A Bayesian Network Approach to Earth Fault Localization in Medium Voltage Electricity Grids

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Abstract

Earth faults are the most commonly occurring fault type in Medium Voltage electricity distribution grids. Electricity distribution grids in Central Europe are compensated, meaning the network continues to operate after an earth fault. However, during the time-consuming search process via grid switching, secondary faults can occur, leading to outages. Digital twins, through their automated physics-informed topology and measurement-integration capabilities, can leverage generated training data and available measurements to pinpoint earth-fault locations without additional hardware to be deployed in the grid. This paper demonstrates how Bayesian networks can aid earth fault localization within a digital twin framework in electricity distribution grids. The proposed method uses stored voltage signatures from the digital twin to train a Bayesian network model. The results of an experimental analysis prove the efficacy of Bayesian networks when applied to observations of EMT voltages of the faulty phase. Ongoing work focuses on integrating this approach into a digital twin framework to actively support distribution system operators in locating earth faults.

Keywords: Earth fault localization, Bayesian networks, Application, Classification

1. Introduction

An earth fault is an unintentional connection between a live conductor and the ground or a grounded object. An earth fault in an electricity distribution grid can cause severe problems, such as unsafe grid operation, equipment damage, and public safety risks. Even though many medium-voltage (MV) distribution grids in Europe are operated in a compensated manner, a double earth fault will cause outages in the grid. Transient earth faults, which are less than one second in duration and generally recover by themselves, are today in most cases not even inspected, although they can be an indicator of a potentially occurring future persistent fault, therefore they are valuable for preventive maintenance of the MV grid.

Earth fault localization in MV distribution grids is for several reasons a difficult problem which is subject to several sources of uncertainty, e.g., measurement uncertainty and topology uncertainty. This paper demonstrates how Bayesian networks, see, e.g., (Pearl, 1988; Cowell et al., 1999; Koller and Friedman, 2009; Kjærulff and Madsen, 2013), can be

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used for earth fault localization in MV distribution grids. The approach uses simulated voltage signatures to learn a Bayesian network model. The learned Bayesian network has a designated target node with one state for each possible earth fault location (elements in the grid topology) and several features representing voltage measurements after the fault has occurred. Using these fault measurements, the learning model can be applied to predict the most likely fault location. Distribution system operators (DSOs) should quickly locate and correct any fault to ensure stable operation of the grid.

Electricity distribution grids are critical infrastructure under the European Union (EU) AI Act. This means that certain requirements should be satisfied before systems can be deployed. Bayesian networks are considered well suited as a technology to meet the requirements of the EU AI Act especially for grid digitization. In related work Bayesian networks have been applied to problems related to the electricity distribution grid. For example, (Olsen et al., 2024) describes how the integration of Bayesian networks into a DigitalTwin can help to ensure reliable electricity distribution, Madsen et al. (2025) presents the application of Bayesian networks for the detection of wrong data in electricity distribution grids, and Jha et al. (2009) describes the use of dynamic Bayesian networks for localizing transient faults (which can be related to transient faults in electricity distribution grids). In related work Wörmann et al. (2021), Wörmann et al. (2024), and Wörmann et al. (2027) have applied other methods for earth fault localization in the same MV Electricity Grid using the same datasets as we use in this paper. We demonstrate how Bayesian networks can produce similar or better results.

Section 2 presents the preliminaries necessary to read the article, and Section 3 presents the case study used in the article. Section 4 introduces the methodology, which is evaluated in an experiment with the findings reported in Section 5. Finally, Section 6 discusses the findings and concludes the article with an indication of future work.

2. Preliminaries

This section details the fundamentals of the Bayesian network architecture utilized in this study alongside the digital twin framework. By leveraging Bayesian networks as a form of explainable artificial intelligence (XAI), the digital twin integrates this method to enhance its existing capabilities for earth fault localization.

2.1. Bayesian Network Architecture

Let $N = (G, P)$ be a Bayesian network with a directed acyclic graph (DAG) $G = (V, E)$ where V is a set of vertices (or nodes) and E is a set of directed edges and a set of conditional probability distributions P, see, e.g., (Pearl, 1988; Cowell et al., 1999; Koller and Friedman, 2009; Kjærulff and Madsen, 2013). Given a directed edge (X_i, X_j) we denote X_i as a parent of X_j and X_j as a child of X_i. The structure of DAG D represents a decomposition of the joint probability distribution $P(X)$:

$$P(X) = \prod_{i=0}^{n} P(X_i \mid \pi(X_i)),$$

where $\pi(X_i)$ denotes the parents of X_i in G. Continuous variables are included under the assumption that they have a conditional linear Gaussian distribution.

Figure 1 shows the structure of the Naive Bayesian Network model (NBM), see, e.g., (Duda and Hart, 1973), where *FaultLocation* is the discrete root node of the DAG with one state for each fault location and all features are continuous variables. The NBM assumes that the features are conditionally independent given the class such that $P(X)$ decomposes as $P(X) = P(T) \prod_{i=1}^{n} P(X_i \mid T)$, where $T = X_0$ is the target variable and $X_1, \ldots, X_n$ are the features. This produces a model that is efficient in terms of both time and space, often with good performance on classification problems. The tree-augmented NBM (TAN), see, e.g., (Friedman et al., 1997), is an extension of NBM where the features induce a spanning tree such that each feature has at most one parent in addition to T.

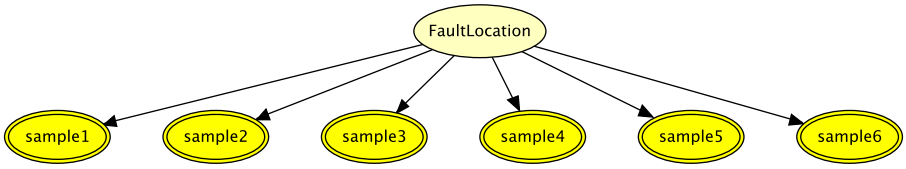


Figure 1: NBM with *FaultLocation* as root and continuous features.

The conditional probability distributions of the variables in all types of Bayesian networks developed are estimated using the Expectation-Maximization (EM) algorithm (Lauritzen, 1995). As the structure learning algorithm, the variant of the PC algorithm (Spirtes et al., 2001) implemented in HUGIN software is applied (Madsen et al., 2017).

To measure the performance of the Bayesian network models, two different types of localization performance are reported. Assigning a highest probability to the true fault location is known as top-1 performance, while top-3 performance specifies that the correct fault location is included in the set of the three fault locations with the highest probability. This follows the performance assessment approach of, for example, Wörmann et al. (2024).

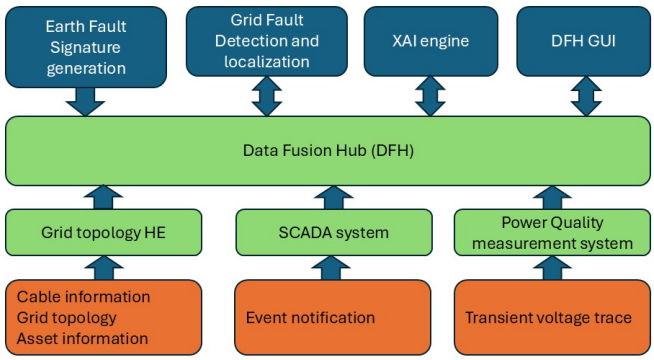


Figure 2: GridData Data Fusion Hub integrates the required data sources for the Earth Fault Detection and Localization application.

2.2. Digital Twin of the Electricity Grid

The conceptual view of the DigitalTwin (GDDT) used to detect and localize earth faults is illustrated in Figure 2 along with relevant components. The system architecture centers on the Data Fusion Hub (DFH), which aggregates data from measurement and topology sources to support the automated modeling and parameterization of the distribution grid. Concurrently, several integrated applications coordinate to enable fault detection and localization. Whenever the grid topology is newly established or significantly altered, a set of earth fault signatures is generated to train the Bayesian network.

Upon the occurrence of an earth fault, a system event (e.g., from a SCADA system or a threshold crossing event of the neutral voltage observed by the transient voltage measurement device) triggers the Grid Fault Detection and Localization application. This application invokes the XAI engine (responsible for running the Bayesian networks) via the DFH to analyze the provided transient voltage measurements. The XAI engine then outputs a probability distribution over the possible fault locations. Finally, the localization application processes these probabilities and generates an alert to be displayed on the graphical user interface (GUI) and distributed through secondary channels, such as email and SMS.

3. Case Study: Grid and Measurement Scenario

The earth fault localization approach is tested on a MV network based in Austria. The topology information and measurements are described in the following subsection.

Topology: The case study for this paper considers a compensated 30kV MV grid, for which the structure is shown in Figure 3. The network in question is a radial system with two feeders, and the left feeder is significantly longer than the right one. The network is a mixture of earth cables and overhead lines Wörmann et al. (2021) with 87 nodes; note that typical MV grid sizes range from a few dozen up to a few hundred nodes.

Voltage Measurement: The primary substation (110kV:30kV), represented by node 87 as highlighted on top in Figure 3, contains a measurement device that can record transient phase-to-neutral voltage measurements at a resolution of 10 microseconds. In addition, node 33 contains earth fault direction indicators, which can improve the localization performance; however, their output is not used in the paper. A plot of the measurements can be seen in Figure 4. This figure shows three-phase voltage measurements measured at the root node, i.e., node 87, as highlighted in Figure 3. The fault-start can be identified via a threshold on the neutral voltage, chosen by a practical deployment rule as 42% of the phase to-neutral RMS voltage, which is also the faulty phase voltage. Previous work on fault localization via such transient measurements showed good success when using only a few milliseconds of transient voltages after the fault-start.

4. Methods

4.1. Voltage Signatures Generation

The Digital Twins for the distribution grid utilize a combination of measurement and topology data to derive a parameterized distribution grid model, see Wörmann et al. (2021). The

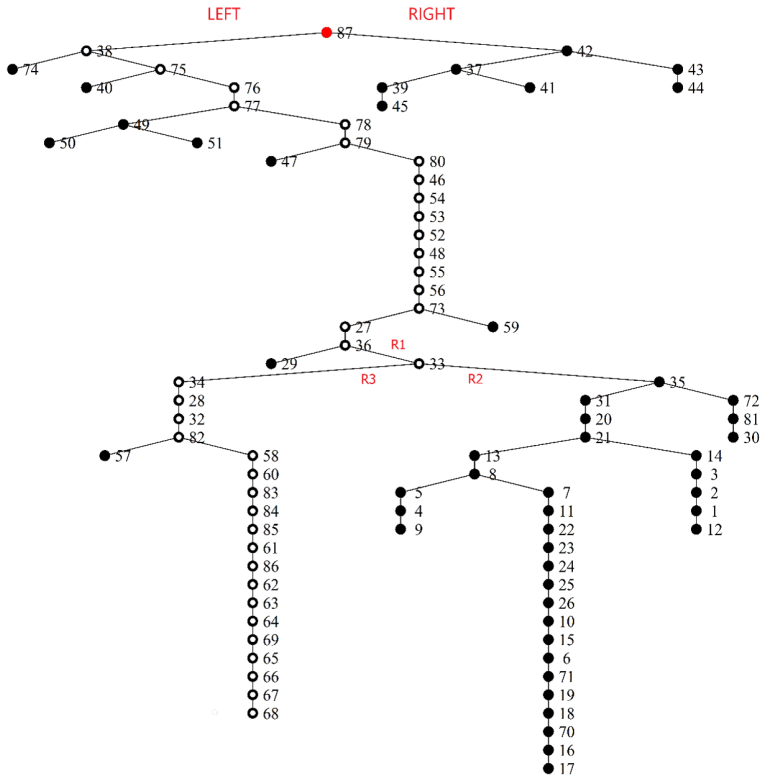


Figure 3: The MV grid topology used in the experiments.

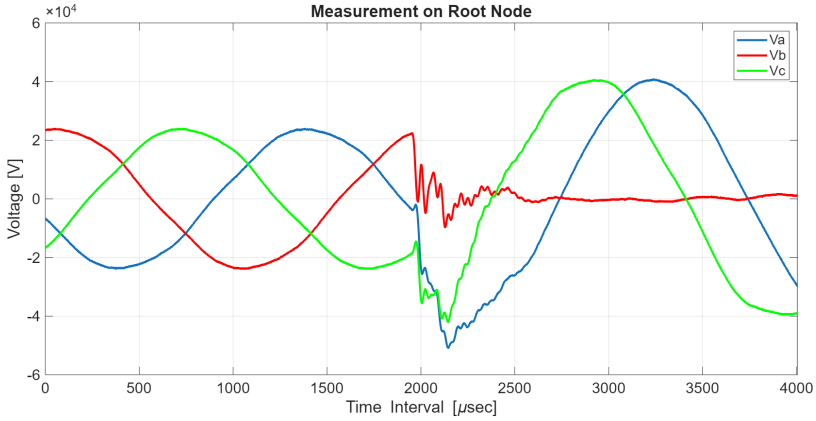


Figure 4: Voltage measurements before and after a fault, for all three phases at the root node, node 87.

digital twin is created through a fully automated process, and is then used to create high-resolution phase-to-neutral voltage signatures with the help of EMT simulations for various fault resistances at different fault locations. In addition, such signatures need to be created for multiple phase angles: four phase angles were used, i.e., 22.5° (denoted Q1), 45° (denoted

hpeak - for half-peak), 90° (denoted peak), and 121.5° (denoted Q3). Since the resolution of the measurement was 10 μsec, the signatures were downsampled to the same resolution. The localization approach in this paper uses a 2ms window, corresponding to 200 voltage samples. The signatures are then automatically generated based on the measurement data for several impedances, namely as $\{0.01, 1, 2, 5, 10, 25\}$ ohm, and for every grid node as fault location.

4.2. Bayesian Network Models

Earth fault localization can be considered as a classification problem where the task is to identify the most likely location of the earth fault given the fault measurements. The fault measurements represent a sequence of voltage measurements right after the error has occurred, see Figure 4. For this reason, in the evaluation we consider structure-restricted models such as the NBM and the TAN as they have demonstrated good performance on classification tasks in the past. However, we also consider unrestricted Bayesian network structures (BBN). A DSO may have many topologies (in the hundreds or even thousands for

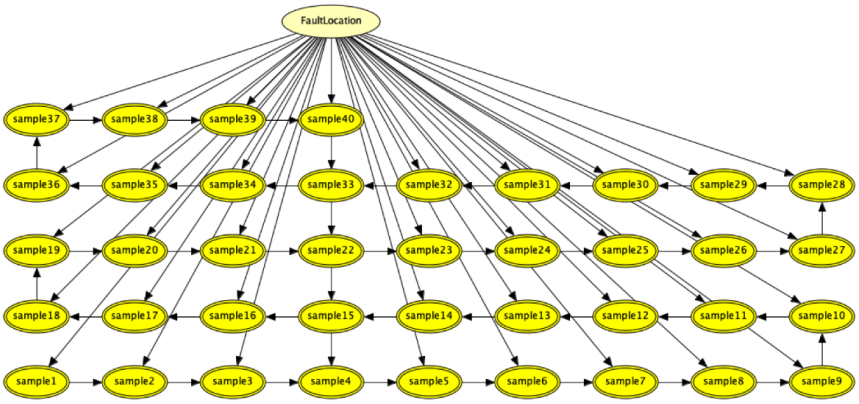


Figure 5: TAN model where 40 samples span a tree reflecting time dependency with the classification node *FaultLocation* as root.

large DSOs). A separate model must be constructed for each topology (and possibly even after a change in the grid topology). Thus, the DSOs need a flexible and scalable approach where the model construction is fast and efficient. Any model will have the *FaultLocation* as the target variable and the measured samples as feature variables. For NBM the structure is fixed in advance, for TAN the structure can either be fixed or learned using the Chow and Liu (1968) algorithm, and finally a general structure over the features may be established using a structure learning algorithm such as the PC algorithm, see, e.g., (Spirtes et al., 2001) and (Madsen et al., 2017).

Figure 5 shows the DAG of a TAN model where the sample features $X_1, \ldots, X_n$ are linked (X_i, X_{i+1}) for $n = 1, \ldots, 40$ reflecting the time dependency of the measurements (in the experiments, 200 samples values are used in the model). The advantage of this model is that the model is fixed and only parameters must be estimated, using, e.g., the EM algorithm (Lauritzen, 1995) in the case of missing values.

4.3. The Algorithm

Algorithm 1 describes in pseudo-code the principle of combining the simulation of voltage signatures and a Bayesian network construction.

Algorithm 1: Building a Bayesian network for earth fault localization

Input: Grid Topology T, fault resistance values F
Output: A Bayesian network N for earth fault localization in T

```
Create empty dataset D ← ∅
for grid element identifier i of T do
    for fault resistance f ∈ F do
        Generate voltage signature σ for fault f at grid element i using the DigitalTwin
        Update D = D ∪ {(σ, f)}
    end
end
Build Bayesian network N from dataset D
```

The pseudo algorithm iterates over the grid element identifiers of the topology and different fault resistances in each step generating a voltage signature for an earth fault with the specified resistance at the considered location. This takes place in the *Earth Fault Signature generation* component of the DFH in Figure 2. The voltage signature and the fault location are added to the dataset to create a complete database of labeled cases. This database of labeled data is used to create a Bayesian network for the grid topology in the XAI Engine component of the DFH in Figure 2. In the experiments, we evaluated different Bayesian network models where the data is split into train and test data by fault resistance.

5. Experimental Design and Results

This section presents the experimental design followed by the experimental results.

5.1. Experimental Design

The database of simulated voltage signatures contains one row for each fault resistance $F = \{f_1, \ldots, f_m\}$ and for each fault location $T = \{i_1, \ldots, i_n\}$ (grid element identifier). This produces a total of $m * n = 6 * 86 = 516$ simulated voltage sequences produced by the DigitalTwin where each sequence has 200 values that represent $2ms$ after the fault.

Algorithm 2 describes in pseudo-code the testing procedure for evaluating the use of Bayesian networks for earth fault localization. The algorithm iterates over the fault resistances. In each iteration, the voltage signatures for the selected fault resistance are used as testing data, and the remaining voltage signatures are used as training data. The predicted fault locations in top-1 and top-3 are stored for each case in the test data.

Algorithm 2 is applied on four different model types the NBN, the TAN where the samples are connected to reflect the time dependency (and illustrated in Figure 5), and the Bayesian network denoted BBN in the rest of the paper. TAN2 denotes a model in which each feature depends on the two previous features.

Algorithm 2: Testing a Bayesian network for earth fault localization

Input: Dataset D with voltage signatures and fault locations
Output: Top-1 and Top-3 fault locations for each fault resistance

Create empty lists L_1 and L_3
for *fault resistance* $f \in F$ **do**
  Let $D_{train} \subset D$ without f be the train data
  Let $D_{test} \subset D$ with f be the test data
  Build Bayesian network N from dataset D_{train}
  for *case* $c \in D_{test}$ **do**
    Remove fault location i from c to produce $c \setminus \{i\}$
    Propagate $c \setminus \{i\}$ in N
    Add $\arg_x \max = P(X = x \mid c)$ where X is *FaultLocation* and i to L_1
    Add $\arg_{x_1,x_2,x_3} \max = P(X = x \mid c)$ where X is *FaultLocation* and i to L_3
  end
end
Return L_1 and L_3 as the list of top-1 and top-3 fault locations for F

The top-1 and top-3 localization performance are used as evaluation metrics. These metrics have been used in related work by Wörmann et al. (2021), Wörmann et al. (2024), and Wörmann et al. (2027) on the same topology with similar results.

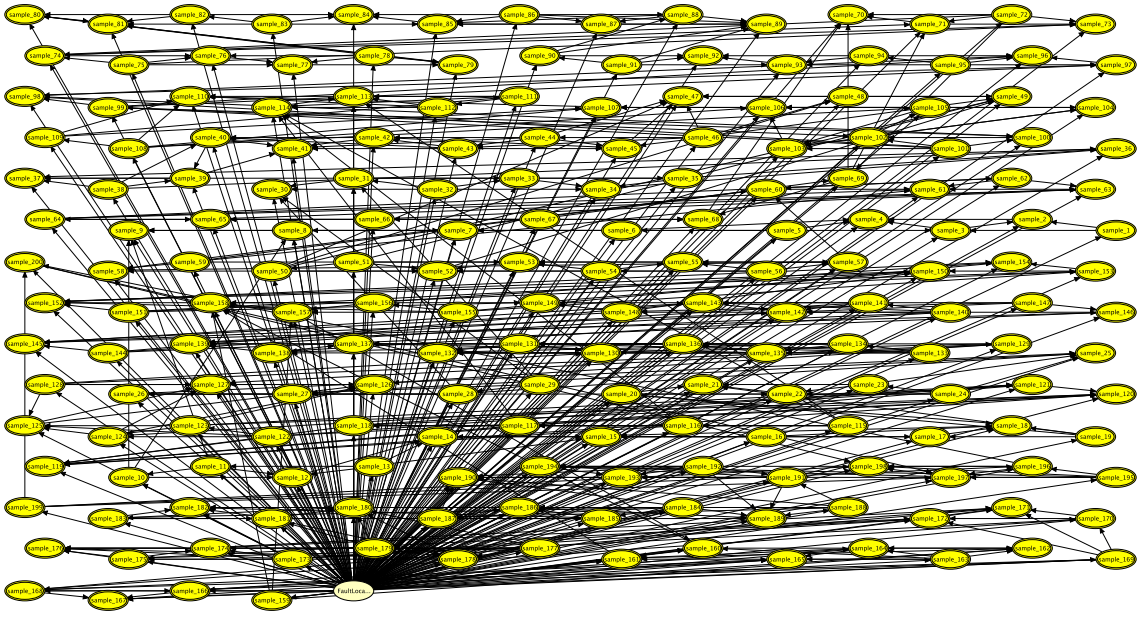


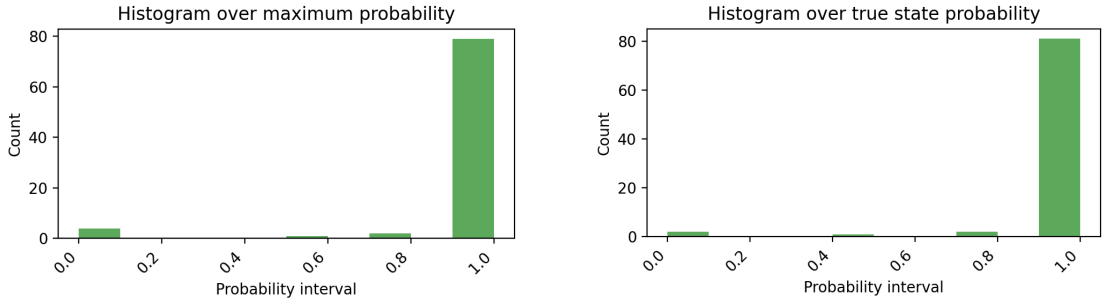
Figure 6: The DAG G of a Bayesian network for fault localization. All fault resistances of PEAK have been used as training data.

5.2. Experimental Results

This section describes the results produced by the experiments. Figure 6 shows the DAG G of a Bayesian network constructed from the PEAK dataset including all fault resistances. The model has 200 feature variables and the single target variable *FaultLocation*. The DAG G appears relatively sparse with many connections from *FaultLocation* to the features. In addition, there are many edges of the type $(sample_i, sample_i + 1)$ (ignoring direction) that capture time dependencies between consecutive sample values.

Table 1 shows the performance of the four different types of models developed from the four different sets of sequences for the six fault resistances considered in the paper. The table clearly shows that the performance of the models is highest for the low values of the fault resistance. Also, the results appear to suggest that the model capturing the time dependency of the samples (i.e, TAN) has a better performance than models with the same or less complexity, e.g., NBM, but adding additional parents does not improve performance consistently, i.e., TAN2 is not always better than TAN. Finally, allowing models of higher complexity (i.e., BBN) has the best performance of the models considered in the evaluation.

Figure 7 shows the distribution of the maximum state probability 7(a) and the probability of the true state 7(b) of *FaultLocation* for the PEAK dataset with fault resistance 2 ohm as the test data using the TAN model. In this example, top-1=0.97 and top-3=0.99. The figure shows that the model is often highly certain about the fault location (i.e., probability of the predicted state is in many case above 90%).



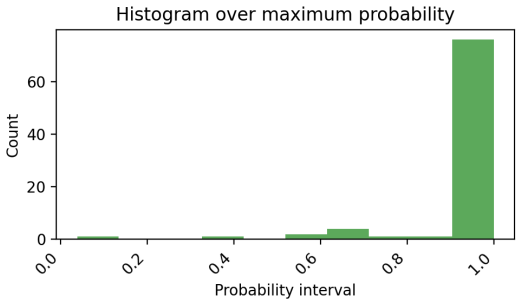
(a) Maximum probability (b) Probability of true state

Figure 7: Histogram of computed probabilities for PEAK signature when testing fault resistance 2 ohm.

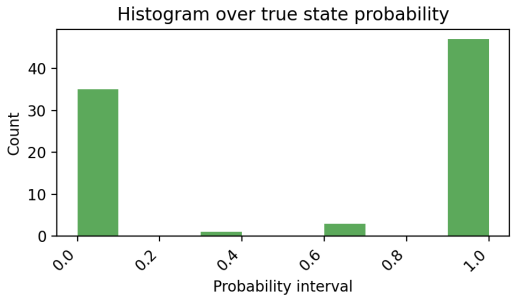
Figure 8 shows the distribution of the maximum state probability 8(a) and the probability of the true state 7(b) of *FaultLocation* for the PEAK dataset with fault resistance 10 ohm as the test data using the TAN model. In this example, top-1=0.58 and top-3=0.70. It shows that the model is often almost certain about the (wrong) fault location (i.e., probability of the true state is much lower than in the case of 2 ohm fault resistance, while the highest probability is still high). Future work includes computing how *close* (in number of hops) the predicted fault location is to the true fault location. It is better to predict that the fault location is one hop away from the true fault location than to predict that the fault is under a different feeder.

Table 1: Top-1 and top-3 localization performance across model types for the four different types of sequences.

Resistance	NBM		TAN		TAN2		BBN	
	Top-1	Top-3	Top-1	Top-3	Top-1	Top-3	Top-1	Top-3
PEAK								
0.01	0.63	0.83	0.93	0.97	0.93	0.97	0.93	0.93
1	0.66	0.84	0.98	1.0	0.98	1.0	1.0	1.0
2	0.66	0.9	0.97	0.99	0.97	0.99	0.99	0.99
5	0.84	1.0	0.79	0.93	0.79	0.93	0.77	0.85
10	0.53	0.79	0.58	0.7	0.58	0.7	0.41	0.45
25	0.01	0.03	0.14	0.15	0.14	0.15	0.13	0.16
1Q								
0.01	0.28	0.4	0.86	0.95	0.8	0.86	0.74	0.85
1	0.31	0.49	0.93	0.99	0.95	0.98	0.87	0.93
2	0.33	0.52	0.91	0.97	0.85	0.93	0.86	0.93
5	0.55	0.81	0.6	0.77	0.43	0.5	0.5	0.58
10	0.24	0.34	0.29	0.42	0.23	0.27	0.21	0.31
25	0.01	0.03	0.03	0.08	0.01	0.03	0.01	0.03
HPEAK								
0.01	0.5	0.62	0.91	0.97	0.9	0.92	0.92	0.93
1	0.57	0.73	0.95	1.0	0.99	1.0	0.99	1.0
2	0.63	0.8	0.91	0.97	0.93	0.97	0.95	0.97
5	0.77	0.98	0.76	0.88	0.77	0.8	0.73	0.78
10	0.31	0.53	0.48	0.59	0.41	0.49	0.42	0.48
25	0.01	0.03	0.07	0.14	0.08	0.09	0.08	0.12
3Q								
0.01	0.28	0.8	0.86	0.98	0.8	0.91	0.74	0.93
1	0.31	0.87	0.93	1.0	0.95	1.0	0.87	1.0
2	0.33	0.93	0.91	1.0	0.85	0.99	0.86	0.97
5	0.55	1.0	0.6	0.92	0.43	0.83	0.5	0.79
10	0.24	0.83	0.29	0.65	0.23	0.55	0.21	0.57
25	0.01	0.07	0.03	0.16	0.01	0.19	0.01	0.19



(a) Maximum probability



(b) Probability of true state

Figure 8: Histogram over computed probabilities for the PEAK signatures when testing fault resistance 10 ohm.

Table 2 shows the performance of the four different types of models when all four sequences are combined into a single dataset for training (and testing). Results are reported for the six fault resistances considered in the paper.

Table 2: Top-1 and top-3 localization performance across model types for all sequences.

Resistance	NBM		TAN		TAN2		BBN	
	Top-1	Top-3	Top-1	Top-3	Top-1	Top-3	Top-1	Top-3
0.01	0.54	0.71	0.77	0.86	0.77	0.86	0.89	0.95
1	0.53	0.71	0.8	0.87	0.8	0.87	0.9	0.99
2	0.54	0.72	0.78	0.84	0.78	0.84	0.89	0.95
5	0.49	0.67	0.68	0.8	0.68	0.8	0.78	0.88
10	0.37	0.55	0.49	0.66	0.49	0.66	0.59	0.71
25	0.01	0.03	0.14	0.27	0.14	0.27	0.27	0.41

The results show that the performance as expected drops a little when the phase angle is unknown. The performance for the lower values of the fault resistance is again better than the performance for the higher values of the fault resistance due to the larger amount of training data for the lower values of the fault resistance.

6. Discussion and Conclusion

In this paper, we present a methodology for applying Bayesian networks to the location of earth faults in electrical distribution grids. The proposed method demonstrates strong localization performance, yielding high top-1 and top-3 fault location performance. Key advantages of utilizing Bayesian networks for this task is its inherent use of probabilities and the availability of professional implementations of the underlying algorithms. While typical grids comprise anywhere from a few dozen to a few hundred nodes, directly corresponding to the state space of the target variable, model estimation remains highly manageable because an equal number of signatures is generated for each node.

Crucially, this methodology significantly enhances the operational value of the digital twin framework. Because structure-restricted models like the Tree Augmented Naive Bayes (TAN) can be constructed quickly and offer fast inference, they are perfectly suited for the dynamic environment of a digital twin. When a grid's topology changes, the digital twin can swiftly generate new training data and re-parameterize, e.g., the TAN model without the extensive computational overhead required by deep learning or existing model-free correlation methods. While learning more complex DAG structures may require additional runtime, the TAN model provides an optimal balance of speed and scalability. Ultimately, integrating this rapid fault localization method allows DSOs to leverage their digital twins not just for monitoring, but as highly responsive, real-time tools for fault localization across thousands of varying grid topologies.

The use of Bayesian networks for earth fault localization offers several advantages over alternative *black-box* methods. For example, it naturally provides a probability distribution over the fault locations, and conditioning on a specific feeder is straightforward, and the approach is robust to missing values in both the training data (unlikely) and the fault measurements. It is easy to compute the performance of the model using shorter time-series. In the experiment, we used all 200 sample values, but a lower number of features could be considered. In addition, determining top-N for any N is easy to compute as the model produces a probability distribution over the fault locations.

Future work includes assessment of model performance on real fault measurements combined with direction indicators that may be installed in a grid. For example, Figure 3 shows a topology where a direction indicator divides the topology into three separate subgrids R1, R2 and R3. Conditioning on a specific subgrid simply amounts to adding a likelihood function on the FaultLocation node of the model.

The approach is flexible and scalable to a large number of grids with many elements. The approach has been integrated as an application into the GridData DigitalTwin and is available to DSOs in Europe. It is currently being evaluated on additional topologies and real world fault measurements.

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