

VOLTAGE VARIABILITY ASSESSMENT IN POWER SYSTEMS

ANCA-PETRUȚA BRÎNCOVEANU¹, RADU PLĂMĂNESCU¹, ANA-MARIA DUMITRESCU¹, MIHAELA ALBU¹

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Processes in large energy systems exhibit a high variability due to the stochastic nature of electricity production and use. However, the control of the energy transfer aims to achieve steady state operation, which is mostly described by signals fully identifiable by a finite set of parameters. Part of the control system is the process of information delivered through measurements. In this paper, we analyze the impact of the measurement system deployed for reporting the RMS parameter of the voltage signal on the quality of information in LV distribution networks. The operation of such networks is highly stochastic, and the chosen models based on averaging are not always appropriate; therefore, we propose to apply a statistic metric, *i.e.*, the coefficient of variation of the root mean square deviation CV(RMSD).

1. INTRODUCTION

Voltage measurements in low-voltage (LV) distribution networks during steady-state conditions presume a periodic waveform with a known constant frequency, with the root mean square (RMS) parameter chosen as the information carrier. Additionally, it is assumed that the signal model remains defined and unique both during the measurement (T_m), reporting (T_r) and the subsequent aggregation time interval (T_a), if such aggregation is embedded in the measurement/ control process.

Deviations from the steady state model [1] of the voltage signal in the power system are currently quantified by assessing the RMS parameter and its profile during standardized time intervals. This assessment is done in [2] using rapid voltage changes (RVC), which are fast variations in voltage levels in electrical distribution systems. They are common, especially at the distribution level, and are expected to become more frequent with the increasing integration of dynamic loads and renewable-based generators into smart grids. This will assist DSOs in expeditiously conducting their services [3]. Integrating renewable sources into smart grids can cause dynamic behavior in voltage profiles [4], which must be examined to comply with regulators' limits [5]. While RVCs are generally less critical than other power quality (PQ) events, such as dips, sags, and swells, they can still pose challenges due to their potential to disrupt the operation of generator control systems and electronic equipment [6,7].

The definition and criteria for identifying RVCs are important in selecting the appropriate measurement systems [8]. For example, the selected time window for assessing the RVC events is the measurement time needed to issue the RMS value (corresponding to the fundamental period of the assumed sinusoidal model), the reporting time window (half of the fundamental period), and the analysis window (1 s). Therefore, any revision or adjustment to the formal definition of an RVC event can significantly impact the identification and quantification of such events in power systems [9]. RVC is also relevant for different applications such as transformer inrush [10], low voltage dc analysis [11], medium voltage network analysis [9], propagation effect using multipoint measurement technique [12], or dynamic RMS voltage tracking [13].

The correlation between the flicker parameters and the magnitude that characterizes the RVC events is also studied and confirmed [14]. Another study [15] concludes that RVC events have a more significant impact than previously

reported in subjective studies. The current policy limits the number of RVCs with magnitudes higher than 3 % of the nominal voltage [15]. Therefore, RVC continues to be a crucial factor in assessing flicker [16].

Another approach to assessing the severity of voltage variability while using the same parameter (RMS) is to use statistical metrics evaluated on time intervals compatible with legacy reporting rates today. This method allows for analyzing voltage profiles using the RMS values reported by the almost ubiquitous smart meters.

Statistical signal processing is pivotal for integrating novel functionalities and deepening our comprehension of measured point behavior. Advancements in statistical implementation necessitate open and adaptable hardware and software solutions and expanded metric considerations [17].

The paper is structured into five sections. Section 2 introduces the statistical approach and evaluates the measurement layer used for data collection. Section 3 discusses RMS voltage assessment in LV networks for the daily horizon, and section 4 covers RMS voltage assessment during a week. The paper concludes with section 5, summarizing the findings.

2. METRICS FOR ASSESSMENT OF SIGNAL VARIABILITY

The measurement process is considered effective when the information extracted from the analyzed phenomena is aligned with the capabilities of the measurement devices. Several methods have been previously suggested in the literature to gauge the disparity between an estimated model and the real process. For example when the signal $x(t)$ is acquired with sufficiently high sampling rate f_s and the samples x_i are available together with the measured (and the reported) value X_m associated with a known model $y(t)$, the goodness of fit (GoF) indicates signal variability compared to the assumed model having m degrees of freedom [18]. The most encountered metric for goodness of fit is based on the root mean squared error [1]:

$$GoF = 20 \log \frac{\hat{X}}{\sqrt{\frac{1}{n-m} \sum_{i=1}^n (x_i - y_i)^2}} \quad (1)$$

For an ac electrical system, we usually select the RMS value as the parameter to be fitted to the sinusoidal model of the signal:

$$y(t) = Y\sqrt{2} \sin(2\pi ft). \quad (2)$$

In this case, in equation (1) \hat{X} is the reported RMS value of the signal: $\hat{X} = X_m = Y$.

¹ Faculty of Electrical Engineering, National University of Science and Technology Politehnica Bucharest, Romania.
E-mails: anca.brincoveanu@upb.ro, radu.plamanescu@upb.ro, anamaria.dumitrescu@upb.ro, mihaela.albu@upb.ro

Let's consider the voltage signal (single phase) acquired with $f_s = 51200$ samples/s in one node of the MicroDERLab laboratories in September 2022. Figure 1 shows the recorded [19] voltage signal during a 200 ms time window, while Fig. 2 presents the GoF computed with (1), for each fundamental period of the 50 Hz signal ($n = 51200/50 = 1024$ samples). The average value of GoF for this signal on the analysis window of 200 ms is 25.42 dB.

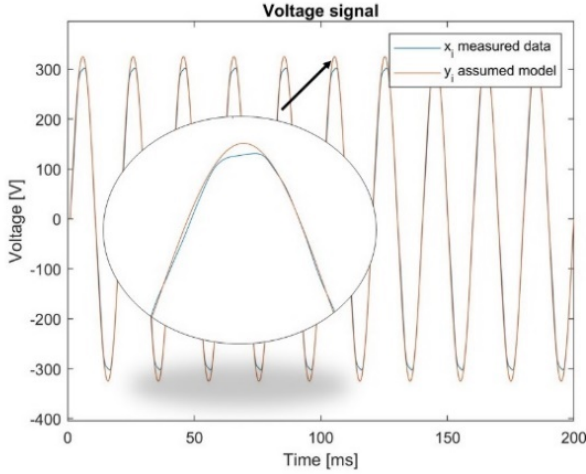


Fig. 1 – Voltage signal acquired in September 2022; x_i measured values (blue) and y_i the values of the assumed model (red).

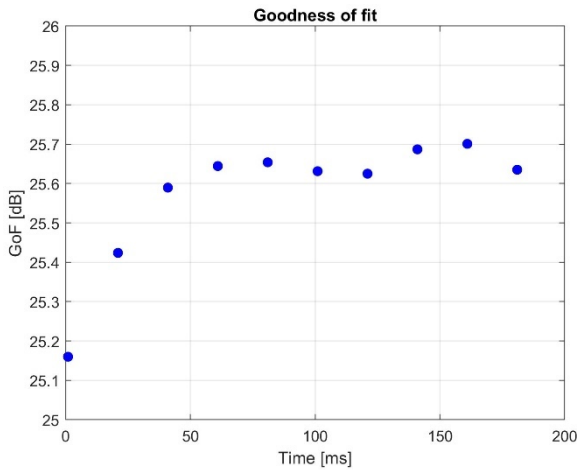


Fig. 2 – GoF values for the signal in Fig.1, $T_a = 200$ ms, $T_r = 20$ ms; voltage signal acquired with $f_s = 51200$ samples/s.

This metric is highly dependent on the choice of the time interval for which the comparison is made and needs to be further assessed using a statistical approach. Therefore, it is useful to analyze the process of deviation from steady-state behavior further when this is understood as described by signals fully aligned to the adopted model (*i.e.*, having a sinusoidal variation).

We proposed another approach in [20–22], using metrics derived from statistical analysis performed for the reported measurement values on the assumed model with predefined time windows. We applied those metrics for the models described by constant (mean) values over designated reporting windows.

In the following, we list the metrics proposed in [22]: mean absolute error (MAE) is a linear measure of the errors between two data sets (x_i, y_i) that express the same phenomenon. This method is one of the most used in the forecasting area of study to compare a real data set with an

estimated one

$$MAE = \frac{\sum_{i=1}^n |x_i - y_i|}{n}. \quad (3)$$

Mean squared error (MSE) gives the average of the squares of the errors (the average squared difference between the estimated values y_i and the actual values x_i):

$$MSE = \frac{\sum_{i=1}^n (x_i - y_i)^2}{n}. \quad (4)$$

Root mean squared error (RMSE) gives the standard deviation of the residues. Residues are a metric that tells how far from the regression line y_i the points x_i are, thus showing how scattered they are:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}} = \sqrt{MSE}. \quad (5)$$

Coefficient of variation of RMSE (CV-RMSE) normalizes the RMSE value in (5) using the mean estimated value \bar{y} :

$$CV(RMSE) = \frac{1}{\bar{y}} \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}}. \quad (6)$$

The coefficient of variation (CV) of the root mean square deviation (RMSD) is a statistical measure that provides a normalized (by \bar{y}_p) measure of the variability of RMSD values [23]:

$$CV(RMSD) = \frac{1}{\bar{y}_p} \sqrt{\frac{\sum_{i=1}^n (x_i - y_i)^2}{n}}. \quad (7)$$

The mean absolute percentage error (MAPE) is the mean or average of the absolute percentage errors of forecasts (y_i):

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{x_i - y_i}{x_i} \right|. \quad (8)$$

Mean squared percentage error (MSPE) represents the sum of the absolute values obtained by the difference between the actual (x_i) and the estimated value (y_i) divided by the real value of each sample, squared, which is then divided by the number of samples and expressed in percentage:

$$MSPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{x_i - y_i}{x_i} \right|^2. \quad (9)$$

The coefficient of determination R^2 is a metric that evaluates the ability of a model (\tilde{y}_i) to predict or evaluate a result in linear regression (y_i):

$$R^2 = 1 - \frac{\sum_{i=1}^n (x_i - y_i)^2}{\sum_{i=1}^n (y_i - \tilde{y}_i)^2}. \quad (10)$$

We adapted the metrics (3)-(10) to the measurements performed on the signal $x(t)$, correlated with every $T_r = 1/RR$ reported measurement value X_m , where RR is the selected reporting rate of the measurement system. The assumed signal model $y(t)$ during T_r is described by the samples y_i , $i = 1 \dots n$, where n is the number of samples available during T_r but not reported. We denoted with \tilde{y} the “best estimation” of the model during a time interval T_{ss} , usually larger than the reporting time T_a , while T_{ss} is defined by the user as a time interval for which a steady state validity of the model is assumed. For those cases where the best estimation is the average of a constant value model ($y_i - \tilde{y}_i$) we have rounded $|y_i - \tilde{y}_i|$ by the Δx_{max} corresponding to the declared quality for the measurement system. We denoted with \bar{y}_p , a presumed model value representing the designated process

time window. When this selected model corresponds to T_r is obtained $\bar{y}_p = \bar{y}$, it relies on the specific context of the application [23].

Based on previous experiences and assessments with the metrics (3) to (10) across multiple measurands and processes [18], and based on this wealth of information, we found that the CV(RMSD) metric (7) is most suitable for characterizing the behavior of the power system based upon voltage assessment. We apply this metric to question the variability of the RMS-reported values of the LV network using several time windows for analysis.

The measurements are made available with 1 s time resolution by an unbundled smart meter (USM, [24]). In contrast, the model is established based on the mean calculated over the reporting time of legacy smart meters [25]. The architecture of the USM adheres to the conventional structure comprising two components: the smart metrology meter (SMM) responsible for measurements and the smart meter extension (SMX), which is a configurable extension to process the SMM values. The metrology aspect of the USM (presumably referring to an energy monitoring or management system) relies on using three-phase SOCOMEC meters, which offer Class 1 accuracy for active energy measurement and Class 2 accuracy for reactive energy measurement [26]. The SMX component of the system incorporates a Raspberry Pi (RPI) 3 board [27], which acts as a single-board computer. Its primary function is to establish a physical connection with the SOCOMEC meter, allowing for the retrieval of instrumentation values with high temporal resolution through specific configuration tasks. The Raspberry Pi is an interface between the meter and the rest of the system, facilitating data extraction and processing. To achieve a high reporting rate, the communication between the SOCOMEC meter and the Raspberry Pi (SMX) utilizes a serial interface, specifically RS485, employing the IEC 62056 communication protocol (DLMS/COSEM) [28]. This protocol is widely used in energy metering systems and supports efficient and reliable data exchange between devices.

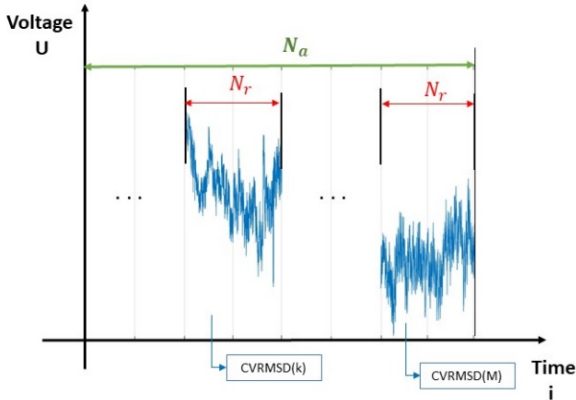


Fig. 3 – Time intervals for voltage variability assessment (discrete sequence of RMS values, computed on 1 s time window).

The following parameters have been used for the voltage assessment:

$$x_i = U_i; y_i = \frac{\sum_{i=1}^{N_r} U_i}{N_r}; \bar{y}_p = \frac{\sum_{i=1}^{N_a} U_i}{N_a}, \quad (11)$$

where U_i is the i -th reported RMS value (estimated from the voltage signal on $T_{sm} = 1$ s measurement time), $N_r = T_r/T_{sm}$, $N_a = N_r \cdot M = T_a/T_r$, $i=1 \dots N_a$.

For this investigation, we chose three legacy smart meters

with reporting time intervals of $T_r = 15$ min., 30 min., and 1 h, respectively. The analysis is conducted over a daily observation window designated as $T_a = 24$ h. To emphasize the continuous sequences of T_r and T_a in relation to the computation of various metrics assessing the deviation from the assumed model $y(t)$, Fig. 3 depicts an illustrative example. The assumed model $y(t)$ is derived from the actual acquired RMS voltage data by calculating the mean value of the time series data within a specified analysis time window.

3. DAILY VOLTAGE VARIABILITY ASSESSMENT

We assess the voltage variability on a 3 phase LV network, where we note the RMS values on each phase as U_k , $k = \overline{1, 3}$, during a summer day in 2023. The CV(RMSD) metric is computed for three different measurement windows: 15 min., 30 min. and 1 h respectively, while the aggregation is performed on a $T_a = 2$ h window.

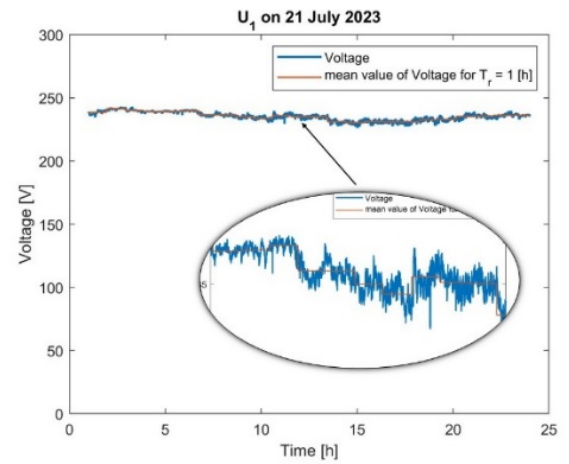


Fig. 4 – Voltage signal on phase 1 (U_1), on 21st July, measured value (blue), assumed constant model (red) on $T_r = 1$ h

Figure 4 presents the daily voltage profile for the first phase (U_1) on 21 July 2023, while Fig. 5 presents the CV(RMSD) values computed for the signal in Fig. 4 using $T_r = 1$ h, $T_a = 2$ h. It can be observed that the maximum value is 0.78 %, reported at the end of the T_{r21} window at 21:00.

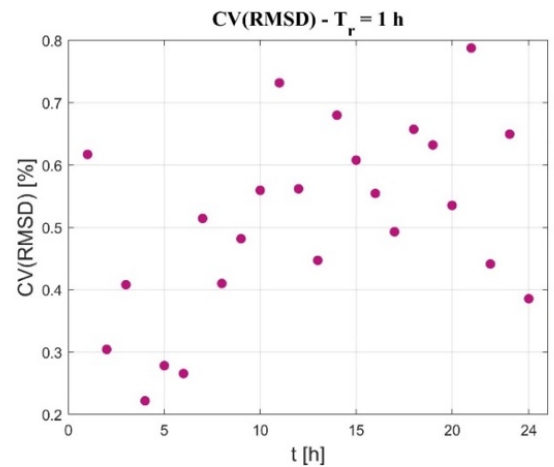


Fig. 5 – CV(RMSD) for the voltage U_1 in Fig. 4.

We repeat the procedure for the other two phases U_2 and U_3 , on, 21 July 2023, and the CV(RMSD) results are presented in Table 1. In the table we observe that the maximum CV(RMSD) value for U_2 is 1.68 %, depicted at 1:00. The maximum value for U_3 is 2.32 % at the end of T_{r16} .

Table 1

CV(RMSD) for voltage (RMS values) on 21st July 2023, $T_r = 1$ h.

| T_r | Reporting interval [hh:mm:ss] | CV(RMSD) for U_1 [%] | CV(RMSD) for U_2 [%] | CV(RMSD) for U_3 [%] |
|-----------|-------------------------------|------------------------|------------------------|------------------------|
| T_{r1} | [00:00:00-1:00:00) | 0.61 | 1.68 | 1.70 |
| ... | ... | ... | ... | ... |
| T_{r16} | [15:00:00-16:00:00) | 0.55 | 0.83 | 2.32 |
| ... | ... | ... | ... | ... |
| T_{r21} | [20:00:00-21:00:00) | 0.78 | 0.46 | 0.43 |
| ... | ... | ... | ... | ... |
| T_{r24} | [23:00:00-24:00:00) | 0.39 | 0.55 | 0.40 |

Figure 6 presents daily voltage profile for the first phase (U_1) on 21 July 2023, while Fig.7 presents the CV(RMSD) values computed for the same signal using $T_r=30$ min., $T_a=2$ h. It can be observed that the maximum value is 0.72% for reported window T_{r30} , at 15:00. We repeat the procedure for the voltages on the other two phases (U_2, U_3), on 21 July 2023, with $T_r = 30$ min. and the CV(RMSD) results are presented in Table 2, where we can observe that the maximum value is 2.34% for U_2 and 2.57% for U_3 .

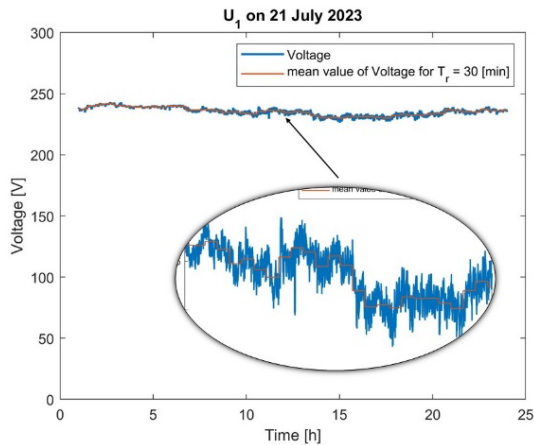


Fig. 6 – Voltage signal on phase 1 (U_1), on 21st July, measured value (blue), assumed constant model (red) on $T_r = 30$ min.

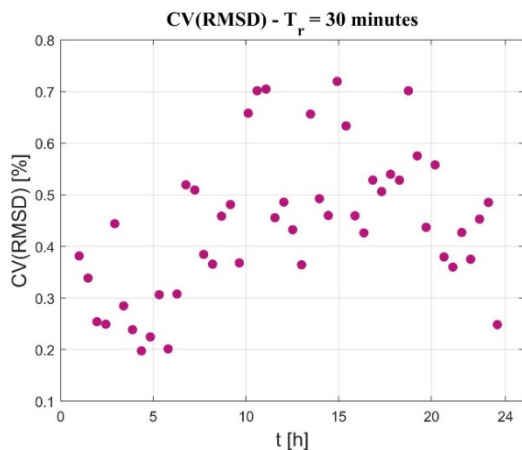


Fig. 7 – CV(RMSD) for the voltage U_1 in Fig. 6

We repeat the procedure for the voltages on the other two phases (U_2, U_3), on 21 July 2023, with $T_r = 15$ min. Results are presented in Table 3, where we can observe that the maximum value is 3.3 % for U_2 and is 2.32 % and 3.28 % for U_3 . Figure 8 presents daily voltage profile for the first phase (U_1) on 21 July 2023, while Fig.9 presents the CV(RMSD) values computed for the signal in Fig. 8 using $T_r=15$ min.,

$T_a = 2$ h. It can be observed that the maximum value is found in window T_{r21} at 10:15 and is 0.91 %.

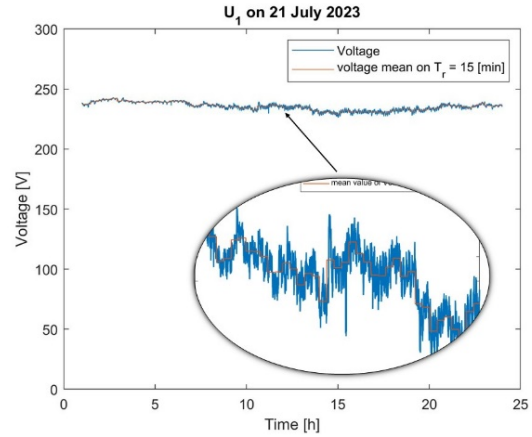


Fig. 8 – Voltage signal on phase 1 (U_1), on 21st July, measured value (blue), assumed constant model (in red) on $T_r=15$ min.

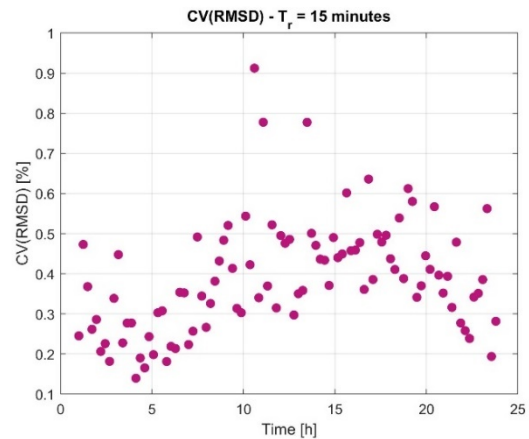


Fig. 9 – CV(RMSD) for the voltage U_1 in Fig. 8.

Table 2

CV(RMSD) for voltage (RMS values) during 21 July 2023, $T_r = 30$ min.

| T_r | Reporting interval [hh:mm:ss] | CV(RMSD) for U_1 [%] | CV(RMSD) for U_2 [%] | CV(RMSD) for U_3 [%] |
|-----------|-------------------------------|------------------------|------------------------|------------------------|
| T_{r1} | [00:00:00-0:30:00) | 0.38 | 2.34 | 2.37 |
| T_{r2} | [00:30:00-01:00:00) | 0.34 | 0.29 | 0.34 |
| ... | ... | ... | ... | ... |
| T_{r30} | [14:30:00-15:00:00) | 0.72 | 0.87 | 2.57 |
| ... | ... | ... | ... | ... |
| T_{r47} | [23:00:00-23:30:00) | 0.49 | 0.46 | 0.24 |
| T_{r48} | [23:30:00-24:00:00) | 0.25 | 0.49 | 0.34 |

Table 3

CV(RMSD) for voltage (RMS values) during 21 July 2023, $T_r = 15$ min.

| T_r | Reporting moment [hh:mm:ss] | CV(RMSD) for U_1 [%] | CV(RMSD) for U_2 [%] | CV(RMSD) for U_3 [%] |
|-----------|-----------------------------|------------------------|------------------------|------------------------|
| T_{r1} | [00:00:00-00:15:00) | 0.25 | 3.30 | 3.28 |
| ... | ... | ... | ... | ... |
| T_{r41} | [10:00:00-10:15:00) | 0.91 | 0.79 | 0.91 |
| T_{r42} | [10:15:00-10:30:00) | 0.34 | 0.47 | 0.23 |
| ... | ... | ... | ... | ... |
| T_{r96} | [23:45:00-24:00:00) | 0.28 | 0.29 | 0.22 |

4. WEEKLY VOLTAGE VARIABILITY ASSESSMENT

We analyzed the voltage profile during one week in April 2023 to better understand voltage variability. For this assessment, we performed CV(RMSD) calculations with two reporting rates (1 and 4 frames per hour, respectively) and $T_a = 2$ h. We applied eq. (7) considering that the presumed model value \bar{y}_p is the nominal voltage ($\bar{y}_p = U_n$).

Table 4 presents the maximum and minimum CV(RMSD) values for one week, for the three-phase voltage signals (U_1, U_2, U_3), $T_r = 1$ h, $T_a = 2$ h. It can be observed that the maximum variability is on U_3 where CV(RMSD) is equal to 3.38 % (Thursday, 08.04.2023). The minimum CV(RMSD) is 0.24 %, also on U_3 (Wednesday 07.04.2023). Table 5 presents the maximum and minimum CV(RMSD) values for one week, for the three-phase voltage signals (U_1, U_2, U_3), $T_r = 15$ min., $T_a = 2$ h. It can be observed that the maximum variability is on U_3 where CV(RMSD) is equal to 3.48 % (Monday, 05.04.2023). The minimum CV(RMSD) is 0.16 %, also on U_3 (Saturday, 10.04.2023).

Table 4
CV(RMSD) during one week in April, $T_r = 1$.

| Day | U_1 | | U_2 | | U_3 | |
|------------|---------------------|---------|---------|---------|---------|---------|
| | CV(RMSD), $T_r=1$ h | | | | | |
| | max [%] | min [%] | max [%] | min [%] | max [%] | min [%] |
| 05.04.2023 | 1.86 | 0.41 | 1.88 | 0.34 | 3.09 | 0.40 |
| 06.04.2023 | 1.38 | 0.37 | 1.59 | 0.38 | 3.10 | 0.25 |
| 07.04.2023 | 1.20 | 0.36 | 1.43 | 0.38 | 2.87 | 0.24 |
| 08.04.2023 | 1.89 | 0.47 | 2.05 | 0.37 | 3.38 | 0.43 |
| 09.04.2023 | 1.20 | 0.33 | 1.03 | 0.37 | 1.80 | 0.31 |
| 10.04.2023 | 1.50 | 0.36 | 1.94 | 0.34 | 2.46 | 0.30 |
| 11.04.2023 | 1.19 | 0.35 | 1.88 | 0.40 | 2.04 | 0.25 |

Table 5
CV(RMSD) during one week in April for $T_r = 15$ min.

| Day | U_1 | | U_2 | | U_3 | |
|------------|------------------------|---------|---------|---------|---------|---------|
| | CV(RMSD), $T_r=15$ min | | | | | |
| | max [%] | min [%] | max [%] | min [%] | max [%] | min [%] |
| 05.04.2023 | 1.48 | 0.22 | 1.85 | 0.21 | 3.48 | 0.20 |
| 06.04.2023 | 1.55 | 0.26 | 2.16 | 0.18 | 2.61 | 0.17 |
| 07.04.2023 | 1.18 | 0.23 | 2.15 | 0.18 | 2.69 | 0.18 |
| 08.04.2023 | 1.81 | 0.27 | 2.15 | 0.18 | 2.93 | 0.19 |
| 09.04.2023 | 1.79 | 0.23 | 1.71 | 0.21 | 2.43 | 0.17 |
| 10.04.2023 | 1.03 | 0.24 | 1.98 | 0.21 | 3.17 | 0.16 |
| 11.04.2023 | 1.13 | 0.25 | 1.90 | 0.2 | 2.02 | 0.18 |

To estimate the daily voltage variability with only one CV(RMSD) indicator we apply eq. (7) with nominal voltage as the presumed model value \bar{y}_p and $T_r = 2$ h:

$$y_i^* = \frac{\sum_{i=1}^{N_r} U_i}{N_r}; \bar{y}_p = U_n. \quad (11)$$

Table 6
CV(RMSD) values for one week in April for the assumed model y_i^* with $T_r = 2$ h.

| Day | CV(RMSD) for U_1 [%] | CV(RMSD) for U_2 [%] | CV(RMSD) for U_3 [%] |
|------------|------------------------|------------------------|------------------------|
| 05.04.2023 | 0.96 | 1.15 | 1.38 |
| 06.04.2023 | 0.80 | 1.05 | 1.44 |
| 07.04.2023 | 0.90 | 0.91 | 1.68 |
| 08.04.2023 | 1.01 | 1.26 | 1.93 |
| 09.04.2023 | 0.77 | 0.77 | 0.96 |
| 10.04.2023 | 0.89 | 1.16 | 1.31 |
| 11.04.2023 | 0.79 | 1.05 | 1.39 |

Results for the considered week in April using the assumed model y_i^* are presented in Table 6. It can be observed that the highest CV(RMSD) value is on Thursday

(08.04.2023) for U_3 . During the entire week, the CV(RMSD) for voltage on phase 3 was higher than 1.3 %, while for the other two phases CV(RMSD) was constantly lower, which indicates that equipment connected on phase 3 (either PV generation or fluctuating loads) impact on the voltage waveform and additional measures for improving the local distribution network should be considered.

The study carried out for the considered week in April provides important information about assessing system variability in the three-phase network based on information measurements. Our interest is not in the global variability of the RMS voltage parameter but rather in its variability within the legacy reporting interval adopted by the power quality community. Our aim is to highlight that this reporting interval is no longer adequate. Therefore, we seek to demonstrate the need for a revised reporting method to better capture the dynamics of modern electrical networks. The study was conducted on a network with specific characteristics, affecting the results' generalizability. However, our idea is to propose a method to quantify the system variability. We plan to extend our research to include a variety of network environments in future studies to validate the generality of the proposed metric CV(RMSD) applied to the RMS voltage values.

5. CONCLUSIONS

This paper assesses the high variability of energy transfer in distribution networks using measured voltage signals and statistical methods. Specifically, the RMS of the voltage signal is used as the basis for the study using the coefficient of variation of CV(RMSD). The main output of the study is that the measurement systems deployed for reporting the RMS parameter of the voltage signal affect the quality of information in LV distribution networks. As such, we suggest employing a statistical metric, the coefficient of variation of the CV(RMSD), to analyze the daily and weekly voltage variability using three methods corresponding to the length of the assessment time window and implicit model, respectively.

The CV(RMSD) metric provides a more accurate representation of voltage variation by normalizing the RMS deviation relative to the mean, allowing for a consistent comparison across different scales. Its ability to reveal intricate patterns of network behavior and assess temporal stability makes it an indispensable and useful tool for advancing the reliability and performance of power distribution systems. Future work aims to integrate CV(RMSD) into standard monitoring practices and explore its potential in predictive maintenance algorithms to enhance power quality management further.

The proposed metrics, derived from statistical tools, can be considered topology agnostic. They are not intended as a replacement for classical methods to evaluate network performance and variability, but they add another dimension to the available information and invite us to reconsider the steady state models and their implicit time constants for power flow analysis in emerging, low-inertia networks. The impact of the measurement chain on the results is part of a future endeavor.

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