Incident Detection in Power Distribution Systems

Nayara Aguiar[1], Jamal Al Hourani[1], Vijay Gupta[1], Rodrigo Trevizan[2], Babu Chalamala[2], Raymond Byrne[2]

[1] University of Notre Dame, Department of Electrical Engineering
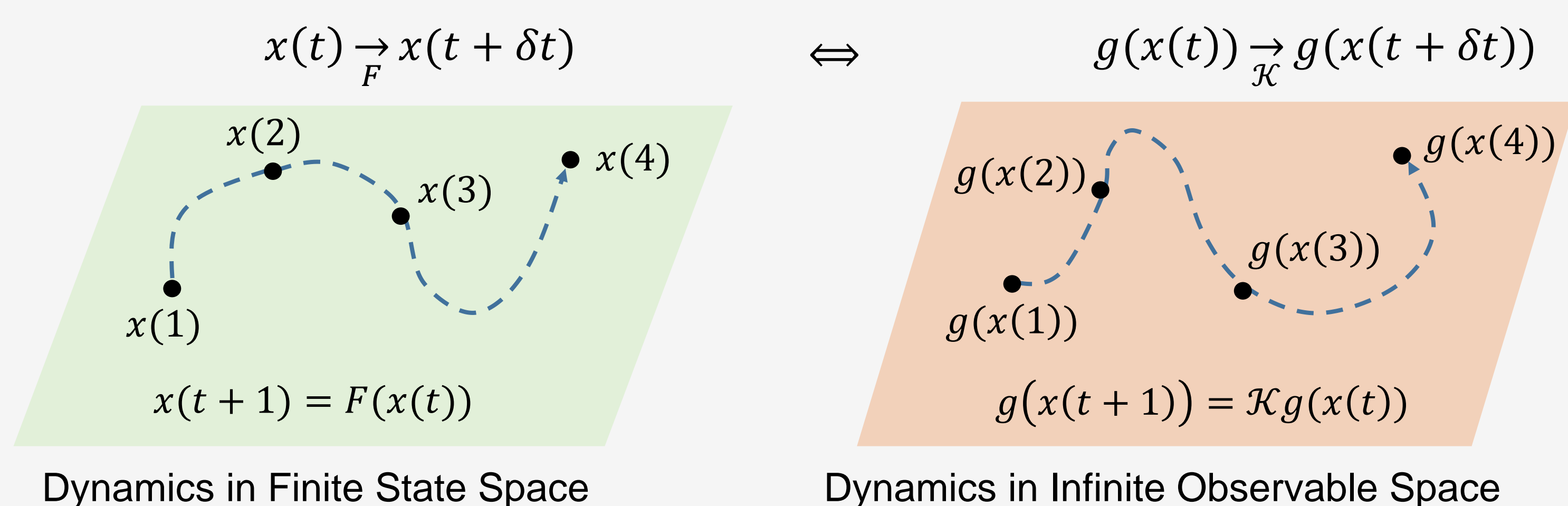[2] Sandia National Laboratories, Energy Storage Technology and Systems Department
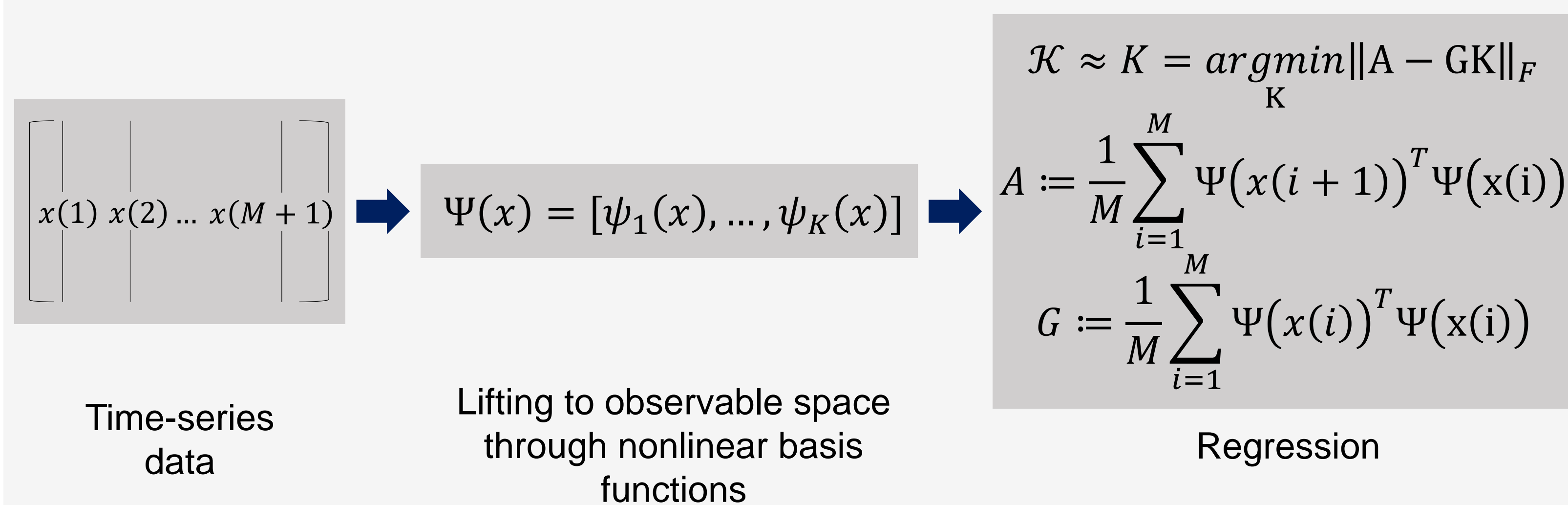
Introduction

- 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.

$$x(t) \underset{F}{\to} x(t + \delta t) \qquad \Longleftrightarrow \qquad g(x(t)) \underset{\mathcal{K}}{\to} g(x(t + \delta t))$$

$$x(t + 1) = F(x(t))$$
Dynamics in Finite State Space

$$g(x(t + 1)) = \mathcal{K}g(x(t))$$
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.

$$x(1)\ x(2)\ ...\ x(M+1)$$
Time-series data

$$\Psi(x) = [\psi_1(x), ..., \psi_K(x)]$$
Lifting to observable space through nonlinear basis functions

$$\mathcal{K} \approx K = \underset{K}{argmin}\|A - GK\|_F$$
$$A := \frac{1}{M}\sum_{i=1}^{M}\Psi\big(x(i+1)\big)^T\Psi(x(i))$$
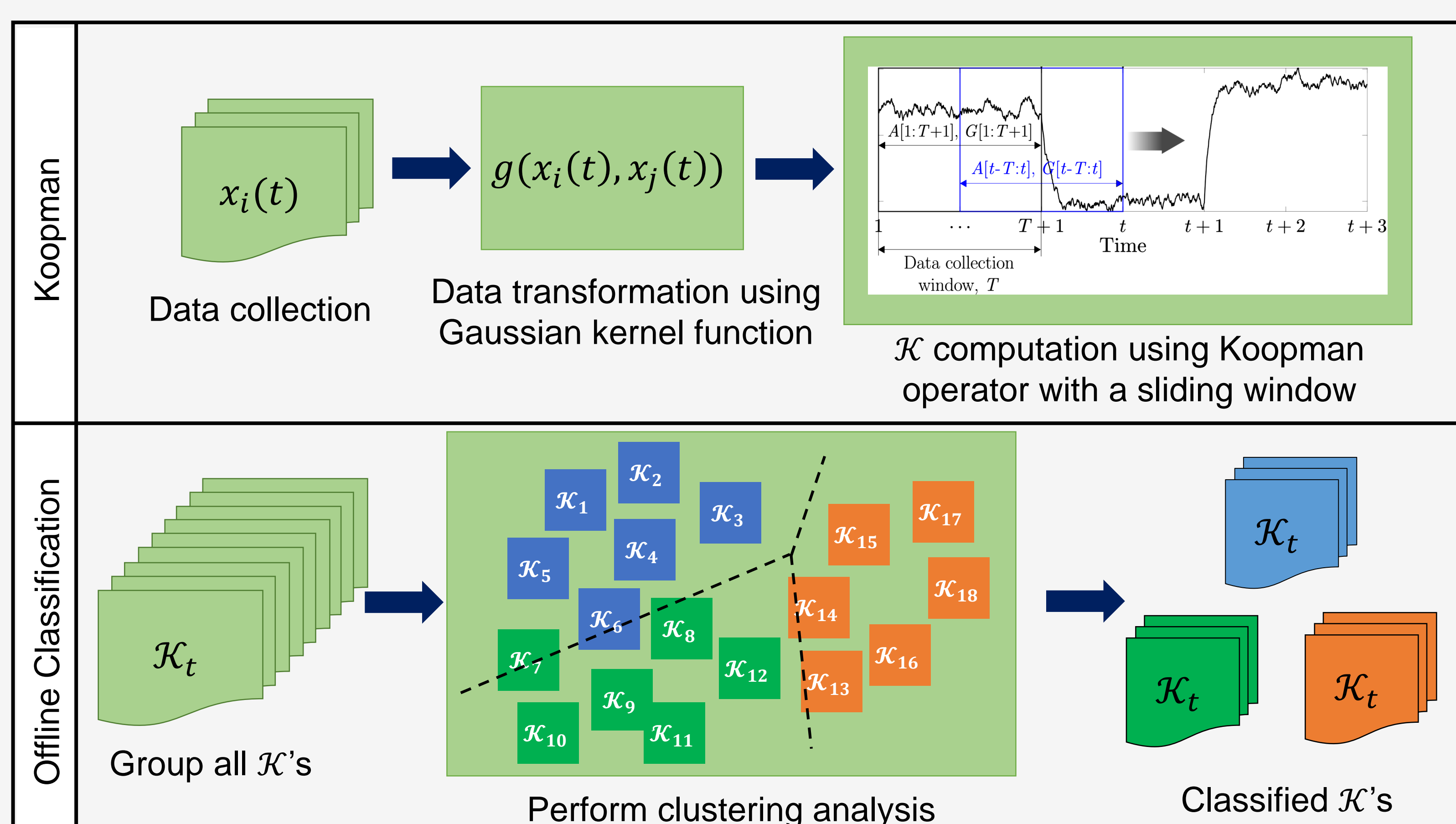$$G := \frac{1}{M}\sum_{i=1}^{M}\Psi\big(x(i)\big)^T\Psi(x(i))$$
Regression

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.

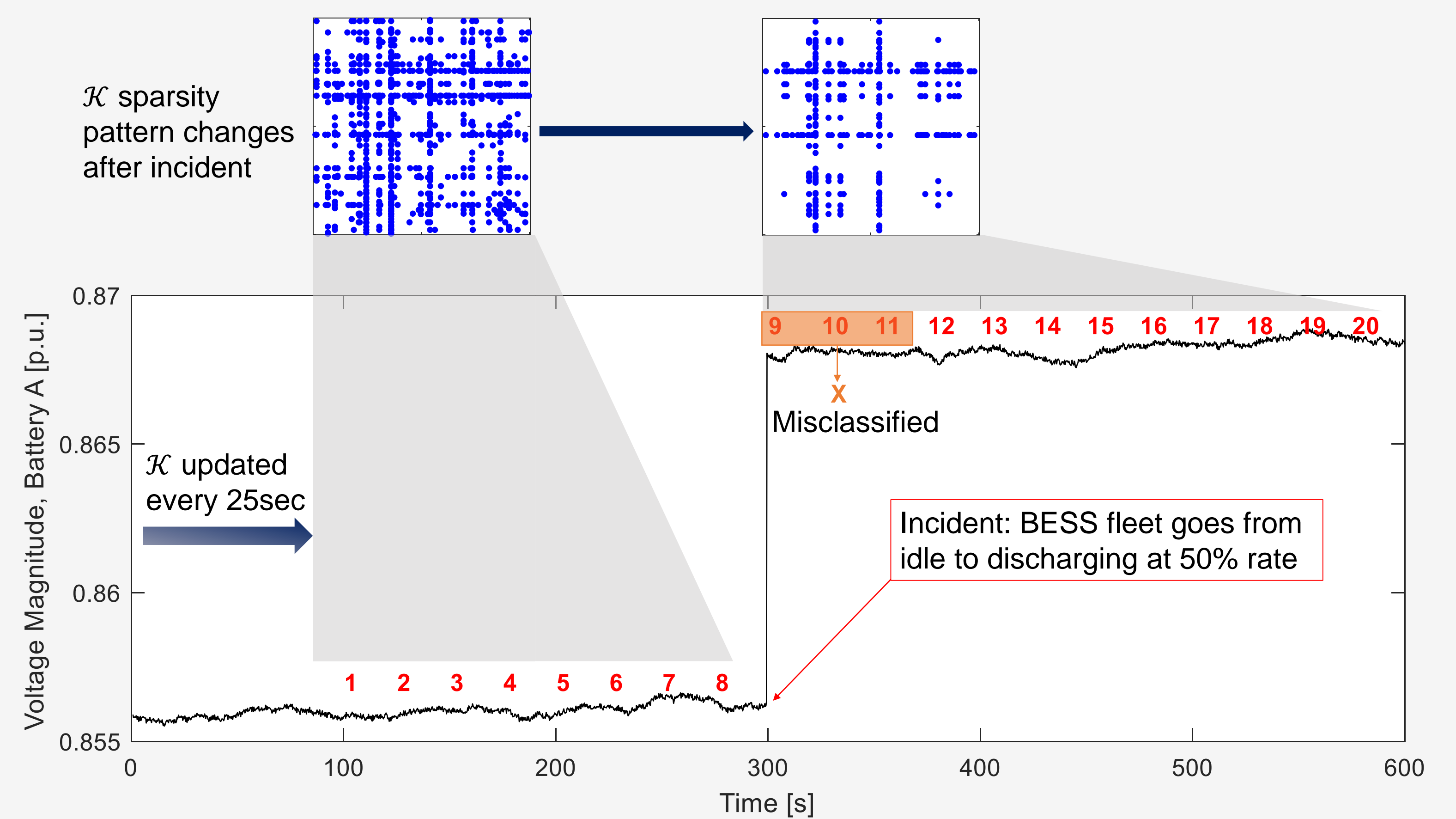$$g(x_i, x_j) = \exp\left(-\frac{\big\|x_i - x_j\big\|^2}{2\sigma}\right)$$

- 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).

Koopman

$x_i(t)$
Data collection

$g(x_i(t), x_j(t))$
Data transformation using Gaussian kernel function

$\mathcal{K}$ computation using Koopman operator with a sliding window

Offline Classification

$\mathcal{K}_t$
Group all $\mathcal{K}$'s

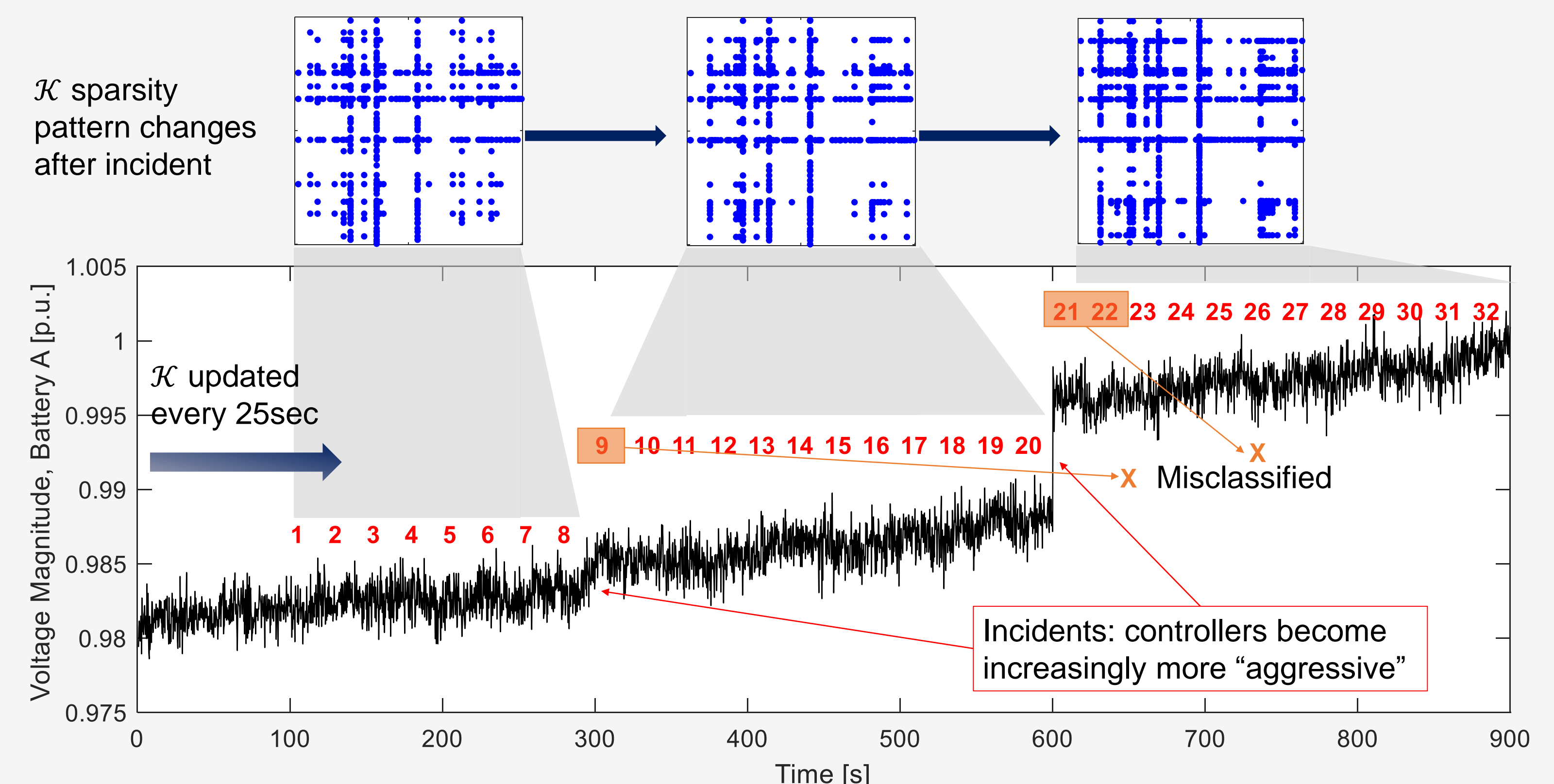Perform clustering analysis

Classified $\mathcal{K}$'s

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 ($\pm0.01\%$) and voltage angle ($\pm0.01°$) 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

$\mathcal{K}$ sparsity pattern changes after incident

$\mathcal{K}$ updated every 25sec

Misclassified

Incident: BESS fleet goes from idle to discharging at 50% rate

2) Detecting changes in battery controller parameters

$\mathcal{K}$ sparsity pattern changes after incident

$\mathcal{K}$ updated every 25sec

Misclassified

Incidents: controllers become increasingly more "aggressive"

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.

Acknowledgements

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.