# On the development of a framework for the advanced monitoring of LV grids

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***Abstract* — This paper aims to describe the main outcomes of the ADMS4LV project which stands for Advanced Distribution Management System for Active Management of LV Grids. ADMS4LV targets the development and demonstration of a framework with adequate tools to optimize the management and operation of Low Voltage (LV) networks towards the effective implementation of Smart Grids. This work details the main functionalities of ADMS4LV and discusses their implementation. The validation of the functionalities is presented from demonstrations in a laboratorial setup, namely regarding the algorithms which using advanced data analytics, accomplish to operate LV networks with low observability, (i.e., with few real-time measurements) and without having full knowledge of the networks' technical characteristics, such as the consumers' phase connection to the grid. The assessment of the results shows the adequacy of the ADMS4LV solutions for deployment in distribution networks with current infrastructures, differing unnecessary investments in sensory devices.**

**Keywords— AMI, Low Voltage, Operation Smart Grids, Smart Meters.**

## I. INTRODUCTION

The ever-growing integration of Distributed Energy Resources (DERs), such as Microgeneration (μG) units, Electric Vehicles (EVs) and the deployment of demand-side integration schemes in Distribution Networks is requiring Distribution System Operators (DSO) to adopt novel solutions which ensure a flexible, reliable and efficient operation of these networks. However, the challenges behind the operation of these networks, namely at the Low Voltage (LV) level, are considerably different from the operation of other voltage levels above. In particular, the entire segment from the secondary substation and its downstream connected LV network is very often not monitored nor controlled.

Despite the current rollout of Smart Meters (SMs) at consumers' premises and some sensing devices along the network, which can provide important data to the operator, in most cases the grid characteristics are not fully known (e.g. branches' physical characteristics, phase connection of the loads) and the ability of these devices to transmit data in real time is still limited (e.g. due to the communications technologies used). Therefore, the deployment of algorithms for monitoring and controlling such networks cannot be undertaken, resulting to the use of this data solely for billing purposes. On the other hand, although the operation and optimization of LV networks have been widely addressed in the literature [1-4], these approaches typically rely on the presence of Advanced Metering Infrastructure (AMI) and a full characterization of the networks' infrastructures.

Most of the aforementioned studies present advanced control schemes for the technical and economical optimization of distribution grids taking advantage of the DER presence. Yet, such schemes rely on Optimal power flow (OPF) applications and subsequent prerequisites of grid topology. Generally, operational control schemes might be sorted based on the data to communicate and exchange among entities as centralized approaches such as on [5], local schemes typically relying on droop-based rules [6], or more distributed such as [7]. A recent work [8], proposes a data-driven approach where no need of communication is deemed necessary. Nonetheless, the training of the proposed scheme is based on off-line OPF, which still premises the full state of the distribution grid.

Several works have focused their interest to provide efficient State Estimator's (SE) application which identify the state of grid with limited measurements. Some methods have proposed SE by exploiting the network structure and particular characteristics of the measurements, such as branch-current-based SE [9]–[11]. Nevertheless, the unbalanced nature of LV grid poses the more extended. In particular, for advanced control schemes it is vital to acknowledge the phase of connection of the consumers. It is vital to create full frameworks which are capable of providing phase identification, automatic feeder mapping and SE. In this work the framework that addresses these functionalities, proposed within ADMS4LV are detailed and validated. Analytical description of the conceptual and technical architecture of ADMS4LV is provided in [12].

## II. PROPOSED METHODOLOGY

The main functional modules of the ADMS4LV system that are used to cope with the current limitations of LV networks regarding their low degree of observability, are depicted in Figure 1.

These modules have been designed to take advantage of historical smart metering data that is processed using advanced analytics for improving the characterization of LV networks (e.g. phase identification) and its observability in real-time, with reduced real-time monitoring requirements.

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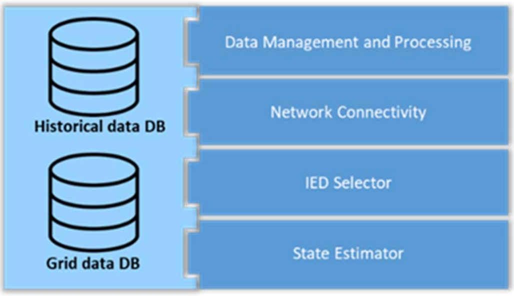


*Figure 1 – Modules of ADMS4LV for tackling the low observability of LV grids.*

This paper will focus on the following distinctive functionalities and respective workflows:

- **Data management and processing:** used to ensure the consistency of data by identifying outliers and data gaps that will be reconstructed using data imputations techniques.
- **Network Connectivity Checker:** automatic feeder mapping of the phase connection of LV customers. The results of this algorithm will enable to run ADMS4LV's grid management functions so that control actions can be computed and effectively applied on the controllable assets.
- **State Estimation framed with IED selection:** operational state of the LV grid estimation using Artificial Intelligence (AI) with reduced real-time measurements through the online selection of the most relevant Intelligent Electronic Devices (IEDs).

### A. *Data Management and Processing*

The main objective of this functionality is to ensure the integrity and coherence of the data gathered from the measuring devices connected to the LV network, which will then be used by other applications. In fact, since one of the basic drives for the ADMS4LV project was to take advantage of the large amounts of data that can be generated by the SMs, it is of paramount importance to improve the quality of the information feeding the data-based algorithms that were developed.

As illustrated in Figure 2, when a new batch of data is available for processing, the Data Management and Processing module accesses the Historical Data Database, reads the configuration file provided by the user and, by the end, it stores the processed data in the Historical Data Database along with a log of all the actions made. The initial access to the historical data has the purpose of building a larger and more representative sample of possible values for each measurement. The configuration file allows the user to define the type of measurements that should be analysed, a bandwidth of acceptable variation, and the method used for filling the missing (or erroneous) data. Finally, the log of changes enables further studies about the origin of bad data. For instance, it may allow identifying a meter that consistently produces bad data, hence indicating some kind of malfunctioning.

This module is carried out in two stages. Firstly, it identifies the data that is missing or may be erroneous and, then, tries to reconstruct it. It should be noted that this is a preliminary phase for the improvement of the data since the State Estimator module developed in the scope of this project will also contribute to the enhancement of the its quality.

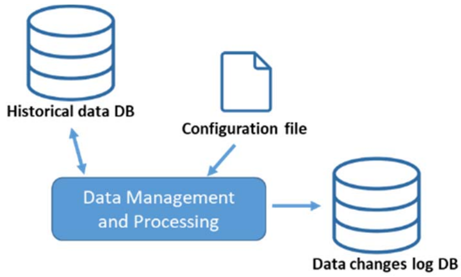


*Figure 2 – Inputs and outputs of the Data Management and Processing module.*

In Figure 3 is presented an overview of the steps comprising the filtering stage. The initial step is achieved analysing any possible gap in the time series. Then, all the values out of the bandwidth defined by the user are discarded. Finally, possible outliers are identified performing a statistical analysis resorting to a modified Z-scores method that considers the MAD (Median of Absolute Deviations) of the observations [13].

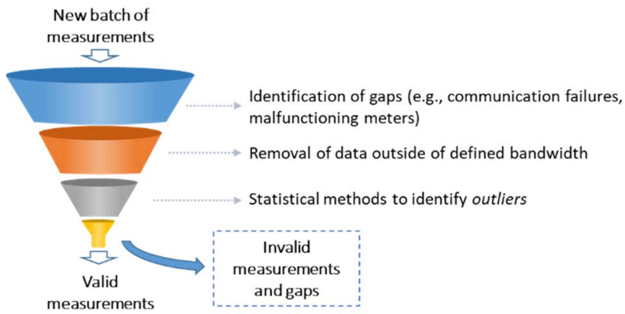


*Figure 3 – Filtering steps of the Data Management and Processing module.*

The second stage of this module aims at reconstructing the dataset and it can use a method based on averages or a multivariate regression. The averages method includes observations around the gap and at the same time in the previous days. The multivariate regression uses, besides the past observations of the variable, calendar data and weather forecasts (i.e., irradiance may give important information about microgeneration).

### B. *Network Connectivity Checker*

This module, based on k-means clustering method [14], is able to map the connection phase of LV customers (with installed SMs) through the analysis of the voltage time series measurements provided by the AMI deployed in LV networks. Based on this information, the module groups the SMs into clusters such that the members of each cluster are as similar as possible to one another, which allows identifying the SMs' connection phases – Figure 4. To perform such analysis, the Network Connectivity Checker module needs a minimum of information regarding the SMs' connection phases, i.e., at least a three-phase SM or three single-phase SMs (one of each connection phase).

The main advantage of this module is to perform phase automatic identification for existing LV networks, where their topology information is usually incomplete or inexistent.

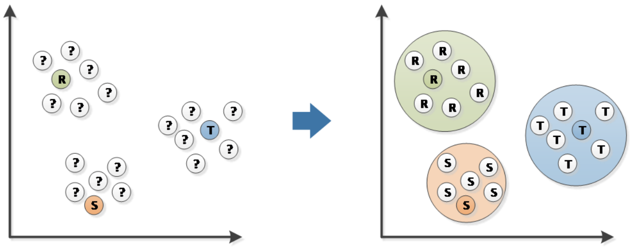

*Figure 4 – SMs' connection phases identification procedure.*

Thus, the need of extensive fieldwork is avoided and at the same time it helps to validate the information existing on the network database. Therefore, this module is able:

- To validate the information existing on the network database regarding the customers' connection phase;
- To determine the customers' previously unknown connection phase.

This information is crucial for other network applications, such as active control tools for the LV networks and other power flow-based applications.

### C. IED Selector

The main objective of this module is to provide a merit order list containing the group of IEDs and SMs with capability of transmitting data in real-time (from an amount of devices with such capability) that ensures the necessary network observability while the data volume is minimised. This list is generated offline to be then used by applications running in real-time.

In offline mode, the IED Selector application receives historical data that was previously processed by the Data Management and Processing module to better represent the network. The application proceeds to a sensitivity and correlation analysis that culminates in a merit order list for the selection of IEDs/SMs that not only minimises its number, but also allows overcoming the unavailability of any of them.

When in real-time mode, the minimum number of IEDs/SMs defined by the network operator will be selected from the first in the list. If an IED/SM is selected but is unavailable, before using the next device in the priority list, the algorithm will check the availability of an alternative device (high correlation with the unreachable one). Figure 5 illustrates the format of the priority list.

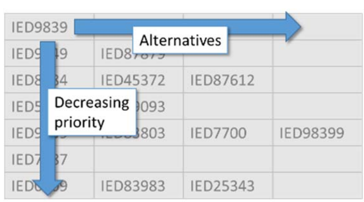


*Figure 5 – Priority list format.*

### D. State Estimator

The state estimation algorithm designed for LV grids (LV SE) is a real-time function based on AI techniques that is able to estimate the operational state of LV networks with a reduced number of real-time measurements and without any knowledge about the network topology and characteristics [15][16].

It is important to bear in mind that an historical database with all data temporally synchronised and free of gross errors is required so that the LV SE model can effectively learn the patterns/correlations between the electrical variables of a given network, and thus perform a reliable state estimation. In this sense, the metering raw information is processed by the Data Management and Processing module, before being stored on the Historical Data Database, to be later used on the LV SE training.

After having the LV SE model properly trained, the available real-time dataset is used as its input to guide the optimisation algorithm towards the state estimation solution. The group of IEDs and SMs communicating in real-time will dynamically change according to the minimum number defined by the network operator, their correspondent location and communication status (online or offline), the network's topology and the location of flexible DERs. This group of devices is determined by the IED Selector module, described in subsection C.

It is also important to highlight that during the LV SE execution under normal operational conditions, the following occurrences deserve special attention:

- <u>Topology changes</u>: whenever topology changes are verified, the selection of an appropriated LV SE model specific for the new topology (whenever a model trained with historical data related to the new topology already exists in memory) is necessary. Otherwise, a new training procedure should be performed for the new grid topology.
- <u>Additional historical data</u>: if new historical data is added to the Historical Data Database, it should be considered the possibility of training a new LV SE model with the new dataset. Other possibility is to perform a retraining of the existing model. In this case, the LV SE model existing in memory (already trained) is loaded and an additional training process is performed over the already trained model, but now only using the new historical information.

## III. CASE STUDY

The modules described in section II were tested using a small (33-node) typical Portuguese LV network (Figure 6), simulating real operating conditions. This network was used to build a simulation environment with load data from a trial by the CER in Ireland [17] and PV generation data from the SuSTAINABLE project [18]. The historical complete operating states of the network were obtained using an in-house unbalanced three-phase power flow tool (based on backward/forward sweep algorithm): a period of almost 7 months in time steps of 30 minutes (i.e., 10000-time instants) was generated.

The grid contains 52 customers with contracted powers that vary in a range between 3.45 to 10.35 kVA for single-phase consumers. The only one three-phase consumer has a contracted power of 27.6 kVA. Several microgeneration units (photovoltaic – PV – panels) were added and randomly distributed through the network clients. Each microgeneration unit represents up to 50% of the contracted power of the correspondent consumer.

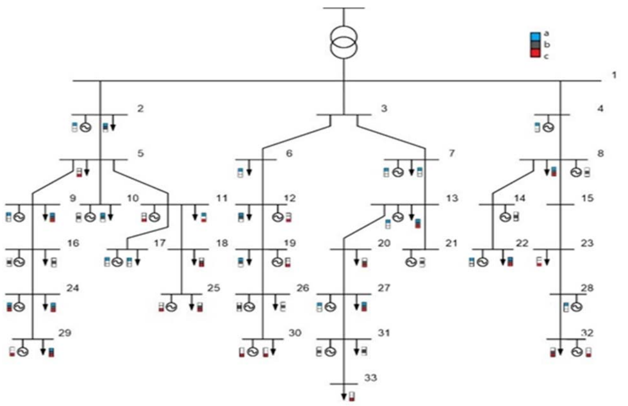


*Figure 6 – Typical Portuguese LV grid used as test case (next to each load and generator it is indicated the connection phase).*

In order to emulate a smart grid environment, it was assumed that the MV/LV substation has a Distribution Transformer Controller as well as the associated measurement equipment with the capability of monitoring in real-time the following electrical variables: active power flows in the transformer and voltage magnitudes at the LV side of the transformer. For the purpose of this work, the term "real-time" is used in the sense of measuring the referred variables in a short period of time, around 30 minutes.

A SM installed at each customer's premise was also assumed. It was considered that these devices were able to synchronously monitor the active power and voltage magnitude at the customer's premise.

The scenarios defined to test each one of the described modules are detailed in the following subsections.

### *A. Data Management and Processing Testing*

In order to test this module, 1% of the data was affected by random noise up to 10 standard deviations. This data, after being processed, was used by the other modules.

### *B. Network Connectivity Checker Testing Scenarios*

This module was assessed considering the four different scenarios described below:

- **Scenario 1:** in this extreme/pessimistic scenario only a minimum number of SMs with known (real) connection phase is given to the module. In this sense, the three-phase SM was the only one considered. The purpose of this assessment is to determine the unknown connection phase of the remaining SMs.
- **Scenario 2:** it is similar to the previous one, but only 20% of the total number of SMs has an unknown connection phase.
- **Scenario 3:** the main goal of this scenario is to validate the known information regarding the customers' connection phase. In this sense, all the SMs' real connection phases are given to the module and no suggestions for change are expected.
- **Scenario 4:** it is similar to scenario 3, but the connection phases of 20% of the total number of SMs are changed and are then given to the module. Thus, the identification of these SMs and the suggestion of their correct connection phase are expected.

It is important to mention that the SMs' connection phases (real or changed) selected to be given to the module were randomly chosen between the scenarios.

### *C. IED Selector and State Estimator Testing Scenarios*

Taking some Portuguese Smart Grid pilot sites as an example, it was considered that all the installed SMs had the capability of transmitting data in real-time through power line communication technology. However, only some of these SMs can effectively communicate within a time range compatible with real-time applications due to technology restrictions. Thus, the group of such SMs is determined by the IED Selector module, which will be evaluated together with the LV SE according to the scenarios described below.

With the purpose of testing both modules, three different scenarios were defined, where the minimum number of SMs communicating in real-time was assumed to be different:

- In scenario 1, 10% of SMs communicating in real-time were considered.
- Scenarios 2 and 3 are more optimistic scenarios and they consider, respectively, 30% and 50% of SMs communicating in real-time.

It should be stressed that the number of IEDs/SMs returned by the IED Selector module can be up to 2 units higher than the minimum number of devices defined by the network operator, in order to provide information equally distributed among connection phases. Taking this into consideration, Table 1 summarises the scenarios used to test the LV SE module.

*Table 1 – LV SE testing scenarios.*

| Scenario | SMs communicating in real-time (%) | No. of SMs defined by the "network operator" | No. of SMs returned by the IED Selector |
|---|---|---|---|
| **1** | 10 | 5 | 5 |
| **2** | 30 | 16 | 17 |
| **3** | 50 | 27 | 29 |

From the 10000 considered time instants (see section III), 9000 samples were used for training purposes and the remaining 1000 samples were used for testing the LV SE module. The results shown in the next section are referred to this testing set.

## IV. Results

In this section, the results obtained for each one of the previously defined scenarios are presented and discussed according to the respective module.

### *A. Data Management and Processing*

In Figure 7 is exemplified how the module works with some voltage magnitude measurements affected by noise, from one of the SMs of the network.

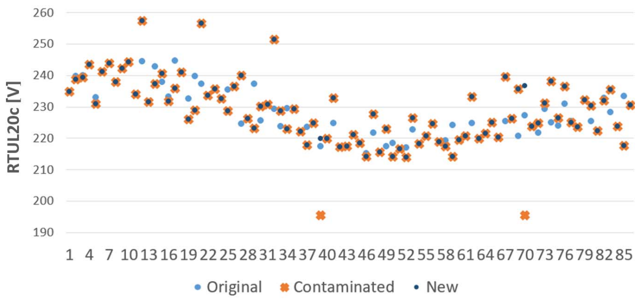


*Figure 7 – Contaminated voltage magnitude observations from one SM.*

It can be observed that two points of this sample were considered outliers and, consequently, replaced by new values determined by a multivariate regression.

## B. Network Connectivity Checker

### 1) Scenario 1

As mentioned in section III.B, the minimum known information given to the module corresponded to the three-phase SM available. Based on this information, the module was able to correctly identify the connection phases of all the remaining SMs, which means 100% of correct identifications.

### 2) Scenario 2

Table 2 shows the 20% of SMs considered with unknown connection phases as well as the identification performed by the module. As it can be observed, the module was able to correctly identify all the unknown connection phases.

*Table 2 – Identification of unknown connection phases by the Network Connectivity Checker module*

| SM ID | Real phase | Identified phase | SM ID | Real phase | Identified phase |
|---|---|---|---|---|---|
| **RTU02a** | R | **R** | **RTU08c** | T | **T** |
| **RTU02b** | S | **S** | **RTU09b** | S | **S** |
| **RTU04a** | R | **R** | **RTU09c** | T | **T** |
| **RTU05c** | T | **T** | **RTU10b** | S | **S** |
| **RTU06a** | R | **R** | **RTU11c** | T | **T** |
| **RTU08b** | S | **S** | | | |

### 3) Scenario 3

Since all the SMs' real (correct) connection phases were given to the module, no suggestion for change was returned, as expected.

### 4) Scenario 4

Table 3 presents the 20% of SMs whose connection phases were changed as well as the identification performed by the module. As it can be noticed, all the wrong connection phases were correctly identified by the module.

*Table 3 – Connection phases changed and afterwards identified by the Network Connectivity Checker module*

| SM ID | Real phase | Change performed | Identified phase |
|---|---|---|---|
| **RTU02a** | R | S | **R** |
| **RTU02b** | S | R | **S** |
| **RTU12a** | R | S | **R** |
| **RTU12b** | S | T | **S** |
| **RTU12c** | T | R | **T** |
| **RTU22a** | R | T | **R** |
| **RTU22b** | S | R | **S** |
| **RTU22c** | T | S | **T** |
| **RTU25c** | T | S | **T** |
| **RTU32b** | S | T | **S** |
| **RTU32c** | T | S | **T** |

## C. IED Selector and State Estimator

For illustration purposes, Table 4 presents the list of priority devices and their correspondent alternatives returned by the IED Selector module for this scenario (10% of SMs communicating in real-time). As mentioned in section II.C, if an IED/SM selected by the IED Selector module becomes unavailable (e.g., offline), the algorithm will check the availability of an alternative device before using the next one in the priority list.

*Table 4 – Merit order list of the IEDs/SMs with capability of transmitting data in real-time returned by the IED Selector module for scenario 1.*

| Priority device | List of alternatives |
|---|---|
| **RTUSS01** | RTU24t |
| **RTU24t** | |
| **RTU22c** | RTU08c, RTU23c, RTU05c, RTU09c, RTU13c, RTU29c, RTU11c, RTU18c, RTU25c, RTU20c, RTU12c, RTU19c, RTU30c, RTU32c, RTU27c and RTU33c |
| **RTU22b** | RTU14b, RTU08b, RTU09b, RTU16b, RTU29b, RTU10b, RTU02b, RTU18b, RTU25b, RTU12b, RTU19b, RTU26b, RTU13b, RTU31b, RTU27b, RTU20b, RTU21b and RTU32b |
| **RTU22a** | RTU08a, RTU04a, RTU13a, RTU07a, RTU02a, RTU27a, RTU28a, RTU06a, RTU10a, RTU09a, RTU11a, RTU29a, RTU17a, RTU12a and RTU19a |

Although the LV SE module is able to estimate both voltage magnitudes and power consumptions, in the present work only voltage magnitudes results are shown due to space constraints.

Figure 9 depicts boxplots with the absolute error computed for the voltage magnitudes in all customers' premises not being monitored in real-time (in each scenario) for the entire testing period (1000 time instants). The absolute error was calculated between the real values (obtained through an unbalanced three-phase power flow algorithm) and the estimated values obtained with the LV SE module. The SMs that do not present a boxplot in Figure 9 are the ones that were selected to communicate in real-time, besides the IEDs installed at the secondary substation.

As it was expected, the estimation accuracy is improved when more real-time measurements are available. The state estimation error obtained in scenario 1 accounts for the worst results in all the scenarios under study. Nevertheless, the value attained is lower than 5 V in 75% of the cases (75% of the analysed samples) in the large majority of the SMs, which gives good indications regarding the estimation accuracy of the LV SE module. Figure 8 depicts the Empirical Cumulative Distribution Function (ECDF) of the voltage magnitude absolute error obtained for all SMs for which state estimation was performed in each scenario.

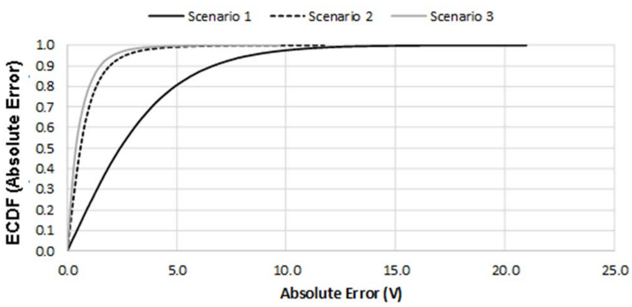


*Figure 8 – ECDF of the voltage magnitude absolute error obtained for all SMs (not being real-time monitored) in scenarios 1, 2 and 3.*

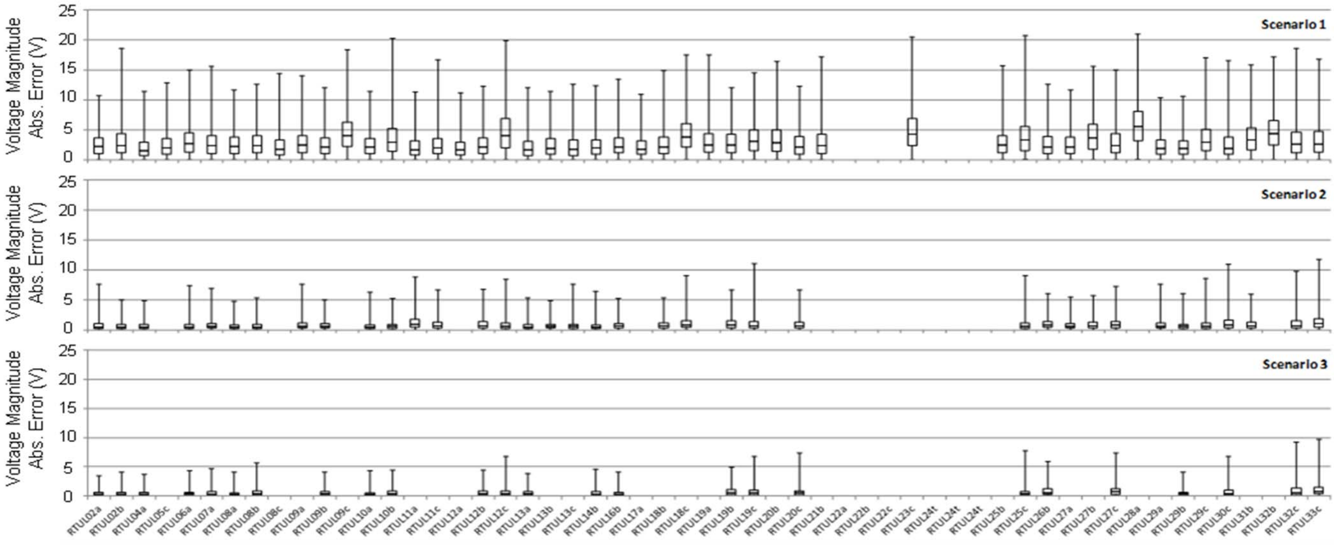


*Figure 9 – Voltage magnitude absolute error by SM not being real-time monitored in scenarios 1, 2 and 3.*

A clear improvement in the voltage magnitudes estimation accuracy considering a larger number of real-time measurements appears when observing this figure, namely by comparing scenario 1 with the remaining ones. However, the accuracy improvement observed from scenario 2 to scenario 3 is not so noticeable. In fact, from Figure 8 it can be seen that in 90% of the cases the absolute error stays below than 6.6 V, 1.9 V and 1.5 V in scenarios 1, 2 and 3 respectively.

## V. CONCLUSIONS

The main aspect of ADMS4LVsolutions refer to its capability of managing the LV network in coordination with the MV network, even when most of the network's characteristics are not known. Additionally, by solely using the most relevant measurements, it guarantees the observability of the network and reduces the amount of data required. Moreover, it is adaptive to the system's dynamic behaviour introduced by changes in the characteristics of the networks' nodes (e.g. installed DER). The results show a high accuracy of the algorithms employed for carrying out the network's operation, attesting the adequacy of this solution. Both state estimation and phase identification algorithm present satisfying results even when only few measurement data is gathered from the field.

## VI. ACKOWLDGEMENTS

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