25th IMEKO TC4 International Symposium
23rd International Workshop on ADC and DAC Modelling and Testing
IMEKO TC-4 2022
Brescia, Italy / September 12-14, 2022

PMU-based metrics for Power Quality Assessment in Distributed Sensor Networks

Guglielmo Frigo [1], Federica Costa [1], Federico Grasso Toro [1]

[1] *Swiss Federal Institute of Metrology METAS*
Lindenweg 50, 3003 Bern-Wabern, Switzerland
E-mail addresses: {guglielmo.frigo, federica.costa, federico.grasso}@metas.ch

Abstract **– In modern power systems, the measurement infrastructure represents the backbone of any monitoring and control application. Indeed, the ever-increasing penetration of renewable energy sources and distributed generation has produced an operating scenario prone to instability and rapid variations. Power quality assessment procedures must evolve in order to address these challenges. In this regard, the use of phasor measurement units (PMUs), which measure the phasor values of current and voltage with high precision time stamp, presents a significant opportunity to evolve current power quality assessment procedures. This position paper suggests the inclusion of novel PMU-based metrics in order to extend quality power assessment procedures at each sensitive network node towards the further use of aggregated data at both local and/or central level. The proposed PMU-based metrics will provide a better description of the behavior of the system, allowing to take control actions as part of the extended quality power assessment procedures.**

I. INTRODUCTION

Power quality (PQ) has been an acknowledged problem in power systems for decades. Power quality can have a large detrimental effect on industrial processes and the commercial sector [1]. While industrial processes typically differ in their requirements, from a power quality perspective, each specific industrial process has particular 'weaknesses' in terms of power quality attributes [2]. Hence, the importance of power quality assessment procedures entails significant considerations to be accounted for to the industrial end-user regarding costs associated with machine down-time, clean-up costs, product quality and equipment failure [3].

Power Quality Assessment Procedure (PQAP) can involve the combination of measurements as well as simulations focusing in the required cooperation between all of the involved parts [4]. From surveys performed to assist in identifying the most important concerns reported by customers on the system, the current focus is advancing the new technologies have been developed under the framework of Smart Grid [5].

One example is the phasor measurement unit (PMU). Considered the most important measuring devices in the future of power systems, PMUs present the unique ability to provide synchronized phasor measurements of voltages and currents from widely dispersed locations in an electric power grid [6].

PMUs measure phasor values of current and voltage with high precision time stamp and together with the values of power frequency, power frequency change rate and optional binary data that are also time stamped are transmitted to a central analysis station [7]. Using PMUs to assess the PQ in the power system is becoming more relevant in context of increasing level of power electronic devices in the grid, e.g. HVDC, FACTS, wind and solar power plants, etc., due to increasing installations and use of PMU measurements [8]. Several test cases were developed and assessments were made based on criteria defined in the IEEE Standards [9]. Early results indicate that PMU data is suitable for some indicative steady-state PQ assessment [8].

For wide-area measurement systems and smart grids, PMUs have become key elements since they provide synchronized information related to the fundamental frequency components of voltages and currents. In recent years, some works have extended the concept of PMU to harmonic analysis due to the proliferation of nonlinear loads [10]. In [11], reference model for P-class and M-class PMUs provided by [9] were expanded with the aim of obtaining the harmonic information and electric power quantities. This approach of global harmonic parameters for PMUs introduced unified quantities regarding the overall harmonic content of voltages and currents signals. With these parameters, the estimation of power quality indices (PQIs) according to the IEEE Standard 1459 [12] was proposed to be carried out with the advantage of a reduced amount of data, reducing correspondent requirements of management, storage, and analysis [11].

This position paper suggests the inclusion of novel PMU-based metrics in order to extend quality power assessment procedures at each sensitive network node towards the further use of aggregated data at both local and/or central level.

II. PMU-BASED METRICS APPROACH

Modern power systems are characterized by an ever-increasing integration of renewable energy sources and distributed generation [13]. In such scenario, the measurement infrastructure is the backbone of any situational awareness application [14], and it consists of a distributed sensor network where, in each node of interest, a Phasor Measurement Unit (PMU) provides time-stamped measurements of voltage and current phasors with an update rate of tens Hz [13].

By means of dedicated communication channels, these measurements are aggregated at local level (digital substation) or central level (control room), in order to guarantee prompt and effective reactions to possible unfortunate events.

In the recent IEC Std 60255-118-1 [9] (briefly, IEC Std), the compliance limits are expressed in terms of Total Vector Error (TVE), Frequency and Rate-of-Change-of-Frequency Error (FE and RFE, respectively).

More precisely, two performance classes are envisioned: P- and M-class for protection and measurement applications, respectively [15], with specific focus on fast responsiveness and high accuracy.

The National Metrological Institutes are responsible for the calibration and characterization of PMUs' performance in laboratory conditions [16, 17]. Once deployed on the field, though, the interoperability between different PMU data streams is questionable [18].

As proven in [18], the PMU measurements might suffer from inconsistencies in the presence of transients. Indeed, the phasor signal model consists of a combination of few narrow-band spectral tones. If such assumption is no more valid, as the signal energy is spread all over its spectrum, a definitional uncertainty issue arises [19].

In the metrology and digital transformation context, this represents a valuable test case for establishing new features and extended characterization techniques, to guarantee a full comparability of the results provided by any type of sensor, even after calibration.

In view of a massive deployment of similar devices in the power system, the development of tools and metrics for the on-line assessment of measurement reliability is necessary, and new regulatory efforts for the standardization of such procedures must be envisioned.

In the following sections, we will discuss the current format employed for the transmission of PMU measurement results and propose a minor yet effective amendment to include a reliability index, computed on-line and thus not significantly affecting the data reporting latency.

Following the same approach, same information employed to refine the results of a state estimation application in a realistic power system scenario can allow us to perform better power quality assessment procedures (PQAP).

III. SIGNAL MODEL AND RELIABILITY INDEX

A generic power signal can be represented by a non-linear dynamic model:

$$x(t) = A\left(1 + \varepsilon_A(t)\right)\cos\left(2\pi f t + \varphi + \varepsilon_\varphi(t)\right) + \eta(t) + z(t) \tag{1}$$

where A, f, and φ are the amplitude, frequency and initial phase of the fundamental component, respectively. The time-varying terms ε_A and ε_φ account for amplitude and phase dynamics, in terms of polynomial, exponential or modulation trends. The additive terms η and z represent the spurious contribution of narrow- and wide-band disturbances: the first one refers to the combination of (inter-)harmonic terms, while the second one account for continuous-spectrum components as white or coloured noise, decaying DC or transients.

In any PMU-based measurement system, the first step of the measurement chain consists in the acquisition process:

$$x[n] \simeq x(t = nT_s), T_s = F_s^{-1}, n = 1, \dots N_s \tag{2}$$

where F_s is the sampling rate and N_s is the sample length.

Given the acquired sample series, the PMU is required to estimate the synchrophasor $\hat{p}$, frequency $\hat{f}$ and ROCOF $\hat{R}_f$ associated to the fundamental component:

$$\hat{p}[m] = \hat{A}[m]\, e^{-j\left(2\pi\left(\hat{f}[m]-f_0\right)mT_r + \hat{\varphi}[m] + \pi\hat{R}_f[m]T_r^2\right)} \tag{3}$$

where the superscript indicates the estimated parameters, while T_r and m are the reporting period and the reporting index, respectively. The subtraction by the system rated frequency f_0 allows for expressing the phase contribution due to off-nominal signal frequencies.

The phasor signal model relies on the assumption that the signal energy is stationary within the considered observation interval and that the signal energy is mostly concentrated in a narrow bandwidth around the fundamental frequency.

When these assumptions are not met (e.g. during an instantaneous step change of amplitude or phase), the PMU estimates suffer from the definitional uncertainty due to the model inconsistency between the spectral properties of the signal under test and its phasor representation.

Consequently, the recent literature has discussed the metrological significance of standard performance metrics in real-world operating conditions and proposed alternative approaches for the assessment of the PMU reliability during transient conditions.

In particular, novel metrics have been introduced in [19], defined in the time domain and not relying on the phasor signal model, thus do not introduce any constraint regarding the spectral bandwidth of the observed phenomenon.

Based on the PMU estimates, it is possible to recover the time-domain trend of the fundamental component as:

$$\hat{x}[n] = \hat{A}\cos\left(2\pi\hat{f}nT_s + \hat{\varphi} + \pi\hat{R}_f(nT_s)^2\right) \qquad (4)$$

and define its discrepancy with respect to the corresponding acquired sample series in terms of Normalized RMSE:

$$\text{nRMSE} = \sqrt{\frac{\sum(\hat{x}[n]-x[n])}{N_s}} \qquad (5)$$

If we consider the PMU estimation as a non-linear fit process, the nRMSE quantifies the residuals' energy, which can be interpreted as an assessment of the signal energy (and thus signal information content) that has been neglected or misrepresented due to the inconsistency between phasor model and acquired sample series.

IV. SUMMARY OF PREVIOUS RESEARCH

As further explained in [19], a correct interpretation of the nRMSE metric requires a preliminary characterization of its variation range and sensitivity to typical grid disturbances.

For this analysis, we simulated test waveforms representative of real-world operating conditions, either normal or critical, and we reproduced a measurement data stream, as provided by a well-known phasor estimation algorithm, namely the Compressive Sensing Taylor-Fourier Model (cs-TFM) [20].

In particular, during our research we considered the following four scenarios:

1. a normal operating condition with steady-state amplitude and phase, while the frequency varies with a "random walk"-like trend (as measured in the EPFL campus) [21];
2. an instantaneous frequency step of -2 Hz followed by a steep frequency ramp of 8 Hz/s until coming back to 50 Hz;
3. a signal characterized by phase and amplitude modulations whose period is in the order of 10 s, as inspired by the inter-area oscillation that was recorded in Lausanne in December 2016 [22];
4. a three-phase fault at the transformer secondary winding (ungrounded terminal) of the bus feeder in the IEEE 34-bus test grid [18].

Table 1 reports the mean μ and standard deviation σ of the nRMSE metric in the four considered test cases.

Based on the reported distributions, the nRMSE metric proves to be able to discriminate between "good" and "bad" data, i.e. data relying on an inconsistent signal model; as in test case 2 and 4, where step changes occur.

Table 1. Mean and standard deviation of the selected performance metrics in the current test waveforms

Test case	Alg.	nRMSE (%)	
		μ	σ
1	cs-TFM	18.22	0.07
2	cs-TFM	66.63	27.94
3	cs-TFM	18.56	0.05
4	cs-TFM	78.94	45.35

V. SUMMARY OF CURRENT RESEARCH

Previous publications have presented very promising early results [19] [21] [22]. However, as suggested in [23], during practical real-time implementations it might be advantageous to calculate at least two sets of phasors to adequately cover slow and fast transients.

During this stage of research, we are aware that the suggested PMU-metrics do not take into account the influence of higher harmonics in the power grid.

In the present position paper, we focus on the evaluation of the proposed PMU-based metrics power quality assessment procedure for real world scenarios.

REAL WORLD SCENARIO 1: SOUTH AUSTRALIA BLACKOUT 2016

To further evaluate the proposed PMU-based metrics power quality assessment procedure for real world scenarios and to assess the sensitivity of nRMSE in real-world scenarios, as well as its dependence on reporting rate, we used the well-known dataset South Australia Blackout 2016 [24]. This dataset consists of the recording of the South Australia blackout on 28th September 2016.

Results are presented in Figure 1. It is worth noticing that, in Figure 1 upper graph, at 3.75 seconds the loss of some wind power plants causes an abrupt fall of the frequency. In Figure 1 lower graph, nRMSE metric is computed with the CS-TFM PMU in P-class configuration with 4 different reporting rates (from 100 frames per second to 10 frames per second, i.e. the configurations suggested by the IEC Std).

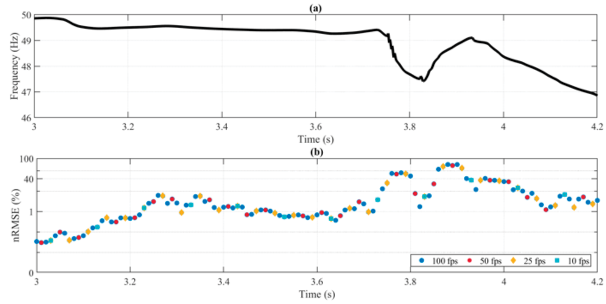

Fig. 1. Evaluation for real world scenario 1
Upper graph: Frequency evolution as function of time.
Lower graph: nRMSE metric computed.

Table 2. Rep. rate and delays for real world scenario 1

Rep. Rate (fps)	10	25	50	100
Delay (ms)	N.A.	55	35	25

As seen in Figure 1, the reporting rate does not affect the computation itself of the nRMSE. However, the higher the reporting rate, the higher the probability to capture promptly an event.

Hence, by using the threshold suggested in [19] (i.e., 40%), we can see how 10 fps are not sufficient to detect the event, whereas the other configurations provide a detection delay that is inversely proportional to the reporting rate, as presented in Table 2.

REAL WORLD SCENARIO 2: TRIP 1.5 GW GENERATOR IN MODIFIED IEEE 39 BUS SYSTEM

For further evaluation, the dataset used for this real world scenario can be found in [25]. In the cited paper, the Authors take the IEEE 29 bus system and replace some of the traditional generators with some wind power plant to mimic the penetration of inertialess generation units. Then they trip some generator (for a total loss of 1.5 GW) and they observe the effects. First contingence at 0.15 s, then nearly 600 ms of a dampened oscillation, then a new contingence at 0.8 s.

As in the previous dataset it is evident that the nRMSE discriminates easily the normal steady-state conditions from the contingencies, but if we look at the delay of the first contingency detection we see how much the reporting rate affects the responsiveness. Related Rep. rates and delays are displayed in Table 3.

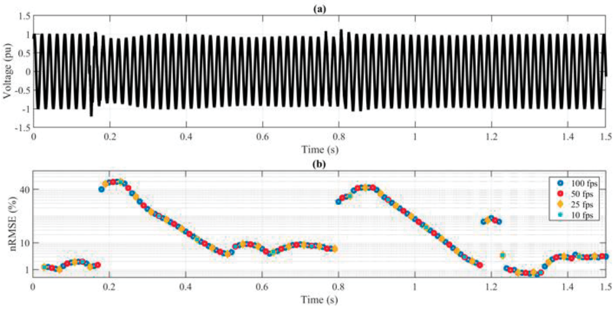

Fig. 2. Evaluation for real world scenario 2
Upper graph: Voltage as function of time.
Lower graph: nRMSE metric with different reporting rates.

Table 3. Rep. rate and delays for real world scenario 2

Rep. Rate (fps)	10	25	50	100
Delay (ms)	85	65	45	35

It can be concluded that the PMU-based proposed seem to be enough, in both simulation [19] and comparison with real world scenarios, seen above, to be consider a valuable approach to further develop toward proper power quality assessment procedures.

VI. STANDARD AMENDMENT PROPOSAL

The IEC Std defines the structure of the measurement data packet as provided by a compliant PMU, as shown in Fig. 3. Focusing on the measurement data field, we can identify six main subfields (byte size in brackets).

All values are in 32-bit floating-point and phasors are in polar format. Analog and digital subfield refer to specific input/output ports, whereas STAT contains bit-mapped flags defining current state and quality info (e.g. internal state, sensor malfunction).

In view of integrating PMU data in more sophisticated control strategies, we propose two possible amendment to the packet structure, as derived from the proposed metrics.

Possible amendment 1:

If a local control application is envisioned, the PMU could verify the bad data detection internally and use a single extra bit as a Boolean flag, where 1 indicates the packet carries potential bad data (i.e., due to model inconsistency and not only on internal malfunction).

Possible amendment 2:

In case of a more centralized approach, an extra subfield of 4 bytes could be dedicated to transmit the nRMSE.

These amendments would not affect the overall packet size in any significant way; neither would request an excessive effort from the computation and transmission capabilities.

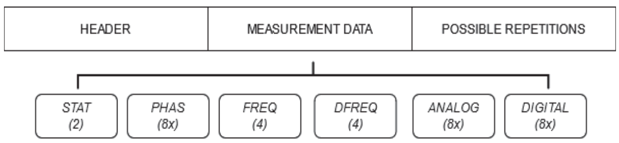

Fig. 3. Measurement data packet structure as defined in [3].

VII. CONCLUSIONS

This position paper suggested the inclusion of novel PMU-based metrics in order to extend PQAP at each sensitive network node towards the further use of aggregated data at both local and/or central level.

The proposed PMU-based metrics provide a better description of the behaviour of the system, as presented in previous research [18-22], allowing to take control actions as part of the extended quality power assessment procedures, while exploiting the advantage of PMUs that require a reduced amount of data.

This position paper focused on the determination of confidence interval associated to metrics for a robust approach for their application in measurement-based controlling efforts. In this preliminary stage of the research, we consider only the systematic error contributions, as we assume that the non-linear effects are covered by noise and harmonics.

The summarized results from previous research proved the scarce accuracy of the PMU-based estimates in dynamic conditions, since nRMSE distributions present inconsistent trends. In addition, due to the present results utilizing well-known datasets from real world scenarios, we can conclude that these proposed metrics would be a new tool for investigating the actual comparability and interoperability of measurements taken from different sensors, and thus quantifying in a more rigorous way the uncertainty in many control applications. Further work regarding its evaluation as performance assessment across the grid is needed.

VII. OPEN SCIENCE

Towards open science, i.e., efforts aimed at achieving more openness in science and the necessary paradigm shift, the current paper follows FAIR principles [26] by the Zenodo community for Sensor Network Metrology: https://zenodo.org/communities/sensornetworkmetrology

REFERENCES

[1] J Stones, in Electrical Engineer's Reference Book (Sixteenth Edition), 2003

[2] S. Mark Halpin, Angela Card, in Power Electronics Handbook (Third Edition), 2011

[3] Shailendra Jain, in Modeling and Control of Power Electronics Converter System for Power Quality Improvements, 2018

[4] McGranaghan, M. Power quality assessment procedure. United States: N. p., 1991. Web.

[5] Rahman, Md & Bin, et al. (2013). Summary of Smart Grid: Benefits and Issues. International Journal of Scientific and Engineering Research. 4. 7.

[6] Yilu Liu et al., "State Estimation and Voltage Security Monitoring Using Synchronized Phasor Measurement". ABB Power T&D Company, CiteSeerX 10.1.1.2.7959

[7] Phadke, A.G. (2002). "Synchronized phasor measurements-a historical overview". IEEE/PES Transmission and Distribution Conference and Exhibition. Vol. 1. pp. 476–479.

[8] Loper, Mari & Trummal, Tarmo & Kilter, Jako. (2018). Analysis of the Applicability of PMU Measurements for Power Quality Assessment. 1-6.

[9] IEEE/IEC 60255-118-1-2018 -International Standard - Measuring relays and protection equipment - Part 118-1: Synchrophasor for power systems, 2018.

[10] Sharma, Rajesh & Dhole, G.M.. (2016). Wide Area Measurement Technology in Power Systems. Procedia Technology. 25. 718-725.

[11] Granados-Lieberman, D. Global Harmonic Parameters for Estimation of Power Quality Indices: An Approach for PMUs. Energies 2020, 13, 2337.

[12] IEEE Std 1459-2010 (Revision of IEEE Std 1459-2000) , vol., no., pp.1-50, 19 March 2010

[13] G. Rietveld *et al*., "Measurement Infrastructure to Support the Reliable Operation of Smart Electrical Grids," in *IEEE Trans on Instr and Meas*, vol. 64, no. 6, pp. 1355-1363, June 2015.

[14] G. Frigo *et al.*, "Characterization of uncertainty contributions in a high-accuracy PMU validation system," in *Measurement*, vol. 146, pp. 72-86, 2019.

[15] G. Frigo *et al.*, "Definition of Accurate Reference Synchrophasors for Static and Dynamic Characterization of PMUs," in *IEEE Trans on Instr and Meas*, vol. 66, no. 9, pp. 2233-2246, Sept. 2017.

[16] G. J. Fitz Patrick and E. Y. Song, “Interoperability Test of IEEE C37.118 Standard-based PMUs,” *2016 International Synchrophasor Symposium*, Mar. 2016.

[17] A. J. Roscoe *et al.*, "The Case for Redefinition of Frequency and ROCOF to Account for AC Power System Phase Steps," *2017 IEEE AMPS*, Liverpool, UK, 2017, pp. 1-6.

[18] G. Frigo *et al.*, "Impact of Fundamental Frequency Definition in IpDFT-based PMU Estimates in Fault Conditions," *2019 IEEE AMPS*, Aachen, Germany, 2019, pp. 1-6.

[19] G. Frigo, F. Grasso-Toro, "On-line performance assessment for improved sensor data aggregation in power system metrology," *XXIII IMEKO World Congress*, Yokohama, JP, 2021, pp. 1-4.

[20] G. Frigo *et al.*, "Taylor-Fourier PMU on a Real-Time Simulator: Design, Implementation and Characterization," *2019 IEEE Milan PowerTech*, 2019, pp. 1-6.

[21] G. Frigo, A. Derviškadić, A. Bach and M. Paolone, "Statistical Model of Measurement Noise in Real-World PMU-based Acquisitions," *2019 IEEE SGSMA*, College Station, TX, USA, 2019, pp. 1-8.

[22] G. Frigo, A. Derviškadić, Y. Zuo and M. Paolone, "PMU-Based ROCOF Measurements: Uncertainty Limits and Metrological Significance in Power System Applications," in *IEEE Trans on Instr and Meas*, vol. 68, no. 10, pp. 3810-3822, Oct. 2019.

[23] A. Ghanavati, H. Lev-Ari and A. M. Stanković, "Sub-Cycle Dynamic Phasors With Adjustable Transient Response," in IEEE Transactions on Power Delivery, vol. 35, no. 4, pp. 1886-1894, Aug. 2020, doi: 10.1109/TPWRD.2019.2956637.

Australian Energy Market Operator, Mar. 2017, [online] Available: http://www.aemo.com.au/media/Files/Electricity/NEM/Market_Notices_and_Events/Power_System_Incident_Reports/2017/Integrated-Final-Report-SABlack-System-28-September-2016.pdf.

[24] Y. Zuo et al., "Impact of Synchrophasor Estimation Algorithms in ROCOF-Based Under-Frequency Load-Shedding," in IEEE Trans on Pow Sys, vol. 35, no. 2, pp.1305-1316, March 2020

[25] Wilkinson, M. D., et al. 2016. “The FAIR Guiding Principles for scientific data management and stewardship.” Scientific Data. Nature.