State Estimation for Distribution Grids With a Single-Point Grounded Neutral Conductor

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Abstract—Distribution system state estimation (DSSE) has been enabled by the deployment of smart meters and is currently the subject of active research, focused mainly in medium-voltage distribution grids (MVDGs). This article proposes a modified weighted least-squares (WLS) DSSE for low-voltage distribution grids (LVDGs) where the neutral conductor is grounded only at the MV–LV substation. DSSE methods developed for MVDGs are not applicable in such systems due to the significant voltage drop across the neutral conductor. The proposed DSSE includes the neutral voltage in the state vector, and the measurement functions are modified accordingly. To address any convergence issues and to enhance the accuracy of the proposed DSSE, virtual measurements are introduced for the neutral voltage. The effectiveness of the proposed DSSE is illustrated in a real LVDG and in the IEEE European low-voltage test feeder under different operating conditions, smart meter classes, and system layouts. In addition, a Monte Carlo analysis is performed for highlighting the importance of the proposed modifications to the WLS DSSE. Among others, the analysis indicates that the proposed method converged in all trials, despite including the neutral voltage in the state vector.

Index Terms—Low-voltage distribution grids (LVDGs), monitoring, neutral conductor, state estimation, weighted least squares (WLS).

I. INTRODUCTION

Low-voltage distribution grids (LVDGs) are entering a new era in which their role in the envisioned cost-effective and sustainable power system is very important. The increasing penetration of distributed energy resources and the impending electrification of the transportation sector are transforming LVDGs into active and complex systems. Due to the different characteristics compared with the transmission system, the monitoring methods developed for the transmission system cannot be applied directly to the DSSE. Considering that the most common transformer configuration in MV–LV substations is \( D-Y_g \), the zero-sequence component of the asymmetrical currents introduced by the LVDG loads is eliminated at the substation and does not propagate into the medium-voltage distribution grid (MVDG). Consequently, the current flow in the neutral conductor of MVDGs is negligible, especially if it is multigrounded, and the voltage drop across it can be approximated to zero. This allows the use of Kron’s reduction [5], [6], which reduces the size of the impedance matrix of each distribution line and the total number of state variables. In order to account for these characteristics, a three-phase coupled weighted least-squares (WLS) DSSE is proposed in [5] where a three-phase, four-wire, multigrounded system is simplified by using Kron’s reduction. A branch-current (BC) DSSE is presented in [7] where both nonsynchronized and synchronized measurements are considered. The proposed estimator is expressed in both polar and rectangular coordinates and can handle both radial and weekly meshed grids. In [8], a DSSE is presented, which can handle voltage drop regulators, tap-changing transformers, and a number of different types of measurements by introducing new equality constraints in the WLS DSSE procedure.
The time skewness of the smart meter measurements is addressed in [9] by proposing a new method to adjust the variance and mean of each measurement. This method significantly improves the accuracy of the traditional DSSE [5] where the asynchronicity of the smart meter measurements is not considered. In [10], a two-step multiarea DSSE is presented. In the first step, a BC-DSSE is executed using local and shared measurements in each area. Then, during the second step, a modified version of the WLS SE is used to refine the voltage profile estimation. The performance of a three-phase DSSE is evaluated in [11] under different types of knowledge, input data, and measurement error models. The authors highlight the significance of not only having accurate measurements but also a good knowledge of the system (layout and grid parameters).

In [12], the DSSE of the MVDG is enhanced by exploiting the smart meters in the LVGDs. A multilevel DSSE is first used to determine the state of the LVGD. The estimated voltage and power flow at the MV–LV substation are then used as measurements in the MVDG DSSE. This method achieves full observability of the MVGD by exploiting the smart meters of the end users without requiring additional measurement equipment. A DSSE for a four-wire MVDG composed of only grounded-wye loads where the neutral conductor is grounded at each system bus through a 1-Ω grounding impedance is proposed in [13]. This formulation allows eliminating the state variables corresponding to the neutral and zero-injection phase voltages, which enhances the overall computational performance.

Most of the aforementioned works regarding the DSSE are under the assumption of a multigrounded neutral conductor. While this is a valid assumption for most MVDGs, for LVGDs, this may not be true. In fact, in Cyprus and in many other countries, the neutral conductor in an LVGD is only grounded at the MV–LV substation. If such a DSSE is used in this kind of LVGDs, then a significant error is imposed on the estimation results [14]. The main reasons for this are the inaccurate system model due to Kron’s reduction and the phase-to-neutral voltage measurements. Since the neutral voltage in these LVGDs is not insignificant and can vary considerably across the system, each voltage measurement is expressed with a different reference. This article aims to address these issues with the following contributions: 1) a modified WLS SE where the neutral voltage is included in the state vector and the measurement functions are adjusted accordingly; 2) to address any potential convergence issues by including the neutral voltage in the WLS SE procedure, virtual measurements are constructed; and 3) two fitness tests are conducted in order to verify the distribution of the virtual measurements’ error and a mathematical calculation of their uncertainty (weighting scheme) is developed so that they are properly incorporated in the WLS SE procedure.

The remainder of this article is organized as follows. In Section II, the considered smart meters in the case studies are presented. The proposed modifications to the WLS SE are presented in Section III. In Section IV, the distribution of the virtual measurements is verified, and their uncertainty is calculated. The performance evaluation of the proposed and traditional WLS SE (CN) is presented in Section V, and finally, this article concludes in Section VI.

### II. Smart Metering Infrastructure

A smart metering system consists of four main elements: the smart metering device (smart meter), a data concentrator, a communication system, and the control center [4]. In recent years, millions of smart meters have been deployed globally, and by 2022, it is expected that around 1000 million of these devices will be installed worldwide. The main reason for their commissioning by utility companies is for automatic billing purposes and, in general, for understanding customers’ behavior, which can aid in improving the system’s operation. However, by utilizing the vast amount of new data related to the LVGD operation, new applications and functionalities can be enabled [15]. For instance, load analysis, load forecasting, load management, energy theft detection, and monitoring of the LVGD are some of the applications that will be enabled by the smart meter data.

In this article, a DSSE for a specific type of LVGD is proposed, which utilizes the existing smart meters of the end users (system is fully observable). A typical smart meter can provide measurements of the active and reactive power consumption as well as phase-to-neutral voltage measurements at the point of connection (premises of the consumer). Each measurement is classified according to the accuracy class of the meter. Assuming directly connected smart meters (no instrument transformers between the smart meter and the circuit), the overall accuracy of the different smart meter classes for the power measurements is presented in Table I as a function of the load current and the power factor. In this article, five different smart meter accuracy classes are considered in the case studies, as presented in Table II. The measurement error is modeled as [11]

\[
\hat{z}_{\text{meas}} = z_{\text{true}} + \text{FS} \cdot N(0, \sigma_{P,Q,V})
\]  

(1.a)

where \(z_{\text{true}}\) is the true value of the measured variable, FS is the full-scale meter reading associated with each type of measurement (9.2 kVA for the power measurements and 300 V for voltage measurements), and \(\sigma_{P,Q,V}\) are the standard errors.
uncertainties are calculated based on the maximum error of the smart meter accuracy class and assuming a 95% confidence interval [16]

$$\sigma_{P,Q,|V|} = \frac{e_{P,Q,|V|}}{1.96}$$

(1.b)

where $e_{P,Q,|V|}$ is the measurement device maximum errors defined by the accuracy class of the smart meters.

**III. Modified WLS State Estimation**

While various techniques have been developed for the monitoring of power systems [3], the WLS SE method is the most established and widely used. In this article, the proposed monitoring scheme, in which the neutral voltage is included in the state vector, is also based on this technique. Since the choice of the form of the state variables (current or voltage and polar or rect.) does not affect significantly the accuracy of the estimated results [3], the formulation of the proposed monitoring scheme is developed using the voltage magnitude and angle as state variables. Without losing generality, a similar approach can be followed for any other form of state variables in order to consider the voltage of the neutral conductor.

**A. Weighted Least-Squares State Estimation**

For a given set of system measurements, the state variables are calculated by minimizing the weighted sum of the measurement residual [17]

$$\min \sum_{i=1}^{n} \frac{[z_i - h_i(x)]^2}{\sigma_i^2}$$

(2.a)

where $z_i$ is the $i$th measurement from the measurement vector $z$, $h_i(x)$ is the measurement function that relates the state variables with the $i$th measurement, $x$ is the state vector, and $\sigma_i$ is the standard deviation of the $i$th measurement. As it can be seen from (2.a), the standard deviation of each measurement is used as a weight in order to give higher priority to measurements that are more accurate than other measurements.

**B. Proposed Modifications**

1) **Four-Phase System:** In $C_N$ for four-wire LVDGs, it is common to use Kron’s reduction method in order to merge the neutral conductor with the phase conductors [5], [6]. This allows us to simplify the problem and treat the four-wire distribution grid as a three-wire system. However, the use of Kron’s reduction method requires the assumption that the voltage across the neutral conductor approximates to zero. In the case of a four-wire LVDG in which the neutral conductor is grounded only at the transformer substation, this assumption is not valid, and its use can lead to inaccurate results [5]. As a matter of fact, in [14], it was shown that due to the significant zero-sequence current that flows through the neutral conductor (and consequently the voltage drop across it), $C_N$ yields inaccurate results. Therefore, in such LVDGs, the use of Kron’s reduction method should be avoided as the resulting system model will not be an accurate representation of the physical system. Instead, the full $4 \times 4$ impedance matrix (3.a) of each of the distribution lines should be used and the system should be modeled as a four-phase system. Hence, every two-wire node is characterized by eight state variables and every two-wire node by four state variables, as given by (3.b) and (3.c)

$$Z_{4\times4} = \begin{bmatrix} z_{aa} & z_{ab} & z_{ac} & z_{an} \\ z_{ba} & z_{bb} & z_{bc} & z_{bn} \\ z_{ca} & z_{cb} & z_{cc} & z_{cn} \\ z_{na} & z_{nb} & z_{nc} & z_{nn} \end{bmatrix}$$

(3.a)

$$x_{abcdn} = (\theta_a, \theta_b, \theta_c, \theta_n, |V_a|, |V_b|, |V_c|, |V_n|)$$

(3.b)

$$x_{pmn} = (\theta_p, \theta_n, |V_p|, |V_n|)$$

(3.c)

2) **Measurement Functions and Jacobian Matrix:** In an LVDG, the main measuring equipment is a smart meter, which can provide the active-reactive power consumption of the consumers as well as voltage magnitude measurements. As aforementioned, smart meters provide phase-to-neutral measurements, and therefore, the measurement functions that are used in the WLS SE procedure must be adjusted accordingly. First, the typical power injection measurements [5], [6] for a three-phase analysis are modified to include the coupling with the neutral voltage

$$P_{i}^p = |V_{i}^p|^2 \sum_{k=1}^{N} \sum_{m=a}^{n} |V_{k}^m| (G_{ik}^m \cos \delta_{ik}^m + B_{ik}^m \sin \delta_{ik}^m)$$

(4.a)

$$Q_{i}^p = |V_{i}^p|^2 \sum_{k=1}^{N} \sum_{m=a}^{n} |V_{k}^m| (G_{ik}^m \sin \delta_{ik}^m - B_{ik}^m \cos \delta_{ik}^m)$$

(4.b)
where \( P^p_i \) and \( Q^p_i \) is the injected active and reactive powers, respectively, at node \( i \) in phase \( p \), \( \delta^m_{ik} = \delta^p_i - \delta^m_j, Y = G + jB \) is the admittance matrix of the system, \( m = a, b, c, n \) corresponds to the system’s phases, and \( N \) is the total number of nodes in the system.

Second, since the voltage measurements are phase-to-neutral measurements, they cannot be directly related to the corresponding state variables as in the \( C_N \) SE. Instead, each phase-to-neutral voltage measurement is now related to four state variables as shown in the following:

\[
\begin{align*}
|V_{i,n}^p - V_{i,n}^m| &= |V_{i}^p| |\theta_{i}^p - \theta_{i}^m| \quad & (5.a) \\
|V_{i,n}^p - V_{i,n}^m| &= \left( |V_{i}^p| \cos (\theta_{i}^p) - |V_{i}^m| \cos (\theta_{i}^m) \right)^2 \\
&\quad + \left( |V_{i}^p| \sin (\theta_{i}^p) - |V_{i}^m| \sin (\theta_{i}^m) \right)^2 \quad & (5.b) \\
|V_{i,n}^p - V_{i,n}^m| &= \sqrt{|V_{i}^p|^2 + |V_{i}^m|^2 - 2|V_{i}^p||V_{i}^m| \cos (\theta_{i}^p - \theta_{i}^m)} \quad & (5.c)
\end{align*}
\]

As it can be seen from the abovementioned expression, each voltage magnitude measurement is now related to the phase and neutral voltage magnitude and angle of the corresponding system node. Consequently, the relevant elements of the Jacobian matrix \( H(x) \) are modified accordingly

\[
\frac{\partial |V_{i,n}^p - V_{i,n}^m|}{\partial |V_{i,n}^p|} = \left\{ \begin{array}{ll}
\frac{|V_{i}^m| - |V_{i}^n| \cos (\theta_{i}^m - \theta_{i}^n)}{h_{|V_{i}^m|}(x)}, & j = i, m = p \\
\frac{|V_{i}^m| - |V_{i}^n| \cos (\theta_{i}^m - \theta_{i}^n)}{h_{|V_{i}^n|}(x)}, & j = i, m = n \\
0, & \text{otherwise}
\end{array} \right. \quad & (5.d)
\]

\[
\frac{\partial |V_{i,n}^p - V_{i,n}^m|}{\partial \theta_{i}^m} = \left\{ \begin{array}{ll}
\frac{|V_{i}^m| |V_{i}^n| \sin (\theta_{i}^m - \theta_{i}^n)}{h_{|V_{i}^m|}(x)}, & j = i, m = p \\
\frac{|V_{i}^m| |V_{i}^n| \sin (\theta_{i}^m - \theta_{i}^n)}{h_{|V_{i}^n|}(x)}, & j = i, m = n \\
0, & \text{otherwise}
\end{array} \right. \quad & (5.e)
\]

where \( h_{|V_{i}^m|}(x) \) corresponds to the measurement function described in IV. In the \( C_N \) SE, in which the voltage measurements can be related directly to the state variables, the \( \partial |V_{i,n}^p|/\partial |V_{i,n}^m| \) element of the Jacobian matrix \( H(x) \) is equal to \( 1 \) when \( j = i \) and \( m = p \) and equal to zero otherwise, while \( \partial |V_{i,n}^p|/\partial \theta_{i}^m \) is always equal to zero.

3) Virtual Measurements for the Neutral Voltage: It is well known that the use of the Gauss–Newton method to solve a set of nonlinear functions can have convergence issues related to the initialization point [20]. Usually, this is not a major problem in \( C_N \) as the actual operating conditions are not very far from the initialization point as the system is regulated to operate near to its nominal values (usually the initialization point). However, by including the neutral voltage, which is normally initialized to \( 0 \) \( V \), the convergence of the WLS can be deteriorated [13]. In such a case, the neutral voltage might fluctuate between some values far from its initialization value. To improve the convergence capabilities when the neutral voltage is also considered, virtual measurements are constructed with the use of the forward–backward voltage sweep (FBS) method and the active–reactive power injection measurements. The term virtual measurements are used for differentiating from pseudomeasurements as \( a \) \( p \) \( r \) information is not required. Rather, the available knowledge from the smart meters (power measurements) is utilized to gain more information (neutral voltage) about the system’s state, during the execution of the DSSE. This new information is then used as measurements in the proposed DSSE scheme to guide the estimation of the neutral voltage.

The general scheme of the FBS method is shown in Fig. 1. This method is an iterative procedure, in which, in every iteration, the load current and BC are calculated using the PQ information of the loads, the grid topology, and an initial guess (flat start) for the load voltages. In [21], the effect of different neutral conductor configurations on the methodology’s convergence is examined. It is concluded that for certain configurations, multiple solutions might exist and the convergence of the FBS depends on the initialization of the neutral voltage, while in some cases, FBS fails to converge. However, for radial systems with the neutral grounded at the loads, FBS converges to the same solution, regardless of the initialization of the neutral voltage. This observation is extended in [22] for radial systems with the neutral grounded only at the transformer substation. Therefore, despite that the results of the FBS are characterized by a considerable uncertainty [12], they are still a good indication for the neutral voltage and can be used as virtual measurements in the proposed WLS SE. The FBS method used in this article to construct the virtual measurements of the neutral voltage is the one described in [22]. The main difference of this method with other FBS methods [23] is that during the calculation of the load currents in the backward sweep, the neutral voltage is also considered

\[
\begin{bmatrix}
I_a^i \\
I_b^i \\
I_c^i \\
I_n^i
\end{bmatrix} = \left( \begin{bmatrix}
S_a^i \\
S_b^i \\
S_c^i \\
S_n^i
\end{bmatrix}^* \begin{bmatrix}
(V_i^a - V_n^i) \\
(V_i^b - V_n^i) \\
(V_i^c - V_n^i)
\end{bmatrix} \right)^* \sum_m I_m^i
\]

(6.a)

where \( m = \{a, b, c\} \), \( i \) is the \( i \)th node with a load, \( S_a^i, S_b^i, \) and \( S_c^i \) are the power measurements of this load, and \( V_i^a, V_i^b, V_i^c, \) and \( V_n^i \) are the voltages of the \( i \)th node. Once the
A. Normality Tests

In \( C_N \), it is usually assumed that the measurement errors follow a normal distribution with a known variance and a zero mean value [i.e., \( \mathcal{N}(0, \sigma^2) \)] [17]. Similarly, in this article, it is assumed that the measurement error of the conventional measurements (\( P_{\text{inj}}, Q_{\text{inj}} \) and \( |V^{p-n}| \)) also follows a normal distribution. Therefore, in order to incorporate properly the virtual measurements in the proposed DSSE, a statistical analysis is necessary in order to identify the statistical distribution of their errors. Considering that for the calculation of the virtual measurements, the active and reactive power measurements are used, whose errors do follow a normal distribution, and it is assumed that also the error of the virtual measurements follows a normal distribution (null hypothesis). Then, the Anderson–Darling [24] and Shapiro–Wilk [25] fitness tests are used to determine whether this hypothesis must be refuted. These fitness tests determine whether the null hypothesis must be refuted by calculating the so-called \( p \)-value index. If this index is below 0.05 [26], then the hypothesis is refuted, and it cannot be assumed that the virtual measurements’ error follows a normal distribution.

In Fig. 2, the LVDG that is considered in this article is illustrated. It is assumed that all consumers are equipped with a smart meter belonging to the C-4 accuracy class (see Table II), and more information about this system can be found in Section V. This system is implemented in MATLAB/Simulink where the power flow results of one time step represent the real state of the system and are used to create the measurement errors for \( P_{\text{inj}} \) and \( Q_{\text{inj}} \) using III. FBS is executed 3000 times with different measurement errors, extracted by normal distributions with the appropriate properties. Then, the results are compared each time to the true state of the system in order to create the measurement error vector for each virtual measurement (72 \( |V^n| \) and 72 \( \theta^n \), one for each low-voltage node). This measurement error vector is used as an input to the two fitness tests, which results in 144 \( p \)-values for \( |V^n| \) (72 from each fitness test) and 144 \( p \)-values for \( \theta^n \). All \( p \)-values are found to be well above the threshold of 0.05, and in Table III, the average \( p \)-value of each type of virtual measurement is provided for each fitness test. Moreover, in Fig. 3, the probability density and probability plot of the |\( V^n| \) error is presented for a random system node. This figure offers a visual inspection of the distribution of the measurement error as it is compared to a fit normal distribution [27]. From Fig. 3 and Table III, it can be concluded that the null hypothesis is valid (based on these fitness tests). In other words, the assumption that the error of the virtual measurements follows a normal distribution that holds true.

B. Measurement Weights

The matrix \( R \), as defined in Section III-A is formulated using the variance of each measurement and its inverse (\( R^{-1} \)) is utilized to weight each measurement used in the WLS estimator. Measurements with high uncertainty (high variance) have a low impact on the WLS SE as their corresponding weight is smaller in relation to more accurate measurements (low variance). For the virtual measurements, after verifying that their error follows a normal distribution, their uncertainty must be defined in order to properly incorporate them in the estimation procedure. To do so, two different strategies are followed to define their uncertainty. The first one (\( W_1 \)) is a simple and straightforward, whereas the second one (\( W_2 \)) is more complex. The effect of the resulting calculated uncer-
Uncertainty of Virtual Measurements—$W_1$ Scheme

| Accuracy class | $\sigma_{W_1}$ [%] |
|----------------|-----------------|
| C1             | 0.283           |
| C2             | 0.707           |
| C3             | 1.118           |
| C4             | 2.236           |
| C5             | 2.828           |

In Table IV, the calculated uncertainty of the virtual measurements for each of the smart meter accuracy classes that are considered in this article is presented.

1) $W_1$: Considering that the calculation of the virtual measurements is achieved through the measurements of the active and reactive power consumption, their uncertainties are directly related. Therefore, a straightforward calculation of the uncertainty of the virtual measurements can be shown in the following:

$$\sigma_{W_1} = \sqrt{\sigma_{R_{\text{m}}}^2 + \sigma_{Q_{\text{m}}}^2}.$$  \hspace{1cm} (7.a)

Expression (8.e) can now be written as

$$f = c \sum_{i=L} (I^i_a + I^i_b + I^i_c)$$  \hspace{1cm} (8.d)

$$f = c \sum_{i=L} \left( \frac{P^i_a + jQ^i_a}{V^i_a} \right)^* + \left( \frac{P^i_b + jQ^i_b}{V^i_b} \right)^* + \left( \frac{P^i_c + jQ^i_c}{V^i_c} \right)^*.$$  \hspace{1cm} (8.e)

where $L$ is the set containing all downstream loads, in relation to the specific receiving end. For simplicity, the voltages are assumed to be equal to their nominal values [12], and by considering the phase shift introduced by the transformer, they are equal to

$$V_a = 1pu \angle - 30^\circ = 0.87 - j0.5 = e - jd$$  \hspace{1cm} (9.a)
$$V_b = 1pu \angle - 150^\circ = -0.87 - j0.5 = -e - jd$$  \hspace{1cm} (9.b)
$$V_c = 1pu \angle 90^\circ = j1 = jg.$$  \hspace{1cm} (9.c)

The neutral voltage is equal to

$$V_n = V_N - z_{na}I_a - z_{nb}I_b - z_{nc}I_c - z_{nn}I_n.$$  \hspace{1cm} (8.b)

where $c \in \mathbb{C}$ and is equal to $c = z_{an} + z_m$ ($z_m$ is the mutual impedance between the conductors). The phase currents are calculated based on the downstream loads of the specific receiving end (node) as

$$f = c \sum_{i=L} (I^i_a + I^i_b + I^i_c)$$  \hspace{1cm} (8.d)

$$f = c \sum_{i=L} \left( \frac{P^i_a + jQ^i_a}{V^i_a} \right)^* + \left( \frac{P^i_b + jQ^i_b}{V^i_b} \right)^* + \left( \frac{P^i_c + jQ^i_c}{V^i_c} \right)^*.$$  \hspace{1cm} (8.e)

Expression (8.e) can now be written as

$$f = c_2 \sum_{i=L} \left( eP^i_a - dQ^i_a - eP^i_b - dQ^i_b + g Q^i_c \right) + j(eQ^i_a + g P^i_c - dP^i_b - eQ^i_a + dP^i_a)$$  \hspace{1cm} (10.a)

$$f = c_2 (R + jX)$$  \hspace{1cm} (10.b)

where $c_2$ is equal to

$$c_2 = \frac{c}{|V|^2} = \frac{z_{an} + z_m}{|V|^2} = Z_r + jZ_i.$$  \hspace{1cm} (10.c)

The terms $R$ and $X$ are derived through the sum of normal distributions with a known standard deviation. Based on the propagation of uncertainty, the uncertainty of these terms also follows a normal distribution with a standard deviation that is a function of the standard deviation of the power measurements.

The neutral voltage can be written as

$$V_n = V_N - f$$  \hspace{1cm} (12.a)

$$V_n = (F^V_X - F^V_R) + j(F^V_X - F^V_X)$$  \hspace{1cm} (12.b)

$$V_n = a + jb$$  \hspace{1cm} (12.c)

where the uncertainty of $a$ and $b$ is calculated similarly as in (11.a)–(11.c). The virtual measurements that will be used in the state estimation are calculated as

$$|V_n| = \sqrt{a^2 + b^2}$$  \hspace{1cm} (12.d)

$$\theta_n = \tan^{-1}(k)$$  \hspace{1cm} (12.e)

where $k = b/a$. Considering the propagation of uncertainty, the uncertainty of each virtual measurement can be
calculated as

\[ \sigma_{V_n} = \sqrt{\sigma_a^2 + \left( \frac{b}{|V_n|} \right)^2 \sigma_b^2} \]  
\[ \sigma_{\theta_n} = \frac{|k|}{1 + k^2} \sqrt{\left( \frac{\sigma_a}{a} \right)^2 + \left( \frac{\sigma_b}{b} \right)^2} \]  

The calculation of the uncertainty of the virtual measurements is conducted in a forward sweep procedure. Considering that the neutral conductor is grounded at the transformer substation (at the second node), then, \( V_n^2 = 0 \), and then, according to (12.a), the rest are

\[ \begin{align*}
V_n^3 &= V_n^2 - f^3 = -f^3 \\
V_n^4 &= V_n^3 - f^4 = -f^3 - f^4 \\
V_n^5 &= V_n^4 - f^5 = -f^3 - f^5 \\
&\vdots
\end{align*} \]  

In Fig. 5, the calculated uncertainty of each virtual measurement is illustrated for all the smart meter accuracy classes that are considered. As expected, the uncertainty of the virtual measurements when accurate smart meters are used is significantly lower than with lower quality meters.

Moreover, (13.a) and (13.b) correspond to the diagonal elements, related to the virtual measurements, of the covariance matrix \( R \). Since the virtual measurements for the neutral voltage are derived through the same power measurements, they are correlated, and as a result, the covariance matrix is not diagonal. Considering this correlation, the covariance matrix \( R \) is then

\[ R = \begin{bmatrix}
\sigma_P^2 & 0 & 0 & 0 & 0 \\
0 & \sigma_Q^2 & 0 & 0 & 0 \\
0 & 0 & \sigma_{V_a}^2 & \sigma(V_a, V_{\theta_a}) & 0 \\
0 & 0 & 0 & \sigma_{\theta_a}^2 & \sigma(\theta_a, V_{\theta_a}) \\
0 & 0 & 0 & 0 & \sigma^2 \end{bmatrix} \]  

where \( \sigma(V_n, \theta_n) \) and \( \sigma(\theta_n, |V_n|) \) are the correlations between the virtual measurements. For the calculation of this correlation, the power measurements from the smart meters at the load nodes are considered (the first term of (8.c) is neglected) due to the high complexity. This is because the neutral voltage at the zero node before a load node is dependent on all the loads in the system. An analytical analysis of this will be too extensive for the potential improvement that it may offer. Considering this simplification, the neutral voltage at a load bus can be approximated as

\[ \begin{align*}
V_n \sim & c_2 e^{j\theta_2} \sqrt{R^2 + X^2} e^{j \tan^{-1} \frac{X}{R}} \\
& \begin{cases}
(eP_a - dQ_a) - j(dP_a + eQ_a), & \text{Phase A load} \\
(-eP_b - dQ_b) + j(eQ_b + dP_b), & \text{Phase B load} \\
gQ_c + jgP_c, & \text{Phase C load} \\
(eP_a - dQ_a - eP_b - dQ_b + gQ_c) + j(eQ_b + gP_s - dP_b - eQ_a - dP_a), & 3-\text{Ph load}
\end{cases}
\]  

In all cases, (15.b) can be written in the polar form as

\[ V_n \sim |c_2| e^{j\theta_2} \sqrt{R^2 + X^2} e^{j \tan^{-1} \frac{X}{R}} \]  

where \( R \) and \( X \) are the real and imaginary parts of (15.b), respectively. The virtual measurements can then be expressed as a function of the power measurements as follows:

\[ |V_n| = |c_2| \sqrt{R^2 + X^2} \rightarrow f_{V_n}(P, Q) \]  
\[ \theta_n = \theta_c + \tan^{-1} \frac{X}{R} \rightarrow f_{\theta_n}(P, Q). \]

Using the propagation of uncertainty, the correlation between the virtual measurements is calculated as

\[ \sigma(|V_n|, \theta_n) = \sqrt{\sum_{k=1}^{2} \frac{\partial f_{V_n}}{\partial p(k)} \frac{\partial f_{\theta_n}}{\partial p(k)} \sigma(p(k))^2} \]  

where \( p(k) = [P, Q] \) are the active and reactive power measurements of the corresponding load and \( \sigma(p) = [\sigma_P, \sigma_Q] \) is the uncertainty of these measurements.

V. Case Studies

In this section, the proposed monitoring scheme for ungrounded LVDGs is evaluated for both \( W_1 \) and \( W_2 \) weight schemes, referred to as \( N_{W_1} \) and \( N_{W_2} \), respectively. The system used in the simulations is shown in Fig. 2, which is an actual suburban residential LVDG in the power system of Cyprus. In total, there are 50 service points and 62 consumers, where most of them are supplied by a single phase and a small number have a three-phase connection. The three-phase load nodes 4 and 6 correspond to apartment complexes with seven residents each. The aggregated consumption of these apartment complexes is considered in the case studies (full-scale meter reading 30 kVA), and therefore, they are modeled as a single three-phase load. This LVDG has also three PV plants at nodes 7, 17, and 42 (denoted with a green font number) with the rated power of 2.5, 7.35, and 4.05 kWp, respectively. The neutral conductor is grounded only at the 11-kV/433 V transformer substation, i.e., at node 2. Daily load profiles for each of the consumers have been constructed with a half-hourly resolution. This data set was provided by the Cyprus DSO (Electricity Authority of Cyprus).

To properly evaluate the proposed monitoring scheme, the \( C_N \) SE is also considered in the simulations. Furthermore, \( C_N \) is also applied to the same system, under the same operating conditions but with a multigrounded neutral conductor (grounded at each end of a distribution line). The results of
this simulation, referred to as $C_{N^+}$, represent the maximum performance of the traditional WLS SE and are valid only for a multigrounded system. Since an ungrounded LVDG is considered, $C_{N^+}$ is only used as a benchmark for the proposed monitoring scheme.

The operation of the LVDG is simulated for five days in MATLAB/Simulink to obtain the true values of the system’s states. Based on the considered accuracy class of the smart meters, the conventional measurements are then constructed by adding a Gaussian noise. The performance of the monitoring schemes is evaluated by calculating the average two-norm $\|\Delta V\|_2$ and max-norm $\|\Delta V\|_\infty$ of the voltage estimation error at each time step.

### A. Accuracy Class of the Smart Meters

In Fig. 6, the voltage estimation errors are illustrated for the C-4 smart meter accuracy class. It can be observed that the proposed monitoring scheme with the $W_1$ weights is considerably more accurate compared with $C_N$. As it was shown in [14], the performance of $C_N$ is highly affected by the zero-sequence current that is flowing in the system and therefore depends on the operating conditions. In $N_{W_1}$, since the neutral voltage is considered in the problem formulation, its performance not only is six times higher (in average) than $C_N$ but also significantly more stable as its affected by the operating conditions in a considerably lower degree. The performance of the proposed monitoring scheme is further enhanced when the $W_2$ weights are used. Under this weight scheme for the virtual measurements, the performance of the proposed monitoring scheme approaches the maximum performance of the traditional WLS SE, highlighting the significance of properly assigning the weights for the virtual measurements. It should be noted that compared with $C_{N^+}$, the proposed monitoring scheme operates under a higher uncertainty. This is due to the neutral voltage whose virtual measurements are derived through erroneous PQ measurements, and therefore, as expected, its performance is lower than $C_{N^+}$. However, with the proper weights for the virtual measurements, the proposed monitoring scheme achieves almost a similar performance, while it can estimate the neutral voltage without any additional measurements from the physical system.

In Fig. 7, the estimation of the voltage profile of node 73 is illustrated for the C-4 accuracy class and for the different monitoring schemes. This node was chosen since in average, the max-norm ($\|\Delta V\|_\infty$) of the estimation error originated from this node. From this figure, the improvement that the proposed DSSE offers over $C_N$ in the voltage profile estimation can be clearly observed. In particular, the estimated states from $N_{W_2}$ are always significantly closer to the true states. Moreover, $N_{W_2}$ can also estimate accurately the neutral voltage of the system. Comparing Figs. 6 and 7, it can be concluded that the peaks of the estimation error of $C_N$ happen when the neutral voltage reaches a significant value, i.e., at $t \approx 1.6$ days. At these time instances, the neutral voltage has a significant value. The two main factors behind this considerable estimation error are the use of Kron’s reduction, which gives results to an inaccurate system model, and the voltage measurements, which are all expressed with significantly different reference points. In comparison, in the proposed DSSE, since the use of Kron’s reduction is avoided, the voltage measurements are expressed as phase-to-neutral measurements and the neutral voltage is considered as a state variable, and its performance is not affected by the operational state of the neutral voltage.

In Fig. 8, the estimation of the voltage profile of the same node is illustrated for the various smart meter accuracy classes
TABLE V
SUMMARY OF RESULTS—CONVENTIONAL MONITORING SCHEME

| Case | Estimation errors $[10^4$ pu] | $C_N$ Average iterations | Estimation errors $[10^4$ pu] | $C_N^+$ Average iterations |
|------|------------------|-------------------------|------------------|-------------------------|
|      | $||\Delta V||_2$ $||\Delta V||_m$ |                      | $||\Delta V||_2$ $||\Delta V||_m$ |                      |
| 1    | 19.61 30.77 3.29 | 0.17 0.38 3.19 | 2        | 19.63 30.82 3.29 | 0.51 1.03 3.20 |
| 2    | 19.66 30.85 3.30 | 0.62 1.61 3.02 | 3        | 19.71 30.96 3.32 | 1.58 3.01 3.19 |
| 4    | 20.21 31.64 3.33 | 2.55 4.52 3.19 | 5        | 20.21 31.64 3.33 | 2.55 4.52 3.19 |

TABLE VI
SUMMARY OF RESULTS—PROPOSED MONITORING SCHEME

| Case | Estimation errors $[10^4$ pu] | $N_{W_1}$ Average iterations | Estimation errors $[10^4$ pu] | $N_{W_2}$ Average iterations |
|------|------------------|-------------------------|------------------|-------------------------|
|      | $||\Delta V||_2$ $||\Delta V||_m$ |                      | $||\Delta V||_2$ $||\Delta V||_m$ |                      |
| 1    | 0.75 2.29 3.45 | 0.51 1.80 3.22 | 2        | 1.38 3.74 3.80 | 0.73 1.62 3.21 |
| 2    | 2.32 6.17 4.27 | 1.01 2.25 3.24 | 3        | 2.32 6.17 4.27 | 1.01 2.25 3.24 |
| 4    | 3.95 11.21 4.97 | 1.93 7.77 3.26 | 5        | 4.82 14.02 5.4  | 2.66 4.95 3.26 |

using $N_{W_2}$. While its accuracy is affected by the quality of the smart meters, even under the worst scenario, the proposed monitoring scheme can still estimate fairly accurate the voltage profile. This shows the robustness of the proposed monitoring scheme as its performance is not greatly affected by the operating conditions nor by the quality of the smart meters.

In Tables V and VI, the average estimation errors (of the five days simulated) as well as the average iterations required for all monitoring schemes and all smart meter accuracy classes are provided. In all cases, the proposed DSSE with both weight schemes ($N_{W_1}$ and $N_{W_2}$) achieves a considerably higher performance compared with $C_N$. Regarding the number of iterations required by the DSSE in order to converge, the weight scheme $N_{W_2}$ significantly improves the computational performance of the proposed DSSE. In all case studies, the proposed DSSE with the $N_{W_2}$ weight scheme required an average number of iterations slightly higher than 3, which is similar to the computational performance of the benchmark.

B. Type of System

In [14], the performance of $C_N$ was evaluated under different types of LVDGs. It was identified that its performance was highly affected by the type of LVDG, where rural systems imposed higher estimation error. To validate the applicability of the proposed DSSE, different types of LVDGs are considered. The results of this case study are shown in Table VII, where case $L$ corresponds to the original line lengths for the system’s distribution lines.

Using the proposed DSSE, the accuracy of the estimation results remains fairly constant and very similar to $C_N^+$, regardless of the system type. On the contrary, the accuracy of $C_N$ is highly affected by the system type, where, as in [14], rural systems impose higher estimation error. The main reason for this is the overall higher line impedance in rural systems, which for the same zero-sequence current as in an urban system, it results in a significantly higher neutral voltage. Consequently, the use of Kron’s reduction in such systems results in a system model that is completely wrong. The higher neutral voltage in rural systems also affects to a greater degree the voltage measurements from the smart meters. Across a rural system, the neutral voltage from one node to another is significantly different, meaning that the reference point of each voltage measurement is also significantly different. In the proposed DSSE, all these issues are addressed with the proposed modifications and the developed weight scheme for the virtual measurements. As a result, the proposed DSSE can be applied to any type of LVDG without a significant change in its performance.

C. Monte Carlo Trials

To unbias the results from the random measurement errors and to calculate their uncertainty, Monte Carlo simulations are conducted for $N_{W_2}$ using the C-4 smart meter accuracy class. The IEEE European low-voltage test feeder (see Fig. 9) is considered, which is a significantly larger system than the LVDG in Cyprus. From this system, 50 different operational points are used for the Monte Carlo analysis. For each operational point, 3000 trials are executed using the proposed DSSE, considering different measurement errors in each trial, resulting in a total of 150 000 Monte Carlo trials. The mean and variance of each measurement error are provided in Table VIII.
TABLE VIII
MONTE CARLO RESULTS

| Estimation error | μ [V] | σ^2 [V^2] |
|------------------|-------|-----------|
| ∥ΔV∥_2           | 0.293 | 0.012     |
| ∥ΔV∥_∞           | 0.570 | 0.042     |

Fig. 10. DSSE convergence without virtual measurements.

Fig. 11. Proposed DSSE convergence with virtual measurements.

A significant advantage of the proposed DSSE is that the convergence issues that are related to the initialization of the neutral voltage [13] are eliminated. The proposed DSSE, despite including the neutral voltage as a state variable, was able to converge in all the 150,000 Monte Carlo trials. In order to highlight the importance of the proposed modifications to the convergence rate of the DSSE, the following scenario is executed. The performance of the DSSE with the neutral voltage included in the state vector but without the proposed modifications regarding the virtual measurements is examined. During this scenario, the initial convergence threshold ε [see (2.c)] is set to 5 × 10^{-4} p.u. If the DSSE fails to converge within 30 iterations, then ε is increased by +5 × 10^{-4} p.u. If ε reaches 0.1 p.u and the DSSE still fails to converge, then the process is stopped as the DSSE failed to converge within a reasonable convergence threshold.

The results of this study are shown in Fig. 10. The right axis with the red circles shows the required threshold setting in each of the operational points for the DSSE to achieve convergence, and the left axis shows the required number of iterations for this threshold setting. In total, there are 11 instances where the upper limit of ε was reached and the DSSE still failed to converge within 30 iterations. For comparison purposes, in Fig. 11, the required convergence threshold and the number of iterations of the proposed DSSE with the virtual measurements are illustrated. With the inclusion of the proposed modifications and virtual measurements, the DSSE becomes significantly more stable. Based on these numerical simulations, the proposed DSSE can achieve convergence in the lowest threshold setting and in average within three iterations. When the virtual measurements are not considered, the threshold limit must be considerably larger in order to achieve convergence, where, in some instances, no convergence can be achieved. This highlights the importance of the proposed modifications to the DSSE scheme when the neutral voltage is considered as a state variable.

VI. CONCLUSION

Current DSSE methods for MVDGs are not applicable in LVDGs with a neutral conductor grounded only at the MV–LV substation. This article presented a novel monitoring scheme based on the WLS SE for such systems. In the proposed DSSE, the neutral voltage is included in the state vector, the measurement functions, and the Jacobian matrix H(x) that are adjusted accordingly, and virtual measurements are incorporated in the WLS procedure. The purpose of the virtual measurements is to address any potential convergence issues and to improve the accuracy of the proposed DSSE. Case studies under different operating conditions and smart meter accuracy classes have demonstrated the effectiveness of the proposed monitoring scheme. In comparison to the conventional DSSE, in which the neutral voltage is assumed that it can be approximated to zero voltage, the proposed scheme has, in average, ten times better performance. Furthermore, when compared to the benchmark (maximum performance of the conventional DSSE), the performance of the proposed scheme is, in average, only 1.22 times lower, despite operating under higher uncertainty. As the case studies have illustrated, the proposed DSSE can operate with very high accuracy, which is not affected by the quality of the smart meters (case study A), the type and size of the LVDG (case study B), and the ungrounded neutral. With the introduction of the virtual measurements and the developed weight scheme, the proposed DSSE is also able to achieve convergence (case study C), something which was lacking when the neutral voltage was considered as a state variable before.

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