Paolo Castello, Carlo Muscas, Paolo Attilio Pegoraro, Davide Sitzia, Sara Sulis

On the Variability of Random Errors Distribution in PMUs: An Experimental Characterization

CONFERENCE PROCEEDINGS - IEEE INSTRUMENTATION/MEASUREMENT TECHNOLOGY CONFERENCE 2025

The publisher's version is available at:
https://dx.doi.org/10.1109/i2mtc62753.2025.11079032

On the Variability of Random Errors Distribution in PMUs: An Experimental Characterization

Paolo Castello
Dept. of Electr. and Electron. Eng.
University of Cagliari
Cagliari, Italy
paolo.castello@unica.it

Carlo Muscas
Dept. of Electr. and Electron. Eng.
University of Cagliari
Cagliari, Italy
carlo.muscas@unica.it

Paolo Attilio Pegoraro
Dept. of Electr. and Electron. Eng.
University of Cagliari
Cagliari, Italy
paolo.pegoraro@unica.it

Davide Sitzia
Dept. of Electr. and Electron. Eng.
University of Cagliari
Cagliari, Italy
davide.sitzia@unica.it

Sara Sulis
Dept. of Electr. and Electron. Eng.
University of Cagliari
Cagliari, Italy
sara.sulis@unica.it

***Abstract*—Recent developments in the field of synchronized measurements based on Phasor Measurement Units (PMUs) have paved the way for innovative applications in monitoring and control of modern power systems, often grounded in the digital twin paradigm. For such systems to function optimally, it is essential to understand the uncertainty models of the devices deployed in the field. This knowledge helps determine the final accuracy of the estimates produced by state-of-the-art monitoring applications. In this context, the objective of this study is to establish a robust foundation for describing the distribution of PMU random errors, by experimentally analyzing three commercial devices from the same manufacturer fed with signals produced in a controlled laboratory setting. The results show that the Gaussian model can always be obtained for magnitude errors. Although the assumption of normality for phase-angle errors does not always perfectly match the data, the modest disparities suggest that standard deviation still reflects error variability.**

***Index Terms*—Phasor Measurement Unit (PMU), statistical model, measurement error, Shapiro-Wilk test, random error, Gaussian distribution, digital twin**

Prof. Castello's work was partially funded by Fondazione di Sardegna for the research project "SENeCO (Smart Energy Network & COmmunity)", call 2022, F73C23001690007.

The work of Prof. Carlo Muscas was funded by the European Union - Next Generation EU through the Italian Ministerial grant PRIN 2022 "Next-generation distributed synchronized measurement systems for smart grids with self-diagnostics capabilities and self-improvement of information quality", N. 2022RYZJT9, CUP F53D23000730006.

Prof. Pegoraro's work was funded by the European Union - Next Generation EU, Mission 4, Component 2, through the Italian Ministerial grant PRIN 2022 "Smart grid-connected power converters based on advanced synchrophasor-inspired harmonics measurements for holistic integration of renewable energy sources (POWERHERO)," n. 20224X2AYH, CUP F53D23000490006.

Prof. Sulis's work was partially funded by the Italian Ministerial grant PRIN 2022 PNRR "Next quantum-based traceability and new accuracy description for synchronized multifrequency phasor measurements in modern distribution grids (QuantAGrid)", n. P20228WW42, CUP. F53D23008280001, "PNRR M4.C2.1.1 PRIN PNRR 2022 Avviso D.D. 1049 del 14/09/2022 Finanziamento dell'Unione Europea – NextGenerationEU".

I. Introduction

In modern power systems, the digital twin paradigm is driving the development of virtual representations of physical components and processes that can enhance the development of management and analysis applications [1]. In this context, the ability to consider reliable models for monitoring systems based on Phasor Measurement Units (PMUs), including realistic models for the measurement uncertainty, is paramount to evaluate and increase the accuracy of applications before they operate with data from the field [2].

Typical monitoring systems based on synchrophasor measurements consist of a hierarchical architecture with several PMUs installed in the field at the base and Phasor Data Concentrators (PDCs) that collect and time-align PMUs' data to send a data stream to the control center. At the top of the monitoring system, the control center processes the data from the PMUs using real-time applications [3], [4]. However, information is also stored for offline analysis, for example after a major event such as a blackout. The obtained measurements are affected by different sources of uncertainty, depending on the elements directly connected to the monitored power system, typically instrument transformers (ITs) and PMUs [5].

These monitoring systems can be made up of PMUs from different manufacturers [6]. Devices in the same location may need to be changed, the number of channels or metering points can increase over time, and system operators may not be able to upgrade the monitoring system with devices from the same manufacturer. Hence, since standards for PMU measurements are updated cyclically, it is possible that PMUs complying with different versions of the standard may be operating in the same network. As reported in [2], different PMUs may have different uncertainty characteristics, which should also be considered when developing the digital twin of a system composed of simulated PMUs from different vendors.

In recent literature, several attempts have been made to statistically characterize the measurement errors of PMUs, using data of varied origin, often far from the electrical steady-state regime, which should be the typical PMU operating condition in transmission networks. In [7], [8], an analysis on real-world data was carried out, and Gaussian Mixture Models (GMMs) were proposed for the statistical modeling of magnitude and phase-angle errors, since, in that case, the normal distribution did not prove to be a suitable choice. In [9], focus was again on GMMs, with the aim of performing parameter tuning for PMU random error modeling. Long-tail non-Gaussian distributions were found in [10], where, once more, measurements coming from the field were used. A characterization based on dynamic signals generated in a laboratory environment was performed in [11], leading to statistical models that deviate from the normal distribution. In [12], the hypothesis of non-Gaussian noise underlying PMU measurements was considered to evaluate its impact on different state estimation algorithms using different simulated statistical models, including Laplace, Weibull and Gaussian-Mixture distributions.

These results, if not contextualized, can lead to erroneous assumptions in applications where the choice of the statistical model of measurement errors is critical, therefore attention must be paid to the measurement conditions under which the model is to be applied. Data collected under uncontrolled conditions or derived from dynamic signals in fact, may not faithfully represent the intrinsic behavior of the measurement instrument, since in the former case they may hide the effects of phenomena external to it, and in the latter they are affected by the variability of signals that may give rise to varied statistical distributions that deviate from the normal.

The authors have investigated the characterization process of PMU errors in previous papers: in [2], the analysis performed on PMUs from different vendors highlights that the Gaussian distribution is often a valid option, especially for the voltage magnitude errors. However, deviations from Gaussianity can emerge depending on the specific PMU model, the measured quantity and the considered channel. In this regard, in [2], the analysis intended to act as a bridge between different conclusions delineated in the recent scientific literature through different approaches and tests. In particular, the statistical distribution of errors makes it possible to distinguish stationary models from non-stationary effects. This prevents misinterpretation of error distributions obtained from raw field data. In [13], a characterization of the current magnitude and phase-angle errors of different PMU models with different current levels is presented to define statistical error models also for currents. The analysis shows that the Gaussian distribution is often a good choice, especially for magnitude errors, regardless of the current level considered. More complex dynamics related to the synchronization system, which is the dominant error source when phase-angle measurements are very accurate, can affect phase-angle errors.

In this scenario, according to the idea firstly developed in [2], this paper provides a further contribution in studying the behavior of PMUs, by investigating the variability of the statistical behavior of a group of PMUs from a single manufacturer. The tested devices were produced in different years, and consequently they have a different history of use.

The analysis still focuses on the characterization of PMUs, without considering ITs. This allows evaluating the performance of a PMU in a controlled environment using reference signals generated by a calibrator, with the advantage that measurement errors can be accurately determined because the reference value is identifiable and traceable [14]. This condition is difficult to guarantee in cases where the reference signals are not traceable, as in the case of signals acquired directly from the grid where the stationarity cannot be guaranteed. The experimental tests include a scenario in which all the PMUs (same manufacturer and same model) receive the same input test signal, via a parallel configuration for voltages and a series configuration for currents. With respect to [2] and [13], this approach allows focusing on the stability of statistical error models in presence of aging or manufacturing variability. The PMUs have been tested in different ways to minimize potential biases from the characterization system. In particular, Shapiro-Wilk test and graphical inspection analysis have been carried out to describe the behavior of measurement errors, with the aim to investigate discrepancies in magnitude and phase-angle error statistics, which should be considered when PMU measurement outputs are planned to be used in higher-level applications.

II. Data Collection and Analysis

A. Test Setup

The laboratory tests involved three commercial PMUs, same type and manufacturer but different uptime, which were tested using three-phase steady-state voltage and current signals, respectively with 100 V root-mean-square (RMS) and 5 A RMS values, thereby simulating the typical operating regime of these devices when they are interfaced with ITs in transmission grids. The PMUs were tested following two different approaches: first individually, in what follows referred to as stand-alone tests, then in a parallel (for voltage tests) or series (for current tests) configuration, feeding them with the same voltage and current test signals, under the condition of negligible load effects, ensured by the high impedance of the PMU voltage input channels and the low impedance of the current ones.

Figure 1 shows the test architecture implemented in the instrumentation and measurement laboratory at the University of Cagliari, Italy. The diagram includes a single device under test, but it is representative of the system also when multiple PMUs are connected in the parallel-series configuration. The high-accuracy power signal generator Omicron CMC 256plus is a central element in the architecture, as it is able to provide stable and controlled three-phase voltage and current signals in input to the device under test (DUT), allowing an accurate evaluation of the PMU behavior under electrical steady-state conditions. The manufacturer declares for the generator a typical accuracy of $0.015\,\%$ of reading plus $0.005\,\%$ of the device full-scale range (FSR), which is translated into $0.02\,\%$

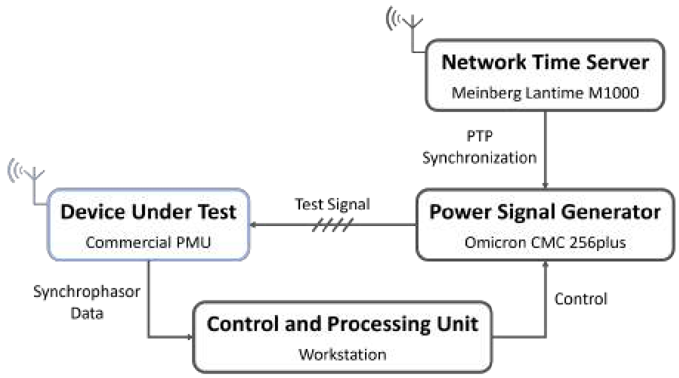

Fig. 1. Laboratory test architecture.

and $0.03\,\%$ typical accuracy values at the considered voltage and current levels, respectively.

Time synchronization was provided to the generator by the external GPS receiver Meinberg Lantime M1000 through the Precision Time Protocol (PTP) in the Utility Profile configuration, thus ensuring the stability of the phase reference in the signal generation stage. PMU synchronization was ensured by the embedded GPS receiver and an antenna for each device under test. To guarantee a good level of time synchronization, all the antennas are installed on the roof of the laboratory at a sufficient distance from each other to avoid interference issues. The antenna cables have the same length.

Each PMU was tested for two hours, first stand-alone, then in the parallel-series setup, with a monitored ambient temperature of 23 °C, and a PMU reporting rate of 50 frames per second.

Data collection was performed through a workstation, which was also used to control the power signal generator and to analyze measurement data. In particular, the analysis of the status word, in order to detect a possible variation in the quality of the time synchronization of the DUT, is performed in real-time during the data acquisition process by means of dedicated software, able to stop the test if a synchronization problem is detected.

B. Statistical Analysis

The aim of this paper is to provide a statistical characterization of the magnitude and phase-angle errors on the voltage and current measurements of the three PMUs, trying to extract a generalized pattern for the devices under test. To do so, both test setup and data analysis approach were chosen with the common purpose of excluding the presence of external influences on the measurement data.

First of all, an evaluation of the PMU performance was carried out using the TVE index, defined in percentage terms as follows:

$$\text{TVE [\%]} = 100 \cdot \frac{\sqrt{\Delta X_r^2 + \Delta X_i^2}}{|\bar{X}|} \tag{1}$$

where ΔX_r is the difference between the real parts of the reference and measured synchrophasors, while ΔX_i is its counterpart for the imaginary parts. Also, $|\bar{X}|$ is the magnitude of the reference synchrophasor $\bar{X}$ (from hereon $|\cdot|$ is magnitude operator).

The TVE index is representative of the overall behavior of PMUs, since it incorporates the error on both magnitude and phase-angle measurements, thus providing a quantitative feedback on performance and the verification of synchrophasor standard compliance, which imposes a $1\,\%$ upper limit in steady-state operating conditions [15]. However, in order to provide a more meaningful contribution to power system applications that rely on PMU data, it is more useful to give a statistical description in terms of magnitude and phase-angle, as these are the typical PMU estimated quantities. Errors on these quantities can be computed starting from the estimated and reference synchrophasors, as follows:

$$\text{ME [\%]} = 100 \cdot \frac{|\hat{\bar{X}}| - |\bar{X}|}{|\bar{X}|} \tag{2}$$

$$\text{PE [crad]} = 100 \cdot (\angle\hat{\bar{X}} - \angle\bar{X}) \tag{3}$$

where $\hat{\bar{X}}$ is the measured synchrophasor and $\angle\cdot$ indicates the angle operator.

The core of the statistical approach, consisting of significance tests for determining the nature of error distributions, was preceded by a preliminary step aimed at mitigating autocorrelation in the data. In fact, high autocorrelation values may reveal the presence of hidden patterns in the data.

The significance test chosen is the Shapiro-Wilk test, as the goal was to assess whether the normal distribution was applicable to the data under analysis. The test provides its response in terms of p-value, which can only take positive values lower than 1. The significance level α chosen to determine whether the Gaussianity hypothesis should be rejected or not is 0.05, a value commonly used in the scientific literature [2], [7], [8]. A p-value below α results in a rejection of the normality hypothesis.

The Gaussianity analysis was also aided by the use of graphical inspection tools, including the magnitude and phase-angle error probability density functions (PDFs) shown in Section III.

III. Experimental Results

A. PMU Errors Evaluation

As a first outcome of the analysis, the results in terms of the voltage TVE $\%$ are shown in Table I for the three PMUs from the same manufacturer (indicated as PMU 1, PMU 2 and PMU 3), which, before the lab tests presented in this paper, had operated with different uptime. The results are given for the three phases and for the two testing approaches: stand-alone and parallel tests. The reported values show that all the PMUs are characterized by TVE % values lower than $1\,\%$ and perform in a similar way. In both the performed tests, PMU 3 has slightly higher errors, while PMU 2 is characterized by lower errors. Similar results are also obtained for the TVE of the currents and, for the sake of brevity, will not be reported here.

TABLE I
MAXIMUM VALUES OF THE VOLTAGE TVE

DUT	Maximum Voltage TVE [%]					
	Stand-Alone Test			Parallel Test		
	Phase A	Phase B	Phase C	Phase A	Phase B	Phase C
PMU 1	0.16	0.16	0.15	0.18	0.17	0.17
PMU 2	0.15	0.16	0.13	0.13	0.15	0.12
PMU 3	0.20	0.22	0.19	0.18	0.21	0.17

Driven by these preliminary results, the focus shifted to the error trends for the amplitudes and phase-angle errors that resulted in the lowest TVE % values (phase C), but the same behavior was found to characterize the other voltage channels. Figure 2 shows the trends of 3000 consecutive voltage phase-angle error values for the three PMUs considered in the parallel test case (the same trends were found in the stand-alone test case). The three plots reveal how the phase-angle errors are distributed according to two different patterns. PMU 2 exhibits peculiar behavior, as PEs clearly appear to distribute along two different levels, whereas the same pattern is absent in the case of PMU 1 and PMU 3. The time trends observed here cannot be attributed to the calibrator, as the test was conducted in parallel, but instead, it is indicative of the performance of the individual device.

B. Quantitative Assessment of Normality

As described in Section II-B, in order to decrease the effect of hidden patterns in the collected data that may not be attributed to the intrinsic behavior of the device, the auto-correlation test and a consequent decimation was performed on the analyzed data set. In particular, the same decimation

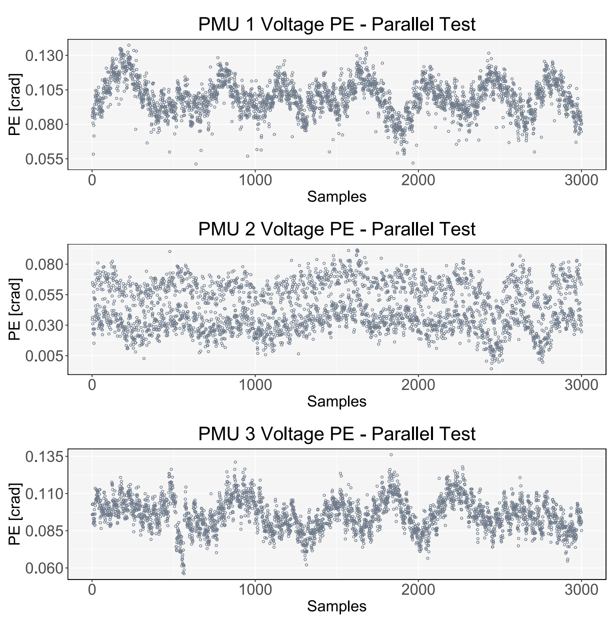

Fig. 2. Time trends of PMU phase-angle errors, voltage phase C, parallel tests.

TABLE II
SHAPIRO-WILK TEST RESULTS FOR VOLTAGE PARALLEL TEST

DUT	Sample Size	p-value from Shapiro-Wilk Test					
		ME			PE		
		Phase A	Phase B	Phase C	Phase A	Phase B	Phase C
PMU 1	**3000**	0.98	0.99	0.98	0.00	0.00	0.00
	1000	0.99	0.98	1.00	0.79	0.13	0.00
	500	0.99	1.00	1.00	0.98	0.94	0.91
	100	1.00	1.00	1.00	1.00	1.00	1.00
PMU 2	**3000**	1.00	0.98	0.98	0.00	0.00	0.00
	1000	0.99	0.99	1.00	0.00	0.00	0.00
	500	0.99	1.00	0.99	0.01	0.04	0.02
	100	1.00	1.00	1.00	0.93	0.98	0.99
PMU 3	**3000**	0.99	0.99	0.98	0.27	0.86	0.95
	1000	1.00	0.99	0.98	1.00	0.99	0.99
	500	1.00	0.99	1.00	1.00	1.00	0.97
	100	1.00	1.00	1.00	1.00	1.00	1.00

TABLE III
SHAPIRO-WILK TEST RESULTS FOR CURRENT SERIES TEST

DUT	Sample Size	p-value from Shapiro-Wilk Test					
		ME			PE		
		Phase A	Phase B	Phase C	Phase A	Phase B	Phase C
PMU 1	**3000**	1.00	0.99	0.98	0.05	0.00	0.00
	1000	0.99	1.00	1.00	0.89	0.49	0.48
	500	1.00	0.99	1.00	0.96	1.00	0.97
	100	1.00	1.00	1.00	1.00	1.00	1.00
PMU 2	**3000**	0.90	0.94	0.97	0.00	0.00	0.00
	1000	0.99	0.99	0.99	0.00	0.05	0.01
	500	0.99	1.00	1.00	0.18	0.42	0.37
	100	1.00	1.00	1.00	1.00	1.00	1.00
PMU 3	**3000**	0.63	0.99	1.00	0.89	0.84	0.87
	1000	0.97	0.99	0.98	1.00	0.98	0.97
	500	1.00	1.00	1.00	0.99	1.00	1.00
	100	1.00	1.00	1.00	1.00	1.00	1.00

value has been chosen for all the PMUs and for both voltage and current magnitude and phase-angle errors, although its value proved not to be critical in the analysis of the magnitude errors, as it led to the same results in the Gaussianity hypothesis evaluation. Tables II and III show the results of the quantitative analysis of the Gaussianity tests on voltage and current measurement errors using the Shapiro-Wilk test, considering the parallel and series setups, respectively. Stand-alone setup resulted in similar Shapiro-Wilk responses, thus these results are not shown, for the sake of brevity. Tests were performed by analyzing the magnitude and phase-angle errors for each phase and considering 4 different data set sizes, from 100 to 3000 samples. The use of different data sizes is justified by the purpose of verifying the behavior of devices over different time intervals and provide a broader-spectrum characterization intended for different applications. The results show that the assumption of Gaussianity can be accepted in all cases considered for the amplitude errors of both voltage and current measurements.

The behavior of the phase-angle error test is different for each PMU examined: in particular, it can be seen that PMU 3

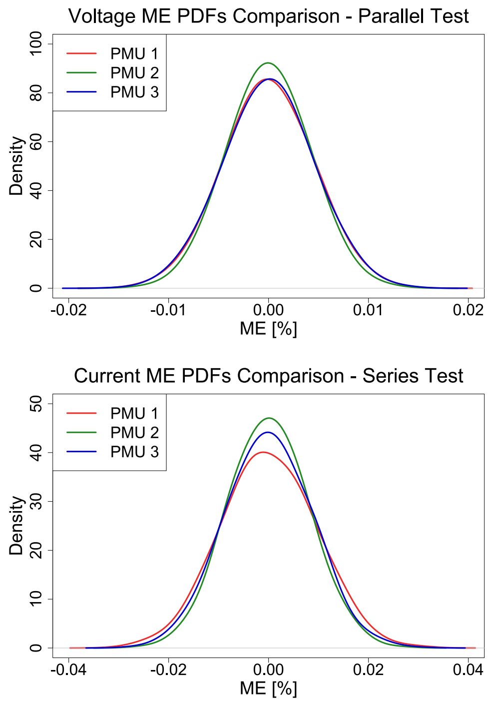

Fig. 3. Zero-mean voltage and current magnitude errors PDFs, parallel-series test.

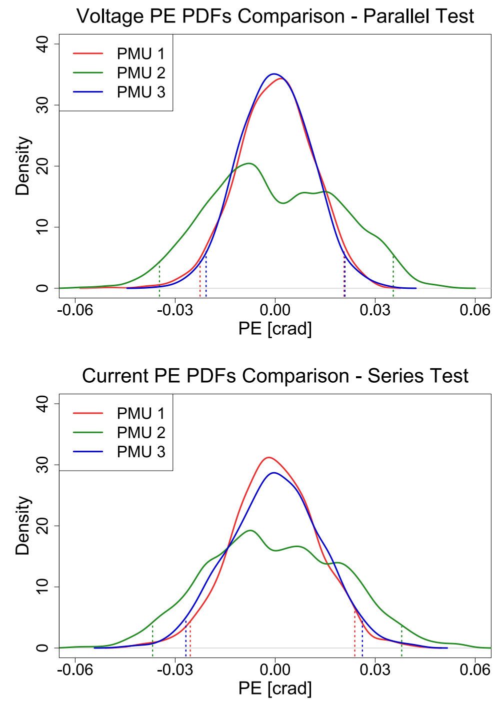

Fig. 4. Zero-mean voltage and current phase-angle errors PDFs, parallel-series test. Dashed vertical lines enclose the portion of the distribution containing 95 % of data.

allows the Gaussianity assumption to be considered valid for all the data sets considered, but this is not always the case for PMU 1 and PMU 2. As it can be seen from the tables, the voltage (Table II) and current (Table III) tests provide similar results: PMU 1 can be regarded as Gaussian from the 1000-value data set down, except for the voltage phase C case; in PMU 2 the Gaussianity assumption can only be considered valid for small data sizes (100 for voltage, 500 for current), whereas in PMU 3 the normality hypothesis is not rejected in all cases.

The followed testing approach allows stating that Shapiro-Wilk outcomes reflect the similarities or differences in the actual behavior of the considered devices, since tests were also performed in parallel and series. It is always possible to use a Gaussian model to describe MEs, whereas, when PEs are considered, the PMUs, even from the same manufacturer, can show different behaviors. The assumption of Gaussianity can be considered rigorously valid only for small sizes of the data set, but, as will be discussed in the next section, this does not appear as a critical finding for PMU error modeling. Indeed, a different analysis using density distributions can help in understanding better the behavior of the errors.

C. Graphical Inspection Analysis

In this section, a graphical inspection analysis of data provided by the PMUs is performed. In particular, here cases concerning the 1000-size data sets and phase C for all the tested PMUs are reported, but similar considerations can also be drawn for the other phases. From this point on, only data obtained from the parallel-series setup will be taken into account. The PDF will be used to analyze the data graphically.

Figure 3 shows the voltage and current ME PDFs of all PMUs, where systematic errors are compensated to emphasize the comparison among the device random errors. The shapes confirm the Gaussianity hypothesis made as a result of Shapiro-Wilk tests. The error variation range associated with voltage measurements is about half that of current measurements.

Figure 4 shows the voltage and current PE PDFs of the three PMUs, focusing only on random errors. In both cases, the plots of PMUs 1 and 3 are almost overlapped, whereas this is not the case for PMU 2, whose distribution significantly deviates, although the maximum random errors are of the same order of magnitude as the values obtained for PMUs 1 and 3.

Looking at the dashed lines in the figure, marking the boundaries that determine the area in which 95 % of the values are concentrated, it can be seen that this range is widest in the case of PMU 2, which is the one where the normal distribution fitted worst, while it is narrower in PMU 1 and PMU 3, in which the Gaussian model proved to be more suitable. This allows drawing the preliminary conclusion that the normality of the data might be reduced for these PMUs when the contribution of random error increases, e.g., due to higher uptime or to network events that may have degraded PMU operation, while it becomes stronger when the variability range decreases.

Notwithstanding the above considerations, the analysis of

TABLE IV
COVERAGE FACTORS IN SAMPLES DISTRIBUTION FOR PEs

DUT	% of Samples Included					
	Voltage Parallel Test			Current Series Test		
	$\pm\sigma$	$\pm 2\sigma$	$\pm 3\sigma$	$\pm\sigma$	$\pm 2\sigma$	$\pm 3\sigma$
PMU 1	68.4	95.6	99.6	70.4	96.0	99.5
PMU 2	64.7	97.5	99.9	65.0	96.4	100.0
PMU 3	66.8	95.3	99.8	66.7	95.7	99.7

PDFs reveals another interesting result. Table IV reports the percentage of coverage given by $\pm\sigma$, $\pm 2\sigma$ and $\pm 3\sigma$ intervals around average values for the PEs of the three PMUs. There is a remarkable similarity among the three devices. Even though PMU 2 shows a smaller percentage for the first interval and higher coverage within 2σ, the percentage of PEs included in 3σ intervals is almost the same and enough to represent faithfully PE range. The discrepancies are limited and illustrate how, even if normality is not perfectly tailored to the data, standard uncertainty always captures the variability of the errors in a similar way. In many applications, this allows considering the assumption of normality as a good trade-off and a meaningful approximation.

IV. CONCLUSIONS

To evaluate the performance of power system applications based on PMU measurements, it is essential to consider error models as close as possible to actual instrument behavior. To make a contribution in this context, this paper has discussed the random errors distribution of three PMUs from the same manufacturer – identical model – obtained using voltage and current signals generated in a controlled environment. The results show that the Gaussian model can always be assumed for magnitude errors. The assumption of normality for phase-angle errors may not always be perfectly tailored to the data, but the limited discrepancies show that standard uncertainty can appropriately capture the variability of errors. Hence, in cases such as in state estimation or control algorithm definition, Gaussian model can be a good trade-off. Furthermore, when generating synthetic data, e.g., in digital twins, modeling the random errors as Gaussian errors can provide a suitable level of approximation.

REFERENCES

[1] A. Mingotti, F. Costa, D. Cavaliere, L. Peretto, and R. Tinarelli, "On the Importance of Characterizing Virtual PMUs for Hardware-in-the-Loop and Digital Twin Applications," *Sensors*, vol. 21, no. 18, 2021.

[2] P. Castello, C. Muscas, and P. A. Pegoraro, "Statistical Behavior of PMU Measurement Errors: An Experimental Characterization," *IEEE Open Journal of Instrumentation and Measurement*, vol. 1, pp. 1–9, 2022.

[3] S. Pandey, A. K. Srivastava, and B. G. Amidan, "A Real Time Event Detection, Classification and Localization Using Synchrophasor Data," *IEEE Transactions on Power Systems*, vol. 35, no. 6, pp. 4421–4431, 2020.

[4] B. Foggo and N. Yu, "Online PMU Missing Value Replacement Via Event-Participation Decomposition," *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 488–496, 2022.

[5] P. Castello, P. Ferrari, P. Pegoraro, and S. Rinaldi, "Chapter 5 - Hardware for PMU and PMU Integration," in *Phasor Measurement Units and Wide Area Monitoring Systems*, A. Monti, C. Muscas, and F. Ponci, Eds. Academic Press, 2016, pp. 63–86.

[6] P. Castello, C. Muscas, P. A. Pegoraro, S. Sulis, G. M. Giannuzzi, M. Pede, C. Maiolini, P. Pau, F. Bassi, and C. Coluzzi, "Integration of power quality and fault data into a PMU-based Wide Area Monitoring System," in *2021 IEEE 11th International Workshop on Applied Measurements for Power Systems (AMPS), Proceedings*, 2021.

[7] C. Huang, C. Thimmisetty, X. Chen, E. Stewart, P. Top, M. Korkali, V. Donde, C. Tong, and L. Min, "Power Distribution System Synchrophasor Measurements With Non-Gaussian Noises: Real-World Data Testing and Analysis," *IEEE Open Access Journal of Power and Energy*, vol. 8, pp. 223–228, 2021.

[8] T. Ahmad and N. Senroy, "Statistical Characterization of PMU Error for Robust WAMS Based Analytics," *IEEE Transactions on Power Systems*, vol. 35, no. 2, pp. 920–928, 2019.

[9] G. Na, W. Song, C. Lu, and X. Chen, "Gaussian Mixture Models and its Parameter Estimation to Describe the Distributions of PMU Random Errors in Power Systems," in *2023 10th International Conference on Power and Energy Systems Engineering (CPESE)*, 2023, pp. 1–6.

[10] S. Wang, J. Zhao, Z. Huang, and R. Diao, "Assessing Gaussian Assumption of PMU Measurement Error Using Field Data," *IEEE Transactions on Power Delivery*, vol. 33, no. 6, pp. 3233–3236, 2018.

[11] D. Salls, J. R. Torres, Antos, C. Varghese, J. Patterson, and A. Pal, "Statistical Characterization of Random Errors Present in Synchrophasor Measurements," in *2021 IEEE Power & Energy Society General Meeting (PESGM)*, 2021.

[12] S. Čubonović, D. Ćetenović, and A. Ranković, "The Impact of the Non-Gaussian Measurement Noise on the Performance of State-of-the-Art State Estimators for Distribution Systems," *Serbian Journal of Electrical Engineering*, vol. 21, no. 1, pp. 113–133, 2024.

[13] P. Castello, G. Gallus, C. Muscas, P. A. Pegoraro, D. Sitzia, and S. Sulis, "A Statistical Investigation of PMU Errors in Current Measurements," in *2023 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2023.

[14] G. Frigo, D. Colangelo, A. Derviškadić, M. Pignati, C. Narduzzi, and M. Paolone, "Definition of Accurate Reference Synchrophasors for Static and Dynamic Characterization of PMUs," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 9, pp. 2233–2246, 2017.

[15] IEC/IEEE 60255-118-1:2018, "IEC/IEEE International Standard - Measuring relays and protection equipment - Part 118-1: Synchrophasor for power systems - Measurements," pp. 1–78, 2018.