



A specialist energy consultancy

Automated Identification of SSO events

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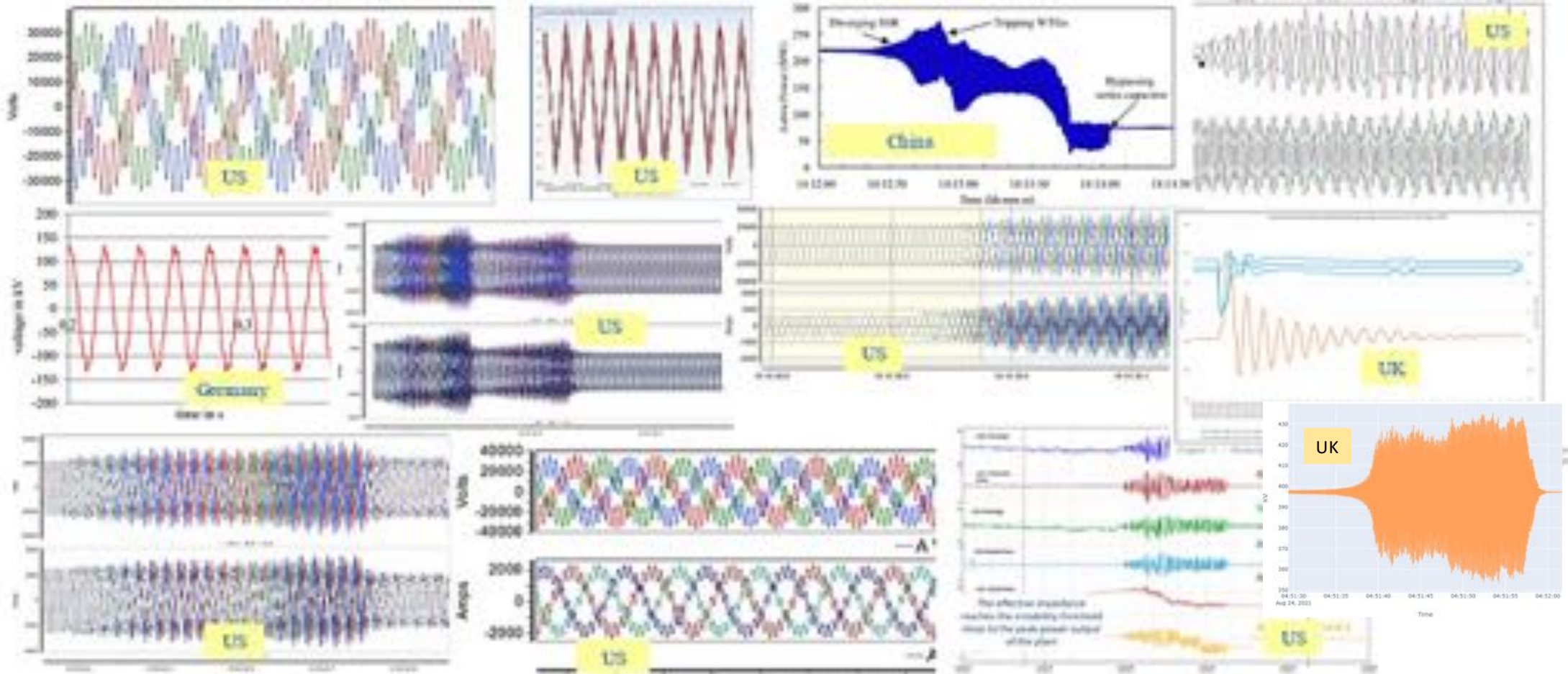
30th June 2023

Cigre UK conference



This project is exploring, developing, and testing a combination of novel frequency domain methodologies and machine learning techniques to identify potential system operating conditions which can lead to Sub-Synchronous Oscillations (SSOs) through an automated control interaction studies framework.

Subsynchronous oscillations



Source: Shahil Shah, 'Impedance Scan Tools for Stability Analysis of IBR Grids', G-PST/ESIG Webinar, June 30, 2022
J. Leslie, Managing Grid Stability in a High IBR Network, GPST/ESIG Webinar Series, Jan. 25, 2022

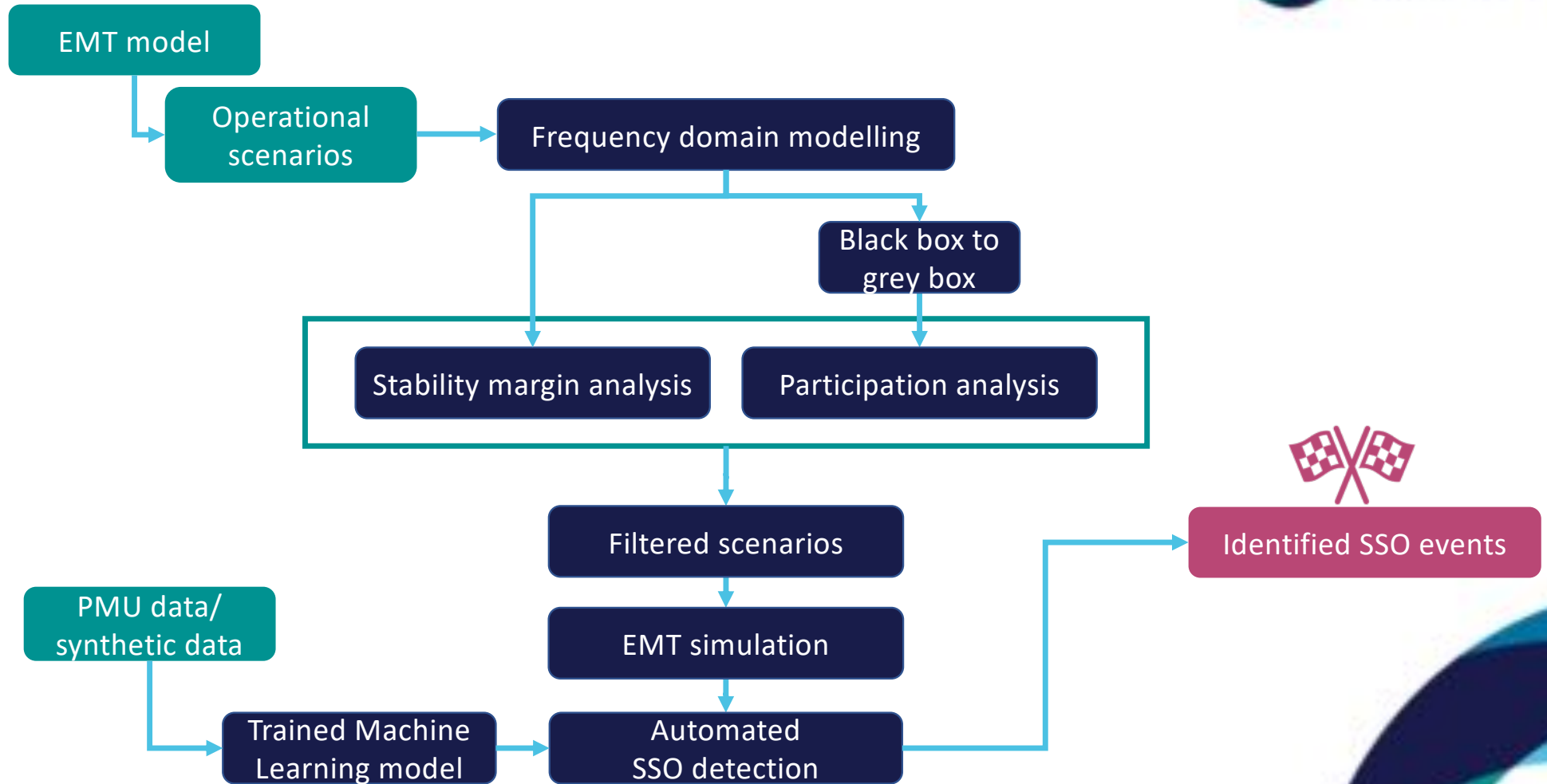
About SSOs

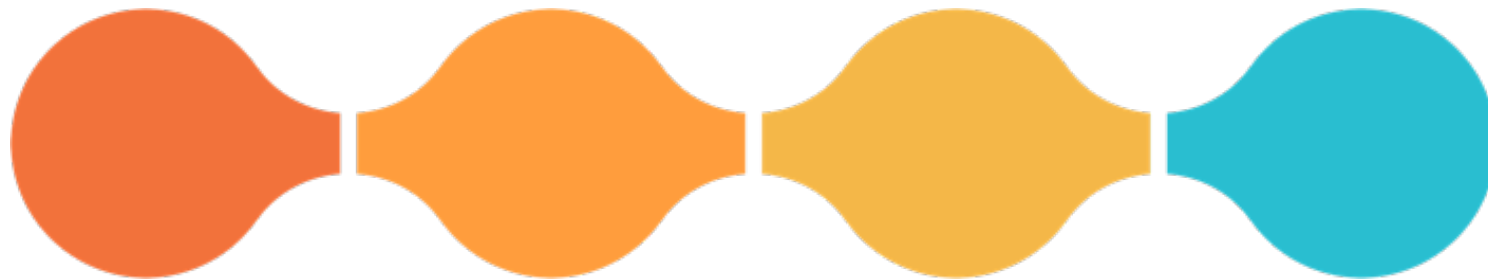
The fundamental reason for SSO in any system is the existence of poorly damped oscillatory modes, which can be induced by the interaction between different technology types.

The challenges in addressing these interactions are -

- a) complex and difficult to identify without exhaustive electromagnetic transient (EMT) studies,
- b) challenging to identify the equipment or assets participating in the interaction,
- c) assessing the degree of participation of equipment parameters in poorly damped modes is difficult, and
- d) future reinforcement decisions and network changes, such as the connection of new sites, can introduce new modes in the system, making compliance studies based on limited scenarios insufficient.


Project overview





Automated identification of SSOs

Consists of three main processes -

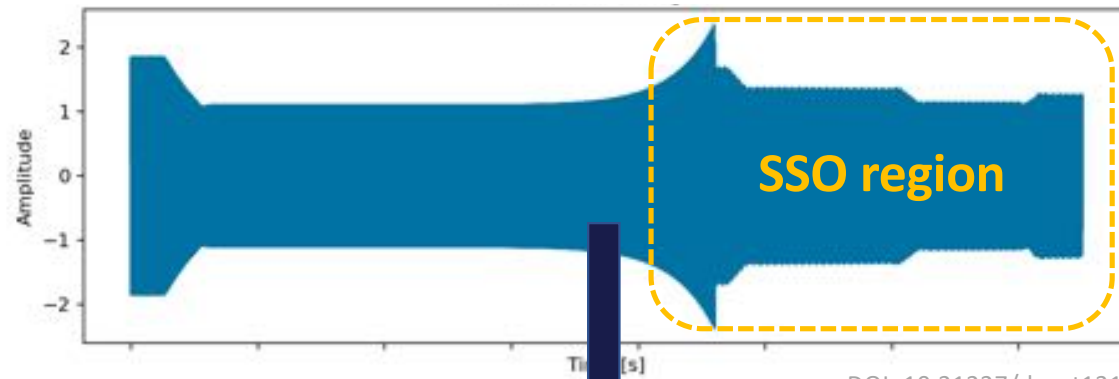
A vertical line on the left side of the slide, starting with a solid blue circle at the top, followed by three dashed white circles, and ending with a solid blue circle at the bottom.

Signal processing of measurement data and calculation of features

Processing calculated features to create training and testing dataset

Train a machine learning classifier to distinguish between SSO and non-SSO events

SSO identification problem



DOI: 10.21227/dvrr-t131

Metric using generic signal properties



Possible approaches from literature

Wavelet Transform

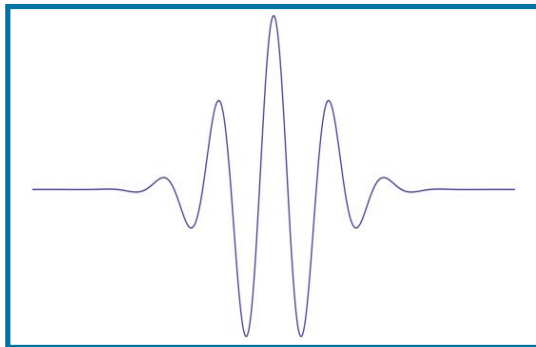


Image courtesy of JonMcLoone on Wikipedia

Shapelet Transform

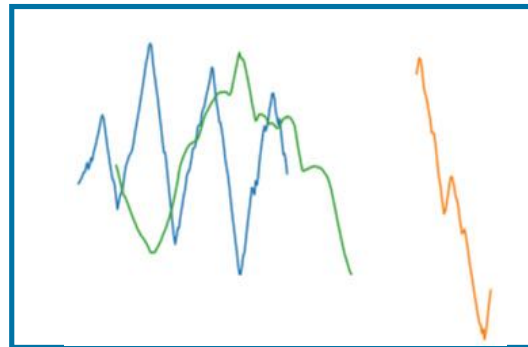


Image courtesy of sktime

Fourier Transform

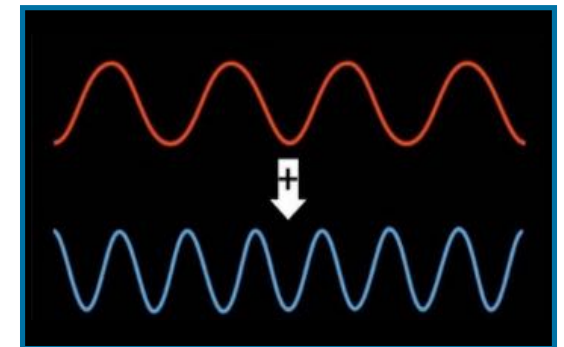
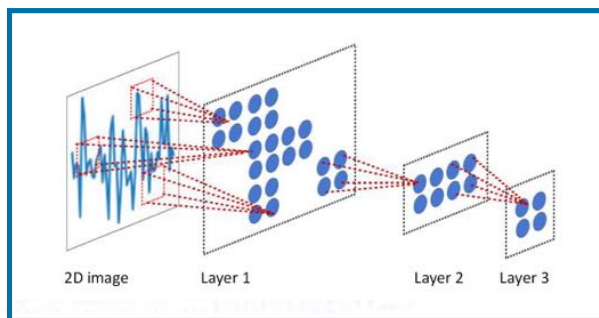


Image courtesy of Christine Daniloff on MIT News

Convolutional Neural Networks



DOI: 10.48550/ARXIV.2012.12183

Extended Kalman Filter

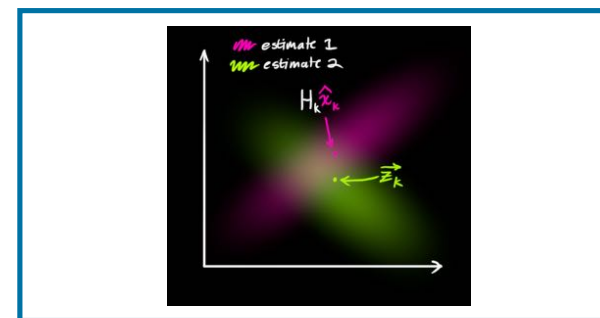

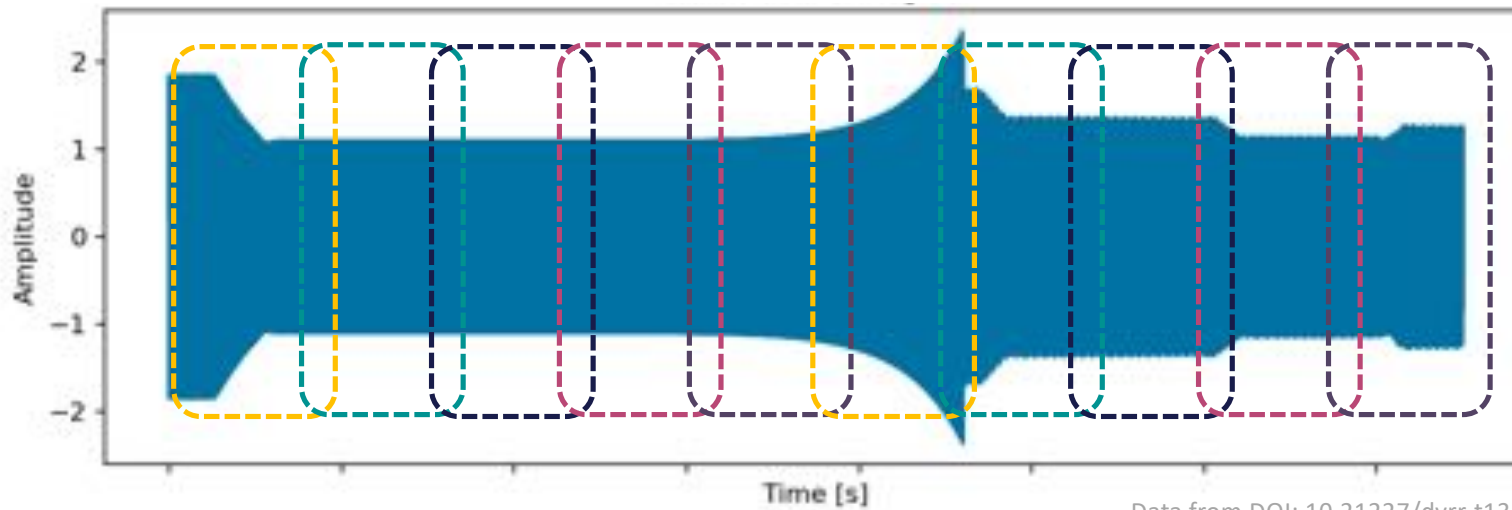


Image courtesy of bzarg.com

Our approach

- 
- A vertical line on the left side of the slide with five circles. The top circle is solid dark blue, the second is solid light blue, and the bottom three are dashed white with dark blue outlines.
- Combine different signal processing methods that extract features and use data driven method to learn the difference between SSO and non SSO regions.
 - Four different features are computed for this purpose
 - The features help to capture the underlying trend in the signal
 - These are used to train a machine learning classifier
 - Based on a consensus approach, the final outcome is decided

Our solution

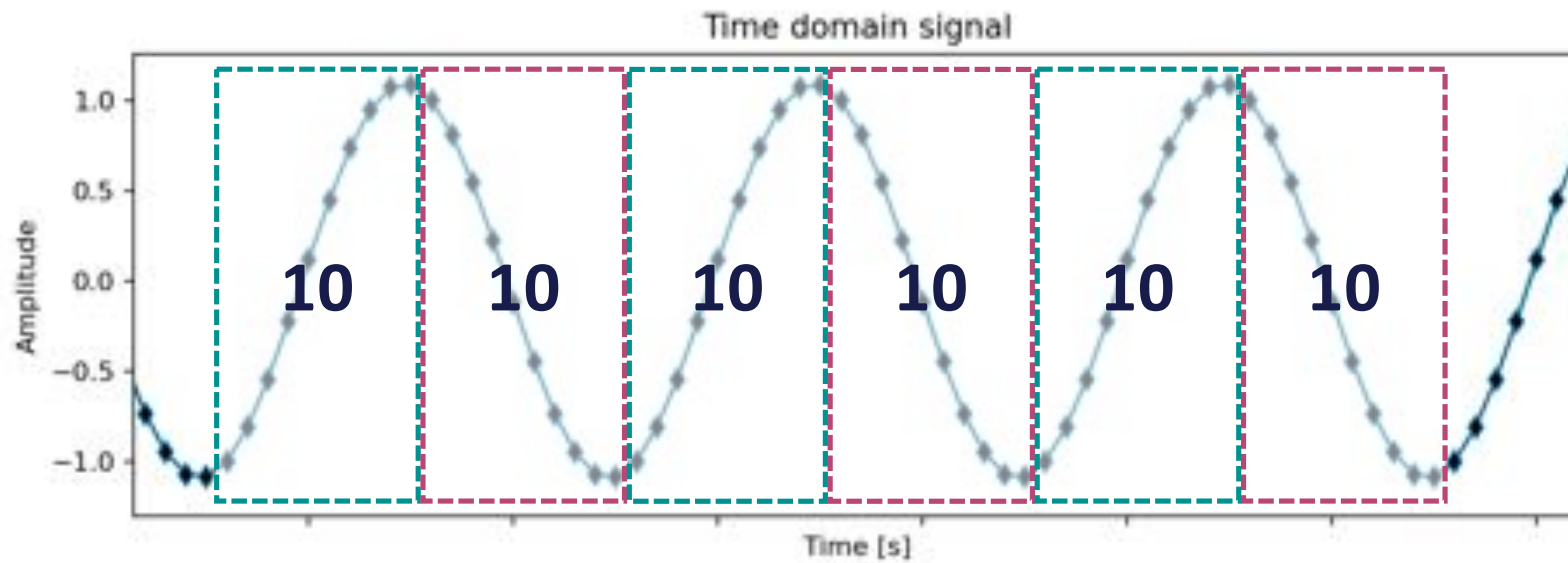


Data from DOI: 10.21227/dvrr-t131

Calculate four features (F1, F2, F3 and F4) from time domain signals and train a machine learning model. Once trained, the model will identify any SSO events from a time domain response.

- F1: Trend**
- F2: Envelope Volatility Index (EVI)**
- F3: Length of Stationary Subsequences (LSS)**
- F4: Fourier Transform Index (FTI)**

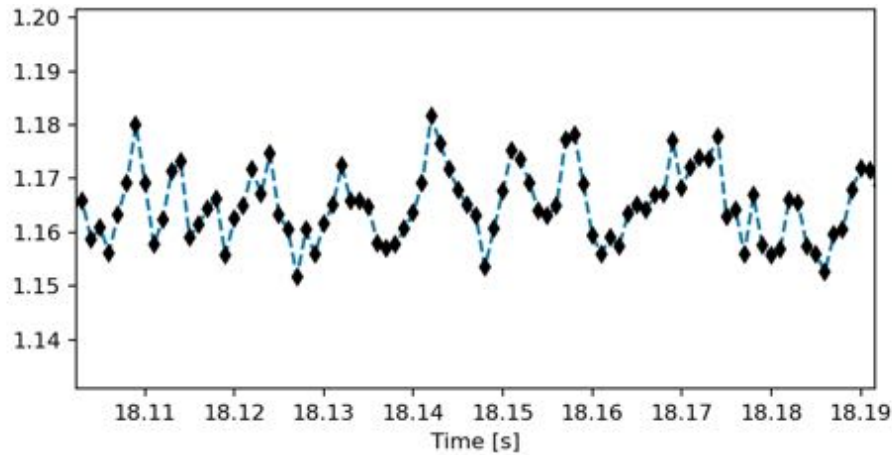
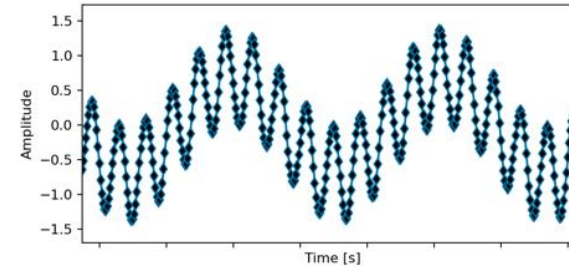
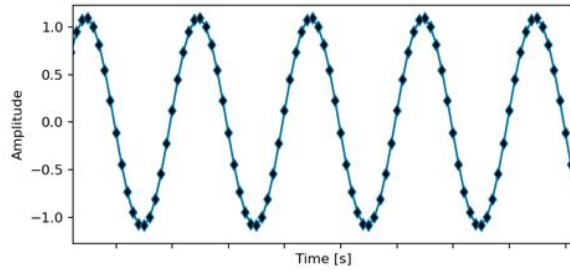
Feature 1: Trend



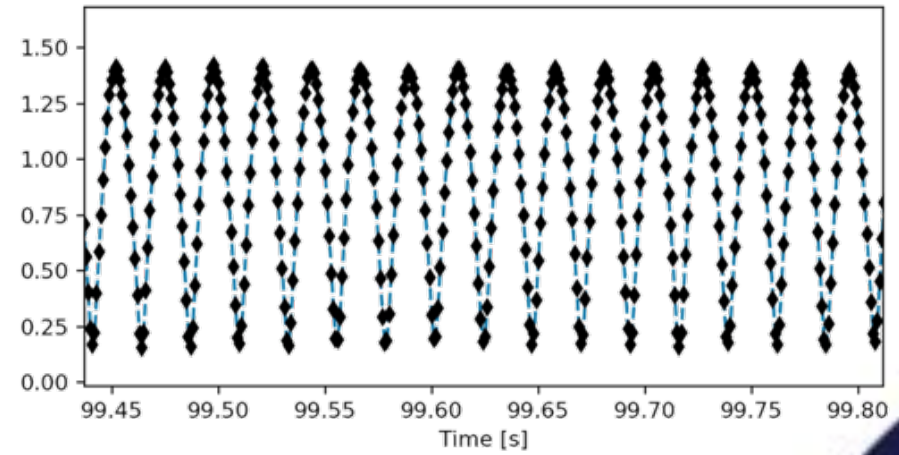
$$F1: 10 + 10 + 10 + 10 + 10 + 10 = 60$$



Feature 1: Trend

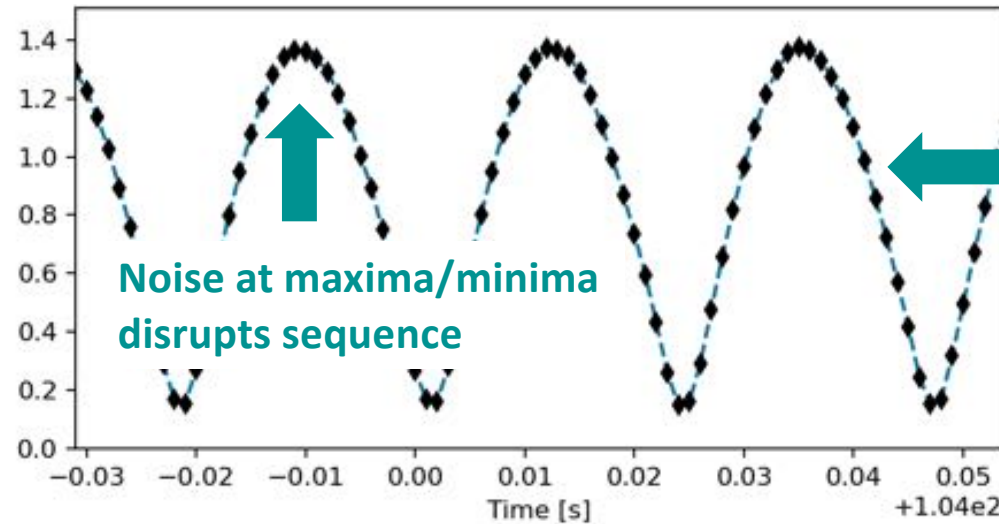
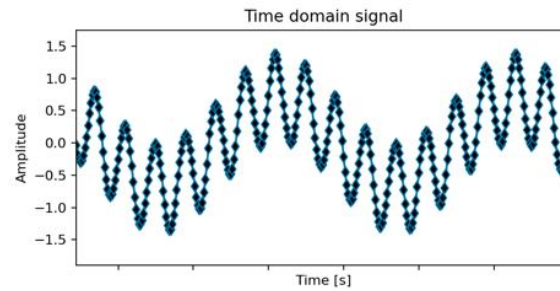


F1: ↓



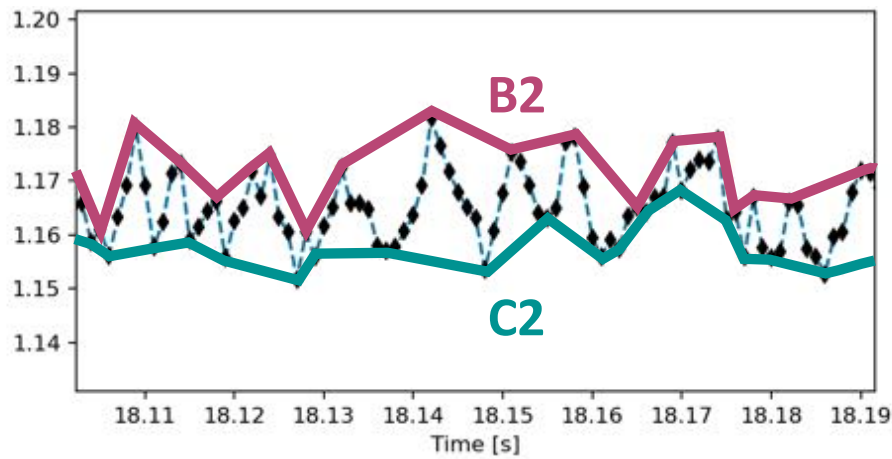
F1: ↑

Feature 1: Improvements

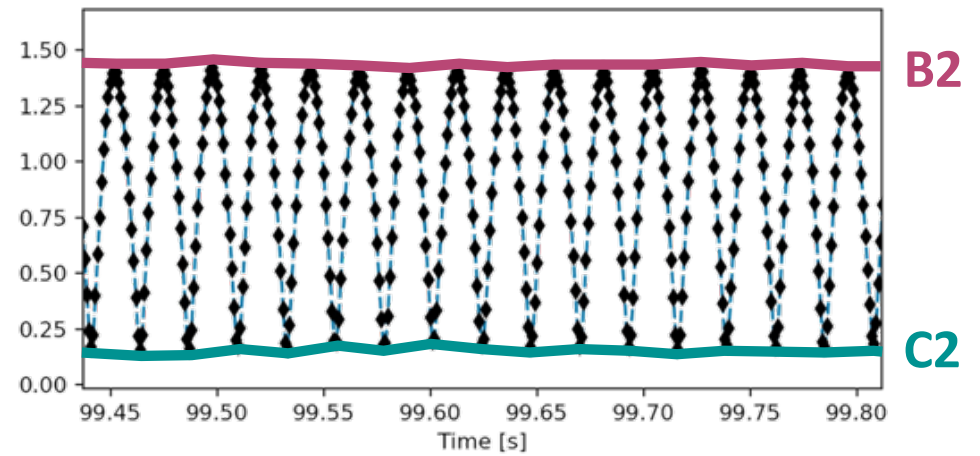


Small mismatch in sample points

Feature 2: EVI



F2: ↑

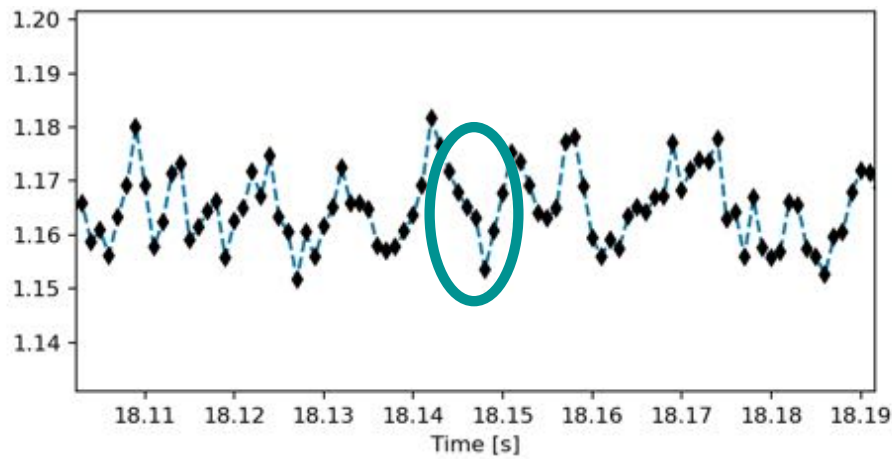


F2: ↓

$$F2 = \sqrt{\frac{\text{var}(B2)}{\text{var}(A)} \cdot \text{len}(B2)} + \sqrt{\frac{\text{var}(C2)}{\text{var}(A)} \cdot \text{len}(C2)}$$

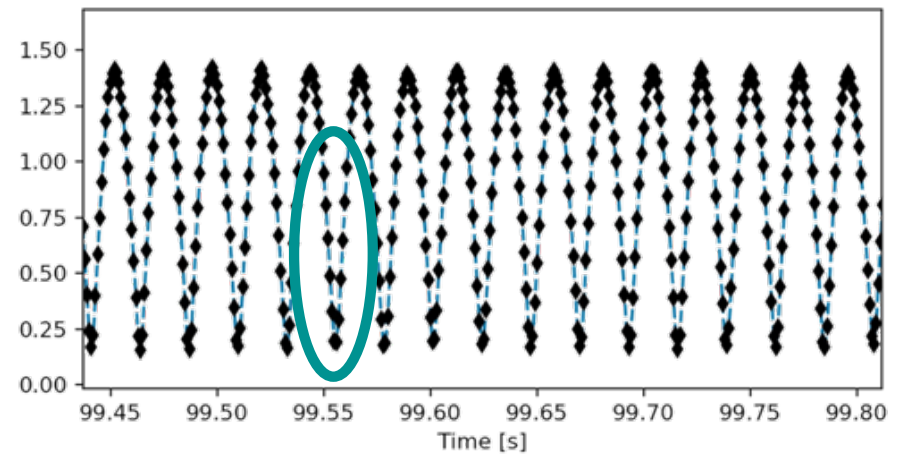
Feature 3: LSS

Smaller deviations between samples



F3: ↑

Bigger deviations between samples



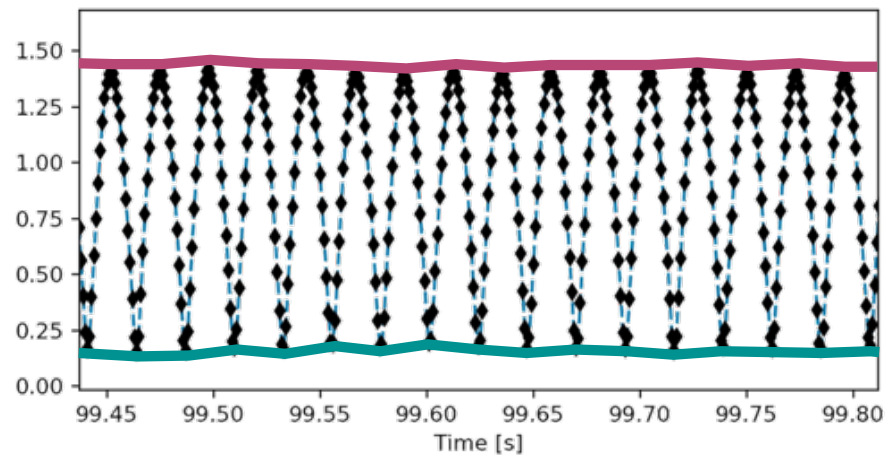
F3: ↓

F3 is the number of points that satisfy: $\frac{|A_i - A_{i-1}|}{A_i} \leq \epsilon$

Feature 2 vs 3



Inter-peaks

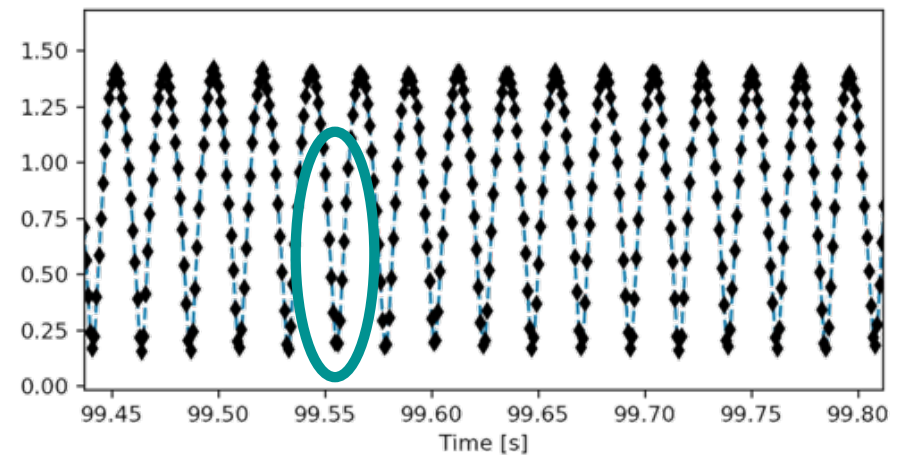


B2

C2

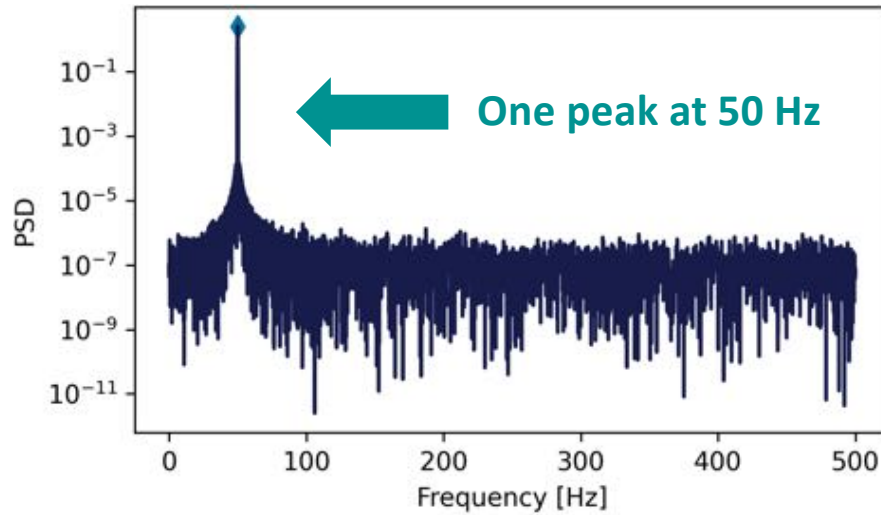
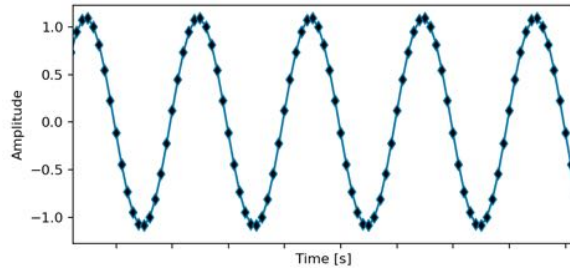
F2: ↓

Inter-samples

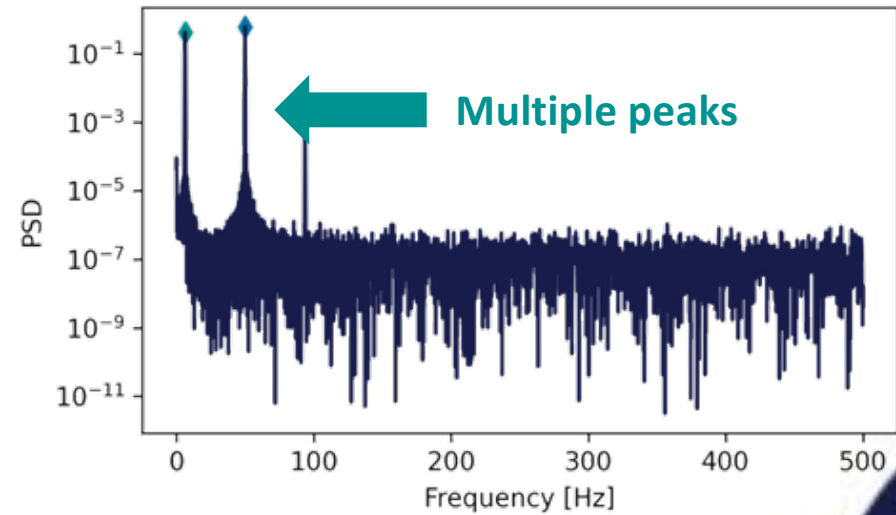
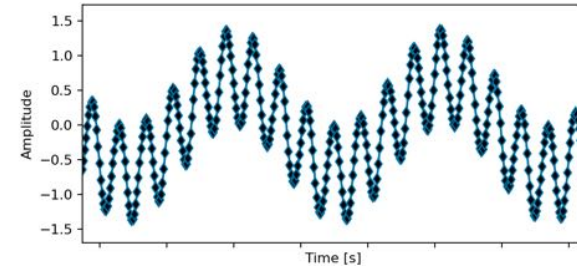


F3: ↓

Feature 4: FTI

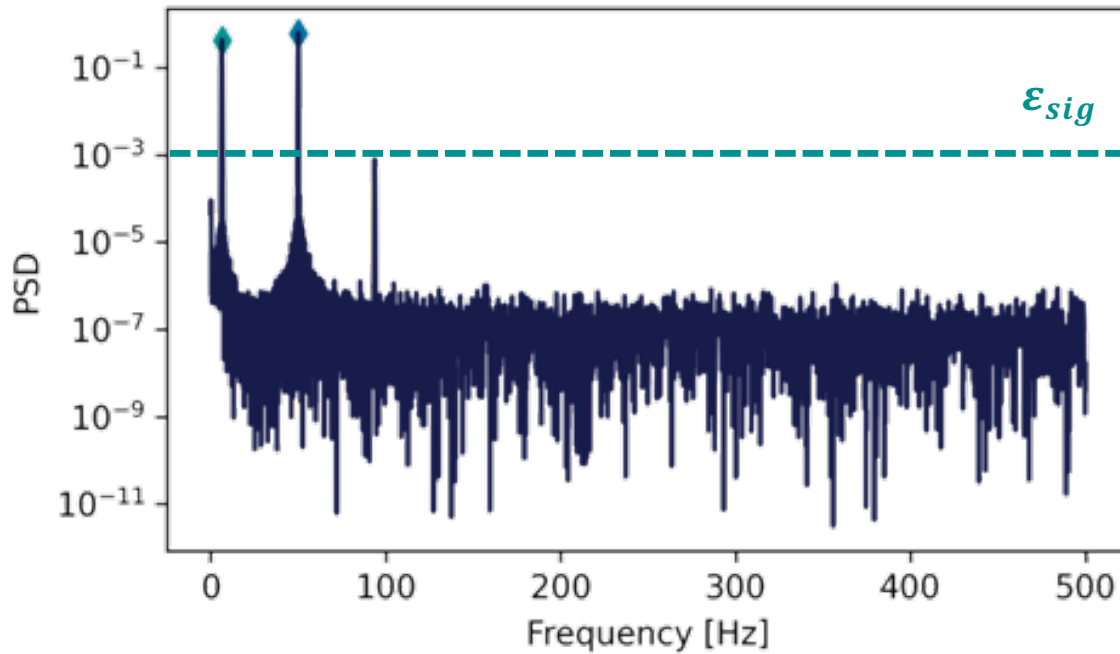


F4: ↓



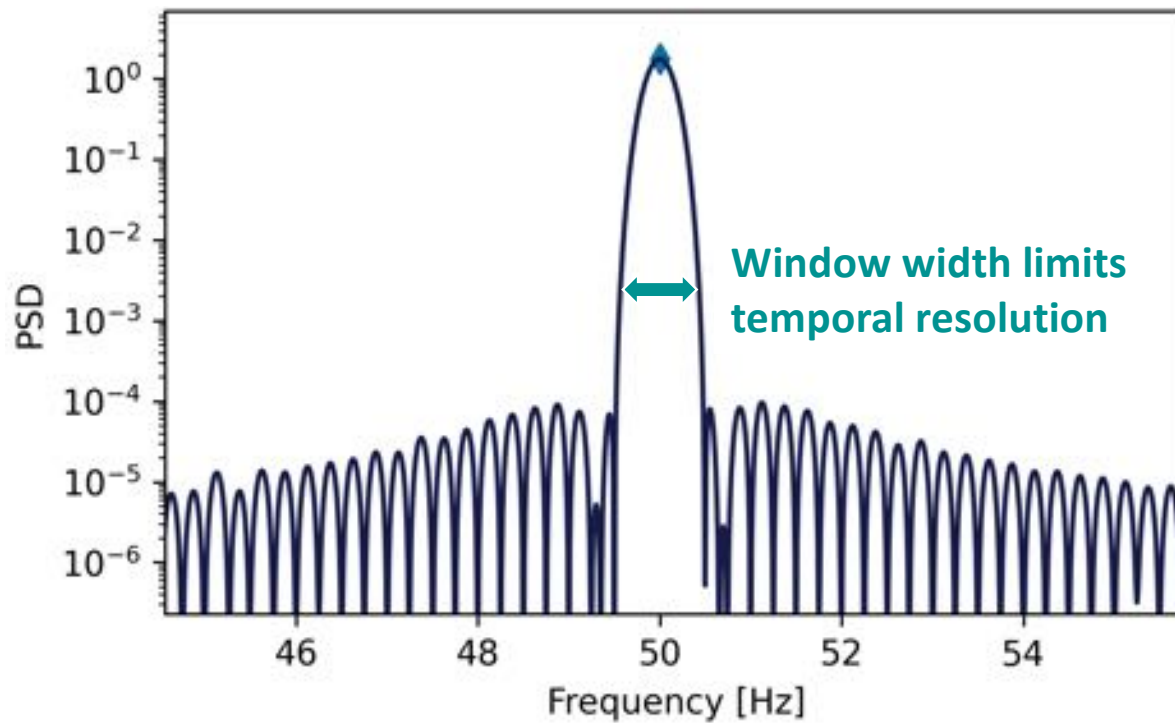
F4: ↑

Feature 4: FTI



$$F4 = \sum_{f_i \in F_{sig}} \frac{PSD(f_i)}{PSD(f_0)}$$

Feature 4: Challenges



Time vs frequency

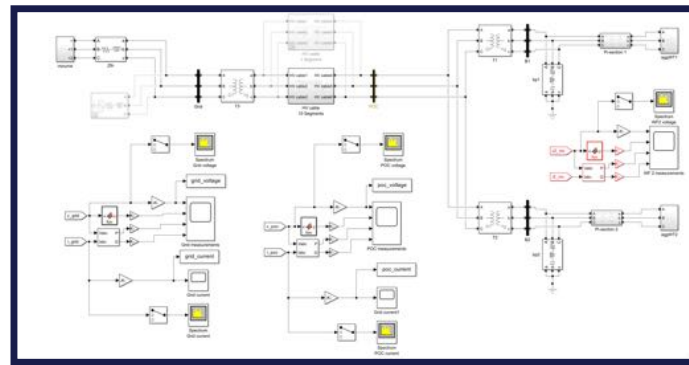
Data sources



IEEE dataset

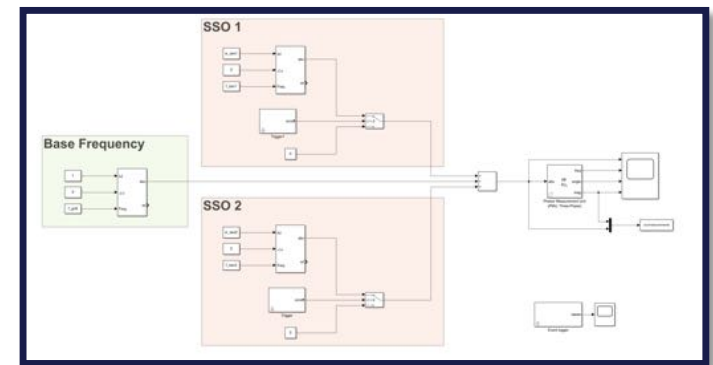
(used in presentation)

DOI: 10.21227/dvrr-t1310I



CIGRE model

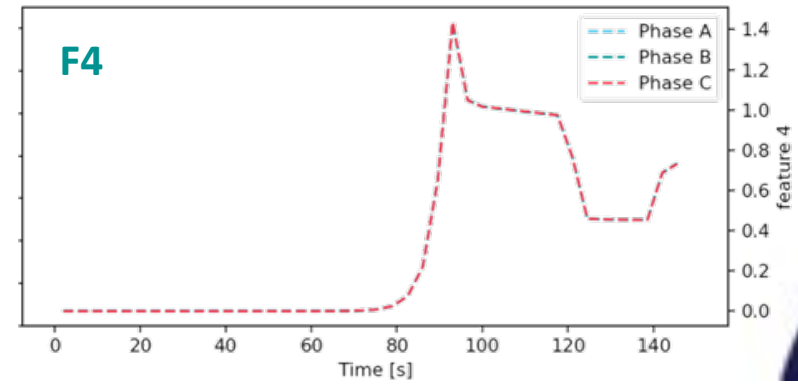
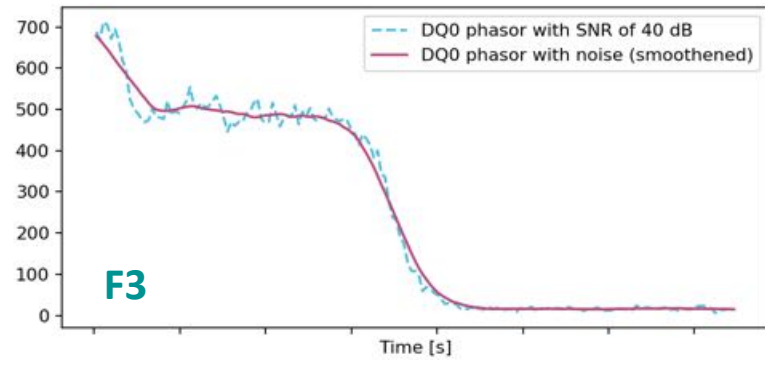
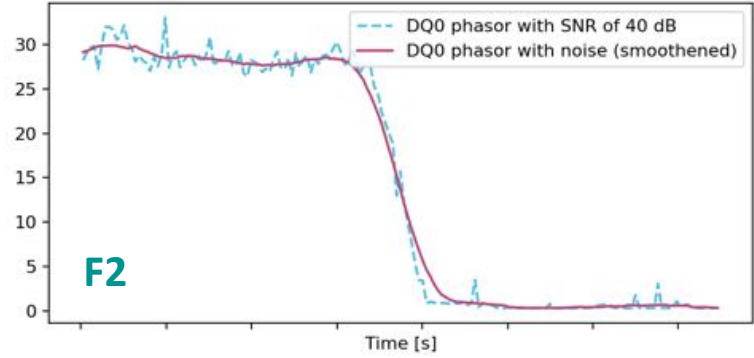
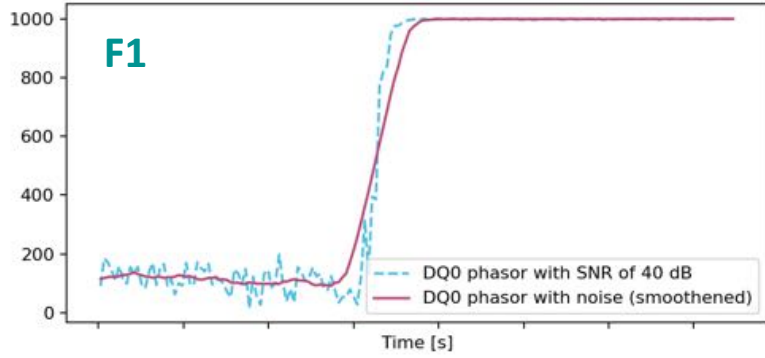
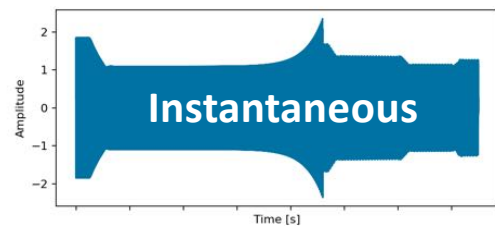
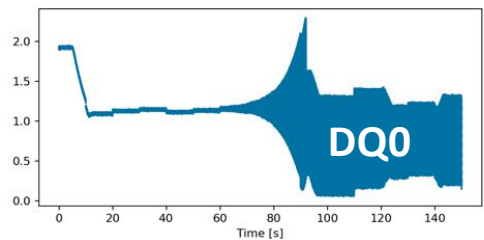
(used for training)



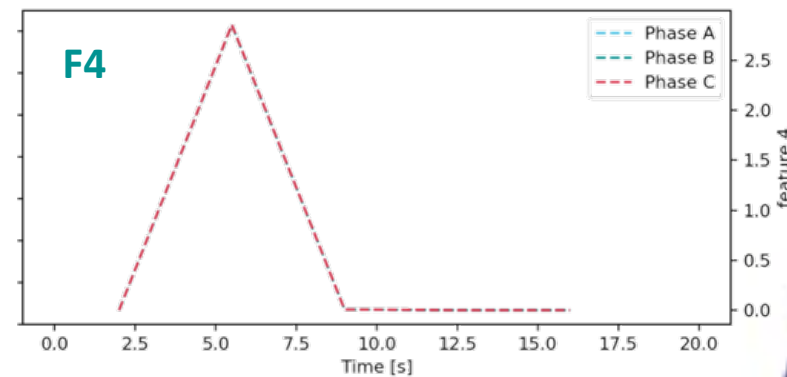
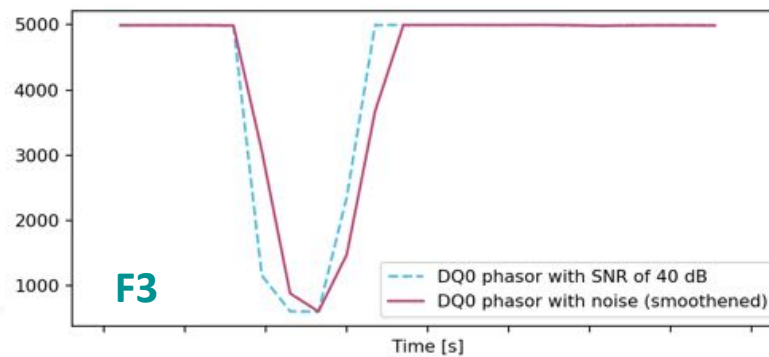
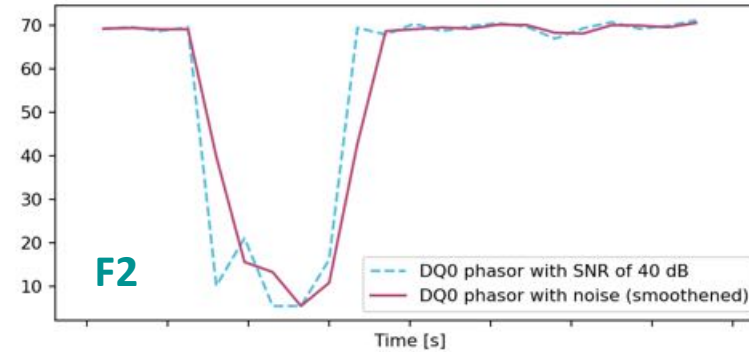
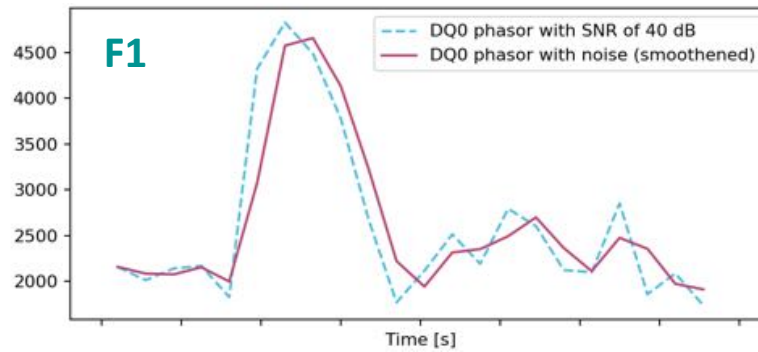
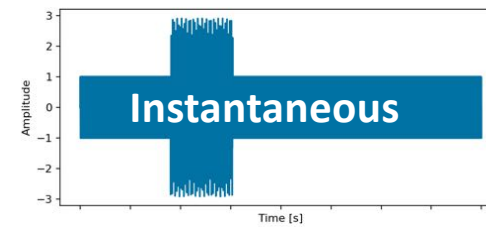
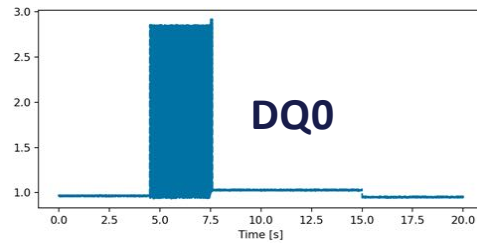
Artificial SSO generator

(used for feature development)

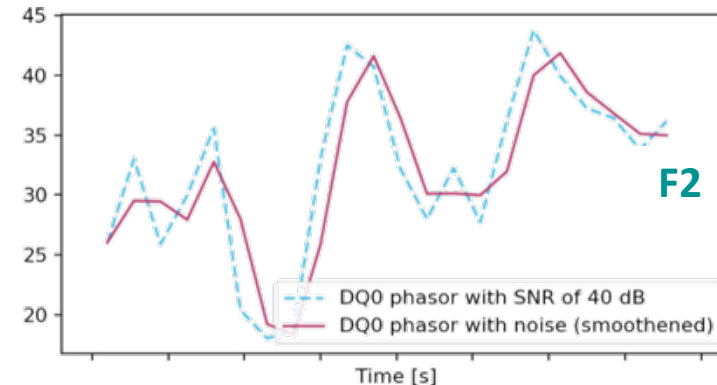
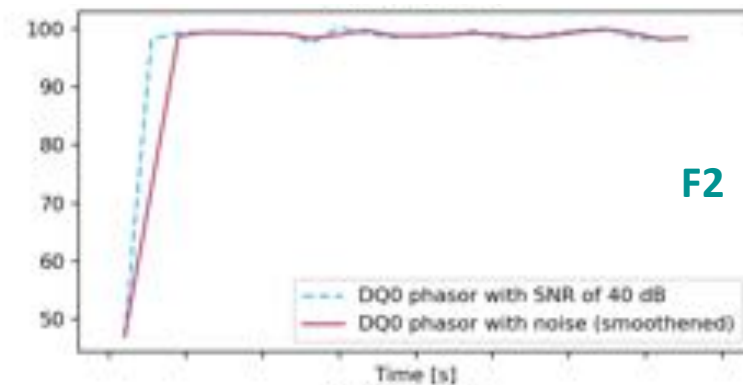
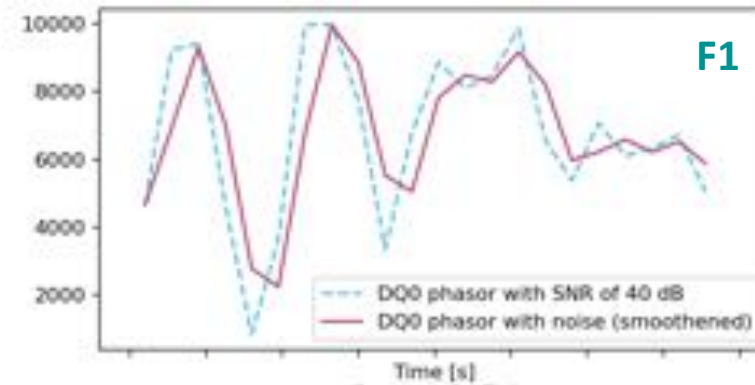
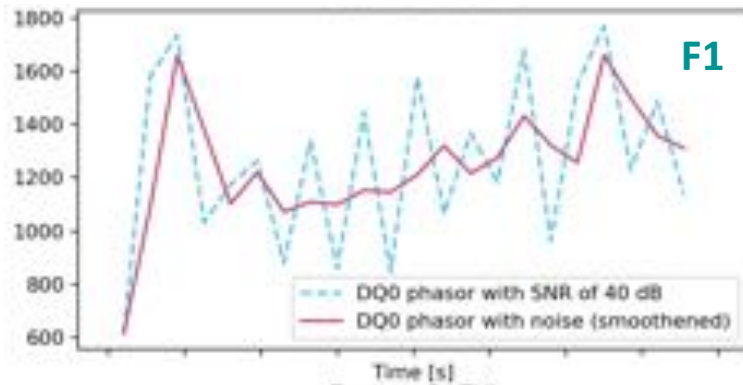
IEEE demo



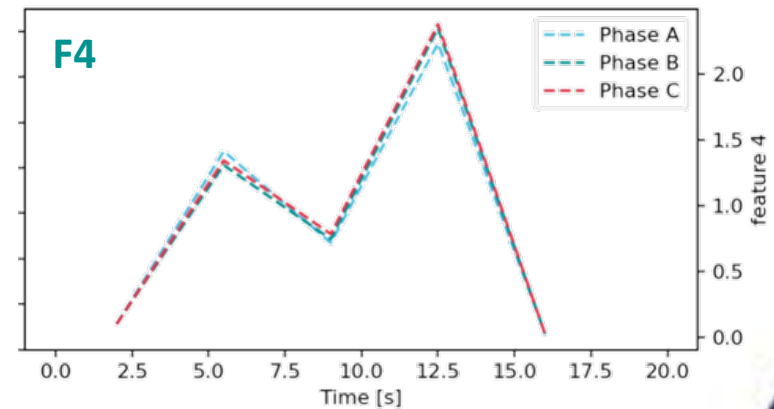
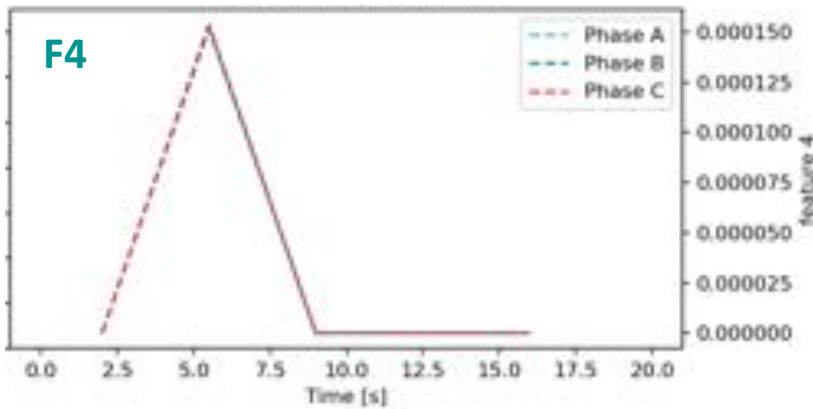
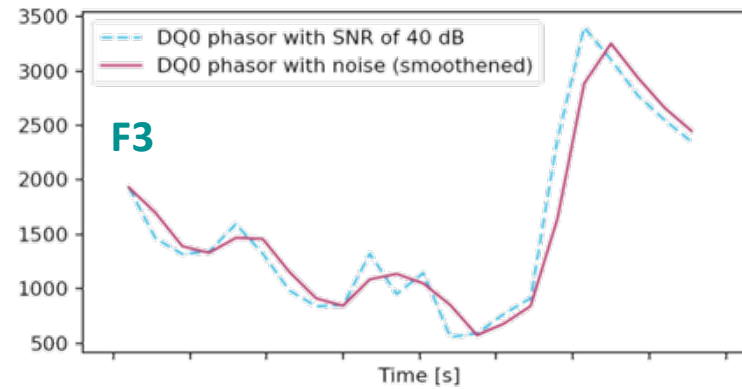
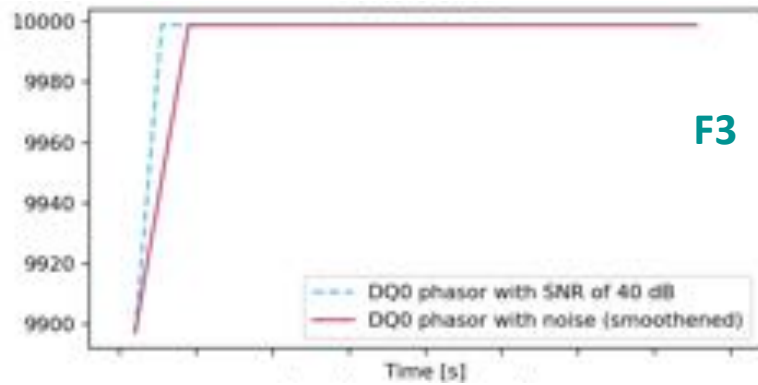
Artificial SSO generator demo



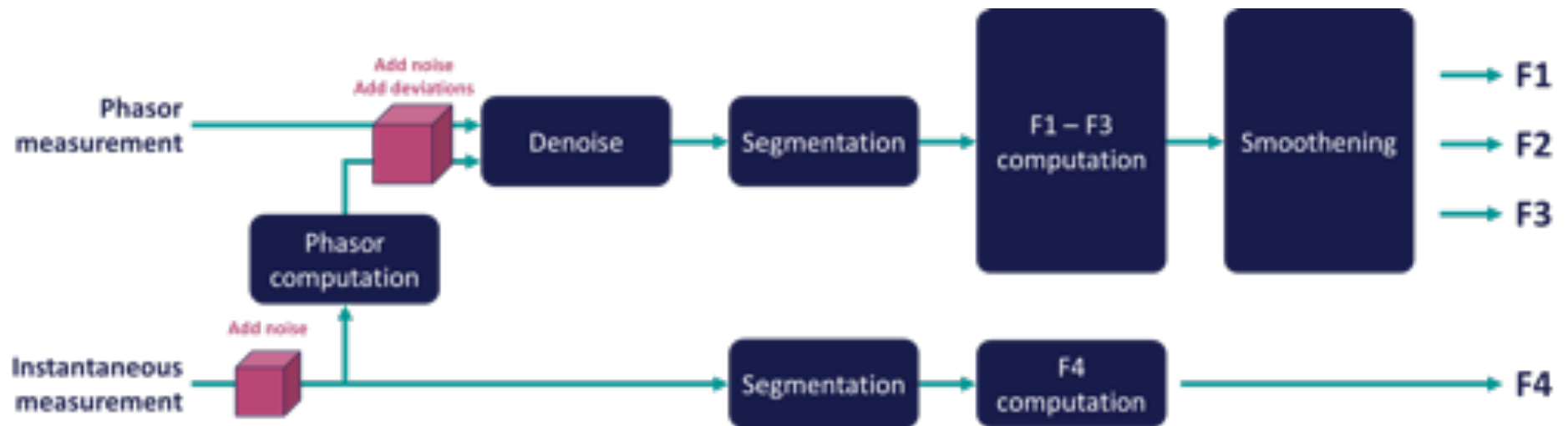
CIGRE demo (features 1 and 2)



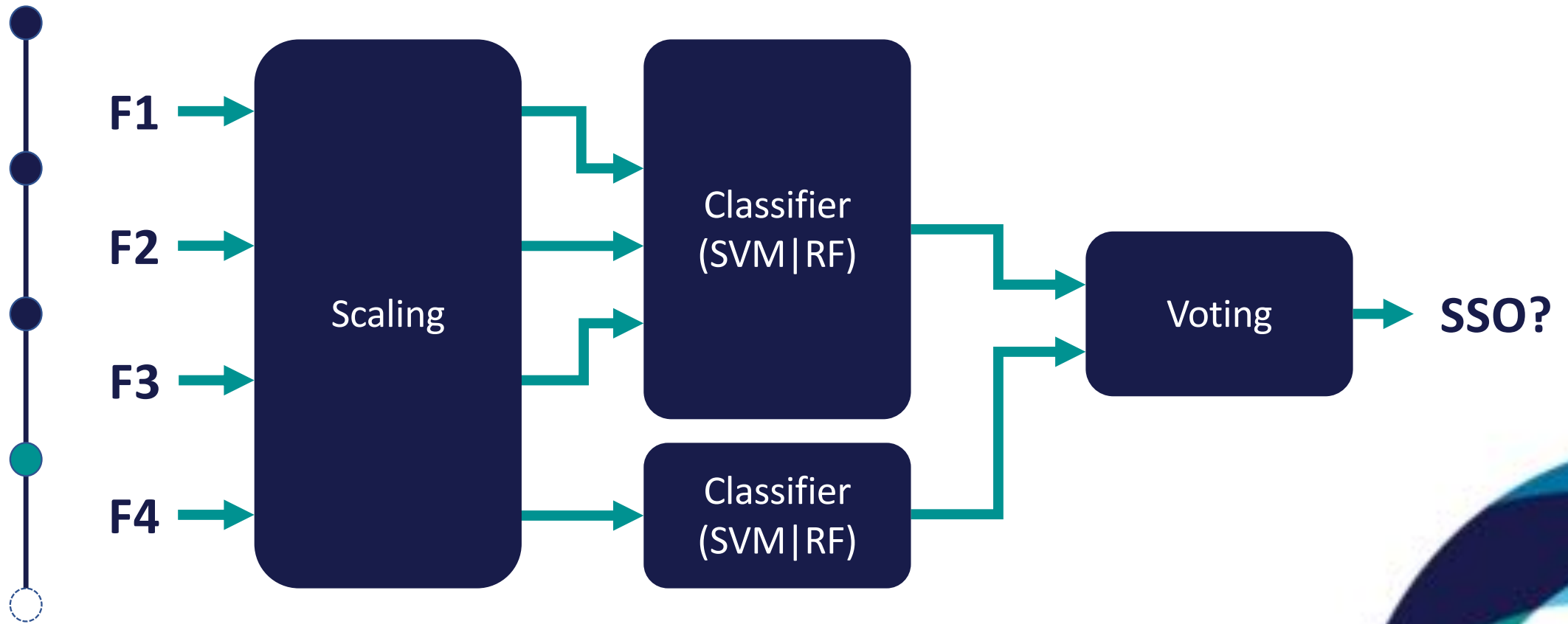
CIGRE demo (features 3 and 4)



Feature Engineering Pipeline

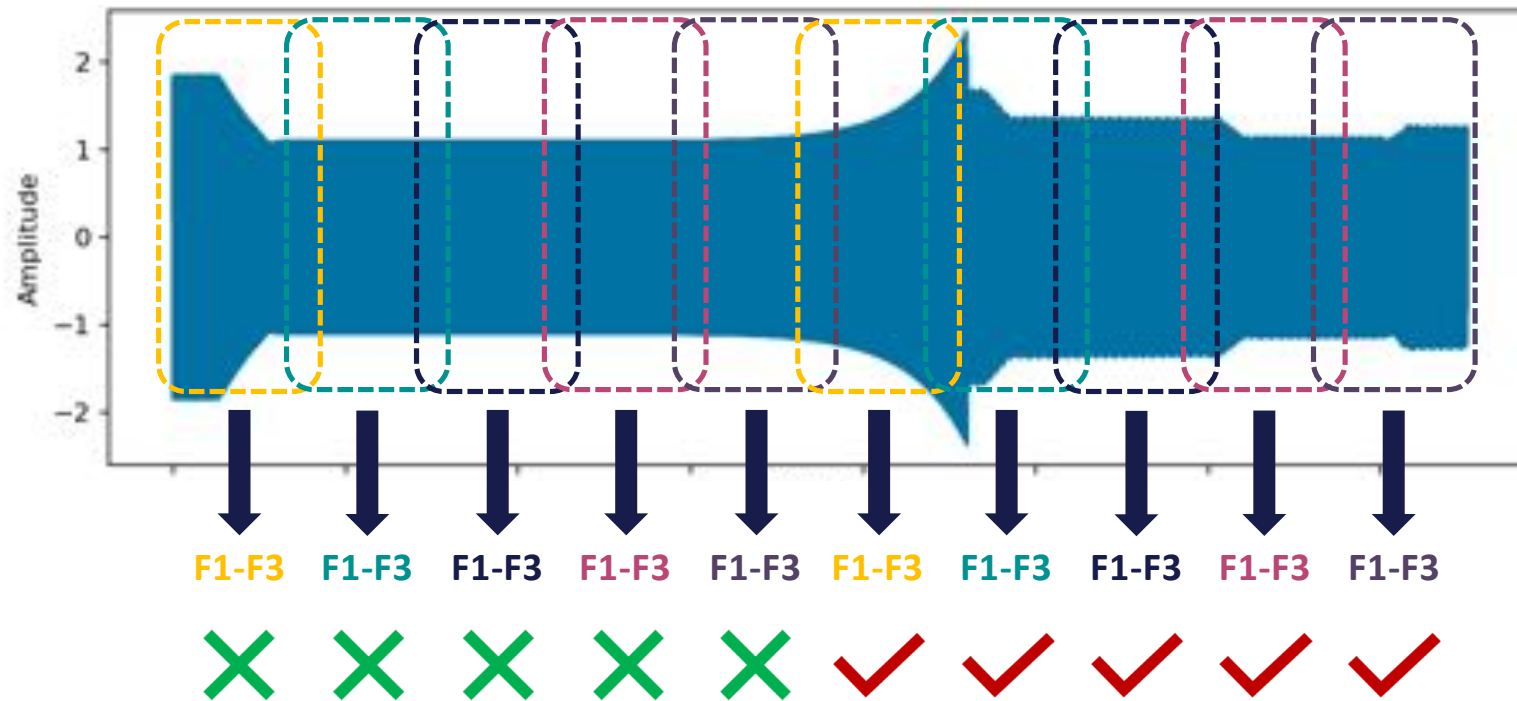


Pipeline – continued



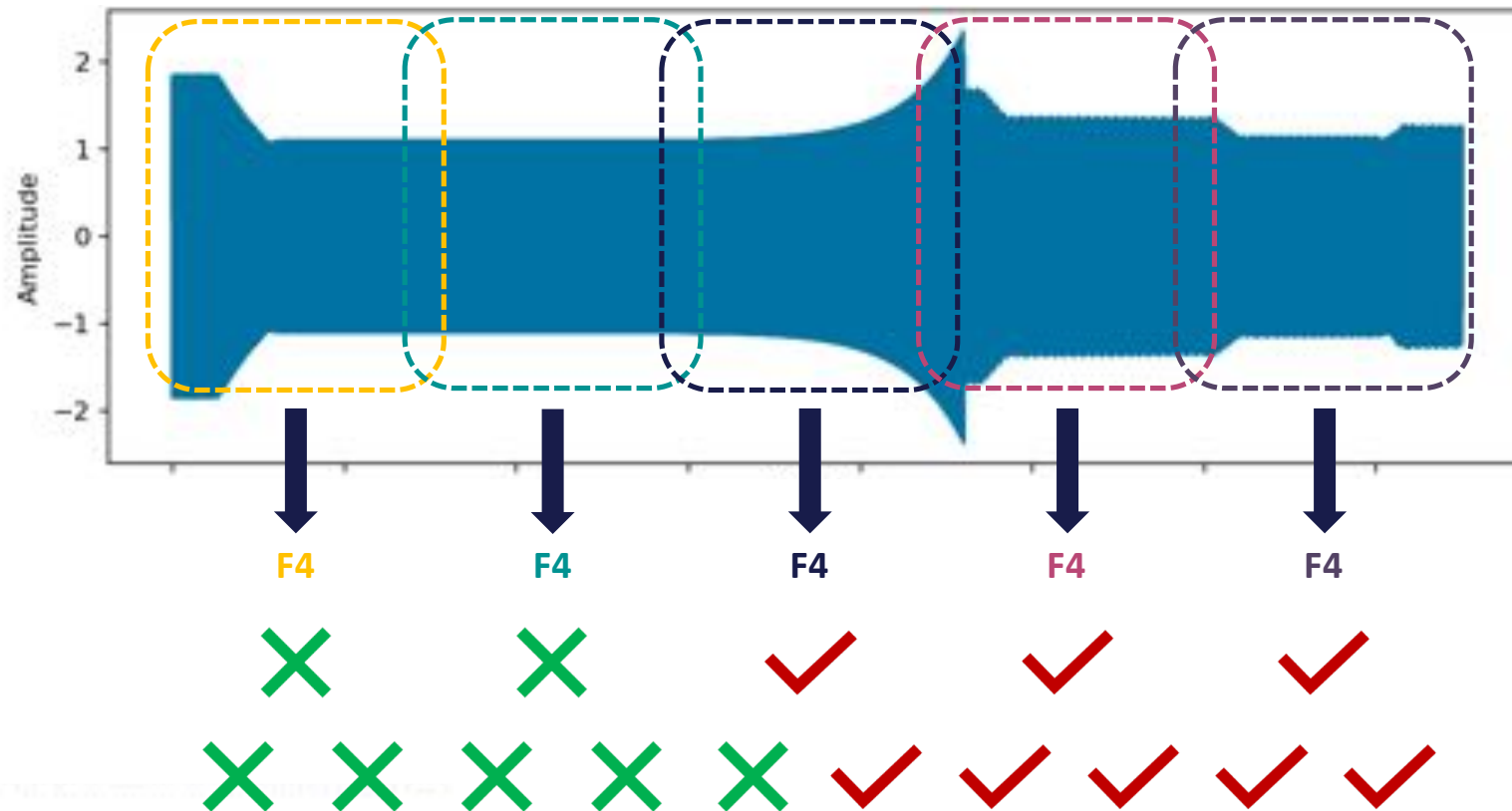
Predicting events

The features are computed using default settings, i.e., a segment duration of 1 second for features 1 – 3

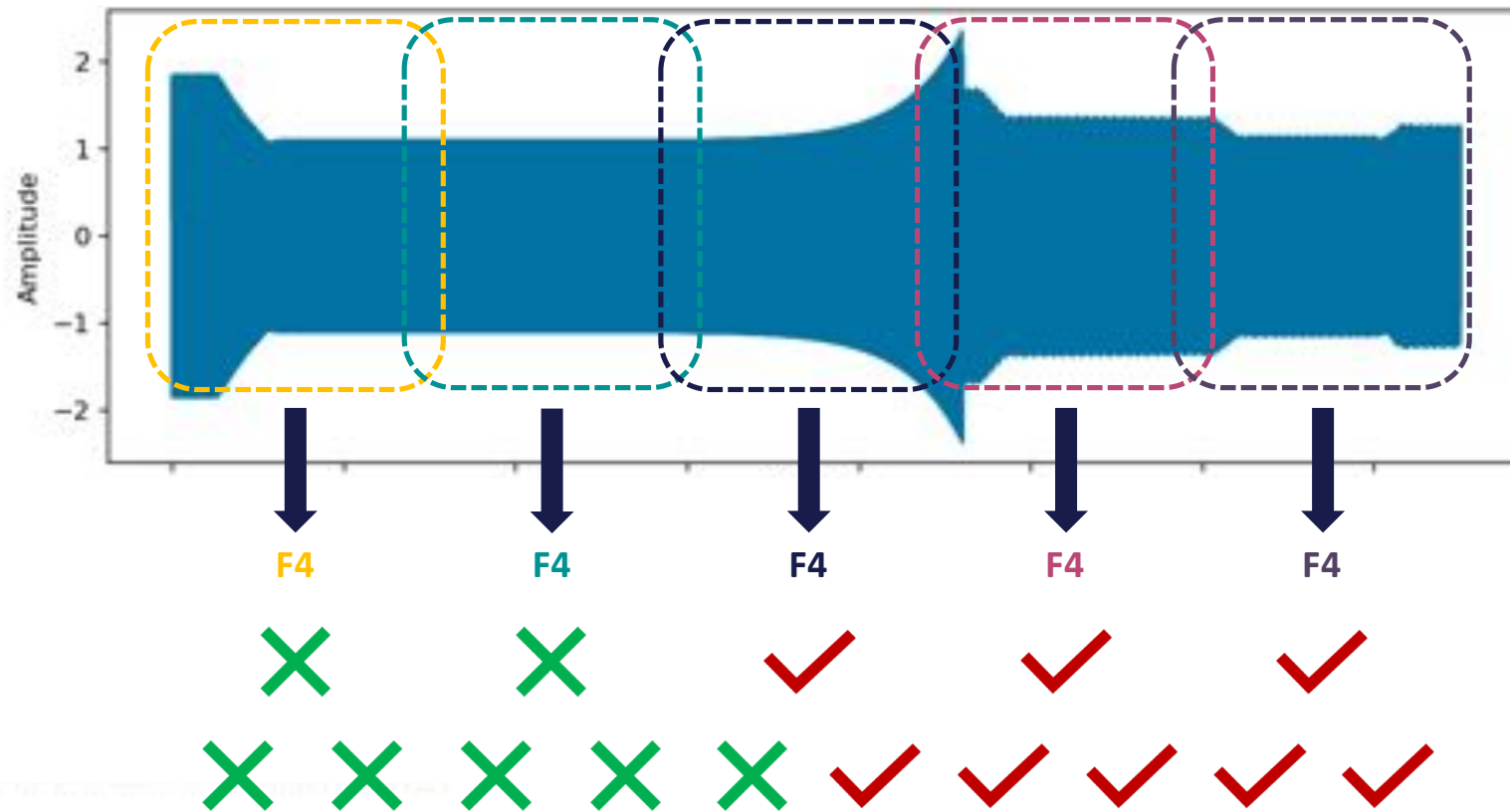


Predicting events

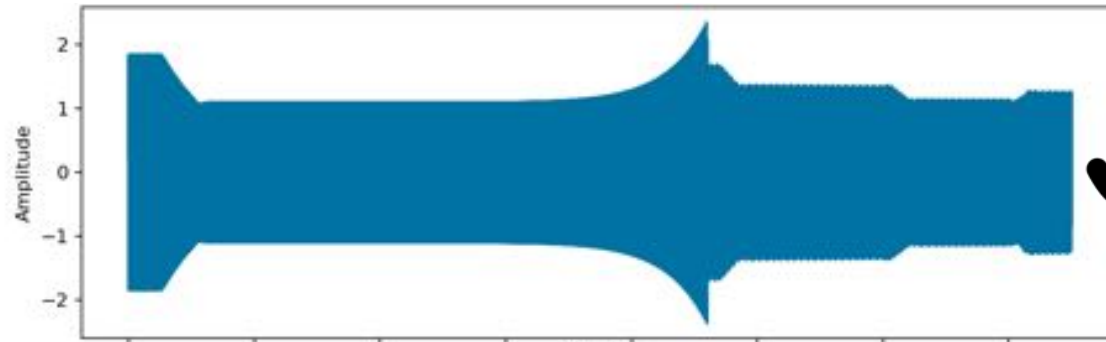
Feature 4 is computed using a 4-second window



Predicting events



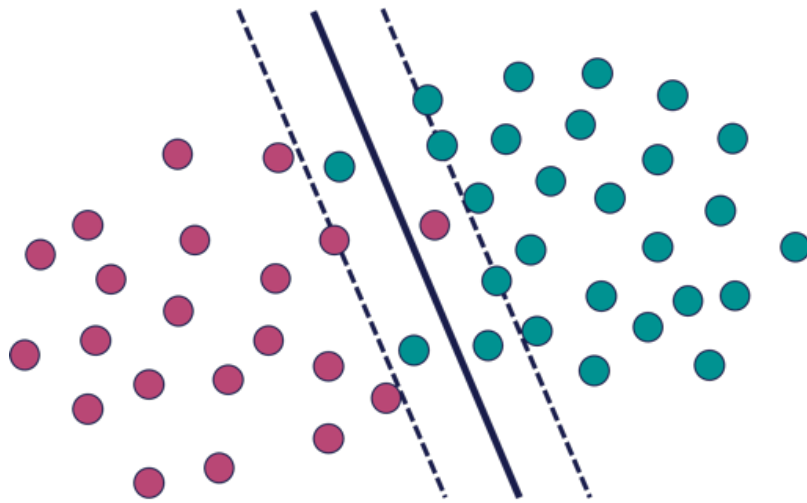
Predicting events



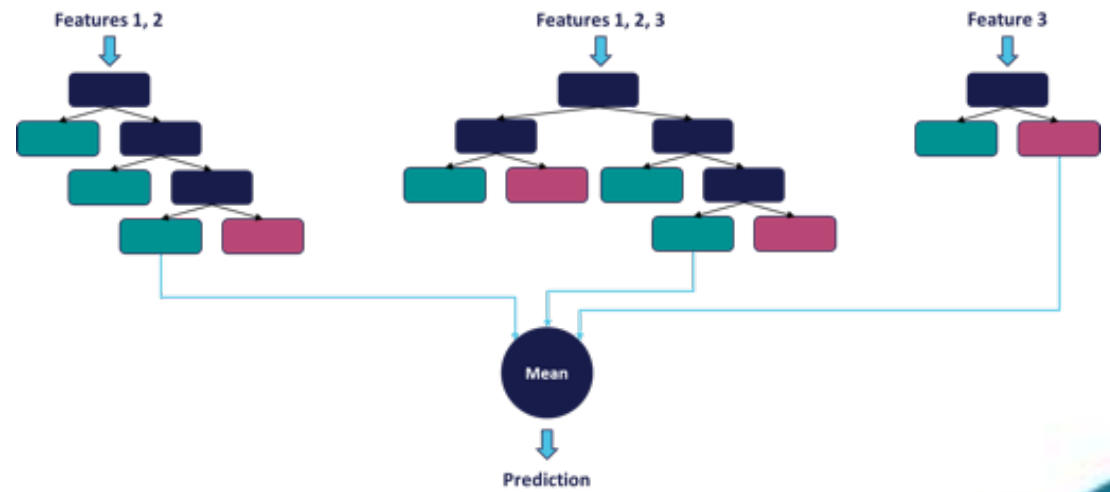
7 non-SSO

8 SSO

Classifier methods

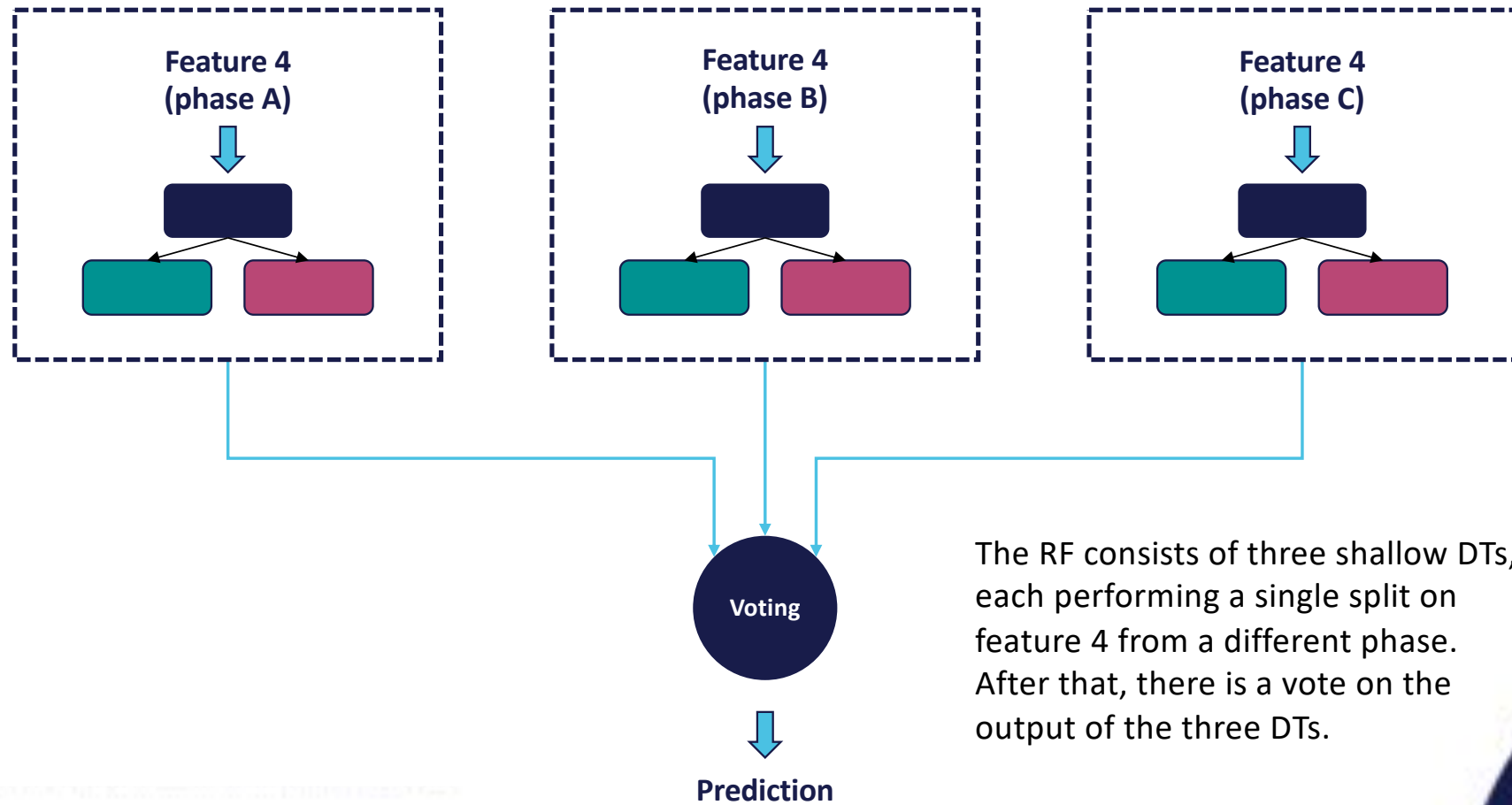


Support Vector Machine (SVM)



Random Forest (RF)

Optimised RF

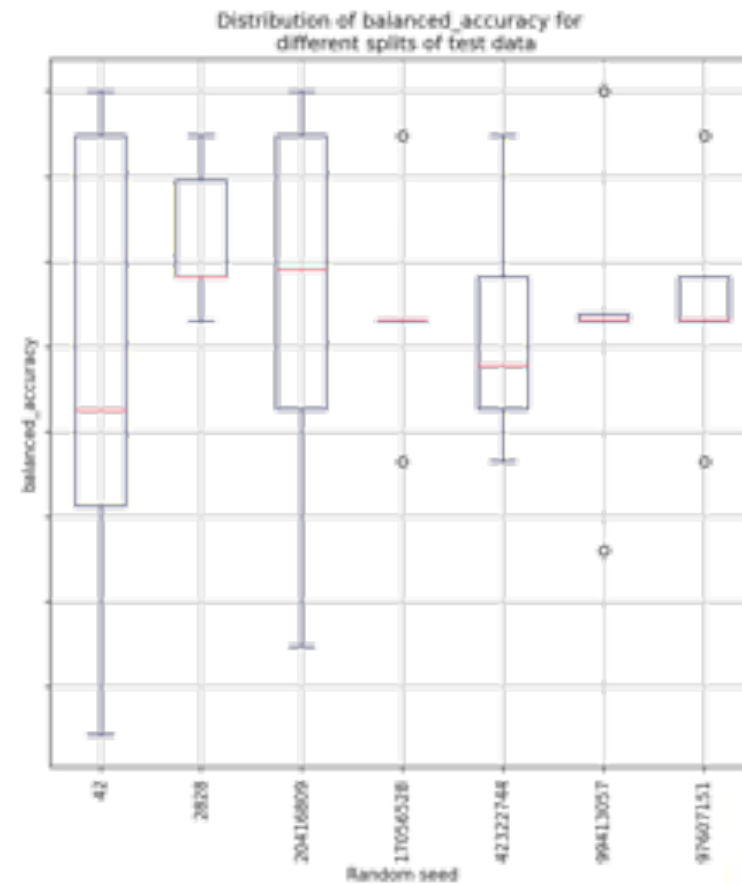
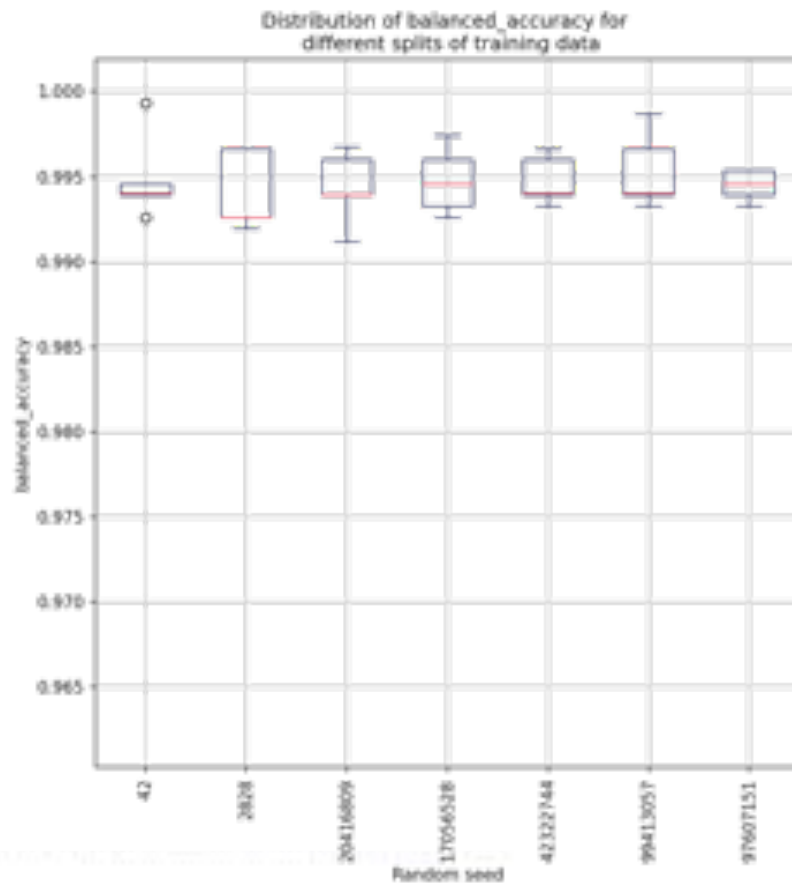


The RF consists of three shallow DTs, each performing a single split on feature 4 from a different phase. After that, there is a vote on the output of the three DTs.

SVM classifier: Features 1 – 3

$$Recall = \frac{TP}{TP+FN}$$

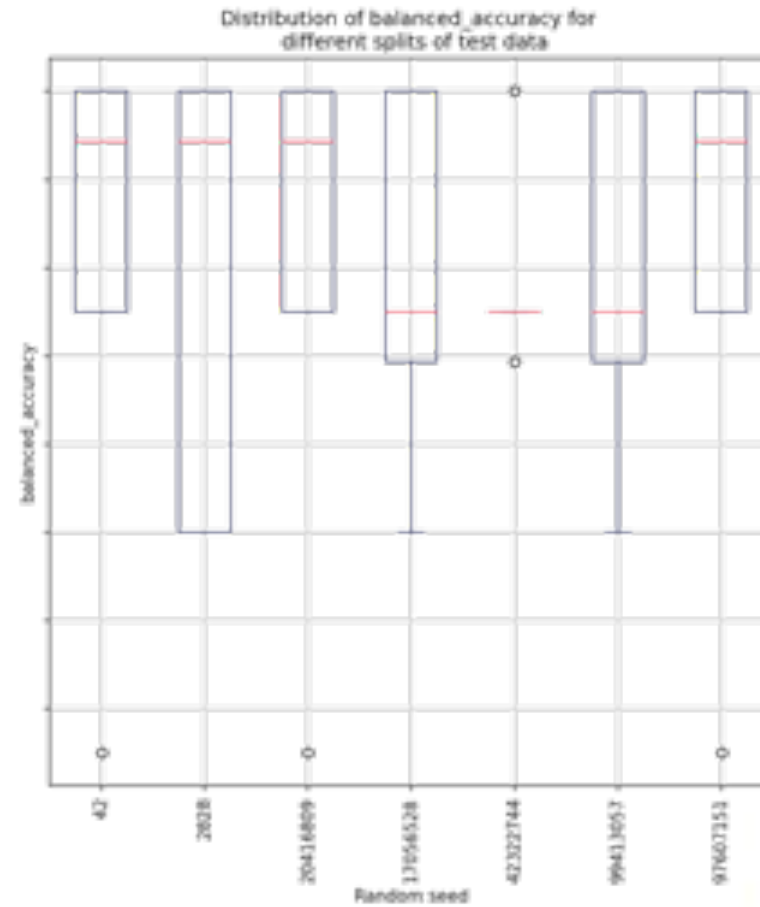
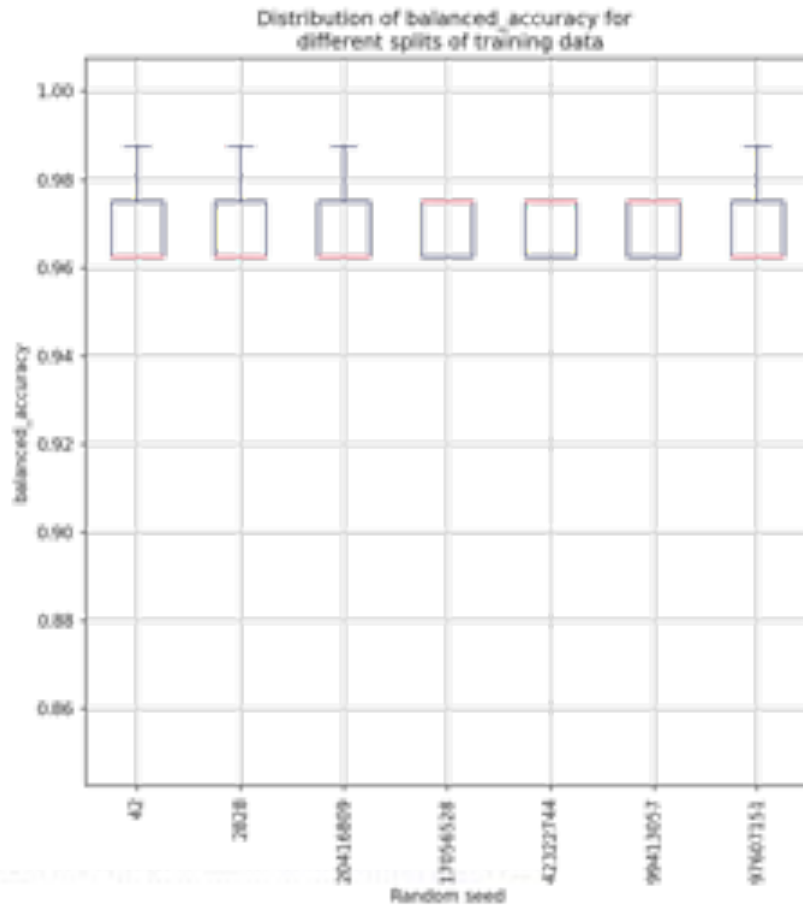
$$Balanced Accuracy = \frac{Recall_A + Recall_B}{2}$$



RF Classifier: Feature 4

$$Recall = \frac{TP}{TP+FN}$$

$$Balanced\ Accuracy = \frac{Recall_A + Recall_B}{2}$$





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Thank you for
listening!

For any questions, please contact me at

diptargha@tneigroup.com

