

PMU-based Distribution System State Estimation with Adaptive Accuracy Exploiting Local Decision Metrics and IoT Paradigm

Paolo Attilio Pegoraro, *Member, IEEE*, Alessio Meloni, *Member, IEEE*, Luigi Atzori, *Senior Member, IEEE*, Paolo Castello, *Member, IEEE*, Sara Sulis, *Member, IEEE*

Abstract—A novel adaptive distribution system state estimation (DSSE) solution is presented and discussed, which relies on distributed decision points and exploits the Cloud-based Internet of Things (IoT) paradigm. Up to now, DSSE procedures have been using fixed settings regardless of the actual values of measurement accuracy, which is instead affected by the actual operating conditions of the network. The proposed DSSE is innovative with respect to previous literature because it is adaptive in the use of updated accuracies for the measurement devices. The information used in the estimation process along with the rate of the execution are updated, depending on the indications of appropriate local metrics aimed at detecting possible variations in the operating conditions of the distribution network. Specifically, the variations and the trend of variation of the rms voltage values obtained by phasor measurement units (PMUs) are used to trigger changes in the DSSE. In case dynamics are detected, the measurement data is sent to the DSSE at higher rates and the estimation process runs consequently, updating the accuracy values to be considered in the estimation. The proposed system relies on a Cloud-based IoT platform, which has been designed to incorporate heterogeneous measurement devices such as PMUs and smart meters. The results obtained on a 13-bus system demonstrate the validity of the proposed methodology that is efficient both in the estimation process and in the use of the communication resources.

Index Terms—Adaptive methodology, Cloud, distribution system state estimation (DSSE), Internet of Things (IoT), phasor measurement units (PMUs).

I. INTRODUCTION

Typical distribution systems (DSs) have a high number of nodes but few measurement points. Because of this chronic lack of measurement devices, the monitoring of the quantities of interest can be obtained by means of state estimation techniques.

The growing incidence of installations of distributed energy resources (DERs) and non-linear loads implies the evolution of DSs into more complex and dynamic systems. DERs are obviously a resource, but they also may cause bi-directional

power flows, over-voltages and voltage transient problems. In such a scenario, significant changes in DS monitoring and management systems are expected, with the aim of supporting safe operation of the network. It is recognized that the presence of a number of measurement devices sufficient for the observability is not likely to happen in DSs, for several economical and technical reasons. It is therefore expected that safe operations still will depend on the estimation of the electrical quantities in the grid [1].

In order to obtain an accurate knowledge of the state of the systems, DSs peculiarities require specific solutions, the so-called distribution system state estimation (DSSE) techniques. Several DSSE methodologies have been presented in the literature (see [2]–[5]). A study on the performance assessment of linear estimators is presented in [6]. Each DSSE solution has led to a step forward in this research topic; nonetheless several challenges are still open. In particular, the geographical extension of the DSs and the high number of nodes to be monitored make the estimation process quite complex. The most advanced techniques face the problem in a distributed manner. Solutions have been recently proposed in the literature to split efficiently the estimation process so that the computational cost can be limited. In this regard, it is possible to mention Multi Area State Estimation methods (see [7]). An efficient communication infrastructure is always required to collect and coordinate the amount of data involved in the monitoring process. In this regard, it is worth noting that a sort of time tag, stating the reference time of the obtained measurements, would be necessary as for the coordination of the measured data.

Phasor measurement units (PMUs) and smart meters (SMs) have gained a crucial role in protection and management systems. PMUs accurately measure synchronized phasors of voltages and currents, namely the synchrophasors, along with frequency and rate of change of frequency (ROCOF) and transmit them to phasor data concentrators (PDCs). The last release of the standard has been presented in two parts: IEEE C37.118.1/2-2011, [8] and [9]. An amendment, [10], now modifies or suspends some of the performance requirements specified in [8]. A guide for synchronization, calibration, testing and installation of PMUs has been also published [11], along with a guide containing the requirements for the PDC [12]. The indications provided by the standards concerning the performance classes and their relevant test conditions and limits have experienced an important evolution. PMUs were originally conceived for the monitoring requirements of power

P. A. Pegoraro, A. Meloni, L. Atzori, P. Castello, S. Sulis are with the Department of Electrical and Electronic Engineering of the University of Cagliari, Piazza d'Armi, 09123 Cagliari, Italy (email: [paolo.pegoraro, alessio.meloni, l.atzori, paolo.castello, sara.sulis]@diee.unica.it).

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transmission systems in steady-state conditions. Currently, dynamic operating conditions are also considered. For this reason, several algorithms have been proposed in the literature to address the challenges due to the difficulty of measuring the corresponding dynamic signals (see [13], [14]). All of them show the significant differences that are obtained for the accuracies in dynamic and steady state conditions. Dynamic conditions are expected to be particularly interesting for the evolving DSs. The recent standards, even if designed for transmission networks, are thus a meaningful starting point for the application of PMUs to DSs.

SMs are intended to be intelligent instruments able to give different measurement types and communicate the obtained data from the locations spread across the network to the control centers. SMs can operate several measurements based on different time window lengths. However, information on the time observation windows is rarely provided and a clear standardization does not exist. Recently, several advanced SM solutions have been proposed in the literature (see [15]).

In order to collect and to process the high volumes of data arriving from these remote devices, the modernization of the ICT infrastructure, or the creation of a new one, is now required. In the presented scenario, Cloud-based solutions are used to address the non-trivial tasks related to storage, manipulation and management of a large amount of data. Indeed, the Cloud ensures a reliable environment for DSSE and every application relying on it, with massive computational and storage capabilities. Moreover, it can elastically react to critical situations in which the need for resources dynamically changes. Last but not least, the IoT (Internet of Things) technologies for the inter-connection of devices in large areas and the management of the relevant services and data are exploited. In particular, the virtualization technologies are put forward to create virtual measurement devices which could be updated, controlled and accessed to in an easier and more reliable way with respect to their physical counterpart, of which they are the virtual representation. Exploiting these technologies boosts reusability of gathered data and is both evolution- and future-proof.

Recently, communication infrastructures for real time IoT applications have been proposed in several domains, each with its own specific needs. A survey of the enabling technologies, protocols, and architecture for an urban IoT is presented in [16]. As to the domain of the smart grid (SG), it is possible to mention [17], where an infrastructure for real time DSSE based on the publish-subscribe paradigm is presented, and the concept of virtualization is applied to the data stream in order to separate the control and data planes. In [18] an IoT platform for the last meter SG is described, where a gateway is used for virtualizing heterogeneous sensors and actuators before interfacing to an IoT server for third-part data retrieval.

It is worth noting that, in normal operating conditions, DSs present near-steady-state signals that do not need intensive monitoring as in the case of dynamic conditions. For this reason, an adaptive estimation process can address the goal of efficiently monitor the network also in case of events.

In this context, founded on the procedure presented in [19], the paper presents a novel adaptive DSSE architecture

based on efficiently updated data obtained by decentralized and virtualized decision points by means of a Cloud-based IoT platform.

Compared to [19] and previous literature, the paper presents an innovative procedure that allows considering adaptive values of the accuracies of different measurement devices in the estimation process. Therefore, not only measurements from heterogeneous devices such as PMUs and SMs can be considered, but information concerning the actual uncertainties to be applied in the estimation process, in light of the actual operative state of the monitored nodes, is collected and used. To the best of our knowledge, this is the first attempt to design a DSSE procedure that considers the quality of service of both the monitoring system and the communication system, by exploiting a dynamic updating of the information provided by heterogeneous measuring devices.

In the following, the whole procedure is described and the results obtained on a 13-bus DS are presented and discussed.

II. BACKGROUND OF THE MONITORING SYSTEM

A. Distribution System State Estimation

The DSSE estimates the state of the network, in terms of node voltages, branch currents and power flows, starting from a few heterogeneous instruments, which measure several electrical quantities with different accuracies and reporting rates (RRs). The aim is to obtain a reliable picture of the network status so that the grid can be safely operated, because the accuracy of the measurement results is decisive for downstream decisions. However, due to the lack of a sufficient number of measurement devices on the field, knowledge obtained from a priori information has to be added to the measurements to make the system observable. This prior information is commonly referred to as pseudo-measurements in power systems literature.

The measurement model adopted for DSSE can be represented as:

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \boldsymbol{\epsilon} \quad (1)$$

where: $\mathbf{z} = [z_1 \dots z_M]^T$ is the vector of the M measurements gathered from the network and of the chosen pseudo-measurements; $\mathbf{h} = [h_1 \dots h_M]^T$ is the vector of the measurement functions; $\mathbf{x} = [x_1 \dots x_N]^T$ is the vector of the N state variables; $\boldsymbol{\epsilon}$ is the so-called measurement noise vector, usually assumed to be composed of independent, zero mean random variables, with covariance matrix $\boldsymbol{\Sigma}_z$.

The state vector \mathbf{x} includes variables that are sufficient to derive all the other quantities of interest. Different formulations of the problem exist and efficient choices for \mathbf{x} are as follows:

- 1) *Node Voltages*: the state can be, for instance, represented in polar coordinates as $\mathbf{x} = [V_1, \dots, V_{N_b}, \varphi_1, \dots, \varphi_{N_b}]^T$, where V_i and φ_i are the amplitude and phase angle of the voltage of bus i and N_b is the number of buses.
- 2) *Branch Currents Plus a Reference Voltage*: the state is typically adopted in rectangular coordinates as $\mathbf{x} = [v_s^r, v_s^x, i_1^r, \dots, i_{N_{br}}^r, i_1^x, \dots, i_{N_{br}}^x]^T$, where i_k^r and i_k^x are,

respectively, the real and imaginary parts of the current phasor at branch k , $v_s = v_s^r + iv_s^x$ is the phasor of the voltage assumed as a reference, and N_{br} is the number of network branches.

The above presented expressions are referred to a single phase of the network for the sake of brevity and clearness of notation, but it should be recalled that DSSE typically requires a three-phase formulation.

The measurements \mathbf{z} can generally include voltage and current amplitude measurements, synchronized phasor measurements from PMUs, active and reactive power measurements. Due to the different measurement types and state formulations, the measurement functions in \mathbf{h} are in general non-linear.

Several methods have been proposed in the literature for the solution of the DSSE. They are mostly based on a weighted least squares (WLSs) approach, [2]–[5]. In the WLS-DSSE approach, the state is estimated iteratively by means of linear system solutions. In particular, the so-called normal equations are solved at each iteration to update the state vector computation as follows:

$$\Delta \mathbf{x}_n = \mathbf{x}_{n+1} - \mathbf{x}_n = \mathbf{G}_n^{-1} \mathbf{H}_n^T \mathbf{W} [\mathbf{z} - \mathbf{h}(\mathbf{x}_n)] \quad (2)$$

where: \mathbf{x}_n is the state vector at iteration n . \mathbf{H}_n is Jacobian, that is it contains all the measurement functions derivatives with respect to the state variables and \mathbf{W} is the weighting matrix, chosen as the inverse of the covariance matrix $\Sigma_{\mathbf{z}}$. $\mathbf{G}_n = \mathbf{H}_n^T \mathbf{W} \mathbf{H}_n$ is the so-called Gain matrix and the covariance matrix $\Sigma_{\hat{\mathbf{x}}}$ of the estimated state vector can be obtained by its inverse (see [20]). The DSSE thus gives as outputs both the evaluation of the state and the estimation of the corresponding uncertainty in terms of covariance matrix. The stop condition for the algorithm convergence is given by $\|\Delta \mathbf{x}_n\|_{\infty} < \delta$, with an assumed small tolerance value δ , meaning that no further updates of the state vector are needed.

It is important to underline that all the WLS estimators can reach similar accuracy in the estimation of both the state variables and the derived quantities (see in [21] for details). For this reason, in the following, the formulation that allows illustrating the concepts in the simplest way is chosen, without loss of generality and keeping the discussion independent from the specific implementation. It is, however, essential to recall that to obtain an accurate estimation the measurement model and in particular the uncertainty description (represented by $\Sigma_{\mathbf{z}}$) must be complete [22], [23].

Fast procedures can exploit the high rate of PMUs measurements, which permits to have an up-to-date DSSE describing the dynamic of the system with the maximum resolution. Nevertheless, an extensive use of the maximum resolution could easily become an issue both for the communication and for the data storage, when economic and logistic constraints are present. A variable resolution able to adapt to the state of the system is thus desirable. A variable resolution poses a main challenge: great computation flexibility is necessary, since estimations could pass from one every few seconds, as in SCADA systems, to one every 20ms for 50-Hz systems. This property can be provided using a Cloud-based IoT overlay.

B. Phasor Measurement Units

PMUs are composed of hardware and software elements and each one of them can be seen as a source of uncertainty that contributes to the overall uncertainty of the measurement system. The measurement algorithm is the PMU component permitting the estimations of the synchrophasor, frequency and ROCOF and, along with the transducers, is one of the main contributors of the overall uncertainty of the system [24]. The synchrophasor standard [8] and its amendments [10] specify the indices to quantify the measurements, the test methods, and the accuracy limits of the PMUs. Nevertheless, they do not suggest a specific algorithm for the estimation of each quantity of interest and, commonly, the characteristics of the measurement algorithm are not included in the PMU data-sheet. Data-sheets usually report only the overall accuracy of the device in terms of Total Vector Error, TVE, and do not include detailed information about the different performance available in presence of both steady-state and dynamic conditions.

The standard [8] defines the limits for TVE: the TVE must be below 1% in case of steady-state conditions (1.3% in case of strong inter-harmonic pollution), whereas it must be below 3% in case of dynamic conditions. It is worth highlighting the significant impact that so different values can have on the DSSE accuracy.

In [8] two performance classes, P and M, respectively, for protection and monitoring-oriented applications, are defined. A standard compliant PMU should meet all the requirements at least for one class. In a number of cases, the options for the choice of the algorithm in a commercial PMU are only two, generally referring to the class P and M, but without information regarding the design of the given algorithm. In few cases it is possible to set the length and the parameters of the acquisition window (see [25]). The choice of the appropriate window should depend on the application (see, for details, [14]). The performance of a measurement algorithm strongly depends on the electrical quantities under test. Therefore, an appropriate calibration process should consider more than one PMU algorithm for different test cases [26]. When a full PMU characterization is not available, the DS operators (DSOs) should rely only on the compliance limits. In this paper, a suitable characterization process has been performed on different PMU algorithms, the results of which are discussed in the Section IV.

As for the data transmission, [9] introduces a protocol for real-time exchange of synchronized phasor measurement data between power system equipment. All the data provided by PMUs must be aligned by the receiver by means of the time-tag included in the data frame, to permit the correlation among measurements made in the same time but at different measurement points of the network.

Required PMU RRs are: 10, 25, 50 frames/s (fps in figures and tables) for 50-Hz systems. The actual rate should be user selectable. Support for other reporting modes is allowed, and higher rates, such as 100 frames/s, and rates lower than 10 frames/s (such as 1 frames/s) are encouraged by the standard. A proper use of such different RRs can significantly improve

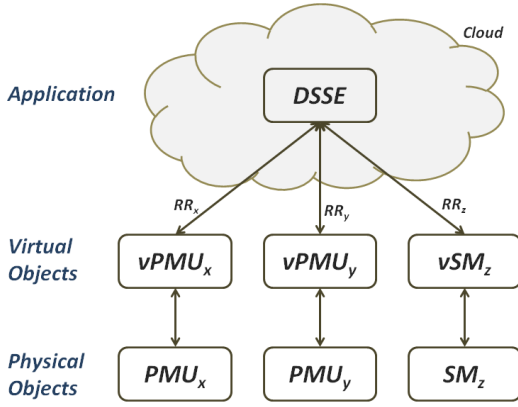


Fig. 1. Monitoring System Overview.

the efficiency of the monitoring process.

C. Cloud IoT systems

In a world where anything can potentially be represented by a cyber counterpart, the goal of IoT is to create an overlay where any entity can be found, activated, probed, interconnected, and updated, so that any possible interaction, involving both cyber and/or physical entities, can take place.

The digital counterpart of any real entity in the IoT is commonly named Virtual Object (VO). In this context, the major goal of relevant platforms is to support the mash up of VOs, which are also cyber entities themselves, fostering the creation of composed and complex services which improve the efficiency of the considered system. Moreover, virtualization has the ability to make heterogeneous objects interoperable through the use of semantic descriptions and enable them to acquire, analyse and interpret information about their context, in order to take relevant decisions and act upon the VOs.

A practical aspect linked to the creation of a cyber world is where these digital entities should reside. IoT platforms are more and more relying on a Cloud-based approach, since it allows for improving reliability, always on availability, elastic processing and memory resource provisioning. As a matter of fact, especially, more complex cyber entities can benefit from the intrinsic advantages of the Cloud, while for more basic virtualization entities, like those interfacing with physical objects, it can still make sense to reside in the local network close to the physical world objects.

Therefore, virtualization and Cloud computing represent the vital technologies for the future IoT solutions. For the same reason, in this paper an IoT platform compliant to these features has been used.

III. ADAPTIVE DISTRIBUTION SYSTEM STATE ESTIMATION ARCHITECTURE

This paper presents an innovative adaptive DSSE solution that exploits the major technologies and concepts used in the IoT domain, of which a high-level functional model is depicted in Fig. 1.

The presented solution allows considering adaptive values of the accuracy of the measurement devices in the estimation

process. Up to now, DSSE procedures have been using fixed values of accuracy for each measurement device, regardless of the actual operating conditions of the network. Nevertheless, as shown in Table I, the accuracy of the measurement devices strictly depends on the actual operating conditions of the network. For this reason, the monitoring architecture is designed so that, along with measurement data, information about the current accuracies is also used.

Basically, in steady-state conditions, the DSSE application, located in the Cloud, receives data at a given slow rate, for example once per second, and consequently runs. In this case, the accuracies used in the estimation process are those commonly provided by manufacturers. Meanwhile, the measurement system monitors the operating conditions at the highest measurement rate through the VOs. Indeed, the virtualized decision points, located in the communication network edge (i.e. close to the physical devices), run the local decision metrics, monitoring the measured quantities, in order to detect possible dynamics in the signals of interest. In the proposed approach, the virtualization concerns not only the control of data but also the data itself, in order to abstract measurement information from the specific data format of the devices. In particular, the VO provides APIs that allow to retrieve the measurement data without the client. This happens locally rather than at the destination server as in [18]. Local context-awareness is implemented in order to guarantee network resource-aware data forwarding depending on the state of the DS. In case dynamics are detected, the architecture adapts the rate of the DSSE and the accuracy values to be applied. In this way, an accurate estimation of the state and a correct evaluation of the uncertainty of the estimation results are obtained, also in a bandwidth-saving and computationally efficient manner. In the following, the proposed procedure is detailed.

A. Virtualized Measurement Devices

The physical measurement devices are located at the lower layer and communicate only with their virtual counterpart, which is then the one that sends the data to the application level and also controls the functioning of the associated physical device. The virtual representations are software agents, typically implemented in web services, that may run in the Cloud or in server facilities at the edge of the telecommunication network to reduce latency in the communication with the physical counterparts.

The considered measurement system is constituted by PMUs (in the paper, real PMU prototypes are exploited) and SMs. Appropriate VOs have been designed. PMU measurements are sent with a GPS-synchronized timestamp to the corresponding VOs, the *vPMU*. SM data are sent to the corresponding VO (*vSM*). The VO virtualizes device capabilities, so that any application can access or request device resources and functionalities in a reusable way, without knowing about the means (communication protocols and hardware primitives) that are needed to physically reach and retrieve information from the physical object.

It is worth recalling that in [9] the commands, for the data collector, to control the streams of data provided by

PMUs are basically limited to enable and disable the real time stream. In this paper, the possibility to change the RR of the measurements, between vPMU and the Cloud, is designed in order to save the bandwidth of the network while using the high RR provided by the PMU only when necessary. In detail, each physical PMU creates a socket with the vPMU and sends measured data according to [9].

SM data can be accessed in two ways: either the vSM forwards them to the higher level users in the Cloud or the users get them by polling the vSM. The vSM can be used to create a simple interface to the SM.

vPMUs and vSMs communicate to the Cloud only necessary information using REST APIs and the JSON format, thus abstracting from the PMU and SM standards. Communications can either take place in *GET* or *PUSH* mode, which means that data can either be asked to the VO with a HTTP GET query or be sent automatically to a given location through HTTP POSTs at a given RR. In the latter case, an appropriate trigger is set in the VO. In this paper, on the basis of the specific characteristics of the considered DSSE application, the focus is on the case of an automatic HTTP POST, for both PMU and SM.

As to the creation and deployment of the VOs, Lysis platform approach, hosted in the Cloud, is followed [27]. It contains various VO templates, each corresponding to a specific physical device. In our specific case, a number of templates are present corresponding to different physical PMUs (e.g. PMUs using different protocols such as IEEE 1344-95, IEEE C.37-118-2005, IEEE C.37-118.2-2011), since a different abstraction layer with the physical object is needed. Once the right interface is selected and the address of the VO location is given, the template is deployed in order to enable communication with the applications implemented in the Cloud. This procedure ensures the correctness of the VO setup and automates the procedure linked to the installation of new PMUs in the distribution network.

B. Local process points

Each PMU sends its measurements to the corresponding vPMU, which works as a local decision point with context-awareness capabilities. vPMU receives data every 20 ms, that is the maximum RR actually prescribed by [8]. vPMU performs processing in order to extract information on the state of the part of DS that is directly measured. In particular, the vPMU adapts its output RR towards the DSSE application depending on the results of the adopted metrics. Basically it is possible to impose a fixed policy for all the VOs in the network, but it is also possible to define a per-VO logic. In any case, the aim is to monitor possible dynamics in the signals of interest. In this regard, the problem of distinguishing steady-state signals from dynamic ones arises. As well discussed in [28], assessing quasi steady-state conditions is a critical point. The standards dealing with this issue do not follow the same way to discriminate the transients. Different thresholds identifying different quantities have been presented to detect rapid or slow changes in voltages. In [15], for example, the definition of the Rapid Voltage Change given in the last release

of the standard IEC 61000-4-30, *A quick transition in RMS voltage between two steady-state conditions, during which the voltage does not exceed the dip/swell thresholds*, is discussed. Several papers have been presented in literature with the aim of addressing the identification of operating conditions different from the steady-state reference conditions, with local and/or distributed techniques. In this regard, just to cite a few examples, it is possible to mention [29]–[31]. It is thus worth recalling that this paper is aimed at presenting a novel adaptive DSSE methodology, where it is possible to apply any kind of local decision metrics. For this reason, as examples of detection methods of immediate understanding, the monitoring of RMS voltage variations have been considered. The vPMU rate can be changed according to the monitoring of the following metrics with respect to given thresholds:

- 1) the variation of RMS voltages between two consecutive input measurements (PMU measurements), α ;
- 2) the variation of RMS voltages between the input and the previous output measurement (vPMU measurement), β .

Each rule can be used to command both the increase of the estimation rate and the decrease, according to the desired monitoring process. In particular, the first rule is aimed at detecting rapid variations in the signals, while the second one is conceived to follow slower dynamics, monitoring the measurements sent by the vPMU towards the application. The choices of the detection metrics and of the threshold levels strictly depend on the DSO needs and, among others, on the specific application requirements, on the grid characteristics and on the operating conditions of interest. As a general consideration, the thresholds directly impact on the promptness of the systems, but keeping them too low would cancel the benefits of the detection and rate regulation.

C. Adaptive DSSE rate

The DSSE application is performed in the Cloud at the application level¹ using the measurements received, at varying RR, from the different VOs. By default, the output rate of the vPMUs (and thus of the DSSE) follows a low (but sufficient for the scope) RR. The measurements (with the corresponding timestamps), originated by the PMUs can, depending on the locally detected events, reach the DSSE at different rates (i.e. 50, 25, 10 and 1 frames/s). For this reason, the DSSE function is performed, coordinating them at the highest RR among the different measurement flows. As a consequence, a higher vPMU rate triggers a higher DSSE update rate, thus allowing to follow more accurately a faster event, even at nodes that are not directly monitored.

In this paper, the DSSE is performed using the fast branch-current state technique presented in [5], exploiting the linearization of power injection pseudo-measurements to obtain a constant Gain matrix in WLS computation. Nevertheless, it is worth noting that the adaptive architecture can be used for different estimation methodologies, without significant differences.

¹The application level is the highest level of an IoT architecture as described in [32] and contextualized in [33].

D. Adaptive PMU measurement weighting in DSSE

As aforementioned, when a dynamic condition is detected, the PMU can not be considered to maintain the same accuracy level available in steady-state conditions. In the literature, the WLS-DSSE is considered to have fixed weights for each measurement and thus, fixed \mathbf{W} in (2). For the PMUs, the accuracies reported in the datasheets given by the manufacturer are considered (see, for instance, [34]). Such values, in terms of amplitude and phase angle uncertainty, are very low and typically correspond to the performance in steady state. No information is commonly given about the accuracies under dynamic conditions. The DSSE implementation can rely only on the limits prescribed by the standards [8], [10] for the compliance under dynamic tests (amplitude and phase angle modulation tests, for instance).

In this paper the proposal is to adapt the weighting of the PMU measurements to the real operating conditions, assuming that a degradation in the uncertainty of PMU measurements occurs in case of dynamics. When the dynamic condition triggers the change in the rate of vPMU transmission to DSSE application, the corresponding PMU needs to be considered in the DSSE with a different accuracy and \mathbf{W} is modified accordingly.

The covariance matrix $\Sigma_{\mathbf{z}}$ change can be represented as follows:

$$\Sigma'_{\mathbf{z}} = \Sigma_{\mathbf{z}} + \Delta\Sigma_{\mathbf{z}} \quad (3)$$

where $\Delta\Sigma_{\mathbf{z}}$ depends on which measurement accuracies are degraded. In particular, considering all the measurements as uncorrelated, and the occurrence of a single measurement z_i degradation, $\Sigma_{\mathbf{z}}$ is diagonal and $\Delta\Sigma_{\mathbf{z}}$ has zero elements except for $\Delta\Sigma_{\mathbf{z}}|_{ii} = \Delta\sigma_{z_i}^2$, corresponding to the variance change.

The weighting matrix thus becomes as follows:

$$\mathbf{W}' = \mathbf{W} + \left(\frac{1}{\sigma'^2_{z_i}} - \frac{1}{\sigma^2_{z_i}} \right) \cdot \mathbf{e}_i \cdot \mathbf{e}_i^T = \mathbf{W} + \Delta w_i \cdot \mathbf{e}_i \cdot \mathbf{e}_i^T \quad (4)$$

where σ' is the updated standard deviation ($\sigma' > \sigma$ in the dynamic condition implies $\Delta w_i < 0$) and \mathbf{e}_i is the i th vector of the canonical basis in \mathbb{R}^M . Considering, for the sake of simplicity, a voltage state vector, when the voltage amplitude measurement $z_i = V_j$ of a specific node j degrades, from (4) the new gain matrix becomes:

$$\mathbf{G}' = \mathbf{H}^T \mathbf{W} \mathbf{H} + \Delta w_i \cdot \mathbf{u}_j \cdot \mathbf{u}_j^T = \mathbf{G} + \Delta w_i \cdot \mathbf{u}_j \cdot \mathbf{u}_j^T \quad (5)$$

since the i th row of \mathbf{H} is $\mathbf{h}_i = \mathbf{u}_j^T$, where \mathbf{u}_j is the j th canonical vector of \mathbb{R}^M . As a consequence, it is possible to see the impact of the degradation on the covariance matrix of the estimates, as follows:

$$\Sigma'_{\hat{\mathbf{x}}} = \mathbf{G}'^{-1} = (\mathbf{G} + \mathbf{B})^{-1} = \Sigma_{\hat{\mathbf{x}}} - \eta \mathbf{C} \quad (6)$$

where:

$$\eta = \frac{1}{1 + \text{tr}(\mathbf{B}\Sigma_{\hat{\mathbf{x}}})}, \quad \mathbf{C} = \Sigma_{\hat{\mathbf{x}}}\mathbf{B}\Sigma_{\hat{\mathbf{x}}} \quad (7)$$

where $\mathbf{B} = \Delta w_i \cdot \mathbf{u}_j \cdot \mathbf{u}_j^T$ is a rank one matrix and $\text{tr}(\cdot)$ indicates the trace of the matrix. By simple passages, it follows that:

$$\Sigma'_{\hat{\mathbf{x}}} = \Sigma_{\hat{\mathbf{x}}} + \frac{|\Delta w_i|}{1 + \Delta w_i \sigma_{\hat{x}_j}^2} (\Sigma_{\hat{\mathbf{x}}})_{*,j} (\Sigma_{\hat{\mathbf{x}}})_{*,j}^T \quad (8)$$

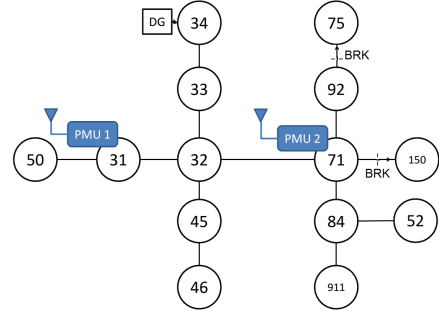


Fig. 2. Test system.

where $(\mathbf{A})_{*,j}$ indicates the j th column of matrix \mathbf{A} . It is clear from (8) that the degradation affects all the estimated state variables depending on the degree of correlation between the degraded voltage and the other estimates. The characteristics of the estimation covariance matrix are discussed in more details in [35]. In this context, it is important to highlight that the adaptive DSSE gives different estimates under dynamic conditions and computes also their uncertainty, thus adapting and enhancing the confidence interval associated to each estimated quantity.

IV. TESTS AND RESULTS

A. Test System

The electric system used in the tests is composed of a sample of a DS derived from the IEEE 13-bus (Fig. 2). The IEEE 13 bus radial distribution test feeder [36] was proposed as a benchmark for the analysis of harmonic propagation in unbalanced networks. For the purposes of this study, the topology and the loads of this network were considered as a starting point to design a simplified test network suitable for the proposed architecture. In particular, the grid used for the tests is, for the sake of simplicity, a totally balanced version of the IEEE 13 bus. In addition, a distributed generator was placed in the network, at the node 34, so that presence of DER can be taken into account.

The implementation of the network was carried out with the PSCAD/EMTDC software [37], a well known design and simulation tool to model power systems, acting as a graphical user interface to the EMTDC simulation engine. The tool allowed the simulation of different events and dynamics, at different locations.

B. Monitoring System

The assumed measurement system is composed of two PMUs, placed in two points of common coupling of the network, and several SMs providing data on the active and reactive powers of the loads. In particular, in all the presented tests, phasor voltages at nodes 31 and 71 are measured and the synchrophasors are computed, along with frequencies and ROCOFs.

As example of decision-making process, the vPMU checks:

- 1) if $\alpha > 2\%$;
- 2) if $\beta > 2\%$

to decide whether to increase the output rate to the maximum rate, i.e. RR = 50 frames/s. The adopted values are intended

TABLE I
TEST MODULATIONS RESULTS IN TERMS OF TVE %

Test	Window Configuration	
	Flat Top 4 cycles TVE %	Triangular 6 cycles TVE %
AM $f_m = 2 \text{ Hz}, k_x = 0.1$	0.0017	0.5197
AM $f_m = 5 \text{ Hz}, k_x = 0.1$	0.0010	2.9163
PM $f_m = 2 \text{ Hz}, k_a = 0.1$	0.0016	0.4687
PM $f_m = 5 \text{ Hz}, k_a = 0.1$	0.0035	2.6493

basically to detect dynamics in the amplitudes as commonly required by DSO. Furthermore, the vPMU monitors if β drops below 0.1% to slow down the RR progressively, and with a given inertia, to 25, 10, 1 frames/s.

Since “true” values can not be established in realistic operating conditions, a reference PMU has been chosen by means of a suitable characterization process. In this way, this reference PMU gives appropriate realistic reference values to be used for performance evaluation of the monitoring system under any test condition. Several tests are necessary to have a comprehensive idea of the PMU performance, especially for dynamic conditions. For instance, some algorithms are more suitable than others in case of low modulation frequencies [38]. As an example of possible differences in the results of the same PMU, Table I shows simulation results obtained applying modulated signals as inputs to two different configurations of a DFT algorithm available in [25].

Table I highlights how the same PMU can show significantly different measurement accuracies in presence of steady-state and dynamic conditions. The aim, in this context, is not to find the “optimal” algorithm, but to highlight how PMUs can change performance in presence of varying operating conditions. Considering the obtained results, the algorithm configuration “Flat Top 4 cycles” has been used in the tests as reference PMU. The other configuration has been supposed as applied to the devices to be placed on the field. Both the configurations prove to be compliant with the requirements imposed by the synchrophasor standard [8] in case of dynamic conditions, when the fixed limit for the TVE is 3%. Nevertheless, it is worth noting how the flat top weighting function, in this configuration and due to its larger bandpass, obtains a level of TVE% significantly lower than the triangular window.

C. Results

As a first check of the validity of the proposed approach, test simulations under Matlab environment have been performed. The aim was to impose a known dynamic condition at a given node (node 150) and verify how the adaptive DSSE performs. In such a controlled condition, the signals at the monitored nodes are known a priori and it is possible to check the effects of their variations on the PMU measurements and on the estimated state. In particular, the PMU algorithms operate as in Table I, with the Flat Top based PMU used as a reference (type 1 PMU). The second PMU algorithm is indicated in the following as type 2 PMU and the DSSE results rely on its measurements. In steady-state conditions, accuracies equal to

0.1% and 10^{-3} rad are assumed for voltage amplitude and phase angle, respectively, whereas in dynamic conditions the accuracy is assumed to degrade down to 3% and $3 \cdot 10^{-2}$ rad. Such values represent a sort of worst case condition for the test, because the declared steady-state limits are often far lower. It is important to highlight that a suitable characterization of the PMUs at hand under test scenarios specific for the given network and operating conditions can help the DSO to better tune the accuracy levels to be employed in the DSSE. An SM is also assumed on the node 150, measuring load power consumption. As for the SMs, different models for the measurement accuracy can be supposed, taking into account the uncertainty sources of the measurement process along with the common lack of time tags in the measurements. In this case, the accuracy of the SMs has been considered in the order of 10% as in [39].

Node 150 undergoes an amplitude voltage modulation with $f_m = 5 \text{ Hz}$ and $k_x = 0.05$. The average mean absolute relative errors (MAREs) are used as estimation performance index in the following. It is defined as

$$MARE(i) = \frac{1}{N} \sum_t \frac{|\hat{V}_{i,t} - V_{i,t}|}{V_{i,t}} \quad (9)$$

where $\hat{V}_{i,t}$ is the voltage amplitude estimation of node i at time tag t , $V_{i,t}$ is its reference counterpart, and N is the number of time points. MARE is used because directly relates to relative estimation errors. Fig. 3 reports the percent MARE values of voltage amplitude estimations for the nodes of the principal feeder that are downstream the primary substation transformer. The chosen test duration is 1 minute, corresponding to 3000 measurements for each PMU. The errors are computed comparing the results of the DSSE with those directly obtained by type 1 PMUs placed at each node. The adaptive DSSE results clearly outperform the results of a fixed weights approach (in [19] and in the classical DSSEs). Besides, and more importantly, the estimated expanded uncertainties (coverage factor 2) are much more useful, when adapting the considered PMU accuracy to the occurred dynamic condition. Fig. 4 shows that the percentage of the reference values falling within the expanded uncertainty intervals (in the following, for the sake of brevity, actual confidence level) computed by classical $\Sigma_{\hat{x}}$ is indeed much lower than the one predicted by the updated DSSE using $\Sigma'_{\hat{x}}$. In the presented test, node 31 always remains in steady-state conditions and this is why the two algorithms behave identically and the estimated uncertainty interval is meaningful.

In general, under dynamic conditions, the PMU uncertainty contribution is underestimated in the DSSE, thus leading to output uncertainty intervals that can be completely incompatible with the reference values.

After this preliminary validation phase, a new test series has been performed exploiting PSCAD environment and real PMU prototypes to evaluate the impact of the same kind of modulated signals in a realistic environment. Each PMU prototype is implemented using the real-time embedded controller NI-cRIO illustrated in [19]. The system is a reconfigurable device and, in the adopted configuration, is composed of

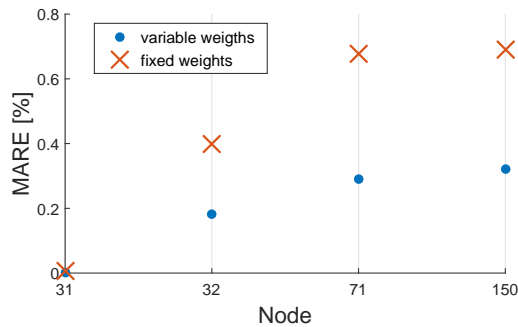


Fig. 3. Percentage MARE of node voltage amplitude estimations.

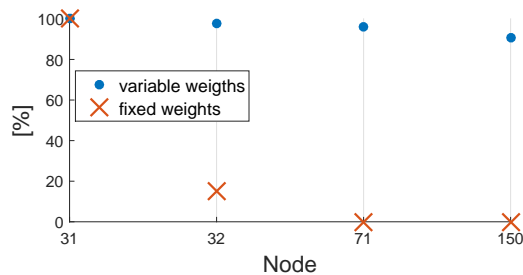


Fig. 4. Node voltage amplitude estimations: actual confidence levels.

a real-time controller NI-9024, a Field Programmable Gate Array (FPGA) module embedded in a chassis NI-9113, a NI 9215 16-Bit Simultaneous Analog Input Module, and a time synchronization module NI-9467. The time synchronization module is a GPS receiver that offers an accurate time source (accuracy ± 100 ns) to synchronize the embedded clock of the FPGA module and to provide the Coordinated Universal Time (UTC) to the real time controller. For this reason, every sample acquired by the PMU can be tagged directly at FPGA level with the UTC timestamp while the real-time controller is in charge of higher level phasor, frequency and ROCOF computations, and of the data frame encapsulation and transmission.

The PMUs can be configured to run both type 1 and type 2 algorithms at 50 frames/s. In this case, the PMU prototypes are modified to compute synchronized measurements on the pre-stored test signals obtained as PSCAD outputs and corrupted by a level of noise of 70 dB, corresponding to a possible noise level of the data acquisition stage. Such noise level can represent a meaningful higher bound scenario considering both the typical data acquisition stage noise of a PMU (more than 12 effective number of bits, [14], [40]) and the wideband noise that can be found in power network signals [41].

The computed synchrophasors are sent in real-time following the IEEE C37.118.2 message format to the vPMUs, where metrics are applied. If dynamics are detected, then data is sent to the DSSE application according to the rate set for the dynamic state, along with a flag indicating the change of conditions (it is a simple addition to the payload). The change triggers the PMU weight variation in the DSSE that can be customized on a per-VO basis. As in the previous test, the DSSE application considers also the measurements obtained

TABLE II
VOLTAGE AMPLITUDE MARE [%] AND RMSE [p.u.] RESULTS

DSSE	MARE [%]				RMSE [p.u.]			
	Node				Node			
	31	32	71	150	31	32	71	150
Fixed weights	0.19	0.43	0.70	0.71	0.0018	0.0046	0.0072	0.0072
Variable weights	0.19	0.27	0.42	0.44	0.0018	0.0030	0.0044	0.0047
Variation [%]	0	-37	-40	-38	0	-35	-39	-35

TABLE III
ACTUAL CONFIDENCE LEVELS [%] OF THE ESTIMATED EXPANDED UNCERTAINTY INTERVALS FOR NODE VOLTAGE AMPLITUDES

DSSE	Node			
	31	32	71	150
Fixed weights	19.8	19.8	0	0
Variable weights	19.8	74.4	98.7	91.9

by an SM in the node 150. Table II reports the differences between the two DSSE approaches in terms of percentage MARE of the voltage amplitude estimations, while Table III shows the comparison in terms of the actual confidence levels of the estimated uncertainty intervals. In Table II, for the sake of completeness, the estimation performance is described also by means of the root mean square error (RMSE) of voltage amplitudes (in p.u. with respect to rated voltage), showing that similar considerations can be drawn by observing relative and absolute errors.

Table III highlights that, as aforementioned, the role of the detection metrics for nonsteady-state conditions is delicate. In node 31 no dynamics are detected; for this reason, the PMU accuracy is not updated and, as a consequence, the used steady-state value remains too low in the case at hand. The determination of more appropriate metrics is beyond the scope of this paper, because it is strictly related to the adaptive application of DSSE, but it is once again evident that keeping constant accuracies for PMU measurements in DSSE is detrimental.

Even though the metrics in the example where intended to detect voltage amplitude dynamics, which are particularly important for the DS monitoring and control applications (see, for instance, [1]), the results for phase angle estimations are also reported in Table IV.

The results in terms of RMSE are almost the same when using fixed and variable weights due to the small dynamics of the phase angles in this case. The estimated expanded uncertainty intervals are more accurate with variable weights (for instance, for node 150, the actual confidence level is 94 % instead of 0 %) even in this case, but this once more highlights the importance of adopting specific metrics for phase angle dynamics when the angles profile is of interest for the DSO. It is also useful to recall that voltage amplitude and phase angle measurements mainly impact on the DSSE accuracy of the corresponding state variables [35].

Another test has been performed considering a 2-MW wind generator. Dynamics in signals are due to the insertion of the generator in the node 150. In this case, three SMs (nodes 34,

TABLE IV
VOLTAGE PHASE ANGLE RMSE [CRAD] RESULTS

DSSE	Node			
	31	32	71	150
Fixed weights	0.26	0.34	0.46	0.45
Variable weights	0.26	0.34	0.44	0.44

TABLE V
VOLTAGE AMPLITUDE MARE [%] IN PRESENCE OF WIND GENERATOR

DSSE	Node			
	31	32	71	150
Fixed weights	0.23	0.53	0.80	0.91
Variable weights	0.22	0.26	0.41	0.49
Variation [%]	-4	-51	-49	-46

71 and 75) are added to the previous monitoring system to consider a more complex hybrid measurement configuration. Table V shows the results for voltage amplitude estimation and allows similar considerations as for Table II, whereas the phase angle estimation results are reported in Table VI and indicate how, when stronger dynamics are present in the angles, the variable weight DSSE benefits from considering the PMU accuracy changes also for phase angles.

TABLE VI
VOLTAGE PHASE ANGLE RMSE [CRAD] RESULTS IN PRESENCE OF WIND GENERATOR

DSSE	Node			
	31	32	71	150
Fixed weights	0.21	0.43	0.68	0.82
Variable weights	0.19	0.18	0.27	0.32

The delay for the transmission of data from the physical device (the PMU or the SM) to the DSSE application passing through the VO has also been analyzed. Indeed, it is an important performance parameter of the Cloud IoT infrastructure that has an impact on the SG applications. This parameter has been analyzed over 2500 trials as the interval between the timestamp of the PMU packets and the moment in which data regarding those packets is received by the application, which was running using the Google App Engines (a cloud-based Platform as a Service). In particular, the location where the application was running has been selected in the closest farm for European users which is located in St. Ghislain, Belgium. The VOs were instead running locally in a Raspberry Pi 2 Model B+ development board (having an 800-MHz ARMv8 processor). Table VII shows the results obtained with specific tests at varying RR values (1, 10 and 50 frames/s). The resulting average delay is around 50 ms, whereas the minimum dependability is of 99% if a threshold of 100 ms is considered. RR affects only partially the delay, due to the increase in the requested processing power at the Raspberry. To understand to which extent this performance impacts on the final DSSE application, it is useful to refer to the performance classes defined by IEC61850 [42] for smart grid management. In this

TABLE VII
DELAY FROM DATA ACQUISITION TO STORAGE AT THE CLOUD WHERE THE DSSE APPLICATION RUNS AT VARYING VOs RATES RR

RR [fps]	Average Latency [ms]	100 ms Dependability [%]	500 ms Dependability [%]
1	51	99.5	100
10	52	99	100
50	55	99	100

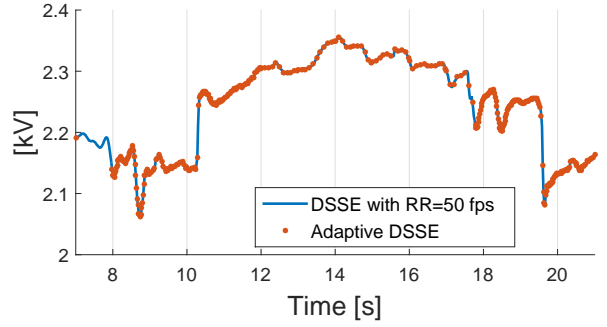


Fig. 5. Adaptive and full-rate DSSE techniques: voltage estimation results for node 150.

document, for class TT3 applications (slow automatic interaction), a transfer delay of 100ms is required, which could be fulfilled by our system. Clearly, all the other applications with less stringent requirements can be implemented in our system, i.e., operator commands, events and alarms, and others.

As a final test, the results concerning some possible unexpected operations on two loads are reported. Such test is similar to those discussed in [19] and is useful to show how the variable RR works also for the new DSSE architecture. The events occur at given moments of the network operation:

- 1) breaker at node 75 opens at 15.6s and closes at 17.6s;
- 2) breaker at node 150 opens at 10.3s and closes at 19.6s.

Fig. 5 reports the results of the DSSE techniques in terms of the RMS voltage estimation at node 150 when both the maximum RR given by PMUs (full-rate DSSE) and the new adaptive DSSE are used. As in [19], the DSSE operates at the highest RR only under dynamic conditions, suitably following the variations in the signals thanks to the adaptive policy of VOs.

For this test, the saving in bandwidth obtained thanks to the adaptivity in the RR controlled by the VOs has also been analysed. In this case an average RR of 17 frames/s has been observed for PMU at bus 71 (the other one works at 1 frames/s), with a saving in the bandwidth of 66% with respect to the static configuration where the PMU works at the maximum rate of 50 frames/s. Considering the lowest possible length of each PMU data frame of 70 B (but a typical packet at least includes additional 44 B of TCP/IP header as in [9]), a rate of 9.52 kb/s against 28 kb/s is obtained. Clearly, these values are both low but it is important to consider that there will be soon networks with many PMUs and SMs and each source generates continuously data to be stored in the cloud.

As a final consideration, it is worth noting that also in this case, the actual confidence levels given by new adaptive DSSE are closer to the theoretical ones: they are 69.0%, 98.0%, 98.0% and 97.9%, respectively, for the four aforementioned nodes.

V. CONCLUSIONS

The paper presents an innovative auto adaptive DSSE built on an Cloud-based IoT paradigm. The new designed solution permits considering the possible significant changes in the actual accuracies of the measurement devices. This is a crucial step forward in the DSSE topic, because the accuracy of a measurement device strictly depends on the actual conditions (steady-state or dynamic) of the monitored signals. The estimation process is now adaptive both in the use of the accuracies of the measurement devices and in the rate of execution. The variations in the process are triggered by the indications of appropriate local metrics, working on data provided by a distributed measurement system. The design of the local decision logics, implemented on the virtual objects corresponding to physical PMUs, is discussed. An appropriate Cloud based architecture now permits to obtain updated information from heterogeneous devices such as PMUs and SMs. The validation of the procedure and the performance analysis are conducted on an example of distribution network derived from the IEEE 13-bus.

The discussed results prove the validity of the approach, since it allows enhancing the estimation results in case of dynamics occurring in the network and tracking possible events with an efficient management of the communication infrastructure.

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Paolo Attilio Pegoraro (S’03-M’06) received the M.S. (cum laude) degree in telecommunications engineering and the Ph.D. degree in electronic and telecommunications engineering from the University of Padova, Padua, Italy, in 2001 and 2005, respectively.

He is currently an Assistant Professor of Electrical and Electronic Measurements with the Department of Electrical and Electronic Engineering, University of Cagliari, Cagliari, Italy. He has authored or co-authored over 70 scientific papers. His current research interests include the development of new measurement techniques for modern power networks, with particular attention to synchronized measurements and state estimation for distribution grids.

Dr. Pegoraro is a member of the IEEE Instrumentation and Measurement Society and of the TC-39 - Measurements in Power Systems.



Alessio Meloni (S’12-M’15) received his Ph.D. degree from the University of Cagliari, Cagliari, Italy, in March 2014.

Since 2011, he has been with the Multimedia and Communications Lab - University of Cagliari. He has been guest PhD student at the German Aerospace Center in Oberpfaffenhofen. His research interests include wireless communications, Internet of Things and Smart Grids. He is a member of IEEE, IEEE ComSoc, CNIT and IEEE Smart Grid-TAC.



Luigi Atzori (SM’09) is Associate Professor at the Department of Electrical and Electronic Engineering at the University of Cagliari, Cagliari, Italy, where he leads the laboratory of Multimedia and Communications.

His interests are in: multimedia communications, NGN service management, and IoT. He is the coordinator of the Marie Curie Initial Training Network on QoE for multimedia services (qoenet-itn.eu), which involves ten European Institutions in Europe and one in South Korea. He is member of the steering committee for the IEEE Trans. on Multimedia, member of the editorial board of the IEEE IoT, the Elsevier Ad Hoc Networks and the Elsevier Digital Communications and Networks.

steering committee for the IEEE Trans. on Multimedia, member of the editorial board of the IEEE IoT, the Elsevier Ad Hoc Networks and the Elsevier Digital Communications and Networks.



Paolo Castello (S’13-M’15) received the M.S. degree in electronic engineering and the Ph.D. degree in electronic and computer engineering from the University of Cagliari, Cagliari, Italy, in 2010 and 2014, respectively.

He is currently a Post-Doctoral Fellow with the Electrical and Electronic Measurements Group, Department of Electrical and Electronic Engineering, University of Cagliari. His current research interests include synchrophasor measurement techniques for power systems, characterization and testing of phasor measurement units, and implementation of IEC 61850 standard.

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Sara Sulis (S’04-M’06) received the M.S. degree in electrical engineering and the Ph.D. degree in industrial engineering from the University of Cagliari, Cagliari, Italy, in 2002 and 2006, respectively.

In 2013, she received the Habilitation to the position of Associate Professor. She is currently an Assistant Professor of Electrical and Electronic Measurements with the University of Cagliari. She has authored or co-authored over 80 scientific papers. Her current research interests include Power Quality issues and distributed measurement systems designed to perform state estimation and harmonic sources estimation of distribution networks.

designed to perform state estimation and harmonic sources estimation of distribution networks.

Dr. Sulis is a member of the IEEE Instrumentation and Measurement Society and the TC-39-Measurements in Power Systems.