

Automatically Discerning Power System Dynamics in Synchrophasor Measurements Data Spectra

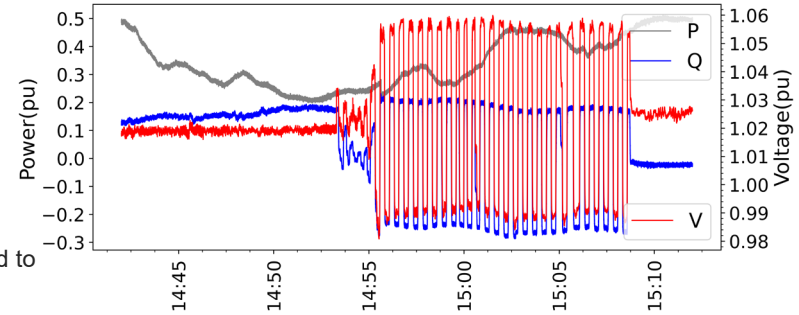
Chetan Mishra, Luigi Vanfretti, Jaime Delaree Jr., Kevin D. Jones

Overview

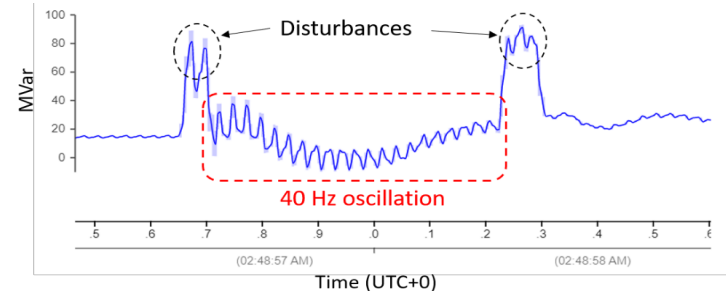
- Value of Measurement Data-Based Analysis
 - Emerging stability issues
 - Historical data analysis
- Towards Labeling Data with Emerging Dynamics
 - Time-frequency representation
 - Thresholding
 - Labeling
- Takeaways

Emerging Stability Issues in Dominion's Grid (Value of Data-Based Analysis)

- **Controller design and testing**
 - Decentralized control designed against a range of Thevenin equivalents, simulations with PSS/E planning model
 - Set it and **forget it** (wait for the next time it goes rogue or trips)
- **Inadequate modeling**
 - **Absence** of models for non-utility owned assets
 - **Inaccuracy** - absence of control limiters, averaging fast dynamics, not updated to reflect changes
- **Result** – unprecedented local **oscillations**
 - Most noticeable from poorly set controllers during maintenance outage season
- Measurement data is left as only recourse for analysis:
 - Helps explain, *in part*, the nature of emerging dynamics.
- Need to go **beyond** oscillation characterization
 - Determining the frequency, damping and source is only one part of the process
- Insights from data help, *in part*, to explain other aspects of emerging dynamics:
 - Could we have anticipated it?
 - How to prevent it?
 - What to do next time it happens?



**Unstable Solar Plant AVR During
“Planned” Outage [A]**

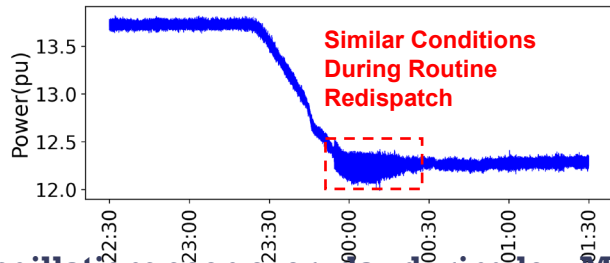
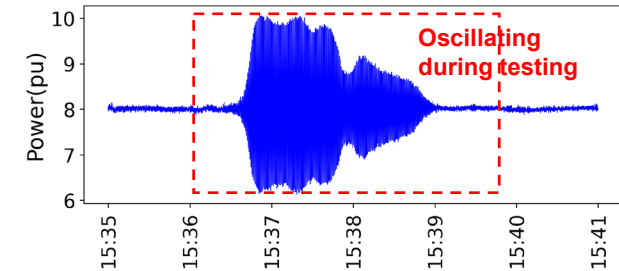


**Unmodeled 40 Hz Excitation
Dynamics from Hydro**

Historical Data Analysis is the Key

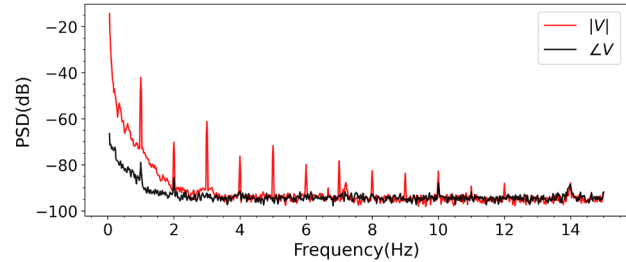
(Collecting Enough Data on “*Features*” to Analyze)

- Most major controller issues **leave clues** because of a cyclical and largely continuous nature of operation



Oscillations seen everyday during low MW [B]

- Discerning the type of data features:
 - **Physical issues (dynamics)** vs **instrumentation/comm issues vs Controlled Inputs**
 - Should **observed periodic** (undamped) motions always trigger alarms? Are they always related to dynamics?
 - *Data features may include artifacts* that are not related to the grid's dynamics but are product of instrument issues.
 - Long-term behavior could help discern the nature of the features in the data.



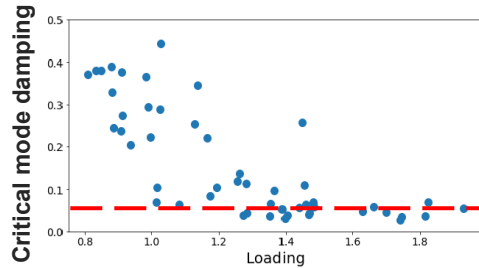
Clock-Error Created Periodic Component in Angle [C]

Historical Data Analysis is the Key

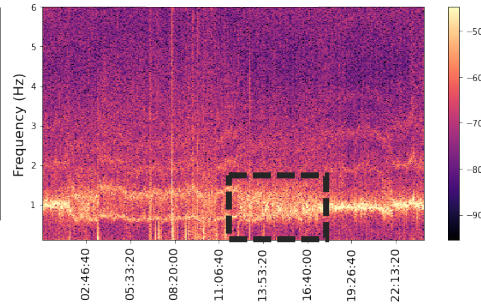
(Collecting Enough Data on “*Similar Dynamics*” to Analyze)

- Preventing future dynamic issues
 - Understanding the **underlying mechanism** (what to fix after the fact?)
- Correcting by learning from the past
 - What **action** to take in real time? (how did an asset respond to past actions?)

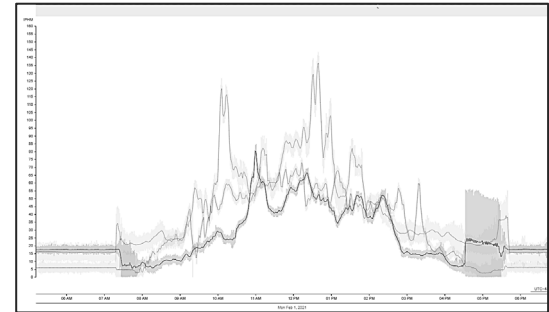
- Looking for **common patterns** between issues at different locations
 - Learning from **issues at other similar sites** and drawing connections (small set of vendors)



Damping Decreased with Loading (2 Months of Data) [D]



Changes During Nearby Filter Bank Switching [D]



Oscillations in Multiple Solar During Low Irradiance Periods

Thresholding Time-Frequency Representation

An Image Segmentation Based Approach [F]

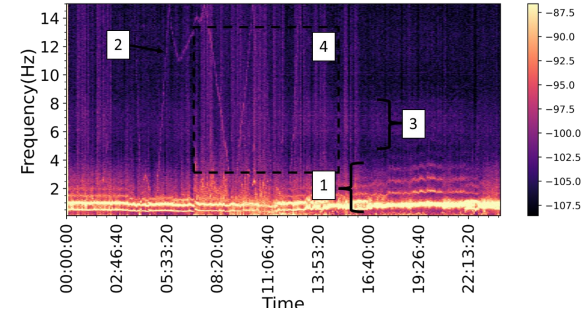
Towards Labeling Data for Unique Dynamics

- System is full of **unaccounted for** / difficult to explain oscillatory dynamic behaviors
 - Need a way to discover them and track them
 - No simulation model** to guide the search
- System mostly in **ambient conditions**
 - Frequency domain to separate underlying processes
- Non-stationary** nature of local modes (adding temporal aspect)
 - Sensitive to system changes, switching on-off, internal changes in control modes
- Approach:** time-frequency characterization of ambient data

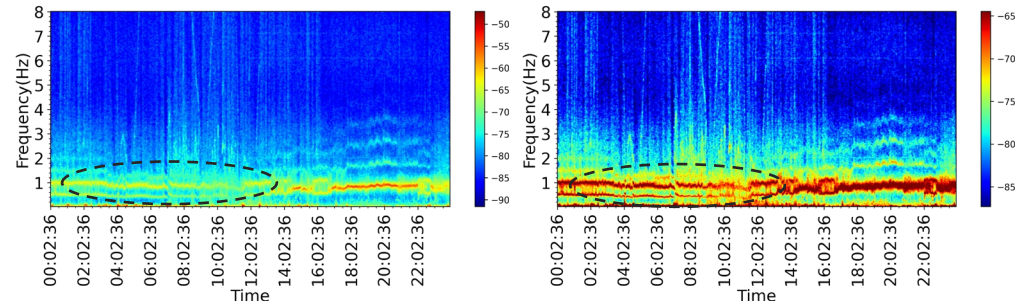
$$x(t) = \int e^{j2\pi ft} H(t, f) dz(f)$$

- Time varying spectrum $S(t, f) = |H(t, f)|^2$
- Modes represent set of local maxima at each time

$$P = \{(t^*, f^*) \in R^2 \mid \partial_f S \Big|_{t^*, f^*} = 0, \partial_f^2 S \Big|_{t^*, f^*} < 0\}$$



Labelling Unique Dynamics



Improperly Set Color Range

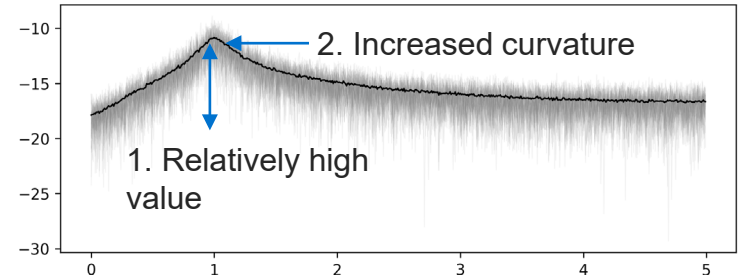
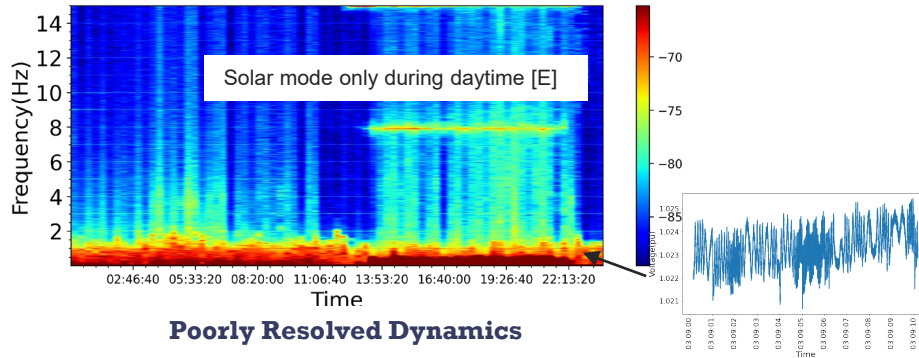
(Analysis Based on Visual Inspection Can be Deceptive)

Problem Formulation and Practical Challenges

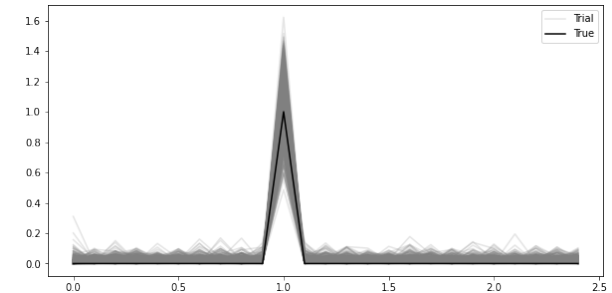
Challenges

- Stochastic system \Rightarrow **estimation noise** in $\hat{S}(t, f)$ makes it difficult to capture low power dynamics
 - Bias-variance tradeoff – goal to estimate peaks and not precision in $S(t, f) \Rightarrow$ more margin of sacrificing bias
- Time-frequency resolution tradeoff**
 - Cannot find an isolated peak

- Constraint** – simple to use it in practice (**few hyperparameters to tune**)



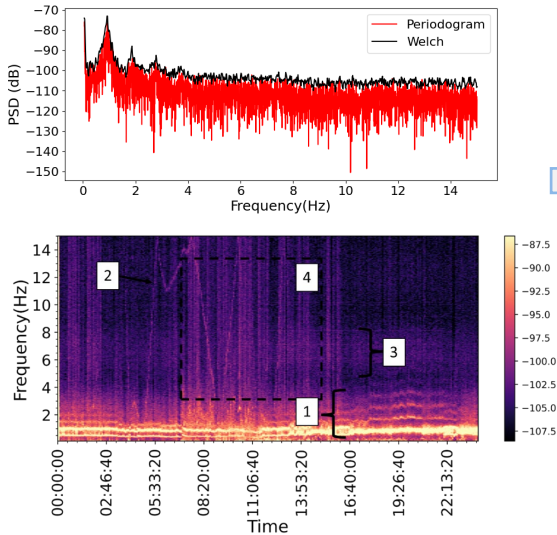
Two Family of Approaches:
1. Threshold vs 2. Pattern Matching



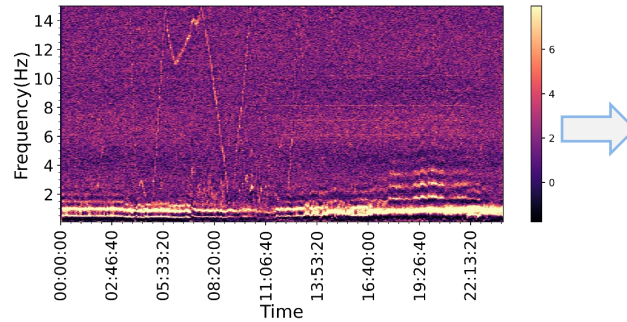
Estimation Noise In $\hat{S}(f)$

Proposed Approach

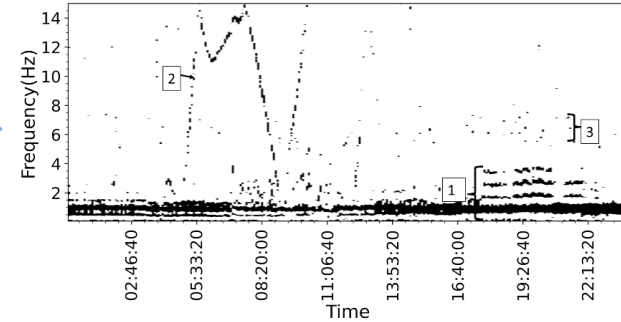
Step 1: Good Starting Time-Varying Spectral Estimate



Step 2: Pre-processing (to enhance features)



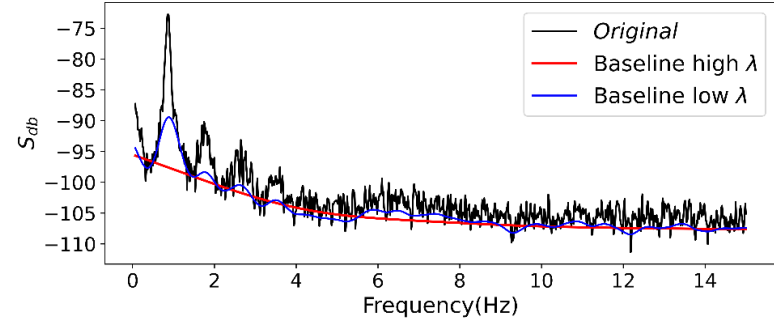
Step 3: Thresholding



Work with $\log(\hat{S})$ as opposed to \hat{S} to get additive estimation noise (yields to linear smoothing)

Pre-Processing

- Dynamics in addition to oscillatory behaviors
 - **Slow trends:**
 - Arise from changing operating conditions (contributing to low frequency range)
 - Require **detrending** prior to spectral estimate
 - **Broad-band:**
 - Random inputs, e.g. arc furnace
 - Or from transients/ discontinuous changes in operation
- Can address these by **estimating and removing spectral baseline**
 - Removing longer scale (in frequency) dynamics
 - Allows for **global threshold** (across time)



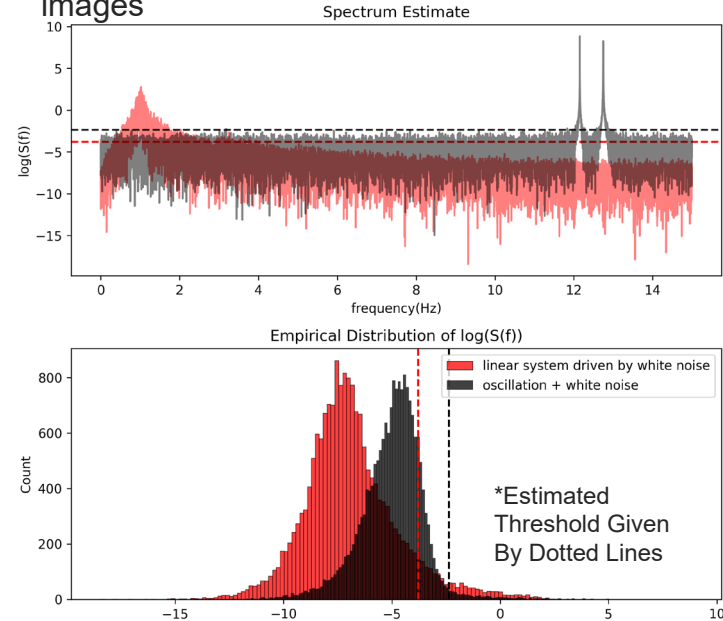
Baseline $\log S(t, f)_b$ defined as a smooth under-approximation to the spectrum

$$\log S(t, f)_b = \underset{\text{skew towards underapprox}}{\operatorname{argmin}_{b(f)}} \sum_f \frac{w(\operatorname{err}(f))}{\log(\hat{s}(t, f) - b(f))} \underbrace{\operatorname{err}^2(f)}_{\text{fit error}} + \underbrace{\lambda}_{\text{penalizes curvature}} \sum_f (\nabla_f^2 b(f))^2$$

Spectrogram Properties and Thresholding

- **Thresholding** spectrogram (for relatively high value regions) equivalent to image thresholding on grayscale images (intensity of $(t, f)^{th}$ pixel given by $\log(\hat{S}(t, f))$)
- **Histogram** based approaches take advantage of pixel intensity distribution, of special relevance in terms of simplicity
 - $\mu(z)$ represents number of pixels with intensity below z
- **No technique** universally applicable to all kinds of images \Rightarrow need to understand the pixel intensity distribution $\frac{d\mu}{dz}$ of ambient data spectrograms
 - Largely **unimodal** (few modes or oscillations (small measure of prominent frequencies at unequal intensities), estimation noise $\log(\chi_2^2)$ unimodal)
 - **Baseline removal further ensures this**
 - Finding dynamics equivalent to finding the **right tail**

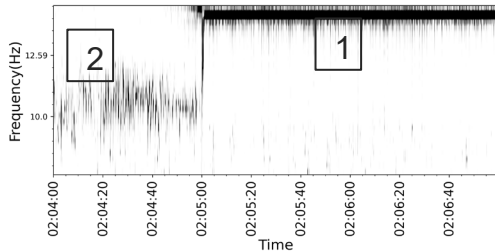
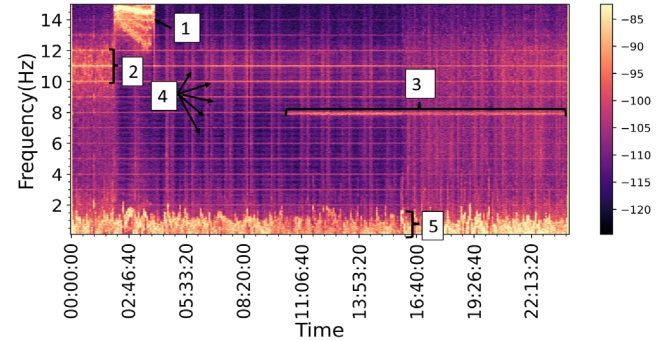
- **Rosin's method** widely used for unimodal images



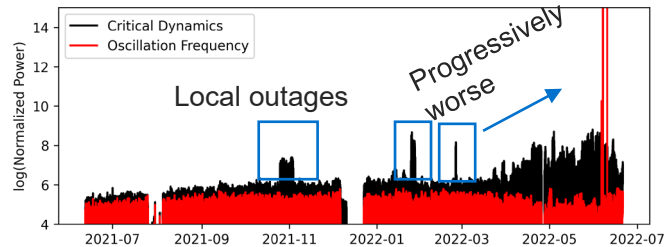
Results

Fast Oscillations from Load [F]

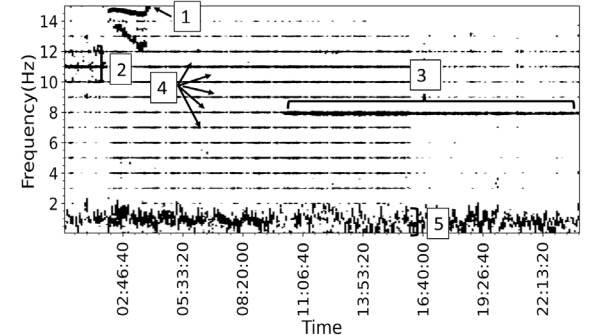
1. 14 Hz oscillation from 2-4 AM.
 2. Difficult to characterize dynamics visible blurred region in 10-12 Hz range
 3. Mode from nearby solar (only during day time) [E]
 4. Repeating and persistent peaks at 1 Hz and its multiples resulting from a periodic voltage sag [H]
 5. Poor frequency resolution (fast varying mode)
- Around 16:00 Hrs, the spectral baseline shifts up, likely due to nearby device connecting/disconnecting.



**Seemingly Unrelated Dynamics (2)
Destabilizing to (1)**

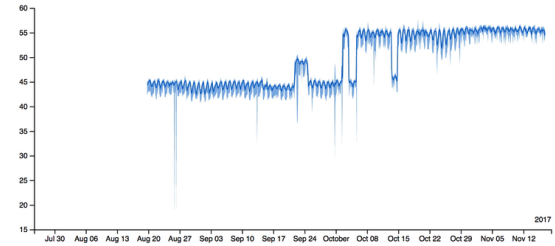


**Critical Dynamics (2) Power
Progressively Increased over Long Term**

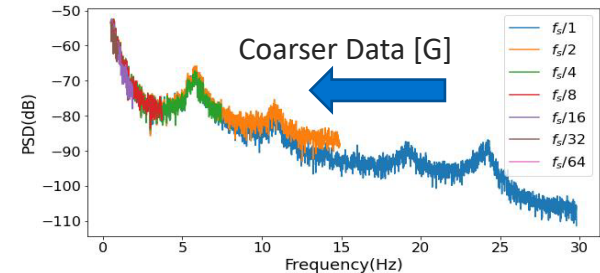


Tooling PingThings + Customizable Workflows in Python

- Speed of data extraction is the biggest **bottleneck** for historical data analysis
- **No tool** solves all the problems
 - Essential to have a good understanding of the underlying theory to use/tune pre-built tool
 - Or better, build what is needed with full access/control on all the algorithms and workflows
- **Best** - a customizable environment to do whatever you want
 - Requires to have access to an **API** to pull data/results
- **Python** support – rich data science libraries
 - We leverage many signal processing libraries to build our own workflows.
- The analyst is the key, not the tool
 - **Tools can be replaced, human experience, insight and understanding cannot.**
- Developing analysts is challenging
 - Incentives not aligned between universities and industry
 - Power engineering knowledge is required to derive insights on data analysis results.



Multiresolution Data Allows for Faster Queries to Analyze Dynamics



Takeaways

- Need to go beyond basic oscillation characterizations (frequency, damping, source) to prevent stability issues
 - Requires collecting enough evidence to draw inference, [efficient access to large scale data is a must.](#)
 - *The analyst is the key: the tool can be replaced, while human experience, insight and understanding, cannot.*
 - Understanding underlying mechanism is essential, need a strong foundation in power systems to interpret the results.
 - Universities should consider expanding the curriculum to cover how to apply digital signal processing for power engineering problems that require both power insight and signals knowledge.
- System is full of unaccounted for / difficult to explain dynamic behaviors
 - Need a way to discover them and track them to prevent stability problems
 - Conventional simulation models to guide the search are not available, would be nice to have (compliment the analysis)
 - Local dynamics can be fairly non-stationary (in terms of spectral characteristics)
- The present work explores automatically identifying prominent dynamics in synchrophasor data spectra – you can find more details in:
 - C. Mishra, L. Vanfretti, J. de la Ree Jr., and K. D. Jones, “Automatically Discerning Power System Dynamics in Synchrophasor Measurements Data Spectra,” 2023 IEEE Power & Energy Society (PES) General Meeting (GM) Orlando, Florida, 16 – 20 July 2023. Online: [here](#)

References

- [A] C. Mishra, L. Vanfretti, J. Delaree and K. D. Jones, "Analyzing a Non-Sinusoidal Response from a Real-World Solar PV," in IEEE Transactions on Power Systems, vol. 39, no. 2, pp. 4771-4774, March 2024, doi: 10.1109/TPWRS.2024.3350377. Author's copy: [here](#)
- [B] C. Mishra, L. Vanfretti, M. Baldwin, J. de la Ree Jr., and K. D. Jones, "Analysis of Generator Forced Oscillations during MOD 25 Testing Exploiting Wavelets," Hawaii International Conference on System Sciences (HICSS), Hilton Hawaiian Village Waikiki, January 3-6, 2024. Author's copy: [here](#)
- [C] C. Mishra, L. Vanfretti, J. de la Ree Jr., T.J. Purcell, R. Orndorff, K. D. Jones, "Analysis of Periodic Clock Errors in Synchrophasor Ambient Data," 2023 IEEE Power & Energy Society (PES) General Meeting (GM) Orlando, Florida, 16 – 20 July 2023. Author's copy: [here](#)
- [D] C. Mishra, L. Vanfretti, D. Yang, C. Wang, X. Xu, K.D. Jones and M.R. Gardner, "Analysis of STATCOM Oscillations using Ambient Synchrophasor Data in Dominion Energy," 2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT 2022), Feb. 21-24, 2022, Washington D.C., USA. Author's copy: [here](#)
- [E] C. Wang, L. Vanfretti, C. Mishra, K.D. Jones, R.M. Gardener, "Identifying Oscillations Injected by Inverter-Based Solar Energy Sources," 2022 IEEE Power & Energy Society General Meeting, 17–21 July 2022, Denver, Colorado. Author's copy: [here](#)
- [F] C. Mishra, L. Vanfretti, J. de la Ree Jr., and K. D. Jones, "Automatically Discerning Power System Dynamics in Synchrophasor Measurements Data Spectra," 2023 IEEE Power & Energy Society (PES) General Meeting (GM) Orlando, Florida, 16 – 20 July 2023. Author's copy: [here](#)
- [G] X. Xu, C. Mishra, L. Vanfretti, C. Wang, K. D. Jones, M. R. Gardner, and S. Murphy, "Fast Oscillation Detection and Labeling via Coarse Grained Time Series Data for ML Applications," 2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference, Feb. 21-24, 2022, Washington D.C., USA. Author's copy: [here](#)
- [H] X. Xu, C. Mishra, L. Vanfretti, C. Wang, K.D. Jones, J. Brian Starling, and R. M. Gardner, "Tracking Periodic Voltage Sags via Synchrophasor Data in a Geographically Bounded Service Territory," 2023 IEEE Grid Edge Technologies Conference & Exposition, April 10-13, 2023, San Diego, California, USA. Author's copy: [here](#)

Thank You Questions ?