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Reliable Fault Detection From Synthetic Data Using Uncertainty Aware Neural Network Models

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Power transmission insulators are important components of the transmission system, which provide physical support to long transmission lines and prevent leakage of current to the ground through the tower (Kong and Yang, 2020). With cyclically changing daily environmental conditions, extreme weather conditions and the deposition of dust on the insulator, the quality of insulation decreases over time (Ramirez et al., 2012). Unhealthy insulators allow current to leak through the tower and result in loss of power during transmission. In extreme cases, neighbouring protection switches can be activated resulting in an interruption of power. The inspection of power transmission insulators and detection of leakage current are important tasks for power system operators (Werneck et al., 2014). A popular approach for fault detection is to create a model of the power line and synthetically introduce faults that simulate leakage of current. This approach allows the creation of a large synthetic dataset of healthy and faulty scenarios without having to wait to collect such data from the real-life system. However, such an approach also relies solely on synthetic data for training a fault detection model, and the validity of the resulting model cannot be evaluated in a real-life system. A recent study further showed that deep learning models trained with synthetic data for the detection of leakage current are sensitive to the physics-based model parameters that are used to generate the synthetic data (Gjorgiev et al., 2022). However, a detailed analysis of the impact of the uncertainty in the data generation process and the randomness involved in the training of neural networks is not performed.

Motivated by this gap in the literature, we present an uncertainty-aware training framework that explicitly accounts for the synthetic nature of the data, specifically the uncertainty associated with the data generation process at the time of training and evaluation.

We adopt the following steps to train uncertainty-aware neural networks for fault detection from synthetic data.

- Dataset preparation: A physics-based model simulates the healthy and faulty operating conditions of the system. Data collected from a healthy real-life power line in Switzerland is used to calibrate the physics-based model with genetic algorithms. Since the amount of data is limited and the tuned parameters have uncertainty associated with them, ten instances of the physics-based model are obtained by starting with ten different initialisations and obtaining ten slightly different calibrated parameters. These equivalent models are used to generate an ensemble of healthy and faulty data that are used to train a fault detection model.
- Uncertainty-aware training: Assumed density filtering (ADF) (Gast and Roth, 2018), a variational uncertainty propagation technique is used to train deep neural networks in an uncertainty-aware manner. This approach replaces each layer of a neural network with a variational counterpart that propagates the mean and variance of inputs, as opposed to only a sample for regular neural networks. Monte Carlo dropout (Gal and Ghahramani, 2016) is used to quantify the epistemic uncertainty. Here, a predetermined fraction of nodes in each layer are dropped out at random, i.e., their activations are set to zero – after the training is completed. The aleatoric and epistemic uncertainty are added to obtain the total prediction uncertainty.

- Neural network architectures: Three commonly used neural network architectures – fully connected (fc), one-dimensional convolutional (conv1d) and two-dimensional convolutional (conv2d) neural networks – are used to train fault detection models. The fc and conv1d architectures are trained with raw time series of leakage current, while the conv2d architecture is trained with the spectrogram of leakage current. Data from the ten physics-based models is used to estimate the mean and variance to train neural networks with ADF.
- Comparative analysis: Three comparative analyses are performed. The performance of deterministic and uncertainty-aware models is compared in terms of classification accuracy. The reliability of models is assessed via reliability diagrams. The generalizability of models is assessed by calculating the performance on data generated from physics-based models that were not used for training. The uncertainty in predictions of uncertainty-aware neural networks is presented.

The accuracy of uncertainty-aware models is 1% to 19% better than deterministic models depending on the type of architecture. The reliability diagrams reveal that all models are under-confident in their predictions, which suggests that while the predictions cannot be interpreted as class probabilities, they can be relied upon to make downstream decisions. A comparison of the generalisability of models reveals that deterministic models exhibit an accuracy equal to a random guess when evaluated on data from physics-based models that were not used for training. Remarkably, the deterministic neural network models exhibit no transferability of features learnt from one physics-based model to another, and by extension, to the real-life system. They are not suitable for real-life deployment. Conversely, the uncertainty-aware models exhibit a drop in performance in the range [5%, 15%], delivering an accuracy of more than 80% on physics-based models that were not seen during training. This demonstrates the advantage of using uncertainty-aware deep learning to train reliable fault detection models with synthetic data. Figure 1 shows the density of aleatoric prediction uncertainty for the three architectures. The uncertainty increases sharply when the abnormality factor increases beyond 2, which represents the boundary between healthy and faulty data. This is an interesting result since the neural networks were not provided with the information of abnormality factor at the time of training, but their uncertainty depends on this quantity, which was used in the data generation process. These models are not only able to provide better performance and generalisability but also able to reflect properties of the data generation process in their predictions.

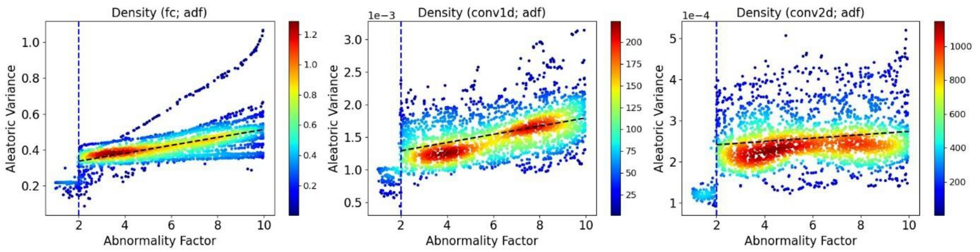

Fig. 1. Aleatoric uncertainty (density plots) of uncertainty-aware models. The abnormality factor represents the presence and severity of faults (<2: healthy, >2: faulty, higher values represent more severe faults). The blue vertical line separates healthy data from faulty data. The black inclined line shows the dependence of aleatoric variance on the abnormality factor for faulty data points. adf: assumed density filtering.

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