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Incident Detection in Power Distribution Systems

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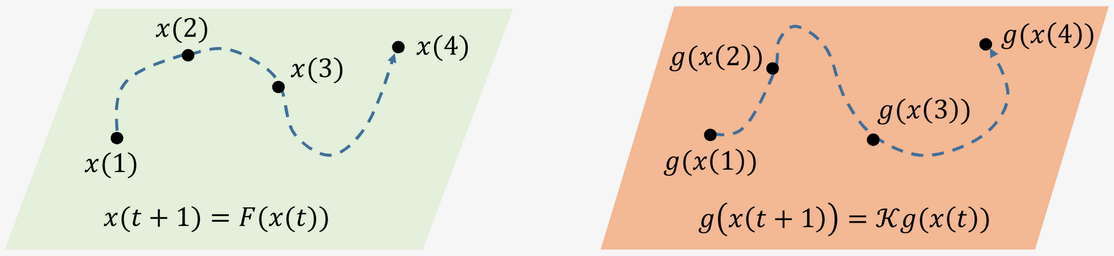
Introduction

- Classical approaches for incident detection rely on some **knowledge of the system topology**, such as in graph-based techniques and methods based on traveling waves.
- With the introduction of PMUs, **data-driven techniques** started receiving more attention, as in the case with SVD-based approaches [1].
- Our proposed approach draws on Koopman operator theory, which accounts for the **causal relationship** among multiple sensor data streams **without prior knowledge of the dynamic model**.

Koopman Operator Theory

- The Koopman operator $\mathcal{K}$ is a linear operator for the dynamics of $x(t)$ in the observable space.

$$x(t) \underset{F}{\rightarrow} x(t+\delta t) \quad \Leftrightarrow \quad g(x(t)) \underset{\mathcal{K}}{\rightarrow} g(x(t+\delta t))$$



Dynamics in Finite State Space

Dynamics in Infinite Observable Space

- The Koopman operator is infinite-dimensional, making computation impractical.
- Extended Dynamic Mode Decomposition (EDMD) overcomes this issue by providing a finite-dimensional approximation of Koopman operator.
- EDMD uses time-series data and hence it is suitable for data-driven frameworks.
- Incident detection method is formulated as a sparsity-promoting variant of EDMD.

$$\begin{bmatrix} | & | & & | \\ x(1) & x(2) & \dots & x(M+1) \\ | & | & & | \end{bmatrix} \rightarrow \Psi(x) = [\psi_1(x), \dots, \psi_K(x)] \rightarrow \mathcal{K} \approx K = \underset{\mathrm{K}}{argmin} \|\mathrm{A} - \mathrm{GK}\|_F$$

$$A \coloneqq \frac{1}{M}\sum_{i=1}^{M} \Psi\big(x(i+1)\big)^T \Psi\big(\mathrm{x(i)}\big)$$

$$G \coloneqq \frac{1}{M}\sum_{i=1}^{M} \Psi\big(x(i)\big)^T \Psi\big(\mathrm{x(i)}\big)$$

Time-series data

Lifting to observable space through nonlinear basis functions

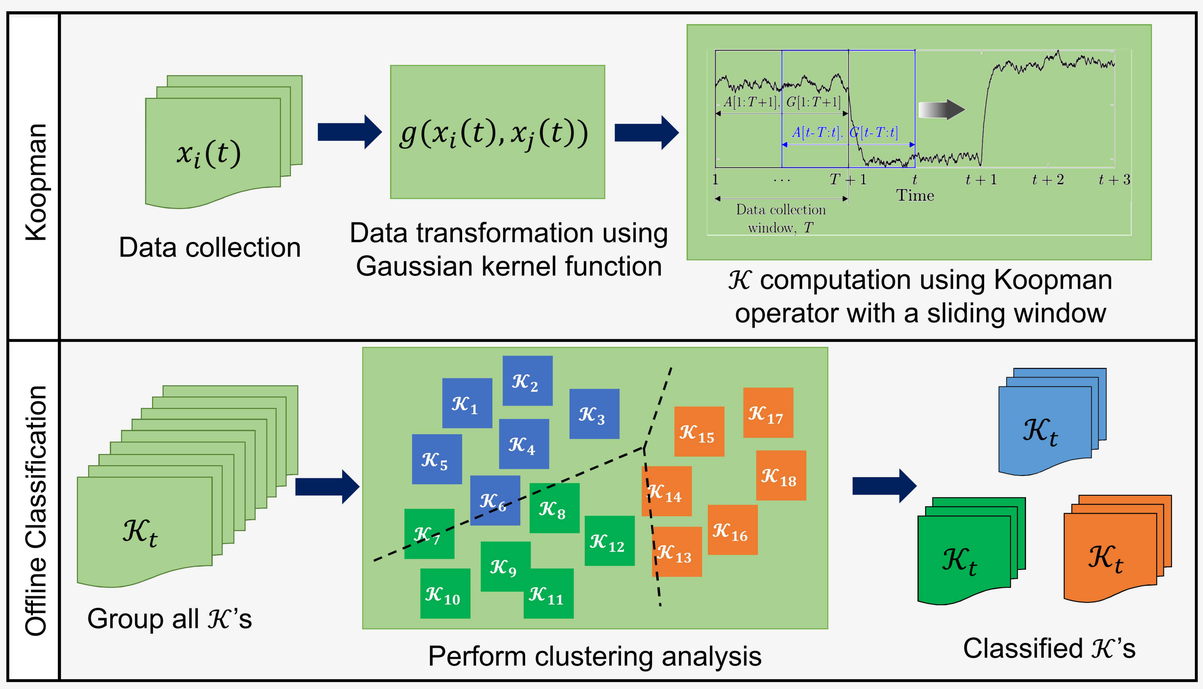
Regression

Methodology for Incident Detection

- We hypothesize that the relationship between different time-series data carries more information than individual data streams.
- Instead of using raw data for the incident detection via Koopman operators, we augment the data with the use of the Gaussian kernel function.

$$g(x_i, x_j) = \exp\left(-\frac{\left|\left|x_i - x_j\right|\right|^2}{2\sigma}\right)$$

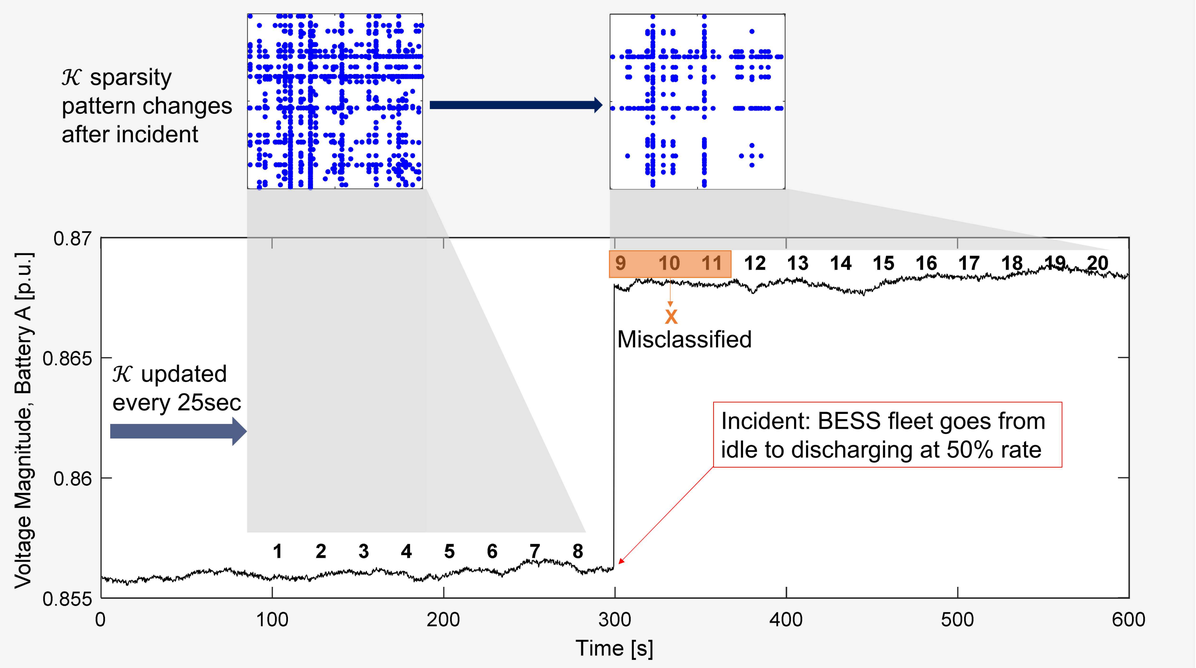
- This nonlinear transformation lifts the data into a higher dimensional space by giving a measure of similarity between states x_i.
- The transformed data is used to compute a sequence of $\mathcal{K}$ matrices through a sliding window, and significant changes in $\mathcal{K}$ indicates altered causality in states (i.e., occurrence of incidents).



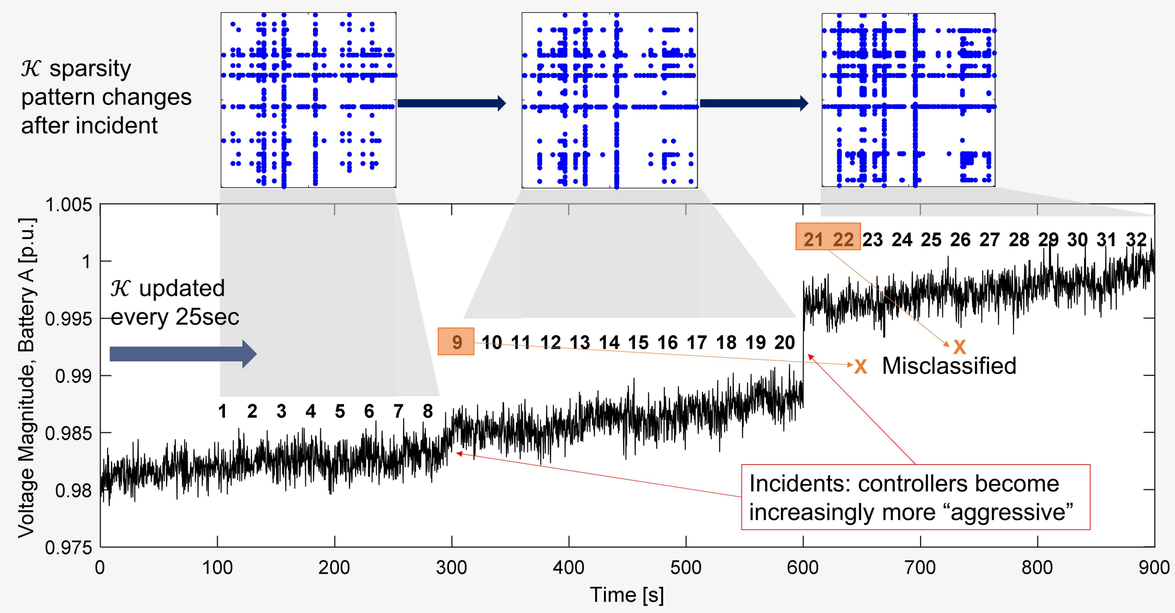
Case Studies

- We considered the IEEE 8500-node Test feeder unbalanced radial network with 7 grid battery energy storage systems (BESS) added.
- BESS can perform Volt/VAR control and take real power dispatch commands.
- The data was generated in OpenDSS, assuming voltage magnitude and phase measurements from PMUs were available at the nodes of 3 of these BESS.
- Gaussian noise was added to the voltage magnitude ($\pm 0.01\%$) and voltage angle ($\pm 0.01°$) measurements.
- Fluctuations in load real and reactive power were considered in the feeder model.
- Changes in the sparsity pattern of the $\mathcal{K}$ matrices indicated the occurrence of an incident.
- To confirm the $\mathcal{K}$ matrices had unique sparsity patterns for each scenario in which the causality of the model was maintained, an offline analysis was performed using k-means clustering to classify these matrices.
- Typical results showed misclassifications immediately after incidents occurred, while remaining $\mathcal{K}$'s were correctly classified.

1) Detecting changes in battery discharge rate



2) Detecting changes in battery controller parameters



Conclusion

- In a distribution network with energy storage systems and advanced controls, traditional monitoring and protection schemes are not well suited for detecting anomalies such as malfunction of controllable devices.
- We propose a data-driven method that requires no prior knowledge of the network dynamic model for the detection of these anomalies.
- The algorithm proposed is robust to load variations and noise measurements.

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References

[1] J. M. Lim and C. L. DeMarco, "Svd-based voltage stability assessment from phasor measurement unit data," IEEE Transactions on Power Systems, vol. 31, no. 4, pp. 2557–2565, 2016.