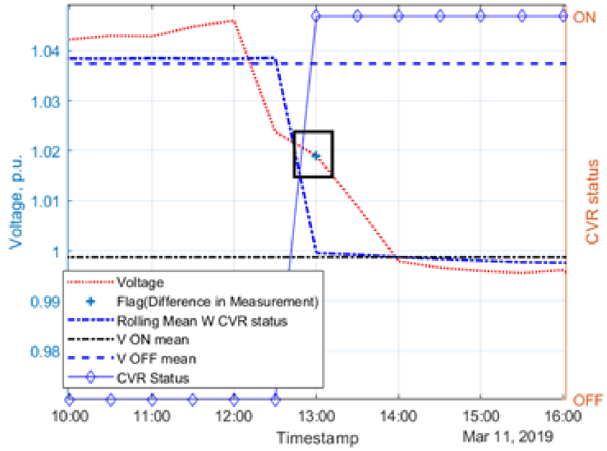

Fig. 5. Detection of measurement lagging.

After the voltage goes below a certain bandwidth of DB, CVR is completely activated at 13:00. However, the voltage data which is collected from the primary source still poses a downward slope. Comparing the rolling mean with the individual instantaneous data provides a larger difference than the difference between the instantaneous and average CVR OFF. This extends that the instantaneous data is still biased to CVR OFF. In contrast, the CVR status is ON and the rolling mean is also inclined to CVR ON. Algorithm 4 discusses a scenario which doesn't occur very frequently. However, this can be assumed as a suspicious data point since it is difficult to distinguish whether the sudden change is an outlier or it happened due to an abrupt system condition change. As discussed in the algorithm, first, the check considers whether the voltage is within the ANSI range to ensure that it is not a typical outlier. Then, it checks whether the data lies with the 3-standard deviation of the rolling mean. The highlighted point in Fig.6, is clearly beyond the defined range which distinguishes the data from the utilized sample.

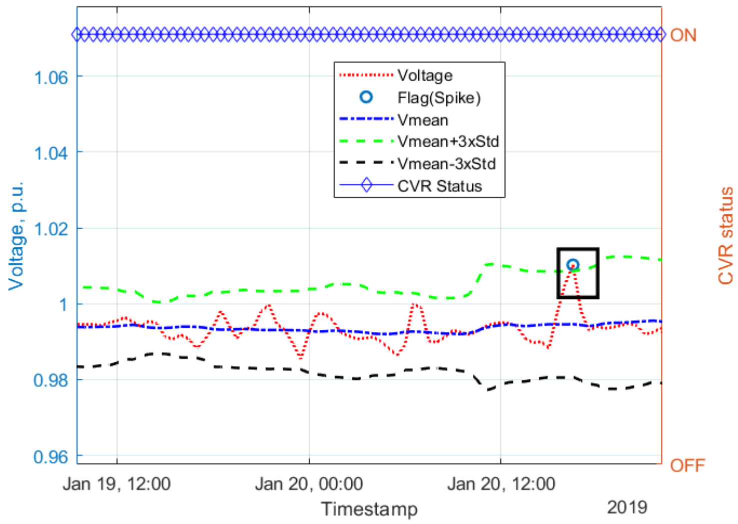

Fig. 6. Detection of sudden voltage spike.

Table I below shows example of three transformers where yearly dataset were cleaned with the algorithms above. The table specifies which algorithm has cleaned what percentage of data considering the usage of yearly dataset. Algorithms 1,2,3, and 4 specifies invalid data due to lolm, phase imbalance, difference in primary and secondary measurements, and voltage spikes, respectively. After cleaning these anomalous data, eliminated data points were reconstructed and counterfactuals (i.e., CVR ON estimated data when CVR is actually OFF and vice versa) were calculated using a lookup table and priority chart of confounding factors (i.e., temperature, season, day type, time of the day, CVR status).

TABLE I. Differences in voltage reduction before and after cleaning.

Xfmr	ΔV w/o cleaning (%)	ΔV w cleaning (%)	Alg1(%)	Alg2(%)	Alg3(%)	Alg4(%)
TR1	4.68	4.72	0.0	0.0	0.10	0.06
TR2	3.99	4.51	0.0	1.68	0.14	0.53
TR3	3.57	3.59	0.01	0.0	0.03	0.23

The details of the algorithm to calculate voltage reduction with actual and reconstructed data is demonstrated in our previous work in [15]. The table above demonstrates the difference in voltage reduction calculation before and after cleaning these anomalous data. The dataset contains 30 minutes interval data for a year when CVR is tested in on/off cycling basis. In all cases, the voltage reduction has improved after cleaning. The improvement is observed significant where more anomalous data are cleaned, for instance TR2.

5. DISCUSSIONS AND CONCLUSION

This paper discussed several scenarios where data points may be suspicious due to any operational issue such as low limit alarm during the period when CVR is turned off, discrepancies on primary and secondary data sources, high phase imbalance if CVR is being operated by phase, and sudden voltage spikes. These suspicious data points may jeopardize any study related to CVR measurement and verification, and provide wrong impression about the actual performance of the system. A thorough process must be in place to find these anomalies to maintain the accuracy of any assessment related to CVR benefits. This is specially true if any utility is running a large scale CVR program where thousands of feeders are running on CVR. Therefore, this paper developed and discussed several algorithms in detail on how to detect those suspicious data points. The developed algorithms are flexible and can be adopted easily by utility engineers based on their evaluation on the system condition. These algorithms can play vital roles in detecting data anomalies which are caused by the operational issues of the system and network. The algorithms can also be utilized in a similar fashion with the AMI data. Addition of these ad-hoc algorithms in any third party vendor tool, connected with SCADA system, can also help utilities to monitor the performance of the CVR deployed feeders with accurate voltage reduction.

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