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DATA QUALITY AND AGGREGATION IN POWER SYSTEM DISTRIBUTED SENSOR NETWORKS

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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. In order to address these challenges, current and voltage phasor measurements are typically acquired at each sensitive network node and then aggregated at local or central level in order to estimate the system state or to take control actions as the opening of a circuit breaker. From a normative point of view, the existing standards focus on the performance compliance of a single sensor, but they do not verify their actual interoperability. In this regard, this paper proposes a minor yet effective amendment to include in the digital format (Ethernet packet) of the measurement result a performance metric to be computed on-line. As proven by the numerical simulations, the proposed metric allows for an improved data aggregation and a more accurate state estimation.

Keywords: Distributed Sensor Network, Measurement Data Aggregation, Interoperability, Power System, Definitional Uncertainty

1. INTRODUCTION

Modern power systems are characterized by an ever-increasing integration of renewable energy sources and distributed generation [1]. In such scenario, the measurement infrastructure is the backbone of any situational awareness application [2], and consists of a distributed sensor network where, in each node of interest, a Phasor Measurement Unit (PMUs) provides time-stamped measurements of voltage and current phasors with an update rate of tens Hz [1]. 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 (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 [3], 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 [4, 5]. Once deployed on the field, though, the interoperability between different PMU data streams is questionable [6].

As proven in [7, 8], 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 [9].

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 this paper, we 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. The same information is employed to refine the results of a state estimation application in a realistic power system scenario.

The paper is organized as follows: In Section 2, the on-line metrics are introduced and thoroughly characterized. In Section 3, we present the data packet format and the possible extension to include the novel performance metrics. In Section 4, a state estimation example proves the efficacy of the proposed metrics. Finally, Section 5 provides closing remarks and outlines future steps.

2. 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:

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

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 Rate of change of frequency (ROCOF) $\hat{R}_f$ associated to the fundamental component:

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

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 [5], 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:

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

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

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

If we consider the PMU estimation as a non-linear fit process, the nRMSE quantifies the residuals' energy, that 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.

As further explained in [10], 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) [11].

In particular, 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) [12];
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 [13];
4. a three-phase fault at the transformer secondary winding (ungrounded terminal) of the bus feeder in the IEEE 34-bus test grid [8].

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

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

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.

3. STANDARD AMENDMENT PROPOSAL

The IEC Std defines the structure of the measurement data packet as provided by a compliant PMU. As shown in Fig. 1, It is composed of three main fields: 1) the header specifies the PMU id, the configuration parameters and the associated time-stamp; 2) the measurement data; and 3) possible repetitions of previously transmitted data (in case of packet loss or aggregation needs).

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 (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. On the metrological side, though, they would provide a new tool for investigating the actual comparability and interoperability of measurements taken from different sensors, and thus quantify in a more rigorous way the uncertainty in many control applications.

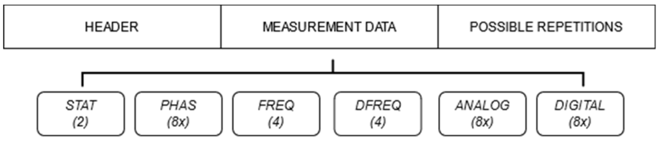

Fig. 1. Measurement data packet structure as defined in [3].

4. STATE ESTIMATION TESTBENCH

The knowledge of this reliability metric opens up new possibilities at different network levels. At the sensor level, it can be seen as a flag of possible instrument failure. At a higher and aggregated level, it can be used to detect fault or anomalies. In this regard, this information has been proven to be capable of improving the accuracy in fault location [14].

In this paper, instead, we evaluate the possibility of using the reliability metric to define the most suitable weights in a Weighted Least Squares (WLS) state estimation [15]. In particular, our focus is on determining the confidence interval of the nRMSE metric and deriving a robust approach for its application in measurement-based applications [16].

In Matlab Simulink programming environment, we reproduced the IEEE 14-bus test case. For completeness, the one-line diagram of the network is reported in Fig. 2. It is worth noticing that the IEEE 14-bus test case represents a portion of the American electric power system (in the Midwestern US) as of February, 1962. It consists of 14 buses, five generators, and 11 loads [17].

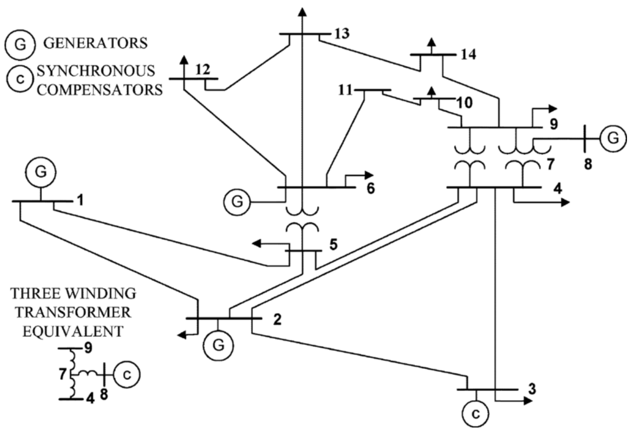

Fig. 2. On-line diagram of the IEEE 14-bus test case [17].

In each bus, we deployed a PMU model that measures both voltage and current phasors. For this analysis, the PMU is set in P-class configuration, with a sampling rate of 5 kHz, an observation interval of 60 ms, and a reporting rate of 50 frames per second (fps).

The measurement uncertainty inherent in the PMU acquisition process is modelled through two independent contributions, namely the distortion due to wide- and narrow-band disturbances, and the systematic error introduced by the instrument transformer. The wide-band distortion is modelled as additive white Gaussian noise, such that the Signal-to-Noise ratio is equal to 45 and 35 dB for voltage and current waveforms, respectively.

As regards the instrument transformers, 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. We consider classes 0.1 and 0.5 for voltage transformers, and classes 0.2 and 0.5 for current transformers.

The cs-TFM is a dynamic estimator, i.e. it recovers not only the fundamental synchrophasor, but also its first- and second-order derivatives as computed around the reporting time instant. The time-domain trend of the fundamental component can be thus computed in two ways:

- *Static*: with only the zero-order parameters: amplitude, frequency, phase, ROCOF;
- *Dynamic*: considering all the derivative terms, i.e. accounting also for the parameter variations within the considered window.

The different formulations result in different nRMSEs and consequent considerations. In the static case, we measure the estimation reliability of the IEC Std parameters, whereas in the dynamic case, we evaluate how much the dynamic model is capable of tracking their time variations.

In Fig. 3(a), we present the voltage waveform as acquired at the node 4 of the IEEE 14 bus network. The effect of the dynamic load model is evident in the amplitude level fluctuations. In Fig. 3(b), the corresponding nRMSE computed according to the static and dynamic phasor formulations are represented in blue and red, respectively. Once again, the static one is more sensitive to the parameter time variations, whereas the dynamic one exhibits a nearly constant value (mainly dependent on the narrow- and wide-band distortion levels).

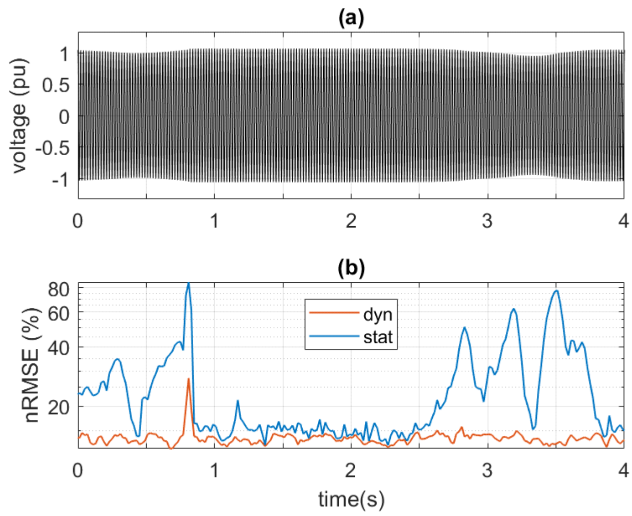

Fig. 3. In (a), voltage signal as acquired by the PMU at node 4 (VT and CT class 0.5). In (b), nRMSE measured based on static (blue) and dynamic (red) phasor representation.

In the absence of ground-truth reference values, a Load Flow (LF) analysis has been conducted to define the instantaneous value of voltage and current at each reporting time instant. In this context, we ran a WLS state estimation with three different weight configurations. As shown in Fig. 4(a), the weights are set equal to the inverse of the systematic error variances or to the inverse of the nRMSE in its static or dynamic formulation.

In Fig. 4(b), it is interesting to observe how the instrument transformer class and the dynamic model provides comparable values, whereas the static one associates a lower weight to any measurement taken during a non-stationary condition.

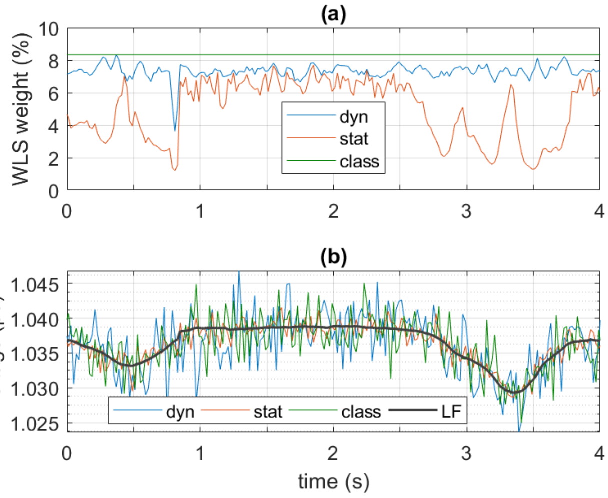

Fig. 4. In (a), WLS weights based on VT class (green), static (red) and dynamic (blue) nRMSE. In (b), WLS estimates of voltage real part in node 4 against the load flow (black) reference values.

As expected, the dynamic formulation does not add any improvement with respect to the class information, whereas the static one allows for a reduction of the noisy oscillations. In a more quantitative way, the RMS error for the three different configuration is equal to 700, 750 and 500 ppm for the class, dynamic and static approach, respectively.

5. CONCLUSIONS

This 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.

By means of numerical simulations, we presented a possible application of the reliability metrics in a WLS-based state estimation, highlighting the performance enhancement and the theoretical limits of the proposed approach.

The simulations results proved the scarce accuracy of the PMU-based estimates in dynamic conditions, since nRMSE distributions present inconsistent trends. Further work regarding these promising findings is required, not only in the PMU level, but also in the potential evaluation of these metrics as performance assessment across the grid.

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 [18] by making all used datasets and codes available in the Zenodo community for *Sensor Network Metrology*:

https://zenodo.org/communities/sensornetworkmetrology

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