DETECTION OF TOPOLOGICAL ERRORS IN DISTRIBUTION NETWORKS USING STATE ESTIMATION RESIDUAL PATTERNS

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Abstract

Distribution system operators (DSOs) traditionally rely on incomplete and heterogeneous data (e.g., historical maps and GIS data) to reconstruct their network models, leading to inconsistencies in the network topology. With the widespread deployment of smart meters, DSOs now benefit from unprecedented data redundancy. With state estimation, DSO can exploit this redundancy and optimally combine measurements and network models to obtain the most likely system state. This study presents the idea of a simple but practical approach to detect probable errors, including topological issues and incorrect smart-meter phase assignments, based on the analysis of the geographical patterns of state-estimation residuals. The approach is demonstrated on an actual distribution network using real smart-meter measurements, and the practical insights gained from this implementation are discussed.

1 Introduction

An accurate system analysis requires an accurate model, and electrical distribution networks are no exception. In reality, however, DSOs often build their network models using different sources such as old maps and GIS data, which are not always complete or consistent. As a result, errors and mismatches can appear, especially in the network topology. With the widespread installation of smart meters, much more measurement data is now available. One common approach to detect such errors is the analysis of voltage profiles by investigating the correlations between them, but as shown in our results, this approach tends to fail for complex cases. Using state estimation, DSOs have a more systematic approach to combine these measurements with the network model to obtain the most likely operating state of the system and to detect bad data.

Bad data detection plays a key role in ensuring reliable state estimation in distribution networks. Traditional weighted least squares estimation (WLSE) with chi-square residual tests, originally developed for transmission systems, does not perform well in distribution grids due to limited measurement redundancy, high R/X ratios, and three-phase unbalance [1]. To overcome these challenges, early studies adapted methods to the radial structure of distribution systems, using forward–backward sweep techniques for observability analysis and bad data processing [2].

Later, approaches such as the maximum normal measurement rate method was introduced specifically for distribution networks, enabling simultaneous state estimation and bad data detection in unbalanced systems, even in the presence of multiple bad measurements [1]. The integration of PMUs further improved estimation accuracy, with branch-current-based methods achieving errors below 1% and applying correction procedures suited to distribution system characteristics [3]. However such approaches are usually deemed impractical for distribution level. Robust and iterative approaches have also been proposed to address topology errors, fault detection, and bad data by adjusting measurement weights and updating pseudo-measurements [4], [5].

More recently, computational methods such as machine learning techniques, especially neural networks, have also been applied to distribution state and topology estimation [6]. Other approaches enhance detection accuracy by incorporating external information such as photovoltaic forecasts in active distribution networks [7]. As distribution networks increasingly include distributed generation and advanced metering, robust and adaptive bad data detection remains crucial for accurately estimating the system state and identifying topology errors [8].

In this paper, the focus is on practicality; proposing an approach that uses available measurements, even when smart meter penetration is very low, to detect topological errors and identify their causes. In collaboration with RESA, the electricity and gas operator in Liège, Belgium, state estimation was applied to actual LV distribution networks using field data to detect likely errors, including topological mismatches and incorrect smart-meter phase assignments. The study introduces the geographical residual pattern analysis idea and presents practical insights gained from its application.

2 Methodology

In this paper, we propose the application of state estimation to detect smart-meter and topological errors. In state estimation, the state x is the set of electrical variables that fully describe the operating point of the network (e.g., voltage magnitudes and angles, transformer tap positions). Once the state is known, all other electrical quantities can be derived from it.

Let us consider we access to a set of noisy measurements z, and let us consider the measurement model $\hat{z} = h(x)$, which expresses how currents, voltages, or power flow measurements relate to the state variables. For each measurement z_i, a residual r_i is computed as in equation (1).

$$r_i = z_i - \hat{z}_i \qquad (1)$$

It represents the mismatch between the observed value and the model prediction. To account for different measurement uncertainties, each residual is normalized by the measurement $\hat{z}_i$ standard deviation σ_i, yielding the normalized residual ρ_i, defined by equation (2).

$$\rho_i = r_i / \sigma_i \qquad (2)$$

Dividing by σ_i expresses each mismatch in units of its expected variability, giving all residuals a common statistical scale and making them directly comparable across measurements of different accuracy. For the exact equations and deeper insight about state estimation and normalized residuals, the reader can refer to [9].

Normalized residuals are compared to a statistical threshold of 3 (following [10]). Large normalized residuals can indicate a measurement inconsistency with the estimated state, or deeper issues, such as topology errors.

2.1. Geographical residual pattern analysis

Classical normalized-residual analysis relies on high measurement redundancy and accurate network models, conditions rarely met in distribution networks. With sparse measurements, uncertain pseudo-measurements, and potential topology inconsistencies, examining single residuals provides limited diagnostic insight. To overcome this, we propose focusing on the geographical patterns formed by normalized residuals across the network rather than individual values. For example, uniformly high residuals along a feeder may indicate a topological error, while an isolated high residual surrounded by low values typically points to a localized metering issue, such as an incorrect phase assignment or a faulty measurement. Generally, global patterns usually highlight topology inconsistencies, whereas local anomalies reveal metering defects.

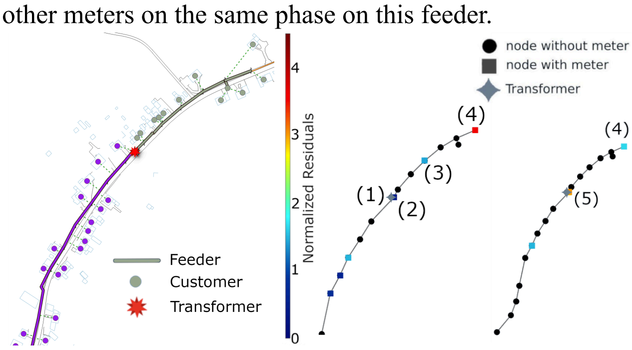
The following section illustrates this approach through several practical examples applied to an actual distribution network and smart meter data, showing how residual patterns can be used to detect both topological and metering errors.

3 Results

We validate the proposed residual pattern analysis on a real-world distribution grid using network data provided by RESA. We apply our test on voltage measurements (z) recorded by smart meters at low voltage level, using pandapower [11] state estimation module. The set of state variables x includes voltage magnitude and phase angles. We begin with examples of single anomalies (high residuals) and then move on to diagnosing broader patterns formed by multiple anomalies across the network. Our normalized residuals analysis is performed in a production scenario, *i.e.*, at noon on a sunny summer day.

3.1 Detection of wrong phase assignment

The first case we illustrate is the detection of wrong phase assignment in the network of Fig. 1(a) with two feeders (the orange going down and the blue one going up). Fig. 1(b) represents the electrical circuit of these feeders, where buses are an aggregation of customers. Among the blue feeder's 8 buses, there are 4 meters on the same phase (meters (1) to (4)) and one of them (meter (5)) on another phase. We see in Fig. 1(b) that we have one isolated high residual at the end of this feeder (meter (4)). This makes it suspicious and it is thus interesting to have a look at the voltage profiles of this meter and to compare it with the other meters on the same phase on this feeder.



(a) *(b)* *(c)*

Fig. 1 (a) Topological map of the feeder, (b) Normalized residuals on the feeder (numbers between parentheses are meter ids), (c) Normalized residuals on these feeders after corrected phase assignment

Looking at the profiles of Fig. 2, it can be seen that meter (4) voltage profile is actually closer to the one of meter (5), which is on another phase. We can thus test an alternative phase assignment and observe the normalized residuals. We see in Fig. 1(c) that by applying this correction we have lower value for meter (4) normalized residual.

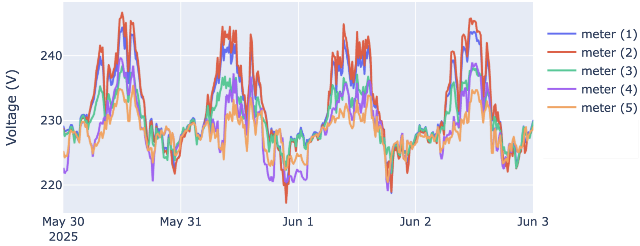
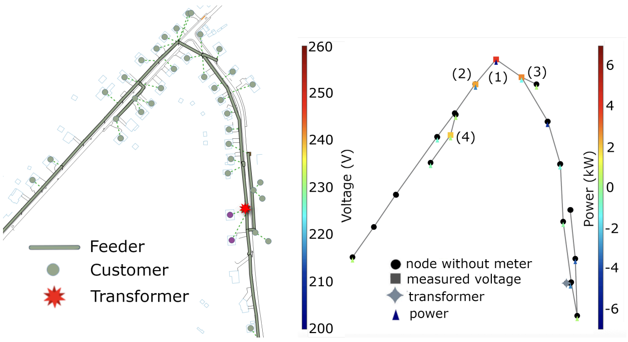


Fig. 2 Voltage profiles of meters on the top feeder of the network depicted in Fig. 1

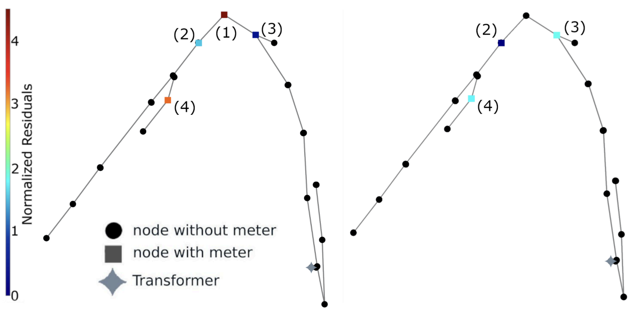
3.2 Data problem detection

For the feeder shown in Fig. 3(a), we have an example where there is a high residual value of 4.5 on an isolated meter (meter (1)) as shown in Fig. 4(a). Checking the voltage profiles in Fig. 5, we can see that all the meters seem to be on the same phase. This is an example of a complex case where simple correlation analysis on voltage profiles cannot help to detect data problems.



(a) *(b)*

Fig. 3 (a) Topological map of the feeder, (b) Voltage values



(a) *(b)*

Fig. 4 (a) Normalized residuals, (b) Normalized residuals after correction

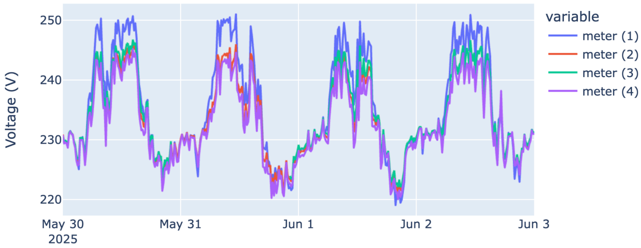
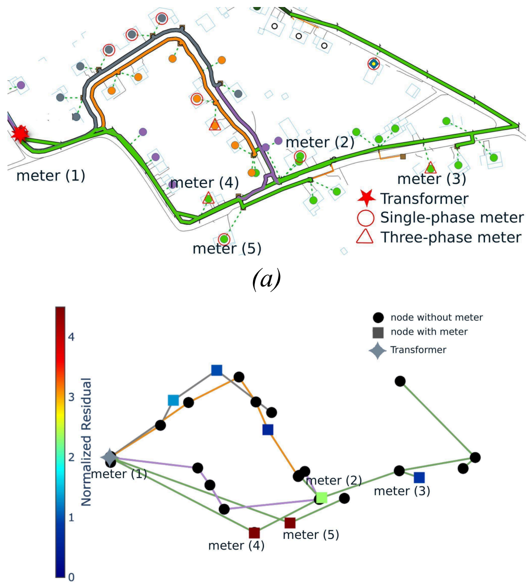


Fig. 5 Voltage profiles of meters depicted in Fig.3

Removing this smart meter data from the state estimation leads to the reduced residuals in Fig. 4(b). It can be observed that residuals are now much lower, which may indicate a problem with this smart meter data, such as a wrong meter localization.

Checking the details of the available smart meter data, it can indeed be verified that these data seem erroneous. As can be seen in Fig. 3(b), the voltage of smart meter (1) is the highest at 246.8 V, with both neighbours having lower voltage at 240.4 and 241.8 V. Such high voltage surges on short distances mean very high currents flowing from this bus in both directions, and thus a very high generation, which is not realistic for the only residential customer connected to the line.

3.3 Wrong feeder assignation



(a)

(b)

Fig. 6 (a) Topological map of the studied feeder, (b) Normalized residuals pattern

Fig. 6(a) shows a distribution feeder (in green) with five smart meters, and Fig. 6(b) shows the magnitudes of normalised residuals for each measured node of the feeder. In the residuals pattern we observe very high residuals equal to 5 and 6.9 for meters (4) and (5), with lower values as we move away from these two, suggesting a probable topological problem in that area. In voltage timeseries of Fig. 7 we can see that we have two distinct classes confirming that there is a topological problem. It seems that a part of the light green feeder including meters (2) and (3) is wrongly assigned and belongs to another feeder. We test a topology modification as in Fig. 8(a), which is more coherent with the voltage curves. This new topology reduces the normalized residuals of meters (4) and (5) to 0.1 and 0.4 in Fig.8(b).

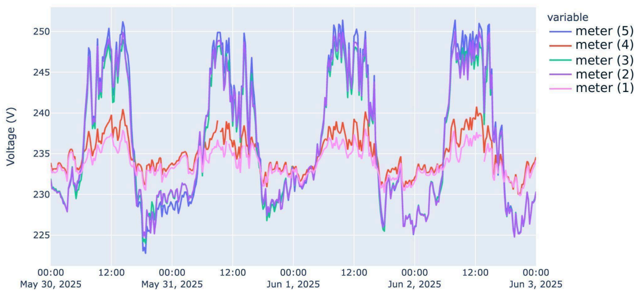
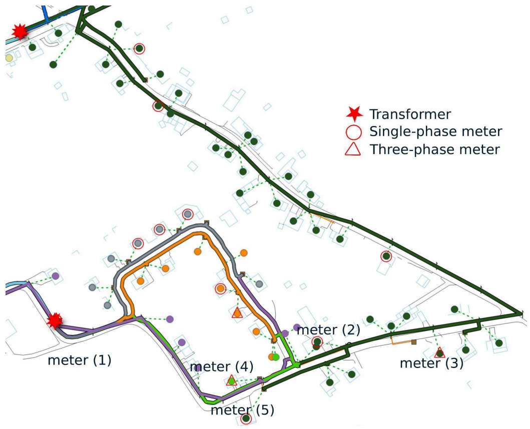
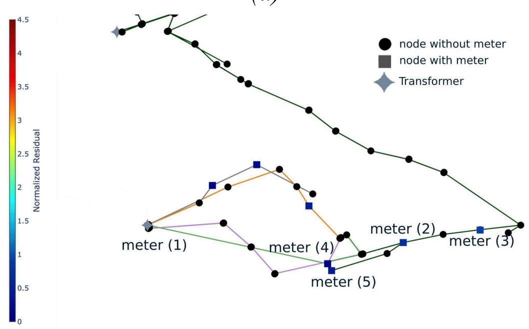


Fig. 7 Voltage profiles of the studied feeder



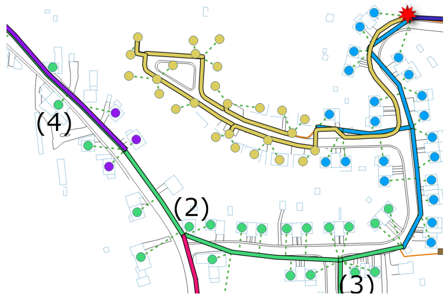
(a)



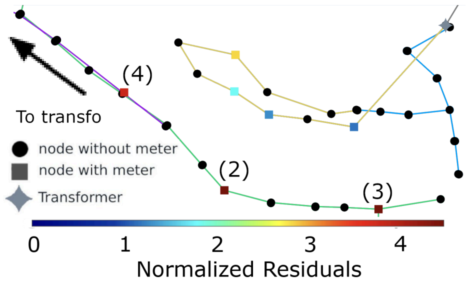
(b)

Fig. 8 (a) Updated topology, (b) Normalized residuals after correction

As another example, in Fig. 9(b) we see many high residuals on one feeder, with values of 3.8, 5.0 and 8.6 for meters (4), (3) and (2), respectively. Our analysis of the smart meters data on a sunny summer day at noon shows that the meter furthest on the feeder (meter (3)) has a voltage of 14V lower than the ones preceding it, which is quite unexpected in this production scenario. The first hypothesis we have is that this meter provides wrong data. Removing this meter from the analysis leads to lower residuals overall than the ones displayed in Fig. 9(b), supporting this hypothesis.



(a)



(b)

Fig. 9 (a) Topological map of studied feeders, (b) Normalized residuals, meters (1) and (5) are not depicted as they are on different phases.

However, voltage profiles of Fig. 10 seem to indicate a wrong feeder assignment: meter (3) profile is very different from the other curves on the same feeder, whatever the phase. It is thus not just a wrong phase assignment problem.

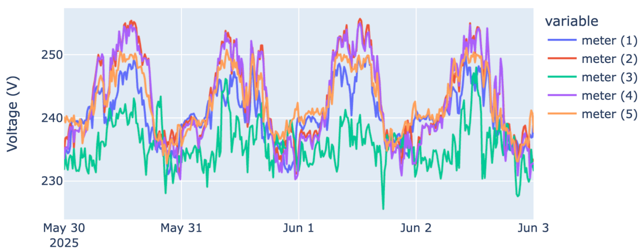


Fig. 10 Voltage profiles of the feeder meters. Meters (1), (2) and (5) are on the three different phases of this feeder

As there aren't smart meters on every feeder of Fig. 9(a), investigation of the meter profiles could not help to identify a possible wrong feeder assignment. But looking at the map we can guess that a part of the green feeder might belong to the blue feeder. Testing this alternative assignment for this meter indeed leads to lower residuals in Fig.11(b), which confirms this hypothesis.

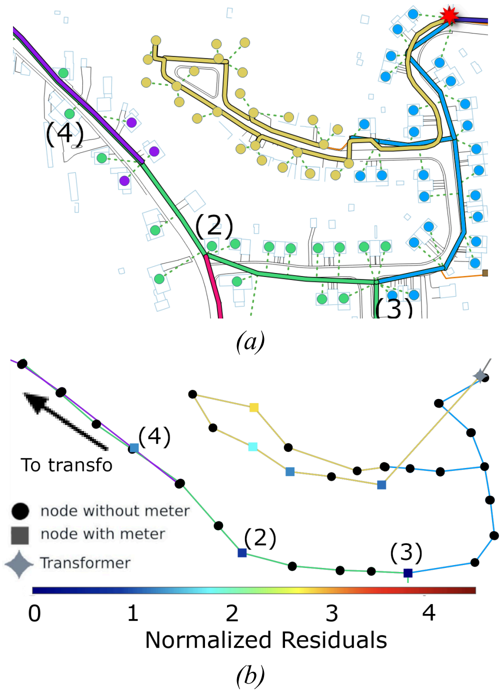


Fig. 11 (a) Updated topology, (b) Normalized residuals after correction

4 Conclusion

We presented an approach that leverages smart meter data to detect topological modeling errors on LV grids analysing the patterns in state estimation normalized residuals. This approach has been tested on RESA's grid real model with real measurements. We showed that our approach allows to detect several interesting cases, such as:

- Wrong phase assignment of a meter,
- Meter or data problem,
- Wrong feeder assignment of a meter.

We also showed that our approach has the potential to be used to validate alternative feeders and phases, thereby correcting the errors in topological modeling.

Future work can include more robust analysis using smart meter time series, possibly combined with a dynamic approach. Another interesting research topic is further automatisation of this analysis, through the translation of these observations into rules that could be programmatically exploited or the construction of a model that would be able to detect these patterns automatically, possibly based on Machine learning.

6 References

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