Impact of Pseudo-Measurements from new Power Profiles on State Estimation in Low Voltage Grids

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Abstract—LV State estimation in distribution power system, because of lack of real time measurements, must heavily rely on pseudo-measurements, primarily originating from standard load profiles. Actual load profiles have been recently suspected of deviating significantly from the standard load profiles, and research work is ongoing to quantify and characterize this deviation and to synthesize more realistic profiles. The analysis of the propagation of error and uncertainty of load profiles in state estimation must be investigated, as distribution system state estimation (DSSE) state estimation in distribution is being experimentally deployed, and the use of any available source of data is under consideration. The findings provide hints on the accuracy to be expected and on corrections to be applied to classical pseudo-measurements.

Keywords— Power System measurements, State Estimation, Uncertainty, Power Distribution, Renewable energy sources, Heat pumps

I. INTRODUCTION

While measurements and monitoring of power systems transmission grids is well established and pervasive, the same cannot be said for distribution grids. Here sensors are very sparse, often limited to primary substations, and absent in some portions of the grid, particularly in the low voltage network. Monitoring in terms of measuring important electrical quantities, aggregation and elaboration of data, is not widely implemented [1] but it is critical in order to verify the security state of the system and perform control actions [2]. A monitoring application like state estimation, well developed in transmission, is currently under development for distribution systems [3].

One of the most difficult requirements for distribution system state estimation is to ensure observability, given the few measurement devices. This issue is addressed by exploiting historical data, namely pseudo-measurements when real measurements are not available. Use of accurate pseudo-measurements will soften the passage from the current state of monitoring infrastructure, to the case with full coverage of smart meters and upgraded substation instrumentation, assuring usability of a high level monitoring systems based on distribution system state estimation (DSSE).

Given the changes the distribution system is undergoing [4], the data used to build pseudo-measurements, as currently available, may not be a faithful representation of the electrical power consumptions over time [1]. In other words, bias errors may be present and the uncertainty of these profiles may be much larger than expected. The challenges to be addressed in relation to the use of existing pseudo-measurements in the state estimation of distribution systems are:

- Qualify and quantify the deviation to be expected between “classical” load profiles and new load profile, in presence of individual and combination influence factors, like renewable injections and combined thermal/electrical heating systems.
- Qualify and quantify the impact of the new profiles on pseudo-measurement uncertainty (as used in the Weighted Least Square (WLS) approach to state estimation solution).
- Develop alternative approaches for pseudo-measurement calculation in order to account the new profiles
- Qualify and quantify the impact of the new profiles on the accuracy of the state estimate.

These aspects are, therefore so addressed in this paper: the classical pseudo-measurements are compared with a new class of pseudo-measurements based on new profiles, such as photovoltaic (PV), combined heat and power plants (CHPs) and heat pumps (HPs), firstly with regard to the expected values and the standard deviation, and secondly with regards to the effects on the accuracy of the estimated states. Such study is supported by tools for the generation of realistic load, PV, CHP and HP profiles, which will be used both for computing the pseudo-measurements and constructing realistic operating conditions of the power system where to test the state estimation. In summary, the objective of this paper is, to explore the validity of existing pseudo-measurements, extracted from standard load profiles, and new pseudo measurements, extracted from statistical analysis and information available by the DSO. The validity of such pseudo measurements is analyzed for the case of active distribution systems, that is with sources as PVs, CHPs and HPs, in terms of consistency with regards to the actual power profile in the grid, and in terms of total error of the state estimation. This work is the technical extension of [5], where some preliminary evaluations were done based on the effects of PV generation on the quality of the state estimation. In section II the framework of the DSSE applied is explained, namely the
algorithm of state estimation and the roles of pseudo-measurements. In section III the tools used to generate realistic profiles of common loads, PVs, CHPs and HPs are presented. In section IV two methods for calculating pseudo-measurements are introduced. In section V the developed DSSE with the aforementioned pseudo-measurements are tested on a typical low voltage (LV) grid during a middle season (spring or autumn) working day.

II. DSSE AND PSEUDO-MEASUREMENTS

A. Algorithm of State estimation

State Estimation (SE) [6] is the process of determining the state of the systems in terms of phasor voltages [7] or currents [8], based on system model, and measurements from the power system. The state is commonly estimated using the so-called weighted least square (WLS) method. The measurement vector $z$ is compared with a measurement function $h(x)$, of the state of the system $x$, and the model of the system. The WLS method minimizes the weighted sum of the residuals, the differences between $z$ and $h(x)$, where the weight $w_i$ is the inverse of the variance of the corresponding $i^{th}$ measurement. The state is calculated, consequently through the equation (1).

$$\hat{x} = \arg \min_{x} J(x) \quad (1)$$

Where $J(x)$ is described in equation (2).

$$J(x) = \sum_{i=1}^{N} w_i (z_i - h(x))^2 \quad (2)$$

The measurements are provided to the DSSE as expected values and standard deviations. Where the expected value is used as measurement and the standard deviation permits to calculate the variance and consequently the weight of each measurement. Given that commonly in DSSE applications, the state may be the bus voltage phasor [9] or the branch current phasor [3], and the measurements are active and reactive powers and RMS voltage and current values, the relation with the measurements is nonlinear, hence the iterative Newton method is usually applied.

The DSSE is a subgroup of the state estimation and concerns the typical conditions of the measurement infrastructure of the distribution systems. In particular, the number of measurements is usually insufficient to apply the WLS method, as the condition of observability would not be satisfied [8]. Consequently, the measurement set is augmented by means of the pseudo-measurements based on active and reactive power consumption profiles expected at several nodes, based on historical and statistical data.

The DSSE used in this paper, is based on [9], and so are the methods and indexes applied to quantify the quality of the estimation. The estimated is the real and imaginary part of node voltage. The measurements considered in input are bus voltage phasors, branch current phasors, bus voltage magnitude, branch current magnitude, the phase angle between the node voltage and branch current and the bus active and reactive power injection. The network model used in the tests is single phase; consequently the DSSE estimates the bus voltage single phase positive sequence. The other inputs provided to the DSSE are model of the network in terms of topology and branch parameters, placement of measurement units and their expected accuracy. On regular basis a set of measurements is provided to the DSSE, the WLS method is applied and the state is provided as output.

B. Role of pseudo-measurements in LV DSSE

In DSSE, pseudo-measurements represent the majority of the inputs; hence have a significant contribution to the total error of the estimated state [9], [10]. They represent a buffer that allows the DSSE to satisfy the condition of observability of the system at the current state of the measurement infrastructure at LV level. Therefore, a monitoring application, such as state estimator can be deployed also in LV grid with low quality input. Whenever new investments upgrade the measurement infrastructure, the same DSSE algorithm can be used and the quality of the estimator will improve. Furthermore pseudo-measurements, represent backup information that can readily substitute real time data in case of failure of the device or the communication infrastructure.

Consequently, in order to obtain good pseudo-measurements it is important to estimate accurately the total active and reactive power consumption and the expected uncertainty of such estimation. The easiest source of pseudo-measurements are standard load profiles [1], [10] representative of the users in the LV grid, e.g. residential customer, provided with time resolution of 1-4 hours. Such profiles are usually provided with an expected maximum error of 50%.

Further knowledge on the features of the power profiles, may enhance the quality of the estimation, like differentiation among seasons and days (e.g. working day, holidays), different profiles for different buses depending on the type of customer (e.g. residential, industrial or commercial) and profiles for generation units like photovoltaic (PV), or thermal units like combined heat and power plants (CHP) and heat pumps (HP), and eventually the use of regional or local statistics.

III. GENERATION OF REFERENCE PROFILES FOR INDIVIDUAL RESIDENTIAL LOADS, PV, CHP AND HP PLANTS

It has been necessary to recreate realistic power profiles to be used as real reference data for the state estimation and in particular as source of observations for the calculation of the pseudo-measurements, in terms of expected values and standard deviations. For the sake of compliance, power profiles, weather data, temperatures and grid data are coming from the same area, which is in Germany. The realistic power profiles has been generated through some statistical tools, whose importance is generally related to the field of network planning, like for integrations of renewables and investments in the grid, or to estimate the total load consumption in the LV grid; however, in many cases such big amount of data
represent also an important source to train the pseudo-measurements.

A. Generation of realistic residential user power profile

The tool developed in [11] generates several realistic power profiles for households’ customers with a time resolution of 15 minutes. Realistic load events, namely continuous load events, which are independent from user activity, (e.g. cooling appliances or stand-by consumption), user activity driven events with constant power consumption, (e.g. lightning) and user activity driven events with measured power consumption, (e.g. dishwashers or washing machines) are distributed across the day by defining a relative probability density, which is based on the desired standard load profile (SLP). The tool hence requires reliable sources for SLPs [12] and statistical data of energy use within households [13]. The average of a large number of the generated profiles will approximate the standard load profile curve, but every single house, will be different from the SLP.

B. Generation of realistic PV power profiles

A weather depending model of a PV plant that includes as parameters solar radiation, temperature, physical module characteristics and number of arrays on the roofs was developed on the model of [14]. The solar irradiance is a factor that has impact on the generation of the PV cell e.g. by cloud coverage and has been described by a beta distribution [15]. The model generates a realistic active power profile, with a time resolution of 15 minutes. Moreover, also reactive power supply is included, with the same time resolution, following the current German regulation [16].

C. Generation of realistic power profiles of thermo-electric devices

Home energy systems (HESs), namely CHPs and HPs are installed in residential buildings to cover the heat demand for both space heating and warm water. The active and reactive power profiles of the HES are generated, with a time resolution of 15 minutes, following the approach of [17]. The input, needed to generate the profiles, includes the thermal parameters of the building, the storage temperature, the user behavior and the devices (radiators, HES, storage). Moreover, the same weather data base used to generate the PV power profiles, is exploited in order to have consistent profiles for the different days of observation.

IV. GENERATION OF THE PSEUDO-MEASUREMENTS

In this work two types of pseudo-measurements are used: pseudo class A (PCA) and pseudo class B (PCB). PCA represents the case in which, the DSSE user expects that only passive loads are connected to the LV busses, all with the same power consumption profile, which follows the common national standard load profile. These active and reactive power profiles have a time resolution of 15 minutes and maximum error equal to 50% in any condition. The standard deviation is obtained from the maximum error, considering the error as Gaussian distributed, and assuming the maximum error equal to the expanded uncertainty with coverage factor equal to 3. In this paper, PCA measurements are obtained from national standard load profiles [12], and the same can be done in real applications. PCB measurements are a new class, proposed in this work to represent in an accurate way new types of power profiles in LV grids.

In PCB case, the DSSE user may count on several power profiles, like households customers’, PVs’, CHPs’ and HPs’ power profiles, together with their standard deviations, with a time resolution of 15 minutes. It is worth to notice that both expected values and standard deviations may vary in time. The DSSE user is supposed to know the location in the network topology, and the nominal installed power of households’ customers, PVs, CHPs, HPs, hence it can associate to each bus dedicated PCB measurements.

PCB measurements are generated by simulating the active and reactive power profiles, with the tools mentioned in section III, for a large number of days. In particular, power consumptions for 25000 working days of a middle season were calculated and their expected values and the standard deviations derived. The standard deviations are obtained through a normal distribution fitting method. Instead, in real applications, the expected value and the expected statistical distribution of the active and reactive power consumption over time, are supposed to come from dedicated regional measurements, or from national statistical services. In the following paragraphs, the probability distributions of residential households, PVs, CHPs and HPs and a method to calculate PCB are presented.

A. Residential households probability distribution

Each of the single family houses is modeled as a three-person single family household, with nominal power 4.8 kW, mean annual consumption of 4246 kWh. The standard load profiles, together with the statistics of energy equipment usage, are given as input to the tool in [11] in order to generate a realistic individual house load profiles for middle season working days.

Fig. 1 shows the probability distribution of the absorbed power during a middle season working day for a residential customer. The power consumption has been divided, in the range between 0 kW and the nominal power, onto 100 bins and the number of observations for each bin has been calculated. The color code represents the number of observations (over the 25000 cases), the x axis is active power value and the y axis is the time of the day. Similarly, Fig. 2 shows the reactive power consumption probability distribution. It is possible to notice, from the figures, that the probability distribution is not symmetrical and that the power factor for residential customer is normally close to 1. During day time, as opposed to night time, not only the expected value of active power is higher, but also the distribution is wider; showing that the assumption of having uncertainty proportional to the expected value is usually true.
B. PV probability distribution

The standard load profiles refer to passive loads, however the PV generation can drastically modify the total power consumption profile. The impact is likely different during different seasons and days of the week. In this work the PV module simulated, through the tool explained in section III paragraph B, has a peak power of 4.8 kW. Fig. 3 shows the probability distribution of the generated power during a mid-season working day. Fig. 4 shows the combination of active power absorbed from the user and generated by the PV power plant, showing a reduction of the expected value in the central hours of the day, but also a significantly broader probability distribution. In Fig. 3 and Fig. 4 the color code represents the number of observations (over the 25000 cases), the x axis is active power value and the y axis is the time of the day.

C. HESs probability distribution

CHPs and HPs are modeled to have a nominal power of 5 kW and 8 kW respectively [17]. Some restrictions based on expected economic choices from the customers are that houses cannot have both CHPs and HPs, as that would mean a useless heating apparatus redundancy. Another restriction is that a house with PV generation does not have a CHP plant as additional power generation system. CHPs and HPs, as common in LV single houses, are considered to have only on and off status [18],[19], thus switching between 0 and nominal power output. These conditions have a strong impact on the total power probability distribution, very far from being Gaussian, and hence on the total uncertainty of the pseudo-measurements.

Fig. 5 and Fig. 6 show respectively the probability distribution of the total active and reactive power consumption at connecting point of a typical residential customer for the case of HP installed at the customers’ premises. Fig. 7 represents the probability distribution of the total active power consumption in the case in which the residential customer owns both PV system and HP. These three figures are valid for a middle season typical working; the color code represents the number of observations (over the 25000 cases), the x axis is active power value for Fig. 5 and Fig. 7 and reactive power value for Fig. 6, the y axis is the time of the day. These figures demonstrate the effect of on-off devices leading to the formation of bimodal distributions both for active and reactive power.
D. Calculating PCB measurements

As previously stated, houses may host different apparatuses that may affect the total power profile in different ways during different times of the day or periods of the year. Fig. 8 and Fig. 9 respectively show the mean total active power consumption and its standard deviation at a LV bus for different classes of residential customers: residential customers (RCs), RCs with PV, RCs with CHP, RCs with HP, RCs with HP and PV. Data are valid for a typical middle season working day.

From Fig. 9 and Fig. 10 we notice that the assumption of constant maximum deviation equal to 50% of the expected value is not realistic in LV. This was already shown to be the case with only passive loads and loads+PV, and even more so when also CHP and HP are present. Such high variability of the power demand is more critical in the LV case than the case in MV, where the customers are more aggregated and hence demands and generations are averaged out more. The PCB measurements in the following test use the expected values in Fig. 8 and the expected uncertainty in Fig. 9. The modeling of the uncertainty for PCB measurements is thus based on a normal distribution fitting, following the conclusions of [1], even though some of the characteristics previously seen are far from being Gaussian. Consequently it may be convenient to exploit the mixture Gaussian distributions to improve the modeling of the pseudo-
measurements [20]. Moreover, in this work no statistical correlation has been considered among pseudo-measurements, even though the conclusions of [21] suggests that important benefits can be obtained including possible correlations in the weighting matrix of WLS.

V. SIMULATIONS AND RESULTS

Based on the PCA and PCB measurements several tests on the performance of the DSSE are performed, for a typical working day of a middle season. The objective is to quantify the effect of increased knowledge of power profiles, consequently more accurate pseudo-measurements, on the quality of the estimated state in new scenarios with high penetration of PV, CHP and HP plants. The results are expressed in terms of average error of estimated bus voltage magnitude in the grid, in order to allow understanding the level of reliability expectable from LV network state estimation.

A. Description of the grid and test case

The tests are performed on a LV distribution grid that represents a portion of a typical urban area in Germany. Data of the grid, namely parameters of lines and transformers and topology, represented in Fig. 10, are taken from [22].

![Fig. 10. Low voltage grid schematic](image)

The grid is assumed to be symmetrical and balanced in loads and network devices. Some feeders supply the 179 single family houses; each household is modeled as a bus with connections to the individual load devices (consumption and generation).

The DSSE estimates the state of the network every 15 minutes for the whole day, yielding 96 state estimations per day. Higher estimation rates are not of interest in this particular application, as the focus is on the effects of the quality of the pseudo-measurements. To assess the behavior of the estimator, 1000 Monte Carlo (MC) simulations have been performed, at each point in time where the state is estimated. This mean that for each of the 96 points in time, the state estimation has been repeated 1000 times, each with a different combination of loads and generation, extracted from the tools described in section III and errors of measurement devices extracted from Gaussian distributions.

The state estimator is fed once with the expected accuracy and placement of measurement units in the grid and the model of the network, thus topology and parameters of the branches and a periodically with a set of measurements updated. Three types of measurement are considered in this paper, namely measurements from real measurement devices, zero injection measurements and pseudo-measurements. In the following simulations real measurement devices measure voltage magnitude and active and reactive power flow at the branches.

Such measurements are artificially created, in simulation environment, using a reference value, that is provided by the load flow calculations, and adding a Gaussian distributed error with standard deviation equal to a third of the maximum expected error, at every MC simulation. The measurement constellation is as follows: voltage magnitude at bus 2, active and reactive power flow at the branches between buses 2 and 65, 2 and 80, 2 and 30, 2 and 3. ). The point of connection between feeders and households are here considered as zero injection buses [9]. Totally 112 buses with zero injection measurements are present, representing nodes where no loads or generator are present. These are considered as active and reactive power consumption measurements with zero value and uncertainty. Consequently a high weight is given to such measurements in the WLS algorithm, as done in [9]. Eventually, pseudo class A and pseudo class B measurements, as explained in section IV, are placed in the buses corresponding to residential households. For every test, in the following sections, we calculate the differences between the estimated and the reference states, that is bus voltage magnitude and phase angle. In the presented tests, at every MC simulation, we calculate the average voltage magnitude error in the grid. The results shown are the $99^{th}$ percentile values, of the aforementioned averages. The $99^{th}$ percentile value represents the threshold below which the error falls in 99% of the MC simulations.

B. Description of the power consumption profiles

We describe here the features of the several power profiles that are fed into the simulations. The power consumption at the buses is a combination of loads, PV plants, CHPs and HPs depending on the test case. The reference test case includes only passive households; in test case “a” PV generation has been added to the passive loads in 35 buses; in test case “b” CHPs, in 27 buses, and HPs, in 27 buses have been added to PVs and passive loads. There are some buses with both PV and HP, representing consumers who have both generation and termal units. Instead, there are no buses with both CHP and HP units, as this would represent a useless redundancy of thermal units for the same household.

The households have nominal power of 4.8 kW and a mean annual consumption of 4246 kWh, typical for a three-person single family household. The base load profiles are taken from [12] and used to generate a more realistic load profile for each house with the tool explained in paragraph A of section III. The PV power consumption is modeled with the weather data based probabilistic approach, using the statistics provided in [23] and tool explained in paragraph B of section III. In this work each of the 35 PV plants, has a nominal power of 4.8 kW. The PV plants are randomly located in the grid and then the same positions are maintained.
for all the following MC simulations. The HES profiles are generated with the assumption that all buildings are alike in terms of renovation status and equipment technology. This choice results in the same power level for CHP or HP plants in every house. For the single family houses the peak power level of the CHP plants is 5 kW and 8 kW for the HPs. Also CHPs and HPs are randomly located initially, in 25 buses of the grid, and the same distribution is maintained for the subsequent MC simulations.

The loadflow that simulate the behavior of the grid, as well as the PCB calculation phase, are fed with power active and reactive injection values, recreated with the statistical tools previously presented. Even if the tools used are the same, two different set of data are created to feed, respectively, the loadflow and the PCB calculation, in order to avoid over-optimistic results.

C. Reference test case

In order to evaluate the test case “a” and “b”, a reference case is defined. In this reference case there are no PV plants, CHPs or HPs; the power consumption is due only to residential customers’ passive load equipment. Pseudo-measurements are modeled through the PCA. The results of the state estimation in this case are shown in Fig. 11 in terms of 99th percentile voltage magnitude average errors in the grid, in absolute values. The error of voltage magnitude is fairly constant during the day, and in average around 0.63 %.

D. Test case a

In test case a, PCA and PCB measurements are compared. PCA does not contain any information regarding PV generation; in PCB, the expected value and the standard deviation in time are available for two classes of buses: with only load and with load+PV. These profiles are fed to the state estimator as pseudo-measurements, coherently with the placement of PV units in the grid. The results in terms of voltage magnitude average errors, in absolute values, in the grid are shown in Fig. 12 for PCA and PCB cases. The average error with PCA is 0.70% and with PCB is 0.62%.

The improved knowledge of load and PV behavior, added to the knowledge of the DSO of the buses in which the PV units are installed, as expected, yields a substantial improvement in the knowledge of the state of the system. In particular, the central hours of the day present a larger error, for the case of PCA, due to the lack of information about the PV generation, which has a strong impact on the voltage on the grid.

Furthermore, it is possible to see that the error for PCA is actually biased, particularly during the central hours of the day when the estimated voltage is lower than the actual one. This is due to the fact that the PV units are not considered in the profiles used in PCA case; hence the voltage increase due to the inverse power flow is not estimated. It is possible to see this issue in Fig. 13, where the error is not taken in as absolute value, showing it’s biased. The average error of voltage magnitude between 9 am and 17pms is -0.16%. Such effect is of course dependent on the season.
E. Test case b

In test case b, also CHP and HP units installed in the grid are considered. As mentioned in paragraph C of section III the on/off nature of such equipment, together with their high power generation and consumption, yields a substantial degradation in the accuracy of the PCA and PCB measurements. Also in this test case, the two classes, PCA and PCB are compared. The result in terms of voltage magnitude average errors, in absolute value, in the grid is shown in Fig. 14.

![Fig. 14. Voltage magnitude relative error of state estimation](image)

As foreseeable, the CHPs and HPs yield a high uncertainty that impacts also the PCB profile. For PCA the error increase is between 0% and 40%, meanwhile for PCB it is between 0 and 30% with respect to the reference case. Indeed, the PCB manages to lower such impact, with regard to PCA. Notice that the curves of the standard deviation of the HP and CHP sources in Fig. 9 are somehow proportional to the error expected in the state estimation. Nevertheless, the PCA case, also in test case b maintains the error under 1.5%, meaning that, also with the most basic knowledge of power profile, it is possible to achieve acceptable estimation results. It is worth noticing, that the actual statistical distribution of power consumption/generation of HPs and CHPs is not Gaussian. However, both the PCA and PCB, use a Gaussian modeling, following the general approach proposed in the paper, that is to use basic and cost effective input to DSSE in LV in order to provide an acceptable state estimation. The results of the test show that also in this case the performance of the estimation is still acceptable. Although not graphically represented, also in this case, PCA measurements bring a certain bias in the error of voltage magnitude estimation, whereas PCB keeps the average error around zero.

F. General remarks on the reliability of DSSE at low voltage level based on pseudo-measurements

The test conditions presented in the previous sections model the existing monitoring infrastructure realistically, real-time measurements are concentrated to secondary substations and load pseudo-measurements are used for individual customers. The results show in general that with the features of PCB measurements the error is well under 0.8% for the case with passive loads and high penetration of PV units, meanwhile HES equipment in the LV grid, bring a degradation of the error to 1.1%. PCA measurements, instead, for the case with PV generation maintain the error under 1%, whereas for the case with also HES, the error goes to 1.5%. Although, PCA and PCB classes provide results that can be accepted for the requirements of LV voltage control, for instance trough centralized distributed generation control [2]; the bias of PCA class may lead to a significant impact in the success of such control actions, as the voltage is constantly underestimated during central hours of the day for instance. In such cases the use of few real-time smart meter measurements, reporting voltage magnitude in the feeder of the grid, may improve sensibly the quality of the estimation, restoring the condition of zero average error of voltage magnitude estimation, and hence having a more performing control. Furthermore, it has been noticed, that better knowledge of pseudo measurements, may decrease the relative voltage magnitude error, from 0% to 0.3%, that means a considerable, but not dramatic improvement of the state estimation. This could be explained, considering that pseudo measurements are many in the grid, but are given a small weight in the WLS method; for this reason, an improvement, with PCB with regards to PCA, is visible, but not dramatic.

VI. CONCLUSIONS

In this paper the authors proposed two classes of pseudo-measurements and compared them in typical LV scenarios. It has been shown that few further information on the power profiles that constitute the pseudo measurements, can improve drastically and economically the performance of the estimation. In particular the absolute error can be reduced and the average error can be brought close to zero. In presence of a high penetration of PV generation the error of voltage magnitude can be maintained under 0.8%, whereas in presence of a high number of HES systems, because of their high random nature, it is expectable to have a larger error, hence the maximum error may be set to 1.1%. This level of error represents an acceptable trade off considering the low quantity and quality of measurement available at LV level.

REFERENCES


