IEC 61850-9-2 based module for state estimation in co-simulated power grids

David Celeita[1,2], Mario A. Rios[2], David M. Laverty[3], Jaime Forero[2], Andres F. Moreno Jaramillo[3], Seán McLoone[3]
[1]School of Engineering, Science and Technology, Universidad del Rosario, Bogotá, Colombia
[2]Department of Electrical, and Electronics Engineering, Universidad de Los Andes, Bogotá, Colombia
[3]School of Electronics, Electrical Engineering and Computer Science, Queen's University of Belfast, Belfast, United Kingdom

Article Info

Article history:

Received June 15, 2022
Revised Aug 1, 2022
Accepted Aug 18, 2022

Keywords:

OpenPMU
Phasor measurement unit
Power system monitoring
Real-time simulation
State estimation
Synchrophasor

ABSTRACT

This paper presents a research context on the virtualization of phasor measurement units (PMUs) and real-time power grids simulation with state estimation. In this research, real-time simulation is introduced to use powerful features for validating state estimation solutions with PMUs. Virtual and online measurement equipment are reviewed in this manuscript to develop an innovative integration of the OpenPMU incorporated with a real-time simulation power grid and additional virtualized PMUs. The implementation of the platform has useful features within the infrastructure that allows the user to reproduce a detailed modeled power grid with simulation software. The use of real-time simulation tools brings several possibilities for improving testing and prototype assessment with higher precision in different applications. In this case, 2 tests power systems are evaluated by realistic integration of IEC61850-9-2 data utilization to observe the performance of a customized state estimation approach. The study implements a versatile methodology for commissioning OpenPMU devices, interacting simultaneously with additional virtual PMUs within the same simulation through sampled values (SV) to validate the measurement frames and assess the estimation with the generated data. Finally, the proposed work identifies the potential of virtualizing PMUs and the features of the OpenPMU applied to state estimation in conjunction with real-time simulation data

Corresponding Author:

David Celeita
School of Engineering, Science and Technology, Universidad del Rosario
Calle 12C Nº 6-25, Bogotá, Colombia
Email: david.celeita@urosario.edu.co

1. INTRODUCTION

Different efforts have been made over the last decade towards the technological evolution of phasor measurement units (PMUs) as well as improving the data management of such equipment in modern power grids. Such equipment initially dedicated for monitoring the state of an electrical net- work is crucial for the timely detection of abnormal operating situations in the power system. This allows decision making for protection and control systems in case of failure and to prevent risks in the system's operation. Network monitoring can be done with state estimation models that use information supplied by measurement equipment located only in some. nodes of the system [1]. Among the measurement equipment, a PMU can collect data between 30 and 60 samples per second in 60 Hz systems. The PMU can even record twice the nominal frequency (120 Hz), unlike other measurement equipment with sampling rates between 4 to

6 samples per second [1], [2]. This allows to monitor dynamics of the system that cannot be observed with measurement devices presenting slower reporting times. Therefore, making use of PMU devices in the nodes of the network allows showing dynamics of the system that are not possible to analyze through the use of another measurement device.

The information collected by phasor measurement units (PMUs) to estimate the status of the network contributes to having a better approximation of the current and voltage values in the nodes without measurement devices. This paper presents a scalable simulation platform to assess state estimation solutions with real-time testing, hardware in the loop integration of measurement equipment (OpenPMU), and the use of virtual PMUs with IEC61850-9-2. There are some research tools available such as GridTeractions, a laboratory that allows testing smart and advanced algorithms for modern power grids [3] where many applications are synchronized with an emulated communication network through transmission control protocol/internet protocol (TCP/IP) communication.

This study is going to take part in GridTeractions since it is capable of detailed modeling, to emulate the behavior of real systems [4], [5] GridTeractions allows communication through a human-machine interface developed on a Raspberry Pi 2 (lowercase i) to acquire information from the other available terminals through a local network. The proposed work will implement a platform integrated to GridTeractions developed in a Python script and managed with the Typhoon HIL Control Center program. It allows to run simulations in time series and obtain results in phase domain, to facilitate the user to continuously evaluate the electrical variables. The power grid can be also modeled using PowerFactory and then exporting the data via IEC61850-9-2 protocol within the same local network of the laboratory. The following section presents a brief context of virtualization research on monitoring equipment, particularly focused on the PMU. Section 3 explains the general details of synchrophasor measurement and data communication. Next, in section 4, state estimation on modern power grids is discussed with different approaches. Section 5 presents the design of the proposed hybrid platform and then validation results are detailed in section 6.

2. VIRTUALIZATION OF PMUS AND STATE ESTIMATION APPLICATIONS

Virtualizing power systems and monitoring equipment al- lows the acceleration of prototyping advanced solutions. The IEEE 1344 standard aimed to define how the data transmission of PMU devices should be framed with a serial protocol in a packet switch world that could open the discussion with legacy issues. Nowadays the technological boundary that existed back in 1980 is no longer applicable [1], [2].

This is a great opportunity to improve the development of measurement equipment, the connectivity, and data management of multiple PMUs prototypes with better hardware and software design. However, certain challenges are focused on the application to improve monitoring, control, dynamic state estimation, protective schemes, cybersecurity and complex solutions for our modern power systems [3]. It has been also proposed the integration of these devices not only at the transmission level for example for voltage stability with online PMU measurements [6], [7] but also distribution systems [8], [9] and microgrids [10]. The PMU is critically important for the operation of modern power systems due to the main desired variable when them (the phase angle with high sampling rate), whereas other instruments cannot. Firstly, the importance of GPS synchronization for estimators is crucial, unlike grids that have local information monitoring system or data that come from a specific location. Power systems with several nodes located in different places lead to a higher degree of complexity due to communication problems and latency. Such context links the challenge of ensuring accurate timestamps to measurement samples. Thus, it avoids the inclusion of significant biases in the estimation or practically unusable data in a dynamic estimation philosophy [11]. Monitoring synchronizations aims to reduce significant errors imposed by the complexity, geographical spread, and separation of the meters in an electrical power system. On the other hand, the importance of developing a dynamic state estimator that allows obtaining system information with a very high relationship with its real data [11]–[13].

Some developments implement a Kalman filter that allows observations and predictions to be processed simultaneously, thus obtaining improved data redundancy. After applying the filter, the error covariance matrices of the predictions would be obtained and the states are updated using expressions derived from the estimator’s total influence function. This filter allows the estimates to be made more robust by monitoring the system variables, such as the speed and angle of the rotor, as explained in [14]. In [12] and [15], a comparison of a state estimation with and without filters in different scenarios is presented. Figure 1 presents a summary of the main features revised in the literature, and some of them will take part on the proposed solution. The selection was done by comparing the characteristics of the research contributions in modern applications of PMUs or measurement equipment virtualization. Important studies have been found when trying to optimize the design of such complex monitoring systems using GPS synchronized measurements [16]. The foregoing suggests steps and conditions that can be taken into account when developing the state estimator that is expected to be implemented in this study, follows the gap of virtual test beds that include IEC 61850-9-2 on the communication models too use sampled values (SV) in the estimation process itself. In [12] the integration of the Kalman filter is mentioned as an initial version of the state estimation algorithm, this in order to allow the linking of dynamic scenarios [17]. The first iteration obtains initial values of the system that are evaluated according to the reliability criteria granted by the noise filters or confidence intervals. The result is re-entered into the system as an input parameter and a second iteration begins [18]. For the proposed algorithm to be implemented, the states are the minimum set of variables that can determine the state of a system. A dynamic model with accurate states can accurately reveal the responses of the system, this allows to improve the stability of the system and the reliability of the data obtained in the monitoring.

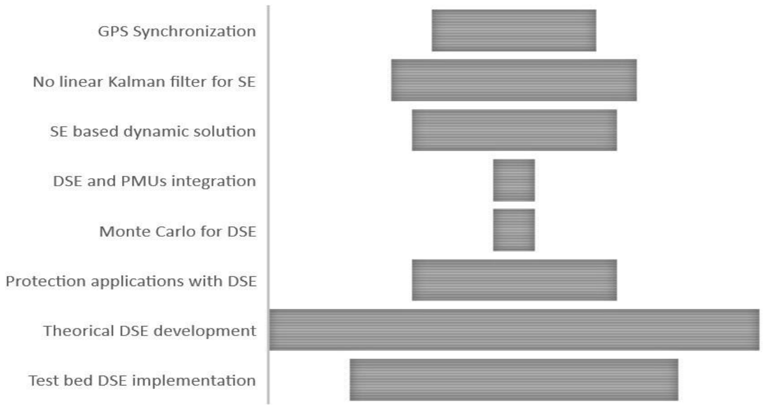


Figure 1. Main features of virtualizing PMUs and state estimation applications found in the literature

3. STATE ESTIMATION OF MODERN POWER GRIDS AND PMUs

The aim of this work is to design and implement a versatile platform where the user is allowed to reproduce the performance of any power system modeled in PowerFactory. Then, some limited electrical measurements are taken into a real-time platform to extract voltage and/or current signals using virtual PMUs [19] and a physical OpenPMU [20] where SV are used as inputs of any state estimator that the user want to assess [18]. The compatibility, accurateness and real-time performance take part of the work as a digital twin. Therefore, a validation of the state estimator is possible, and the user is able to locate the virtual PMUs or the physical OpenPMU [21] with the better convenience (multiple scenarios can be evaluated trough the proposed platform).

During most of the development of traditional state estimators, the idea of accurate simultaneous collection of system- wide measurements was something difficult to achieved [22]. A big assumption that held all traditional state estimation techniques together was that the static state of the power system changed very slowly, and operators could afford significant exploration times. Although some current estimators have scan times close to a few seconds, this could take longer for several protection and control applications. PMUs allow the synchronized collection of phasor measurements and, with this technology becoming so prevalent in utilities over the last decades, it is inevitable that it will be used for state estimation applications. This study take advantage not only of PMUs but also the use of open-source tools and non-expensive phasor measurement units to validate in a comprehensive real-time platform the performance of a user-defined state estimator. PMU measurements can be strategically included using a slightly different formulation than traditional nonlinear weighted least squares or they can be considered after a preliminary state of the system has already been determined [23].

3.1. Phasor state estimation background

To understand the fundamental difference between the measurements used in a traditional state estimator and the measurements used in a linear state estimator, it is best to start with the simple two-port π model equivalent for a transmission line. The state of this simple system will be the magnitude of the voltage and the angle at each terminal of the transmission line. Assuming that a PMU is installed at each end of the transmission line, the set of measurements for this system will consist of the voltage phasors of both terminals of the line and the line currents. All values will be considered rectangular because, at the most basic level, this is what the PMU [24] will return.

The state estimation with phasor measurements is initially developed with the calculation of the cartesian equivalent of the measurement, which is presented in (1).

$$A\angle\Theta = (A\cos\Theta) + j(A\sin\Theta) \tag{1}$$

The set of measurements without errors is considered to be the vertical concatenation of the voltage phasors at each terminal of the transmission line and the line current flows from each end of the transmission line, therefore:

$$Z = \begin{bmatrix} V_i \\ V_j \\ I_{ij} \\ I_{ji} \end{bmatrix} \tag{2}$$

The state of the system can clearly be related identically to the voltage measurements on this complex vector. However, the linear relationship between the state of the system and the line flows requires some effort. First, several quantities must be defined. The series admittance and shunt susceptance of the transmission line are as (3).

$$\begin{aligned} Y_{ij} &= \left(r_{ij} + jx_{ij}\right)^{-1} \\ Y_{i0} &= G_i + jb_i \\ Y_{j0} &= G_j + jb_j \end{aligned} \tag{3}$$

The relationship between the state of the system and the line current flows for the case of a simple transmission line is defined as (4).

$$\begin{bmatrix} I_{ij} \\ I_{ji} \end{bmatrix} = \begin{bmatrix} y_{ij} + y_{i0} & -y_{if} \\ -y_{if} & y_{ij} + y_{i0} \end{bmatrix} \begin{bmatrix} V_i \\ V_f \end{bmatrix} \tag{4}$$

Then, the state matrix is completed in such a way that the voltages in each of the nodes that have meters are considered and, finally the following state equation would be generated.

$$\begin{bmatrix} V_i \\ V_j \\ I_{ij} \\ I_{ji} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ y_{ij} + y_{i0} & -y_{if} \\ -y_{if} & y_{ij} + y_{i0} \end{bmatrix} \begin{bmatrix} V_i \\ V_f \end{bmatrix} \tag{5}$$

3.2. Gaussian noise modelling of instruments

The current and voltage transformers (CTs and PTs) are sensitive to random vibrations of conducting electrons caused by the conditions of the environment and materials. The collective sum of these vibrating elements is one off the reasons of noise in the stored data. This generated noise creates interference in the information obtained leading to degradation of the signals in the communication channels. Such situation could interfere with state observations in systems. By generating controlled amounts of noise and sending them together with the signals, it is possible to study the behavior of the system in the presence of each type injected of noise signal. The density function of a normal distribution complies with a symmetric bell-shaped behavior, which can take values between $\{-\infty, \infty\}$, where the central range of the variable will be obtained more frequently than the extreme values. Due to the equivalence between the behavior of the normal distribution and the Gaussian noise that is implemented for the tests, 95.5% of the distribution will be in the $\mu \pm 2\sigma$ and 95.7% of the distribution will be in the interval $\mu \pm 3\sigma$. So, the density function for the variable that exhibits this behavior is (6),

$$f(Z) = \frac{1}{\sqrt{2\pi}} \epsilon^{-\left(\frac{Z^2}{2}\right)} \tag{6}$$

where Z is defined by (7).

$$Z = \frac{X - \mu}{\sigma} \tag{7}$$

Let X be a variable that is distributed as a normal with mean μ and variance σ^2.

4. DESIGN OF THE EMULATION FRAMEWORK

The implementation of the linear state estimator integrates a pre-designed power system modeled in PowerFactory that will simulate in a non-interactive mode through a Python script. With this tool, it is possible to do the corresponding tests to verify that the state estimator complies with the necessary parameters to be integrated in the platform. The power system modeled in PowerFactory are 6-bus and 9-bus standard cases. The main elements of the proposed platform are listed as follows:

- One computer (working station 1 in Figure 2) with the power system simulation software. The user can load any power system previously modelled with PowerFactory.
- A local network where the virtual PMUs and the OpenPMU will be connected. In this case the proposed platform is connected to an existing network of a dedicated laboratory for multipurpose simulation in real-time (GridTeractions [4], [5]).
- A script to co-simulate PowerFactory (the case study selected by the user) while running the real-time hardware.
- Real-time simulator (Typhoon) to integrate a limited set of measurements trough the virtual PMUs and the OpenPMU (using sampled values with IEC 61850-9-2).
- A script to model the state estimator: the code recognizes the number of meters of any modeled system, since this value may vary depending on the availability assigned to each node. The status of the nodes where the PMUs are located will be entered into the code as input parameters. Then, it generates a vector with the estimated states for all nodes in the system. The error of the estimation should be computed in several scenarios.
- A typhoon master project that organizes the supervisory control and data acquisition (SCADA) of the platform and the real-time hardware simulation (working station 2).

The SCADA window is divided into three sections. The first section shows the status of measured buses. The user can select which buses are going to be monitored by the OpenPMU and virtual PMUs. Different scenarios are going to be established to assess the performance of the proposed platform for two power systems.

Once the user has defined the measured points, the signals are plotted in real-time for voltage, and current at each pre-selected node where a meter was assigned. In addition, next to each signal, a checkbox widget is ready to be selected so that the state estimator takes into account the measurements of that node to make the calculations and generates the results. In Figure 2 those components are illustrated in the third module at the left (working station 2). In the second section the Graph Phasor widget is configured for each of the nodes, where it is possible to see the estimated state and error depending on the state estimation algorithm previously designed by the user.

The SCADA also illustrates the single line diagram of the power system and each bus show the estimated state (p.u). Therefore, the proposed platform also works as a digital twin of a control center where the users can reproduce different scenarios in the first working station, and then a second user will see how the state estimator performs in real-time. The scenarios for each case study are summarized in Table 1.

Table 1. Definition of reliability indices for HVDC grids–extraction zones test scenarios: measurement points for each case study

Case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
6-bus system	Virtual PMU: Bus 2 Virtual PMU: Bus 4 OpenPMU: Bus 5	OpenPMU: Bus 2	OpenPMU: Bus 5	Virtual PMU: Bus 2 OpenPMU: Bus 5
9-bus system	Virtual PMU: Bus 4 Virtual PMU: Bus 6 OpenPMU: Bus 8	Virtual PMU: Bus 2 Virtual PMU: Bus 4 OpenPMU: Bus 6	Virtual PMU: Bus 3 Virtual PMU: Bus 4 OpenPMU: Bus 8	Virtual PMU: Bus 1 Virtual PMU: Bus 4 OpenPMU: Bus8

4.1. The link of virtual PMUs and the OpenPMU through IEC61850

A python script is used to link the power system simulation model, and the real-time state estimator in Typhoon using IEC 61850-9-2. A macro widget is available so the user can select the state estimator algorithm on the interface (execution rate of the state estimator: 250 ms). This to update the signals if there is a change in the network due to a failure. As it was initially proposed on the design of the platform, the data exchange between PMUs and the estimator algorithm should be through a communication that complies with IEC 61850-9-2. Typhoon has available a module to export those measurements packages as SV. This allows the user to establish a Publisher/Subscriber type communication with other hardware or virtual equipment through the Ethernet ports of the real-time equipment. The feature was included to add realism and consistent behavior in the testing stage.

The SV assigns a machine as Publisher and then it sends messages periodically (in this case the virtual PMUs and the OpenPMU). The messages are sent with a description, which allows the subscriber machines selecting and filtering messages where the description matches. Finally, the state estimator receives only messages pre-selected by each machine and analyzes only the information that is addressed to it, voltage and current of the measured buses. In the schematic editor (Typhoon HIL 402) it is possible to find communication modules that allow to implement communication with SV and then the user can capture them using Wireshark.

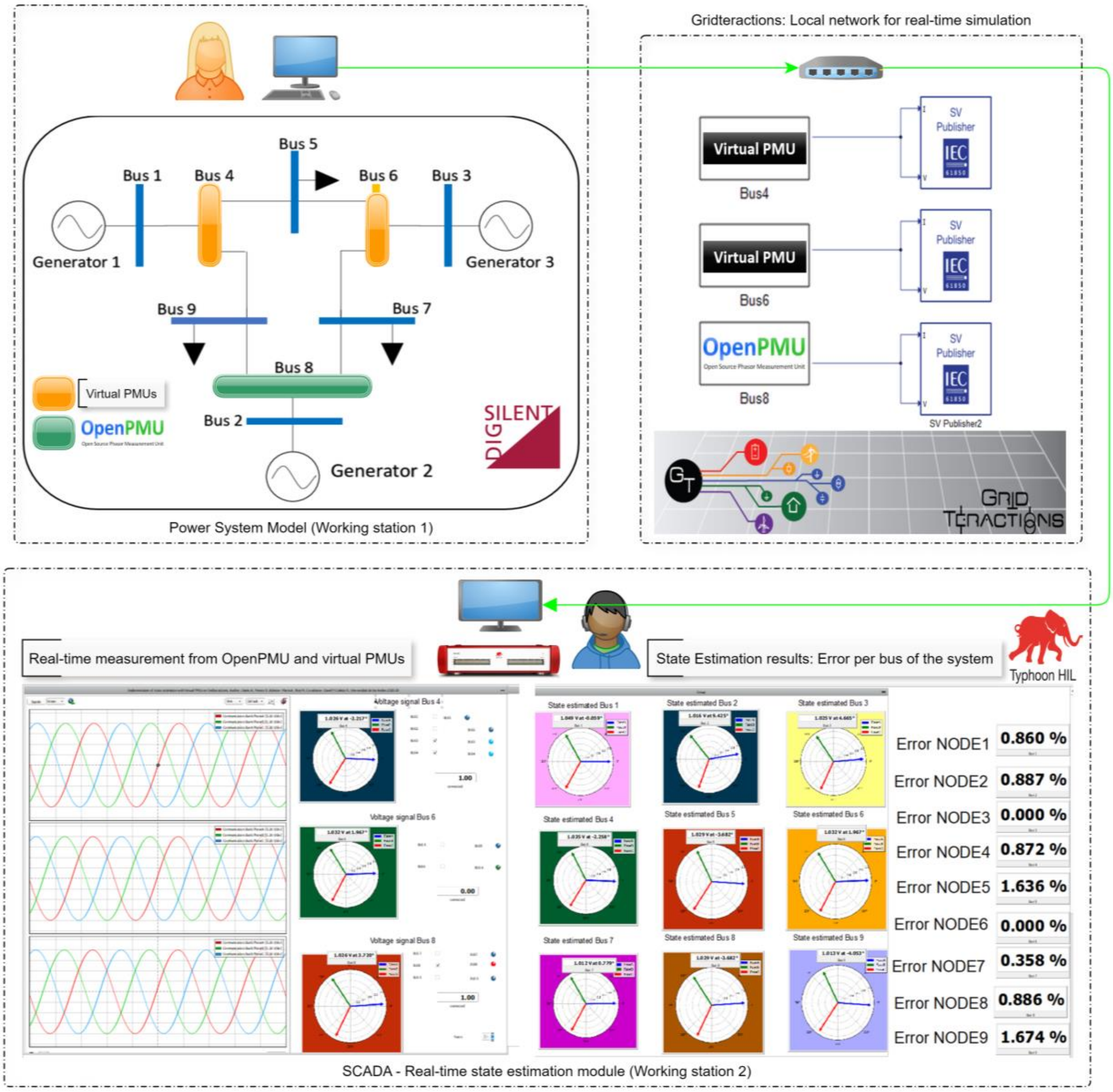


Figure 2. Main features of virtualizing PMUs and state estimation applications found in the literature

4.2. Integrated state estimation method in real-time

This state estimation algorithm was developed in the Python following with eight steps:

Step 1: Define a function that builds the Y_{bus} matrix and the Shunt admittance matrix from the system information.

Step 2: Define the number of system nodes and location of measurements with PMUs (physical or virtual).

Step 3: Build the Incidence Matrix *A*. This matrix satisfies the condition that each row represents a line of the system and each column a node. The rows must be filled with the value of -1 at the output node of the line and 1 at the arriving node.

Step 4: Build the arc Matrix II. This matrix meets the condition that each row represents a meter in the system and each column a node. The rows must be filled with 1 at the node where a PMU is located.

Step 5: Compute Matrix M, which corresponds to the dot product between Y_{bus} and Matrix A and adding at each position the corresponding Shunt value of the line:

$$M = Y_{bus} \cdot A \tag{8}$$

$$M(i,j) = M(i,j) + Y_{shunt}(i,j) \tag{9}$$

Step 6: Build Matrix B, by the concatenation of II and M:

$$B = \begin{bmatrix} II \\ M \end{bmatrix} \tag{10}$$

Step 7: Build the voltage and current measurements vector Z according to the SVs of the PMUs (2).

Step 8: Finally, the solution will be given by (11).

$$\{(B^T W^{-1} B)^{-1} B^T W^{-1}\} \cdot Z \tag{11}$$

5. RESULTS: THE IMPACT OF DATA NOISE AND DELAYS ON STATE ESTIMATION

5.1. State estimator comparison: 6-bus system

To check the functionality of the platform and versatility to implement different state estimators, three different methods were first implemented in Python. The aim is to compare the performance of each one using the 6-bus system previously modeled in PowerFactory. Table 2 presents the results for each of at each node. After comparing between the 3 state estimation methods and the measurements of each node in the system, the user can consistently assess the error performance and accurateness of the estimation method. One of the main capabilities of the proposed platform is reached, where the user could integrate any state estimator algorithm designed in Python. In this case, the weighted least squares (WLS) and least absolute value (LAV) [25], [26] state estimation methods have both a higher error rate compared to the Linear state estimation. As mentioned in previous chapters, the linear state estimator works with voltage and current phasor measurements, which is why it is compatible with the requirements that were established to integrate it with GridTeractions, virtual PMUs and the OpenPMU.

Table 2. Test of 6-bus system: comparison of different state estimator's algorithm using the proposed platform

Bus	Real measurements	WLS state estimator	LAV state estimator [25]	Linear State estimator
1	1.0500 0°	1.082 0°	1.0500 0°	1.0565 -0.1183°
2	1.0500 -3.6710°	1.0676 -3.9367°	0.9140 -4.1310°	1.0516 -3.6767°
3	1.0700 -4.2730°	1.0709 -4.3176°	1.0405 -4.2540 °	1.0723 -4.2929°
4	0.9890 -4.1290°	1.0427 -2.9247°	1.0020 -3.8770°	0.9906 -4.1360°
5	0.9850 -5.2760°	1.0103 -5.4631°	0.9980 -5.3410°	0.9864 -5.2234°
6	1.0040 -5.9470°	1.0084 -5.9563°	1.0110 -6.9130°	1.0064 -6.1290°

5.2. Linear state estimation performance: 6-bus and 9-bus system scenarios

A suitable feature to add scalability to the platform aims that the user can reproduce the performance of any other power system previously modeled in PowerFactory. Therefore, in this section, two case study (6-bus and 9-bus standard systems) are evaluated under 4 different scenarios each, refer to Table 1. The user is able to select and check the location of the measurement equipment, virtual PMUs and real hardware (OpenPMU). The user selects the measurement points and the state estimator method, which in this case is the Linear state estimation due to the results in the previous section. Once the user has the testing configuration, results of a digital twin are easily obtained with the proposed platform, with particular focus on the state estimation error.

In Figure 3 the error behavior of each tested scenario in both case study (6-bus and 9-bus system) is plotted. Note that in the 6-bus system the user can select one measurement point (scenarios 2 and 3) where the linear state estimator is capable to reach a consistent solution for each of the non-measured buses. It is important to mention that there is no modeling of noise in the measurement equipment, so the error could be result of communication between the power system simulator and the real-time simulation hardware. Yet, this value is not critical for the estimation since the less accurate estimation is scenario 3 for 6-bus system (note a peak in bus 4 colored in yellow in the plot at the left). It is visible that most of the scenarios and the error values for most of the buses are in the blue range between 0-0.05%.

On the other hand, the results of real-time state estimation for 9-bus system showed a slightly higher error. All the scenarios required at least 3 measured points, where almost all of them performed similar estimation errors (%). It is visible in the right plot of Figure 3 that between bus 3 and 6 the error shares the range 1-2%. The worst performance was located at bus 9 for scenario 4 where the error reaches its maximum close to 2.9%.

The summary of the error behavior on both power systems when using the linear state estimation method with the real-time simulator and linking SV of the virtual PMUs and the OpenPMU is shown in Figure 4. It is important to note that adding a new case study requires to configure the parameters of impedance, reactance and susceptance in each transmission line. The linear state estimator uses these measurements in its algorithm to give the output values required by the user. The Python code was implemented so that it is possible to change systems without getting deep into these modifications by the user if the power system is simply modeled in PowerFactory.

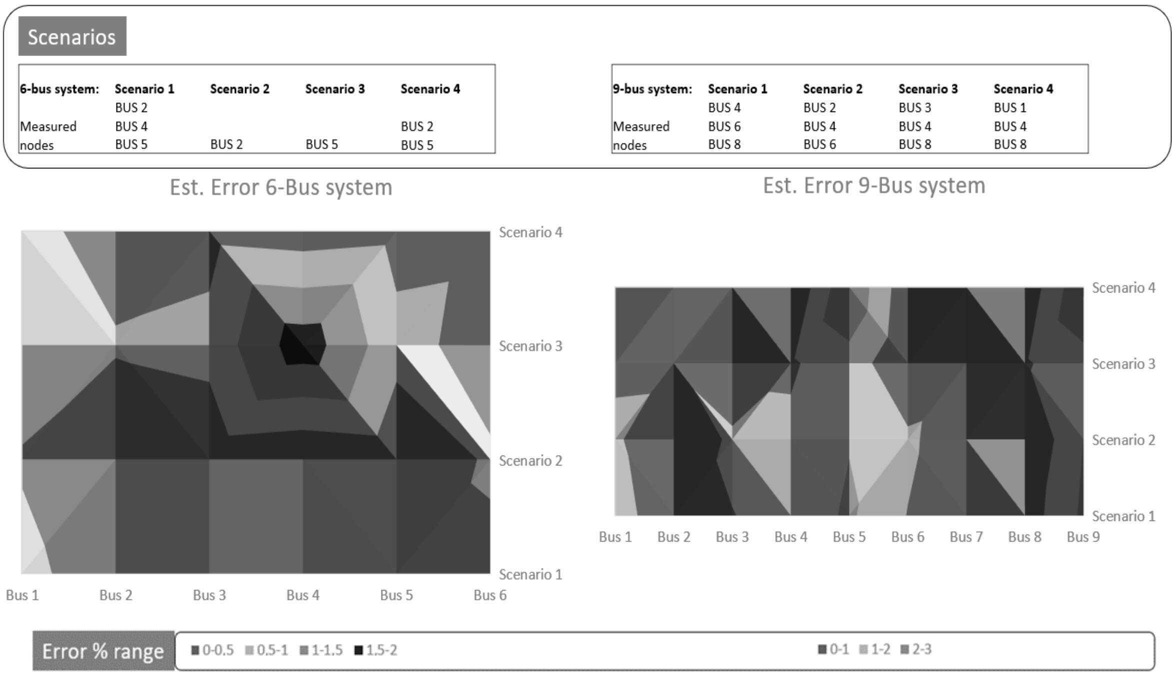


Figure 3. Linear state estimation performance: 6-bus and 9-bus system for different limited measurement scenarios

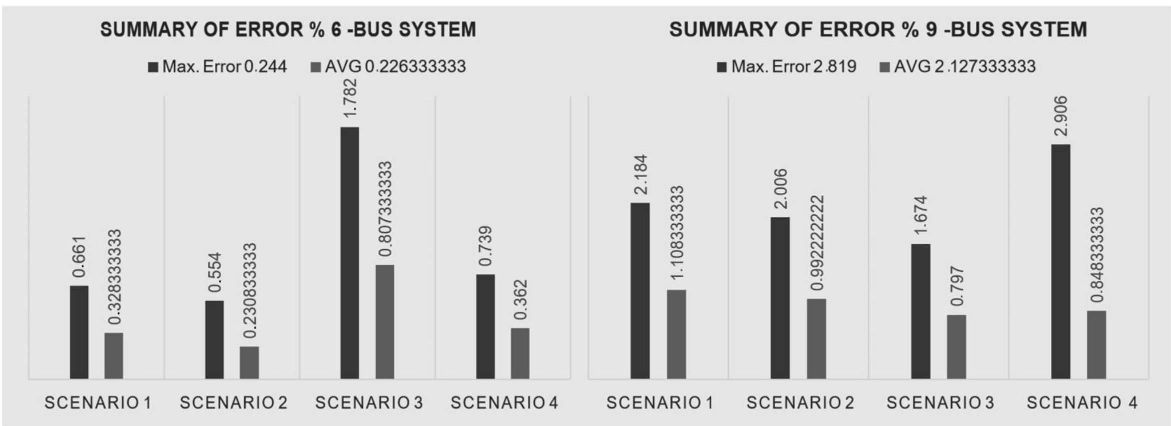


Figure 4. Max and AVG error summary: linear state estimation performance using virtual PMUs and OpenPMU with real-time hardware

5.3. Bad data detection

In order to reproduce this feature, the input signals of the system are taken to corrupt them in a controlled manner to observe the state estimator performance under different scenarios. In this case the measurements have a tolerance that depends on each piece of equipment. This will give a range in which the signals will vary. The behavior that this noise injection would have in the signals would be similar to that shown in Figure 5 where the values can change between -0.1 and 0.1 respectively.

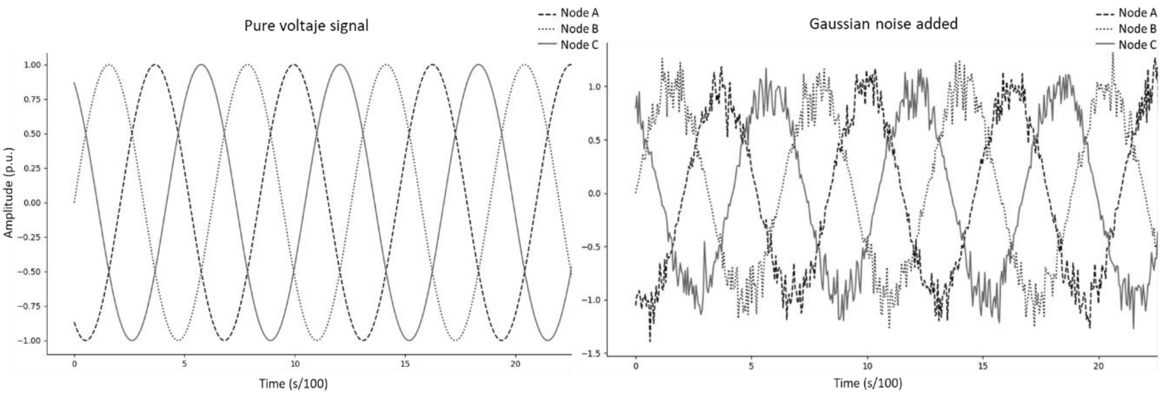


Figure 5. Voltage signal (pu) reproduced with and without noise from a PMU SV acquisition example

The detection of erroneous measurements in the estimator is carried out through a confidence interval, which describes the variability between the voltage and current signals obtained in the estimation and the real measurements. The confidence interval corresponds to a range of values, whose distribution is normal and indicates that the values calculated by the algorithm will meet the desired probability. This high probability has been set to 95% and indicates that the true value of the node state is within the given range with 95% certainty. The way in which each of the measurements is evaluated corresponds to taking the value of the measurement that was entered into the system as an input parameter. From this stage, then a subtraction of the value delivered by the estimator for the same node. When using Cartesian measurements, the magnitude of the result of such difference will be considered, where this value will be divided by the covariance corresponding to the device that supplied the measured signal. The confidence interval is the range obtained by multiplying the variable τ with the standard deviation of each measurement and then adding to the true value. This deviation is calculated as (12).

$$(B^T W B)^{-1} = \begin{bmatrix} \sigma_{V1}^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_{In}^2 \end{bmatrix} \tag{12}$$

The transposed matrix B is taken and multiplied with the covariance matrix. This result is multiplied with the matrix B and the inverse is applied. The components of the diagonal correspond to the squared standard deviations of each of the measurements $\sigma_{\mathrm{meas}} = \sqrt{\sigma_{\mathrm{meas}}^2}$. The confidence interval is given by the true value minus τ times the standard deviation and the true value plus τ times the standard deviation, which means $[\mu - \tau * \sigma; \mu + \tau * \sigma]$.

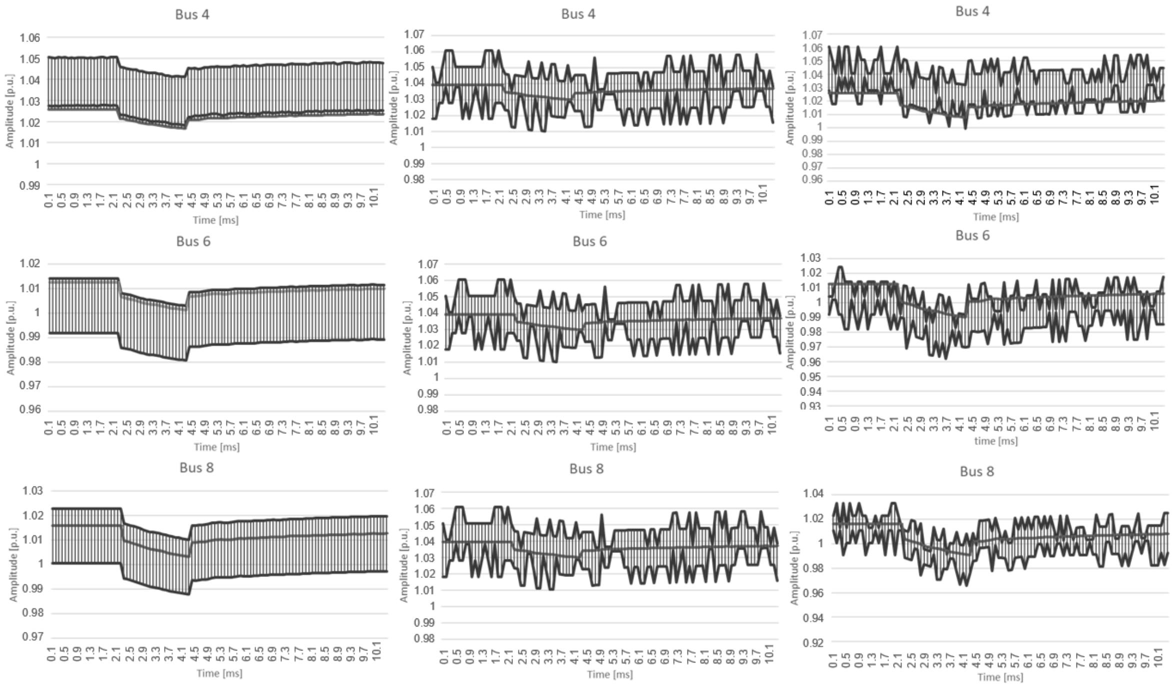
Then the residuals are compared, where the calculated $\hat{Z}$ is subtracted from the measured Z. That is, the measurements are compared with the values resulting from the estimation by subtracting between.

$$\left|\frac{Z-\hat{Z}}{\sigma}\right| < \alpha \tag{13}$$

Since the algorithm works with Cartesian values, the result magnitude must be calculated to divided by the PMU metering deviation corresponding, which must be less than the α (95% confidence is equal to 1.96 for the case study).

5.4. Performance and response of the SE interface with an OpenPMU and virtual PMUs including noise

A first evaluation allows the user to load the SE and assess the performance with the increment of the system loads (4 scenario: 5%, 10%, 15% and 20% for 2 seconds). Then the loads return to the original value. A DC offset (0.1 pu) is intentionally included in the input signal of Bus 4 in the IEEE 9-bus system. The results obtained show a change in the state estimates. The values begin to present a certain difference with the real values and this change is attributed to the fact that the offset present in the input values of the system causes the algorithm to try to compensate the calculations and biases are presented in the results of the other estimates depicted in Figure 6(a). The next scenario to analyze that allows visualizing the error detection behavior in the algorithm consists of adding Gaussian noise to the input parameters of the simulator, which will take values between -0.1 and 0.1 as shown in Figure 6(b). Finally, the last scenario is developed, which was considered important to dynamically evaluate the methodology state estimators. This consists of implementing a DC offset in the input parameter that sends the information from Bus 4. Additionally, Gaussian noise is injected into the values sent by the nodes with meters to the algorithm shown in Figure 6(c).



(a) (b) (c)

Figure 6. Plots of case study 1-response of the SE with confidence interval plotted for Bus 4, Bus 6 and Bus 8 for different scenarios-5% load increase: (a) insertion of DC offset in the measurements (b) insertion of Gaussian noise in the measurements and (c) DC offset insertion and Gaussian noise in the measurements

The two main requirements are crucial for a user to run the hybrid platform: the consistency and stability of pre-modeled systems that can be integrated and the link with GridTeractions. Also, among the characteristics of the estimator is that the systems must be implemented in PowerFactory. Since its implementation is done through the Typhoon HIL 402 device, the system conditions must be also compatible with the characteristics of the device. In general, most of the monitoring equipment, relays, PMU based devices and virtual monitoring/protection devices are compatible with this platform because it integrates and centralizes the standardized protocol IEC 61850-9-2 to analyze data in real-time.

The IEC 61850-9-2 compatibility of the platform was integrated to take advantage and build new approaches consistent with the ongoing digitalization of substations. For digital substations, IEC 61850 gives a series of requirements that must be met when purchasing equipment to keep the substation in force over time. Among the requirements found in the standard, the communication protocols are taken into account to develop this hybrid platform for state estimation, since it is seeking to emulate the behavior of the information, particularly the SV which is used in all the stages of the estimator. The communication of the monitoring equipment takes advantage of the local network and the Ethernet ports of the Typhoon HIL 402 where the OpenPMU or any other device that handles the communication type subscriber-publisher, allows reproducing the data interaction between several measured nodes.

6. CONCLUSION

This paper presented the design, implementation and validation of a hardware/software platform capable of reproducing the real-time performance to assess state estimation methods in modern power systems. The main features reached on the design allows the user to load a pre-modeled system in PowerFactory. Given the advantages of GridTeractions Laboratory, the user can extract data of certain nodes of the system to connect virtual PMUs and real monitoring equipment such as the OpenPMU, among others. The real-time simulation hardware was the core to centralize the Sampled Values of each measured point and run every 250 ms the customized state estimation algorithm for different monitoring scenarios. This hybrid platform offers a versatile work environment so the user can focus more on the analysis of data rather single simulation limitations. Advance applied solutions with PMUs and fast prototyping of algorithms are expected due to the capability of validation under a digital twin philosophy. The proposed test scheme was developed to allow the integration of new components and scale the solutions involved with protection, monitoring and control of modern power systems using IEC 61850-9-2.

ACKNOWLEDGMENTS

This work was funded by an allocation of the GCRF from the Department for the Economy NI (DfE-GCRF). Andres F. Moreno Jaramillo has also received support from the Department for the Economy (DfE), CREDENCE project (Grant number USI 110).

REFERENCES

[1] A. G. Phadke, “Modern wide area measurement systems: an overview,” in *8th International Conference on Advances in Power System Control, Operation and Management (APSCOM 2009)*, 2009, pp. 1–1. doi: 10.1049/cp.2009.1870.

[2] IEEE, “IEEE standard for synchrophasor data transfer for power systems,” in *IEEE Std C37.118.2-2011 (Revision of IEEE Std C37.118-2005)*, 2011, pp. 1–53. doi: 10.1109/IEEESTD.2011.6111222.

[3] J. Zhao, L. Zhan, H. Yin, F. Li, W. Yao, and Y. Liu, “Recent development of frequency estimation methods for future smart grid,” *IEEE Open Access Journal of Power and Energy*, vol. 7, pp. 354–365, 2020, doi: 10.1109/OAJPE.2020.3029984.

[4] C. Zambrano, C. Trujillo, D. Celeita, M. Hernandez, and G. Ramos, “GridTeractions: simulation platform to interact with distribution systems,” in *2016 IEEE Power and Energy Society General Meeting (PESGM)*, Jul. 2016, pp. 1–5. doi: 10.1109/PESGM.2016.7741563.

[5] C. Trujillo *et al.*, “An advanced laboratory for research and training of smart grid control and protection schemes,” in *2020 IEEE/IAS 56th Industrial and Commercial Power Systems Technical Conference (I&CPS)*, Jun. 2020, pp. 1–7. doi: 10.1109/ICPS48389.2020.9176780.

[6] P. Sahu and M. K. Verma, “Online monitoring of voltage stability margin using PMU measurements,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 2, pp. 1156–1168, Apr. 2020, doi: 10.11591/ijece.v10i2.pp1156-1168.

[7] Y. Zhang, J. Wang, and J. Liu, “Attack identification and correction for PMU GPS spoofing in unbalanced distribution systems,” *IEEE Transactions on Smart Grid*, vol. 11, no. 1, pp. 762–773, Jan. 2020, doi: 10.1109/TSG.2019.2937554.

[8] P. M. De Oliveira-De Jesus, N. A. Rodriguez, D. F. Celeita, and G. A. Ramos, “PMU-based system state estimation for multigrounded distribution systems,” *IEEE Transactions on Power Systems*, vol. 36, no. 2, pp. 1071–1081, Mar. 2021, doi: 10.1109/TPWRS.2020.3017543.

[9] S. You *et al.*, “Non-invasive identification of inertia distribution change in high renewable systems using distribution level PMU,” *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 1110–1112, 2018.

[10] S. Kumar, N. Das, and S. Islam, “Performance monitoring of a PMU in a microgrid environment based on IEC 61850-90-5,” in *2016 Australasian Universities Power Engineering Conference (AUPEC)*, Sep. 2016, pp. 1–5. doi: 10.1109/AUPEC.2016.7749356.

[11] E. Farantatos, G. K. Stefopoulos, G. J. Cokkinides, and A. P. Meliopoulos, “PMU-based dynamic state estimation for electric power systems,” in *2009 IEEE Power & Energy Society General Meeting*, Jul. 2009, pp. 1–8. doi: 10.1109/PES.2009.5275407.

[12] J. Zhao *et al.*, “Power system dynamic state estimation: motivations, definitions, methodologies, and future work,” *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 3188–3198, Jul. 2019, doi: 10.1109/TPWRS.2019.2894769.

[13] A. Rouhani and A. Abur, “A robust dynamic state estimator against exciter failures,” in *2016 North American Power Symposium (NAPS)*, Sep. 2016, pp. 1–6. doi: 10.1109/NAPS.2016.7747998.

[14] J. Zhao and L. Mili, “Power system robust decentralized dynamic state estimation based on multiple hypothesis testing,” *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4553–4562, Jul. 2018, doi: 10.1109/TPWRS.2017.2785344.

[15] J. Zhao, Y. Tang, and V. Terzija, “Robust online estimation of power system center of inertia frequency,” *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 821–825, Jan. 2019, doi: 10.1109/TPWRS.2018.2879782.

[16] V. V. R. Raju, K. H. P. Shree, and S. V. J. Kumar, “Development of cost-effective phasor measurement unit for wide area monitoring system applications,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 6, pp. 4731–4739, Dec. 2021, doi: 10.11591/ijece.v11i6.pp4731-4739.

[17] S. Rao Padupanambur, M. Riyaz Ahmed, and B. P. Divakar, “Optimal state estimation techniques for accurate measurements in internet of things enabled microgrids using deep neural networks,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 4, pp. 4288–4301, Aug. 2022, doi: 10.11591/ijece.v12i4.pp4288-4301.

[18] N. Zhou, D. Meng, Z. Huang, and G. Welch, “Dynamic state estimation of a synchronous machine using PMU data: a comparative study,” *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 450–460, Jan. 2015, doi: 10.1109/TSG.2014.2345698.

[19] D. Celeita, D. Clavijo, and G. Ramos, “PMU and PDC server implementation integrated to real-time simulation tools,” in *2019 IEEE Workshop on Power Electronics and Power Quality Applications (PEPQA)*, May 2019, pp. 1–7. doi: 10.1109/PEPQA.2019.8851546.

[20] D. M. Laverty, R. J. Best, P. Brogan, I. Al Khatib, L. Vanfretti, and D. J. Morrow, "The openPMU platform for open-source phasor measurements," *IEEE Transactions on Instrumentation and Measurement*, vol. 62, no. 4, pp. 701–709, Apr. 2013, doi: 10.1109/TIM.2013.2240920.
[21] D. M. Laverty, L. Vanfretti, I. Al Khatib, V. K. Applegreen, R. J. Best, and D. J. Morrow, "The openPMU project: challenges and perspectives," in *2013 IEEE Power & Energy Society General Meeting*, 2013, pp. 1–5. doi: 10.1109/PESMG.2013.6672390.
[22] K. D. Jones, J. S. Thorp, and R. M. Gardner, "Three-phase linear state estimation using phasor measurements," in *2013 IEEE Power & Energy Society General Meeting*, 2013, pp. 1–5. doi: 10.1109/PESMG.2013.6672516.
[23] M. Zhou, V. A. Centeno, J. S. Thorp, and A. G. Phadke, "An alternative for including phasor measurements in state estimators," *IEEE Transactions on Power Systems*, vol. 21, no. 4, pp. 1930–1937, Nov. 2006, doi: 10.1109/TPWRS.2006.881112.
[24] J. De La Ree, V. Centeno, J. S. Thorp, and A. G. Phadke, "Synchronized phasor measurement applications in power systems," *IEEE Transactions on Smart Grid*, vol. 1, no. 1, pp. 20–27, Jun. 2010, doi: 10.1109/TSG.2010.2044815.
[25] V. Ozdemir and M. Gol, "A robust parameter estimation method based on LAV estimator," in *2015 Modern Electric Power Systems (MEPS)*, Jul. 2015, pp. 1–5. doi: 10.1109/MEPS.2015.7477163.
[26] M. Gol and A. Abur, "LAV based robust state estimation for systems measured by PMUs," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1808–1814, Jul. 2014, doi: 10.1109/TSG.2014.2302213.

BIOGRAPHIES OF AUTHORS

David Celeita received the degree in Electronic Engineering (2011) from the Universidad Distrital, along with an M.Sc. (2014) and a Ph. D (2018) in Electrical Engineering from Universidad de los Andes, Bogotá, Colombia. He worked as an automation engineer in low and medium voltage applications, and he was a visiting researcher at Georgia Institute of Technology. He worked as postdoc researcher in the field of protection algorithms for HV lines at Centrale Supélec and an industry partner in France. He is currently a research fellow at Universidad de los Andes and professor at School of Engineering, Science and Technology of Universidad del Rosario. His research interests include protective-relaying control, smart grids, advanced distribution automation, fault location, and real-time simulation. He can be contacted at david.celeita@urosario.edu.co.

Mario A. Ríos received a degree in electrical engineering in 1991 and a M.Sc. Degree in electrical engineering in 1992, both from Universidad de los Andes, Bogota´, Colombia. He received a Ph.D. degree in electrical engineering from INPG-LEG, Grenoble, France, in 1998, and a Doctoral degree in engineering from Universidad de los Andes, in 1998. He worked as a consultant engineer in ConCol (now WSP), Bogotá, Colombia, during 12 years. Also, he was a Research Associate at the University of Manchester (formerly, UMIST). Currently, he is Full Professor at the Department of Electrical Engineering, School of Engineering, Universidad de los Andes, Bogotá. He can be contacted at email: mrios@uniandes.edu.co.

David M. Laverty was born in Belfast, Northern Ireland, in 1984. He received the M.Eng and Ph.D. degrees from Queen's University Belfast, Belfast, UK, in 2006 and 2010 respectively. He is currently a Reader with the Energy, Power and Intelligent Control (EPIC) Cluster at Queen's University Belfast, with research interests in anti-islanding detection, telecommunications, cyber-security and Synchrophasor measurement. Dr. Laverty is a senior member of the IEEE and an associate editor for the IEEE OAJPE. He can be contacted at david.laverty@qub.ac.uk.

Jaime Forero received the B.S degree in electrical and electronic engineering in 2021 and MSc in Electrical Engineering 2022 from the Universidad de Los Andes, Bogotá, Colombia, where he is currently working toward the master's degree in electrical engineering. He has academic experience in power electronics, control systems analysis, and power quality on distribution networks. He can be contacted at email: ja.forero15@uniandes.edu.co.

Andres F. Moreno Jaramillo was born in Medellin, Colombia, in 1990. He received the B.Eng. degree in Control Engineering from Universidad Nacional de Colombia, and M.Sc. degree in Power Engineering and Sustainable Energy from Swansea University, U.K., in 2012 and 2018 respectively. He is currently doing his 3rd year Ph.D. in Electrical and Electronic Engineering in the Energy, Power, and Intelligent Control (EPIC) Cluster at Queen's University Belfast. His current research interests include integration of distributed energy resources (DER) in the electrical network (photovoltaic systems, wind turbines, electric vehicles, and battery storage). During his research he has focused on the implementation of time-synchronized measurements (OpenPMU), machine learning algorithms, and telecommunications to enable online DER identification. He can be contacted at email: amorenojaramillo01@qub.ac.uk.

Seán McLoone received the M.Eng. degree (Hons.) in electrical and electronic engineering and the Ph.D. degree in control engineering from Queen's University Belfast (QUB), Belfast, U.K., in 1992 and 1996, respectively. From 1996 to 1997, he was a Post-Doctoral Research Fellow with QUB, where he was a Lecturer from 1998 to 2002. He joined the Department of Electronic Engineering, National University of Ireland Maynooth, Maynooth, Ireland, in 2002, where he served as a Senior Lecturer from 2005 to 2012 and the Head of Department from 2009 to 2012, before returning to QUB in 2013 to take up his current position as a Professor and the Director of the Energy Power and Intelligent Control Research Cluster at the School of Electronics, Electrical Engineering, and Computer Science. His current research interests are in the general area of intelligent systems, with a particular focus on data-based modeling and analysis of dynamical systems. His research has a strong application focus, with many projects undertaken in collaboration with industry in areas such as process monitoring, control and optimization, time-series prediction, and inline sensor characterization. Prof. McLoone is also a Chartered Engineer and a Fellow of the Institution of Engineering and Technology. He is a Past Chairman of the U.K. and Republic of Ireland Section of the IEEE. He can be contacted at s.mcloone@qub.ac.uk.