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# VOLTAGE VARIABILITY ASSESSMENT IN POWER SYSTEMS

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**Keywords: Models of the energy transfer; Measurement; Root mean square (RMS) voltage value; Metrics; High reporting rates; Signal variability.**

**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]:

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

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

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

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

Let's consider the voltage signal (single phase) acquired with $f_s$ =51 200 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 ($n = 51\,200/50 = 1024$ samples). The average value of GoF for this signal on the analysis window of 200 ms is 25.42 dB.

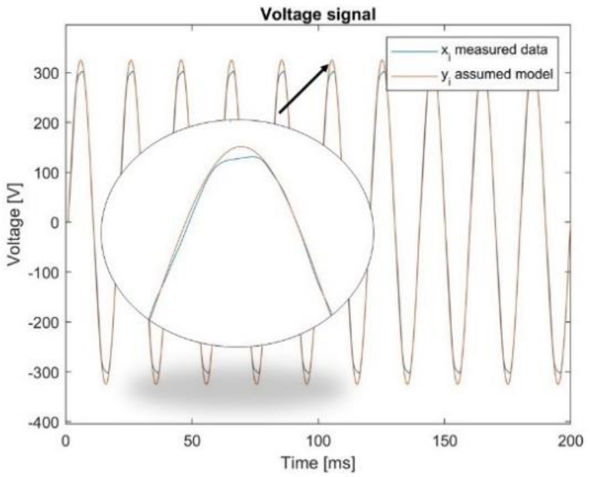


Fig. 1 – Voltage signal acquired in September 2022; $x_i$ measured values (blue) and $y_i$ the values of the assumed model (red).

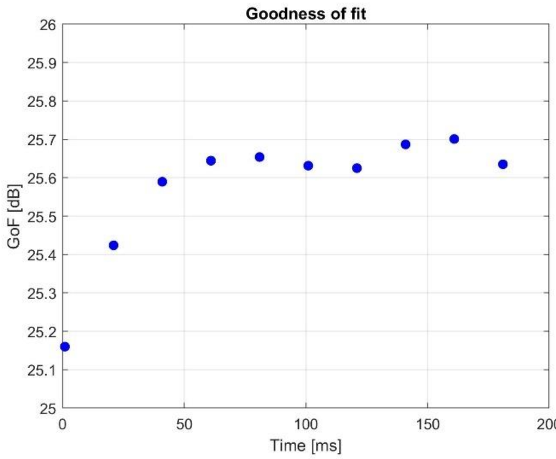


Fig. 2 – GoF values for the signal in Fig.1, $T_a$ = 200 ms, $T_r$ = 20ms; voltage signal acquired with $f_s$ = 51 200 samples/s.

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

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

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 $x_i$):

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

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:

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

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

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

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]:

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

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

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

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:

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

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 $x(t)$, corelated 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 $y_i$, $i = 1 \ldots n$, 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 $\Delta x_{max}$ 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.

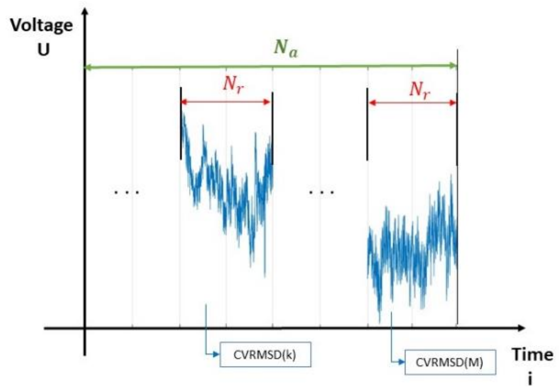


Fig. 3 – Time intervals for voltage variability assessment (discrete sequence of RMS values, computed on 1 s time window).

The following parameters have been used for the voltage assessment:

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

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

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.

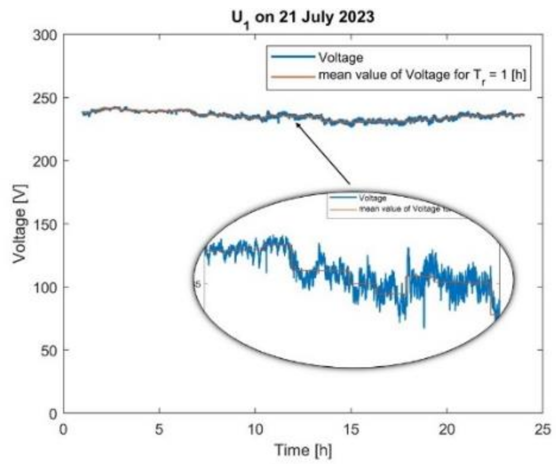


Fig. 4 – Voltage signal on phase 1 ($U_1$), on 21st July, measured value (blue), assumed constant model (red) on $T_r$=1 h.

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.

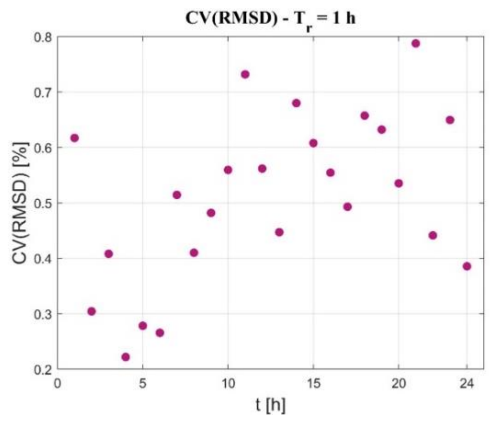


Fig. 5 – CV(RMSD) for the voltage $U_1$ in Fig. 4.

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 maxim CV(RMSD) value for $U_2$ is 1.68 %, depicted at 1:00. The maxim 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

| $T_{\mathrm{r}}$ | Reporting interval [hh:mm:ss] | CV(RMSD) for $U_1$ [%] | CV(RMSD) for $U_2$ [%] | CV(RMSD) for $U_3$ [%] |
|---|---|---|---|---|
| $T_{\mathrm{r1}}$ | [00:00:00-1:00:00) | 0.61 | **1.68** | 1.70 |
| … | … | … | … | … |
| $T_{\mathrm{r16}}$ | [15:00:00-16:00:00) | 0.55 | 0.83 | **2.32** |
| … | … | … | … | … |
| $T_{\mathrm{r21}}$ | [20:00:00-21:00:00) | **0.78** | 0.46 | 0.43 |
| … | … | … | … | … |
| $T_{\mathrm{r24}}$ | [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 $T_{\mathrm{r}}$ = 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 $U_3$.

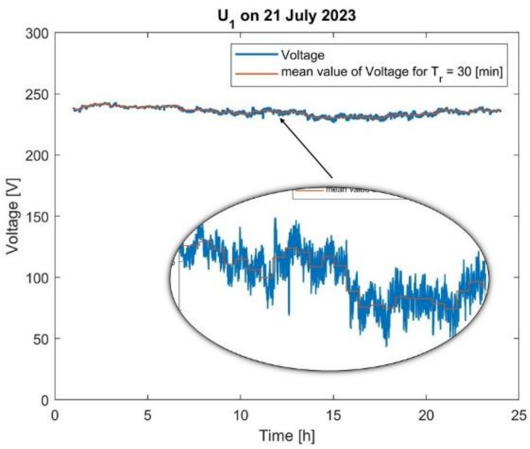


Fig. 6 – Voltage signal on phase 1 ($U_1$), on 21st July, measured value (blue), assumed constant model (red) on $T_r$= 30 min.

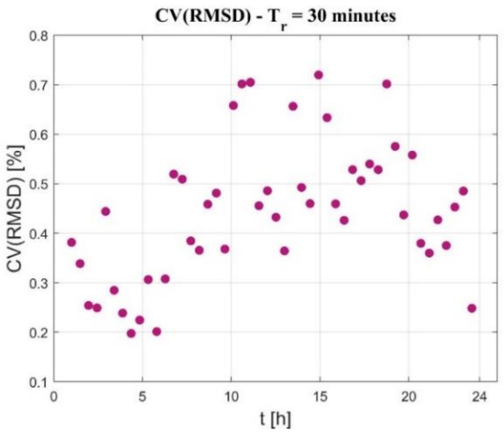


Fig. 7 – CV(RMSD) for the voltage $U_1$ in Fig. 6.

We repeat the procedure for the voltages on the other two phases ($U_2$,$U_3$), on 21 July 2023, with $T_{\mathrm{r}}$ = 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 find in window $T_{r21}$ at 10:15 and is 0.91 %.

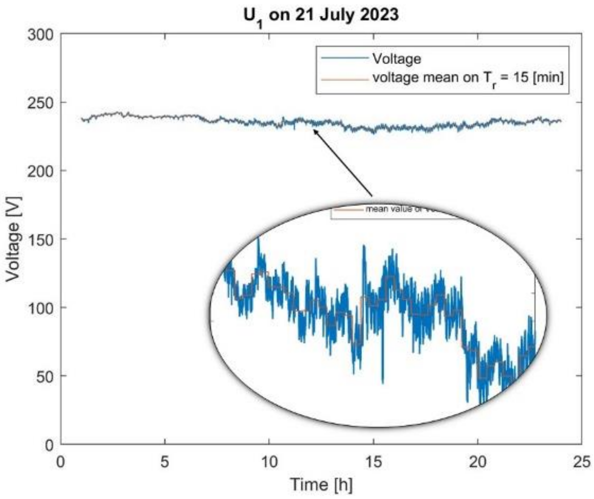


Fig. 8 – Voltage signal on phase 1 ($U_1$), on 21st July, measured value (blue), assumed constant model (in red) on $T_r$ = 15 min.

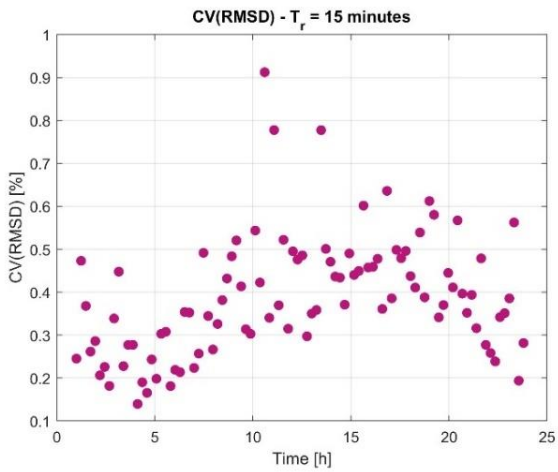


Fig. 9 – CV RMSD) for the voltage $U_1$ in Fig. 8.

*Table 2*

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

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

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

*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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## REFERENCES

1. A. Riepnieks, H. Kirkham, *An introduction to goodness of fit for PMU parameter estimation*, IEEE Transactions on Power Delivery, **32**, *5*, pp. 2238–2245 (2017).
2. IEC 61000-4-30:2015+AMD1:2021 IEC 61000-4-30 ed3.0, *Electromagnetic compatibility (EMC) – Part 4-30: Testing and measurement techniques – Power quality measurement methods*, 2021.
3. A. Ioanid, D. Palade, *The role of distribution system operators in the decentralized power system*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **69**, *1*, pp. 33–38 (2024).
4. M. Gavrilaș, R. Toma, *Flexible alternating current transmission system optimization in the context of large disturbance voltage stability*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **66**, *1*, pp. 21–26 (2021).
5. G. Shahgholian, S.M.A. Zanjani, *A study of voltage sag in distribution system and evaluation of the effect of wind farm equipped with doubly-fed induction generator*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **68**, *3*, pp. 271–276 (2023).
6. D. Macii, D. Petri, *Rapid voltage change detection: limits of the IEC standard approach and possible solutions*, IEEE Transactions on Instrumentation and Measurement, **69**, *2*, pp. 382–392 (2020).
7. A. R. Toma, A.M. Dumitrescu, M.M. Albu, *Impact of measurement set-up on RVC-like event detection*, IEEE International Instrumentation and Measurement Technology Conference Proceedings, Taipei, Taiwan, 2016, pp. 1–5.
8. D. Macii, D. Petri, *On the detection of Rapid Voltage Change (RVC) events for power quality monitoring*, IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Turin, Italy, 2017, pp. 1–6.
9. I. Löfgren, E. Gutierrez-Ballesteros, S. Rönnberg, *Modified method of detecting rapid voltage changes in a medium voltage network*, 20th International Conference on Harmonics & Quality of Power (ICHQP), Naples, Italy, 2022, pp. 1–6.
10. G. Singh, C. Miller, W. Howe, *Assessment of best practices for mitigation of rapid voltage change due to transformer inrush*, IEEE Milan PowerTech, Milan, Italy, 2019, pp. 1–6.
11. A. Bhuyan, B.K. Panigrahi, S. Pati, H. Sahoo, R.K. Pradhan, *Contingency analysis of low voltage dc microgrid*, International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 1108–1111.
12. M.I. Sudrajat, N. Moonen, H. Bergsma, R. Bijman, F. Leferink, *Evaluating rapid voltage changes and its propagation effect using multipoint measurement technique*, International Symposium on Electromagnetic Compatibility, EMC Europe, Rome, Italy, 2020, pp. 1–6.
13. D. Macii, D. Petri, *Fast detection of rapid voltage change events through dynamic RMS voltage tracking*, IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Houston, TX, USA, 2018, pp. 1–6.
14. J. Barros, J.J. Gutiérrez, M. de Apráiz, P. Saiz, R.I. Diego, A. Lazkano, *Rapid voltage changes in power system networks and their effect on flicker*, IEEE Transactions on Power Delivery, **31**, *1*, pp. 262–270 (2016).
15. J. Barros, M. de Apráiz, R.I. Diego, J.J. Gutiérrez, P. Saiz, I. Azcarate, *Minimum requirements for rapid voltage changes regulation based on their effect on flicker*, IEEE International Workshop on Applied Measurements for Power Systems (AMPS), Liverpool, UK, pp. 1–5, 2017.
16. T. Garn, C. Biedermann, B. Engel, *Parameters of rapid voltage changes and their effects on power quality*, Power and Energy Student Summit (PESS), Online, 2021, pp. 1–6.
17. O. Florencias-Oliveros, J.J. Gonzalez-de-la-Rosa, *Continuous and non-intrusive energy monitoring challenge: smart choices in difficult situations*, IEEE 13th International Workshop on Applied Measurements for Power Systems (AMPS), Bern, Switzerland, 2023, pp. 1–6.
18. A. P. Brîncoveanu, E. Fiorentis, A.M. Dumitrescu, M.M. Albu, *Signal model adequacy indicator for measurements in LV grids*, IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Kuala Lumpur, Malaysia, 2023, pp. 1–6.
19. ELSPEC— *Where Power Meets Quality*, Available online: https://www.elspec-ltd.com/metering- protection/power-quality-analyzers/g4400-power-quality-analyzer/ (accessed on 13 July 2022).
20. A.P. Brîncoveanu, R. Plămănescu, A.M. Dumitrescu, M.M. Albu, *Assessment of power profiles in LV distribution grids*, 8th International Symposium on Electrical and Electronics Engineering (ISEEE), Galati, Romania, 2023, pp. 69–74.
21. A.P. Brîncoveanu, E. Fiorentis, A.M. Dumitrescu, M.M. Albu, *Assessing frequency variability using long term high reporting rate measurements*, International Conference on Electromechanical and Energy Systems (SIELMEN), Craiova, Romania, 2023, pp. 1–6.
22. R.J. Hyndman, A.B. Koehler, *Another look at measures of forecast accuracy*, Intern. Journal of Forecasting, **22**, *4*, pp. 679–688 (2006).
23. P. Bharadwaj, J. Agrawal, R.I. Jaddivada, M. Zhang, M. Ilic, *Measurement-based validation of energy-space modelling in multi-energy systems*, 52nd North American Power Symposium (NAPS), 2021.
24. M. Sanduleac, L. Pons, G. Fiorentino, R. Pop, M.M. Albu, *The unbundled smart meter concept in a synchro-SCADA framework*, IEEE International Instrumentation and Measurement Technology Conference Proc., Taipei, Taiwan, 2016, pp. 1–5.
25. R. Plamanescu et al., *Open-source platform for integrating high-reporting rate information using FIWARE technology*, IEEE 13th International Workshop on Applied Measurements for Power Systems (AMPS), Bern, Switzerland, 2023, pp. 1–6.
26. SOCOMEC, *Socomec – innovative power solutions, three-phase power monitoring system*, countians e23 and e24. https://www. victronenergy.com/
27. Raspberry Pi Foundation, *Raspberry Pi 3 model b*, https://www. raspberrypi.com/products/raspberry-pi-3-model-b/
28. IEC 62056-1-0:2014, *Electricity metering data exchange – the DLMS/COSEM suite* – part 1-0: Smart metering standardization framework, 2014.