Data Analytics for Power Network Anomaly and Fault Detection

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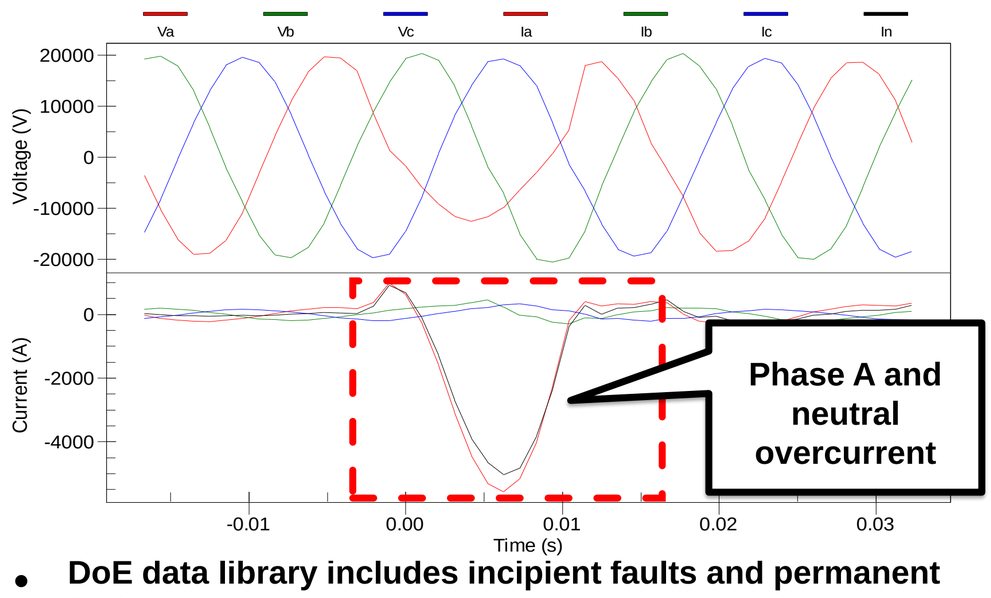
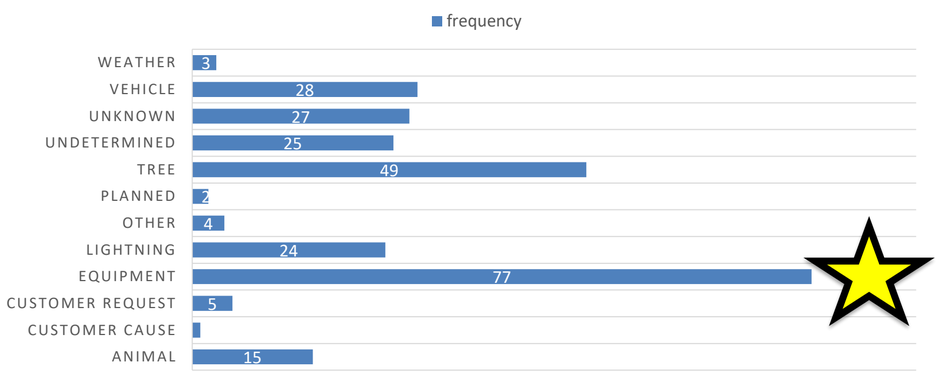
Introduction

Low observability on distribution networks can obscure the signs of incipient faults which can develop into costly and unexpected plant failures. While low cost sensing and further reaching communications infra-structure is improving this, it is also highlighting the complex nature of operational fault signals, a challenge which entails extracting anomalous regions from operational data before classifying the underlying fault. Here a solution in the form of a Bayesian online changepoint detection model is presented allowing a Multilayer Perception to classify the resulting segmented signal. MV fault and abnormality datasets are used to demonstrate its capability for operational detection.

DoE/EPRI Fault Library



- **DoE data library includes incipient faults and permanent faults**
- **Library records voltage and current signatures and their causes**



- **Multiple causes of power system events**
- **The majority of the faults are equipment related**
- **The fault are not equally prevalent**

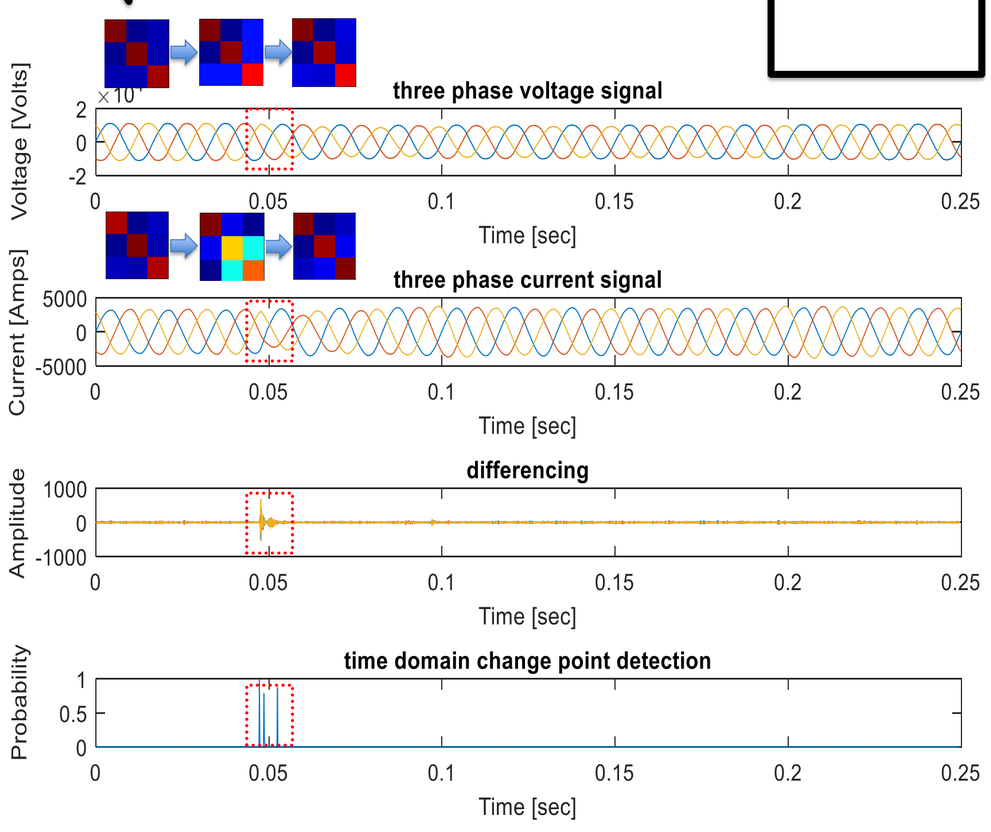
Online Bayesian Learning

Online estimate of a Gaussian distribution

$$u_m = \frac{k_0 u_0 + n\bar{x}}{k_0 + n} \qquad \alpha_m = \alpha_0 + \frac{n}{2}$$

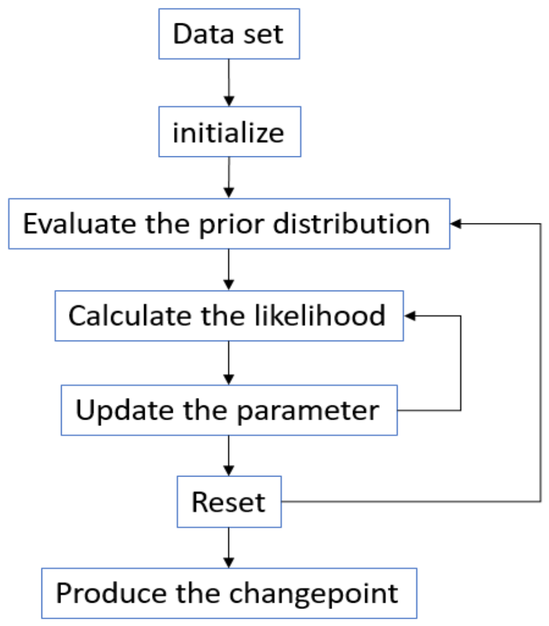
$$\beta_m = \beta_0 + \frac{1}{2}\sum_{i=1}^{n}(x_i - \bar{x})^2 + \frac{k_0 n(\bar{x} - u_0)^2}{2(k_0 + n)}$$

Rolling updates of Gaussian hyper-parameters

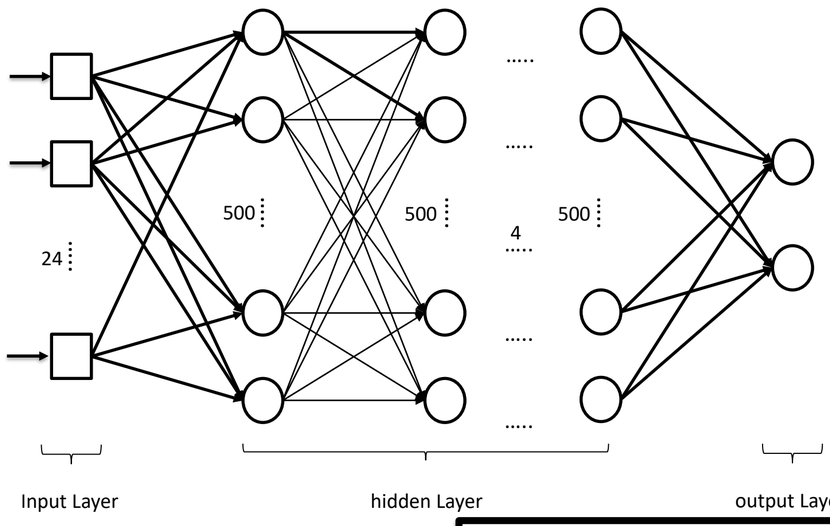


Change Point Detection

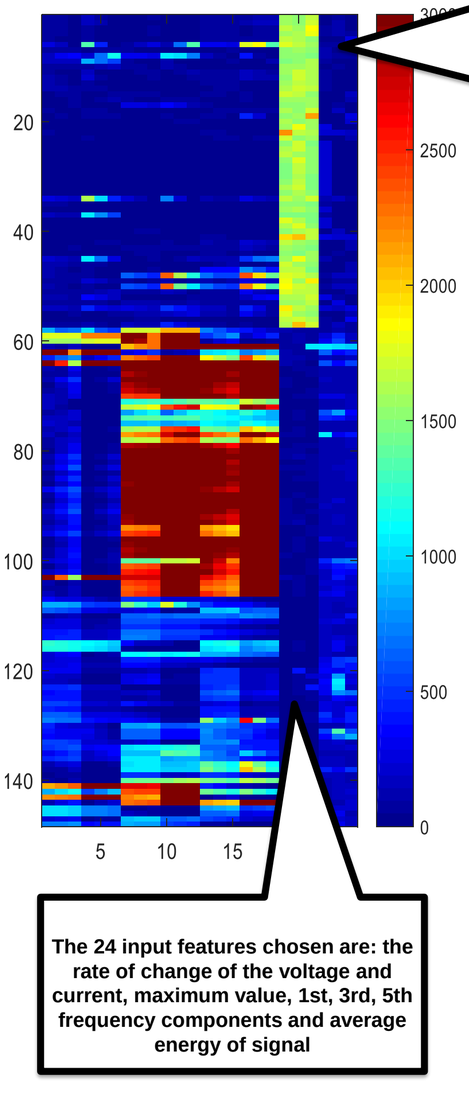
- **Self Learning: The model is able to learn the historical normal waveform to find the anomaly point**
- **Automatic: The model can online monitor power network without human behavior**
- **Inputs: Actively learns the expected value of an input variable along with its variance and dependency structure on other input variables**



Multilayer Perceptron for Cause Identification



- **Feed-forward Neural Network classifier**
- **Fully connected layers**
- **24 features**
- **Split 50% training dataset & 50% test dataset**
- **Monte Carlo cross validation**



First, segment the monitoring data stream with the changepoint analyser; then classify the events bounded by the 140+ changepoint pairs with a Neural Network classifier

Conclusion

True\Predict	Non-equipment caused fault	Equipment caused fault
Non-equipment caused fault	32	5
Equipment caused fault	13	24

- **Machine Learning can be applied to anomaly detection and fault classification on distribution networks**
- **The Bayesian Changepoint Model detects the anomaly and fault without significant delay**
- **MLP can identify the equipment caused fault in 65%**
- **Further development of the fault classifier will**

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