Event-Driven State Estimation for Monitoring the Voltage Quality of Distribution Systems

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Abstract—This work proposes a method for monitoring the voltage quality of distribution systems based on event-driven state estimation. A scenario of wide-scale deployment of smart meters is expected to occur. Simulation tests are conducted for a real 1,682-bus feeder and actual load profiles from low-voltage and medium-voltage customers. The results show the improved performance of such method compared to the alternative of time-driven state estimation.

Index Terms—Distribution system state estimation, event-driven approach, smart meters, voltage quality.

I. INTRODUCTION

The integration of an Advanced Metering Infrastructure (AMI) to distribution systems considerably increases their monitoring level and in a few years, a large-scale deployment of smart meters is expected to occur. As a result, the Distribution System State Estimation (DSSE) becomes a potential supervision tool to support important functions of the Distribution Management System (DMS) such as the ones dedicated to monitor and assure the voltage quality.

Differently from the transmission system state estimation, in which measurements are communicated at regular time intervals of 3 to 5 s [1], the DSSE is expected to receive smart meters’ data at each 10 or 15 min [2], due to economic constraints and privacy issues. Between two intervals of data communication, the instantaneous measurements are aggregated in time, so that at the end of the period of 10 or 15 min the meter provides a single value to describe an electric quantity, losing information about its behavior during that period. This approach, known as time-driven (TD), may limit the identification of voltage quality problems.

Recent studies have shown the advantages of using event-driven (ED) approaches [3], in which the communication of the data from a smart meter is triggered whenever a power change higher than a threshold occurs. This process results in the communication of lower data volumes and tends to allow a better monitoring of load and voltage changes compared to the use of TD approaches. In [4], the authors propose a method combining time-driven and event-driven approaches for electricity metering. In [5], the efficacy of the ED approach to represent load profiles in low voltage (LV) systems is discussed. No previous work, however, has investigated the effect of using the detection of significant events to rule the communication of measurement data used as input of the DSSE algorithms.

In this context, this work proposes and investigates the use of an event-driven state estimation method to monitor the voltage quality of distribution systems. It is important to emphasize that the authors do not suggest a new state estimation technique, but a method to rule the communication of smart meters’ data to be used as input of a DSSE focused on monitoring the voltage quality of distribution systems. A three-phase state estimator for unbalanced networks, using the Weighted Least Square (WLS) formulation, is implemented. The original aspects of this work are related to the proposal of the threshold values of load variation that trigger data communication from smart meters and also to how this data can be weighted in a WLS technique. The performance of the proposed method to estimate the voltage magnitudes and unbalances is evaluated in a Brazilian distribution feeder composed of 1,682 medium voltage (MV) and LV buses, using real load profiles.

This paper is organized as follows. Section II characterizes the load events and Section III describes the proposed method of event-driven state estimation. In Section IV, the indicators used to assess the method performance are presented, followed by the simulation results, in Section V. The main conclusions are summarized in Section VI.

II. CHARACTERIZATION OF THE EVENTS

According to [4], the basis of the ED approach is that smart meters’ data is communicated to the management center whenever a relevant load change occurs, characterizing an event. In this work, instead of using voltage events to monitor the voltage quality, load events are adopted, as in [4]. This choice is justified as by observing the load events one can more easily identify the source of the voltage quality problem, which refers to the meter that report the load event. For instance, if a voltage sag occurs because of a motor
starting, the meter from the customer that owns the motor reports the load event allowing identifying the source of the problem. Then, the state estimator provides more information about the voltage sag.

The relevance of a load change, which characterizes a load event, is defined by its comparison with a predefined threshold. In this method, based on [4] and [5], two types of load events, event $PQ_1$ and event $PQ_2$, are defined as follows.

The event $PQ_1$ occurs when the difference between two consecutive measurements of active (or reactive) power – corresponding to measurements of two consecutive elementary time intervals, $\tau$ – exceeds the active (or reactive) power thresholds, $\Delta P_{lim}$ (or $\Delta Q_{lim}$), as expressed in (1), for active power, and in (2), for reactive power.

\[
|\Delta P(t_i)| = |P(t_i) - P(t_{i-1})| > \Delta P_{lim}
\]

(1)

\[
|\Delta Q(t_i)| = |Q(t_i) - Q(t_{i-1})| > \Delta Q_{lim}
\]

(2)

where $t_i = t_0 + n(0,1) \cdot \tau$; $t_{i-1} = t_0 + (n(0,1)-1) \cdot \tau$; $t_0$ is the instant in which the measurement process starts; and $n(0,1)$ is a positive integer that refers to the number of elementary intervals $\tau$ included in the time interval between $t_0$ and $t_i$.

The event $PQ_2$ occurs when the accumulated differences between consecutive active (or reactive) power measurements exceed $\Delta P_{lim}$ (or $\Delta Q_{lim}$), as in (3), where $t_{m+1}$ is the time instant subsequent to the last event $PQ_1$ or $PQ_2$ registered in the management center, i.e., every time an event occurs each total sum in (3) is reset.

\[
\sum_{t=t_0}^{t=t_{i-1}} \Delta P(t) > \Delta P_{lim} \text{ or } \sum_{t=t_0}^{t=t_{i-1}} \Delta Q(t) > \Delta Q_{lim}
\]

(3)

When an event $PQ_1$ or $PQ_2$ is identified by a smart meter, the following measurement values are communicated to the management center: a) instantaneous active power, reactive power, and voltage magnitude, obtained during the latest elementary interval $\tau - P(t_i)$, $Q(t_i)$ and $V(t_i)$; and b) average active and reactive power values corresponding to the time interval between the last and the current event, $t_{m+1}$ and $t_i$, respectively – $\bar{P}(t_{m+1},t_i)$ and $\bar{Q}(t_{m+1},t_i)$.

The instantaneous measurements $P(t_i)$, $Q(t_i)$ and $V(t_i)$ describe the present condition of the load and they are used as inputs of the DSSE algorithm. The average measurements are not used for voltage monitoring, but they provide more accurate information for billing purposes. Alternatively, the average active and reactive power can be sent at regular time intervals, associating the ED with the TD approach, as in [4].

III. THE PROPOSED EVENT-DRIVEN STATE ESTIMATION

In this work, the distribution system state estimation uses a three-phase formulation of the WLS method [6] (which represents network unbalance and asymmetry), implemented by the authors in Matlab. The state variables are defined as the three-phase voltage magnitudes and phase angles of each bus of the distribution system. It is assumed that all load buses and the distribution substation are remotely monitored.

The smart meters, installed at every load bus, register active power, reactive power, and voltage magnitude, per phase, at each elementary time interval, $\tau$ ($\tau = 1$ s). Moreover, the meter installed at the substation provides the local active power, reactive power, and voltage magnitude, all per phase.

Whenever a smart meter identifies an event $PQ_1$ or $PQ_2$ it communicates the measurement data mentioned above (at $t = t_i$), updating the inputs of the DSSE algorithm and, subsequently, the estimated state of the system. In the state estimation process, for the smart meters that do not identify an event at the same time ($t = t_i$), the active power and reactive power values communicated at the last event $PQ_1$ or $PQ_2$, occurred in $t = t_{m+1}$, are used as inputs. They characterize pseudo measurements with values within $P(t_m) \pm \Delta P_{lim}$ and $Q(t_m) \pm \Delta Q_{lim}$ for active and reactive power, respectively.

In Fig. 1, the proposed ED state estimator is illustrated for a hypothetic system composed of three smart meters. In $t = t_0$, the measurements $P(t_0)$, $Q(t_0)$ and $V(t_0)$ are communicated, where $k = 1$, 2 and 3 are the meters’ number. In $t = t_1$, there is an event ($PQ_1$ or $PQ_2$) in the load monitored by meter 1, when it transmits $P(t_1)$, $Q(t_1)$ and $V(t_1)$. These measurements, joint with the last active and reactive power measurements sent by meter 2 and meter 3, in $t = t_0$, are used as inputs of the DSSE algorithm. Similar procedure is performed in $t = t_2$, when an event is detected by meter 3.

![Illustration of the ED state estimator](image)

Figure 1. Illustration of the ED state estimator.

Two important aspects of the proposed method are following discussed: the choice of the thresholds $\Delta P_{lim}$ and $\Delta Q_{lim}$ that characterize the events $PQ_1$ and $PQ_2$, and the weights assigned to the DSSE input measurements.

A. Definition of $\Delta P_{lim}$ and $\Delta Q_{lim}$

The choice of the thresholds of power changes $\Delta P_{lim}$ and $\Delta Q_{lim}$, from which the events $PQ_1$ and $PQ_2$ are characterized, directly impacts the performance of the method. The larger the defined limits, the greater the loss of information, increasing the errors of the estimated variables. On the other hand, large limits reduce the number of events and consequently the rate and amount of data sent to the
management center. Therefore, it is important to establish an acceptable range to the errors and simultaneously avoid excessive data communication. With that in mind, a previous knowledge about the distribution network and the load is needed. Although the events are characterized by active and reactive power variation, the network loads can be voltage dependent, they are not necessarily constant power loads. The load type does not affect the performance of the DSSE. The procedure used in this work to obtain \( \Delta P_{\text{lim}} \) and \( \Delta Q_{\text{lim}} \) is following described.

As the proposed approach is focused on monitoring the voltage quality, reasonable limits of voltage change, \( \Delta V_{\text{lim}} \), caused by a load change, can be specified. Once \( \Delta V_{\text{lim}} \) is established, the limits of power changes per load bus \( k \) and per phase \( ph \) (\( \Delta P_{ph}^{k \text{lim}} \) and \( \Delta Q_{ph}^{k \text{lim}} \)) are defined as the maximum values of \( \Delta P_{ph} \) and \( \Delta Q_{ph} \) that satisfy the inequalities (4) and (5), respectively.

\[
\begin{align*}
\max \left| J_{\text{VP}}(k,ph) \cdot \Delta P_{ph}^{k \text{lim}} \right| & \leq \Delta V_{\text{lim}} \\
\max \left| J_{\text{VQ}}(k,ph) \cdot \Delta Q_{ph}^{k \text{lim}} \right| & \leq \Delta V_{\text{lim}}
\end{align*}
\]

in which the vectors \( J_{\text{VP}}(k,ph) \) and \( J_{\text{VQ}}(k,ph) \) provide the sensitivity of the voltage magnitudes of the network nodes in relation to \( \Delta P_{ph} \) and \( \Delta Q_{ph} \), respectively. The vectors \( J_{\text{VP}}(k,ph) \) and \( J_{\text{VQ}}(k,ph) \) are obtained from the Jacobian matrix, \( \text{Jac} \), by taking the column corresponding to bus \( k \) and phase \( ph \) from submatrices \( J_{\text{VP}} \) and \( J_{\text{VQ}} \), calculated as in (6)-(8) [7].

\[
\begin{align*}
J_{\text{VP}} &= \Delta V / \Delta P = \left( J_{\text{PV}} - J_{\text{QV}} \cdot J_{\text{QV}}^{-1} \cdot J_{\text{PV}} \right)^{-1} \\
J_{\text{VQ}} &= \Delta V / \Delta Q = \left( J_{\text{QV}} - J_{\text{QV}} \cdot J_{\text{QV}}^{-1} \cdot J_{\text{PV}} \right)^{-1} \\
\text{Jac} &= \begin{bmatrix} J_{\text{PV}} & J_{\text{QV}} \\ J_{\text{QV}} & J_{\text{PV}} \end{bmatrix} \begin{bmatrix} \Delta \theta \\ \Delta V \end{bmatrix}
\end{align*}
\]

Because the main purpose is to obtain a sensitivity index rather than the actual operating condition, \( \text{Jac} \) is calculated for the nominal operating point of the network – using the nominal load values – and only the PQ buses are represented. The limits for PV buses are discussed later. Alternatively, the values of \( \Delta P_{ph}^{k \text{lim}} \) and \( \Delta Q_{ph}^{k \text{lim}} \) can be updated during the day (for instance, every hour), by calculating the \( \text{Jac} \) in (8) for a more recent operating point of the network.

To avoid high values of \( \Delta P_{ph}^{k \text{lim}} \) and \( \Delta Q_{ph}^{k \text{lim}} \) for some nodes, resulting in loss of information, they can be limited by \( \delta_{AP} \) or \( \delta_{AQ} \), as in (9)-(10), where the function \( \min(A, B) \) returns the minimum value between A and B.

\[
\begin{align*}
\Delta P_{ph}^{k \text{lim}} &= \min \left( \Delta P_{ph}^{k \text{lim}}, \delta_{AP} \right), \\
\Delta Q_{ph}^{k \text{lim}} &= \min \left( \Delta Q_{ph}^{k \text{lim}}, \delta_{AQ} \right)
\end{align*}
\]

For the PV buses, \( \Delta P_{ph}^{k \text{lim}} \) and \( \Delta Q_{ph}^{k \text{lim}} \) are assumed to be equal to the respective \( \delta_{AP} \) and \( \delta_{AQ} \). This work adopts different values of \( \delta_{AP} \) and \( \delta_{AQ} \) for load buses located at LV networks (\( \delta_{AP(LV)} \) and \( \delta_{AQ(LV)} \)) and at MV networks (\( \delta_{AP(MV)} \) and \( \delta_{AQ(MV)} \)). Thus, the parameters needed to define \( \Delta P_{\text{lim}} \) and \( \Delta Q_{\text{lim}} \) are \( \Delta V_{\text{lim}}, \delta_{AP(LV)}, \delta_{AQ(LV)}, \delta_{AP(MV)} \) and \( \delta_{AQ(MV)} \), which are chosen according to the acceptable variations of voltage magnitude and injections of active and reactive power.

B. Weights Assigned to Measurements for the DSSE

The weight assigned to each measurement in the process of state estimation employing the WLS algorithm is defined based on the maximum expected error of the measurement (\( \text{Err} \)). The higher the expected error, the lower should be the corresponding element in the WLS weight matrix. The measurements used as input of the DSSE algorithm, performed for a time instant \( t \), are classified into three types:

- **Type 1** – measurements \( \{P(t), Q(t), V(t)\} \), sent by the smart meters that identify the event \( \{PQ\} \) at the time instant \( t \).
- **Type 2** – pseudo measurements \( \{P(t), Q(t)\} \) for the load buses in which the events are not identified at \( t \).
- **Type 3** – virtual measurements \( \{P(t), Q(t)\} \), corresponding to the active and reactive power injection at no-load buses, assumed equal to zero.

The maximum expected error of the type-1 measurements is obtained using the uncertainty of the smart meter (in percentage), \( U_{\text{sm}} \), and the measured quantity, \( Z_{\text{mea}} \), as in (11). The uncertainty value can be found in the meter data sheet.

\[
\text{Err} = \pm Z_{\text{mea}} \cdot U_{\text{sm}}/100\%
\]

The maximum expected errors of the active and reactive power pseudo measurements (type 2) are assumed to be equal to \( \pm \Delta P_{\text{lim}} \) and \( \pm \Delta Q_{\text{lim}} \), respectively. For the measurements of type 1 and 2, the diagonal elements of the WLS weight matrix \( (W_{ii}) \) are given by the inverse of measurement variance, \( \sigma^2 \), calculated using (12).

\[
W_{ii} = \sigma^2 = (\text{Err/3})^{-2}
\]

The virtual measurements (type 3) have a low uncertainty and the weights assigned to them are higher than those calculated for measurements of types 1 and 2. In this work, weight values of 10\(^6\) pu and 10\(^{10}\) pu are assumed for the virtual measurements from MV and LV networks, respectively, in which the power base is 100 kVA.

IV. DSSE PERFORMANCE INDICATORS

To assess the performance of the proposed method, the accuracy of the estimated voltage magnitudes and unbalances is evaluated. In addition, the amount of data packets communicated during a time period is quantified. Comparisons are made with the results obtained from the TD approach, based on the following performance indicators.

A. Voltage Magnitude

For each elementary time interval, \( \tau \), the maximum and minimum voltage magnitudes (\( V_{\text{max}} \) and \( V_{\text{min}} \)) estimated by the DSSE are compared with the maximum and minimum voltage magnitudes obtained from load flow (LF) simulations. This comparison is made using (13), where \( X_{qu} \) represents the analyzed variable (\( V_{\text{max}} \) or \( V_{\text{min}} \)), in pu, and
superscripts $SE$ and $LF$ indicate estimated and load flow values of variable $X$, respectively.

$$
\Delta X_{\text{SE}} = \left( X_{\text{pu SE}} - X_{\text{pu LF}} \right) \times 100\% \quad (13)
$$

It is also evaluated whether the DSSE can accurately indicate the buses where $V_{\text{max}}$ and $V_{\text{min}}$ values occur, defined as ‘critical buses’ $k_{V_{\text{max}}}$ and $k_{V_{\text{min}}}$, respectively. At the end of the 24-hour simulation, the percentage of the time that the critical buses are correctly indicated is verified.

### B. Voltage Unbalance

In this work, the voltage unbalance, $V_U$, is calculated as the ratio between the magnitude of the negative-sequence voltage ($V_2$) and the positive-sequence voltage ($V_1$), i.e., $V_U = 100\% \times \frac{V_2}{V_1}$. For each elementary time interval $\tau$, the maximum $VU_{\text{SE}}$ ($VU_{\text{SE max}}$) estimated by the DSSE – considering all the buses of the system – is compared with the respective value obtained from LF simulations, by using (14).

$$
\Delta VU_{\text{SE max}} = VU_{\text{SE max}}^\text{SE} - VU_{\text{SE max}}^\text{LF} \quad (14)
$$

At the end of the 24-hour simulation, it is verified the percentage of the time that the DSSE correctly indicates the bus where $VU_{\text{SE max}}$ is detected ($k_{VU_{\text{SE max}}}$).

### C. Data Packets

The set of data sent by a smart meter whenever a load event is identified at a monitored load is defined as a data packet. To assess the amount of data communicated due to the load events, the number of data packets ($N_p$) transmitted by all meters during a period ($T$) is quantified. This number is given as a percentage of the number of data packets that would be sent if the data communication happened at each elementary time interval $\tau$, as in (15), where $n_{(T)}$ is the number of $\tau$ intervals contained in $T$ and $N_m$ is the number of smart meters in the network.

$$
N_{p_{\text{SE}}} = 100\% \times \frac{N_p(n_{(T)}T)}{N_m} \quad (15)
$$

### V. SIMULATION STUDIES

The test system used in the simulations is a Brazilian 13.8-kV feeder, with a short-circuit level of 500 MVA and ratio X/R of 4.0, totaling 1,682 buses and 1,826 customers. This feeder comprises 55 LV networks (0.22 kV). Eight LV networks are 100% commercial while the others are 80% residential and 20% commercial. The 159 MV loads are all commercial loads. Feeder data are available at [8].

To represent the loads of the distribution test system, real load profiles with 1-second resolution are used. The data was obtained from measurements performed in Brazil during a research conducted by the authors’ research group. It consists of active and reactive power profiles from different commercial loads – connected to MV or LV level – and from residential customers, with different consumption habits. The measurements used as input of the DSSE are generated by adding random noise to the results of load flow simulations, which are performed each second, as the resolution of the load profiles. The measurements’ noises follow a Gaussian distribution and are limited to meter uncertainty, $U_u$, defined as 0.2% for voltage magnitude measurements and 1.0% for active and reactive power measurements.

Two case studies are following presented. In Section V.A, the performance of the ED state estimator in a 24-hour simulation is assessed, considering the indicators proposed in Section IV. The sensitivity of the method to the parameters $\Delta V_{\text{lim}}$, $\Delta \delta_{P}$ and $\Delta \delta_{Q}$ is investigated in Section V.B.

#### A. Case Study 1

In this example the ED state estimator is applied to the test system considering the following parameters that characterize the events $PQ_1$ and $PQ_2$: $\Delta V_{\text{lim}} = 0.25\%$, $\Delta \delta_{P(LV)} = 0.6$ kVAR, $\Delta \delta_{Q(LV)} = 0.6$ kVAR, $\Delta \delta_{P(MV)} = 10$ kW and $\Delta \delta_{Q(MV)} = 10$ kVAR. The maximum and minimum voltage magnitudes calculated by the LF simulations and estimated by the ED state estimator are shown in Fig. 2 (letters $a$ and $b$ respectively). One can observe from Fig. 2 that most of the time the ED approach satisfactorily detects the extreme values of voltage magnitude and the curves overlap.

**Figure 2.** Comparison of voltage magnitude obtained by the LF and by the ED state estimator.

The distribution of the errors $\Delta V_{\text{SE max}}$ and $\Delta V_{\text{SE min}}$ are presented in Fig. 3, using boxplot representation [9]. In these figures, it is also shown the distribution of the errors obtained for the TD state estimator, when the time interval ($\Delta t$) between two data communication is 15 min, considering that all network meters send the average measurements – $\bar{P}(\Delta t)$, $\bar{Q}(\Delta t)$ and $\bar{V}(\Delta t)$ – at the same instant. In this case, the DSSE variables estimated for a time instant $t$ are replicated during the interval $t-\Delta t$ to $t$ to allow the use of (13) for each second. When the ED approach is used, the maximum errors of the estimated $V_{\text{max}}$ and $V_{\text{min}}$ are considerably low, attaining maximum values, in module, of 0.4% and 1.0%, respectively; while for the TD approach these errors reach 1.4% and 6.9%, respectively.

**Figure 3.** Distribution of $\Delta V_{\text{SE max}}$ and $\Delta V_{\text{SE min}}$ for the ED approach and TD approach with $\Delta t = 15$ min.

Fig. 4 presents the $VU_{\text{SE max}}$ in percentage, obtained by the LF and by the ED state estimator as well as the distribution of the errors $\Delta VU_{\text{SE max}}$ for both ED and TD approaches. The maximum $\Delta VU_{\text{SE max}}$ in module, is 0.37% for the ED approach and 1.38% for the TD approach (with $\Delta t = 15$ min), which is
a high error considering the typical regulatory limits of 2% or 3% at distribution systems.

Figure 4. Comparison of $V_{\text{Umax}}$ obtained by the LF and by the ED state estimator and the distribution of $\Delta V_{\text{Umax}}$ for both ED and TD approaches.

Table I shows the percentage of the time that the buses $k_{\text{Vmax}}$, $k_{\text{Vmin}}$ and $k_{\text{VUmax}}$ are correctly indicated.

<table>
<thead>
<tr>
<th>Approach</th>
<th>$k_{\text{Vmax}}$ (%)</th>
<th>$k_{\text{Vmin}}$ (%)</th>
<th>$k_{\text{VUmax}}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TD (15 min)</td>
<td>94.6</td>
<td>84.2</td>
<td>67.7</td>
</tr>
</tbody>
</table>

The results show that the loss of information about the network quantities is reduced when the ED state estimator is used. Thus, a question that may arise is about the data volumes associated with each approach. To answer that, the number of data packets, $N_{P_{%}}$, generated by the ED approach is shown in Table II, which also presents the values of $N_{P_{%}}$ obtained for the TD state estimator, when $\Delta t$ is equal to 5, 15 and 30 min. For this analysis, the volume of data communicated when the ED approach is used is similar to the volume of data communicated when the TD approach is adopted with $\Delta t$ equal to 15 min.

<table>
<thead>
<tr>
<th>Approach</th>
<th>$N_{P_{%}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ED</td>
<td>0.12</td>
</tr>
<tr>
<td>TD</td>
<td>0.33</td>
</tr>
<tr>
<td>TD</td>
<td>0.11</td>
</tr>
<tr>
<td>TD</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Besides observing the minimum/maximum voltage magnitude and unbalance, an important application of the ED state estimator is the identification of the loads responsible for the voltage quality problem. It can be achieved by locating the meters that report a load event at the same moment the voltage problem starts. In addition, to identify the loads that contribute the most to the voltage unbalance, the magnitude of the negative-sequence apparent power, $S'$, injected by each load bus can be calculated from the state estimation results and the buses associated with high values of $S'$ possibly contribute more to the voltage unbalance.

B. Case Study 2

To analyze the influence of the defined parameters on the performance of the ED state estimator, five different sets of parameters are simulated, as described in Table III. The set number 1, used in the previous case study, is highlighted.

Table IV presents, for each set of parameters, the results of the 24-h simulation, showing the value of $N_{P_{%}}$ and the maximum and mean errors, in module, of the estimated $V_{\text{max}}$, $V_{\text{min}}$ and $V_{\text{Umax}}$. It is important to note that the parameters $\delta_{\Delta P(MV)}$, $\delta_{\Delta Q(MV)}$, $\delta_{\Delta P(LV)}$ and $\delta_{\Delta Q(LV)}$ (varied on sets number 2, 4 and 5) considerably affects the volume of data communicated, which is not observed when the parameter $\Delta V_{\text{lim}}$ is varied (sets number 1, 2 and 3). On the other hand, the estimated variables and the resulting errors are more sensitive to $\Delta V_{\text{lim}}$.

### Table III. Sets of Parameters Used in the Analysis

<table>
<thead>
<tr>
<th>Set of Param.</th>
<th>$\Delta V_{\text{lim}}$ (%)</th>
<th>$\Delta Q_{\text{PV}}$ (kW)</th>
<th>$\Delta P_{\text{PV}}$ (kW)</th>
<th>$\Delta Q_{\text{PV}}$ (kvar)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.25</td>
<td>10</td>
<td>10</td>
<td>0.6</td>
</tr>
<tr>
<td>2</td>
<td>0.50</td>
<td>10</td>
<td>10</td>
<td>0.6</td>
</tr>
<tr>
<td>3</td>
<td>1.00</td>
<td>10</td>
<td>10</td>
<td>0.6</td>
</tr>
<tr>
<td>4</td>
<td>0.50</td>
<td>5</td>
<td>5</td>
<td>0.3</td>
</tr>
<tr>
<td>5</td>
<td>0.50</td>
<td>20</td>
<td>20</td>
<td>1.0</td>
</tr>
</tbody>
</table>

### VI. Conclusions

By utilizing the potential information obtained from smart meters installed at all load buses, this work proposes an event-driven state estimator to monitor voltage quality in distribution systems. The identification of relevant changes in the network loads triggers the data communication, allowing to estimate the main voltage changes and, consequently, to detect possible voltage quality problems. The simulations results show the improved performance of the proposed approach to monitor the voltage magnitude and unbalance in distribution systems when compared to the traditional TD approach. It is important to note that this improved performance is achieved by extracting the relevant measurements from the network, avoiding the simultaneous transmission of high data volumes.

### References


