# Adaptive Kalman Filtering for Robust Power System State Tracking

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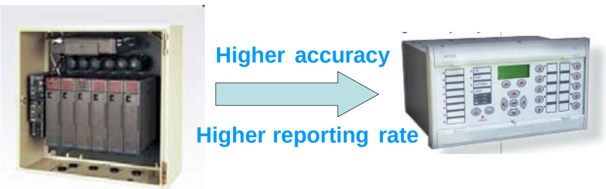
## Kalman Filters (KF) in Power System State Estimation

• For decades, the Kalman filter (KF) has been extensively studied and applied as a powerful method for dynamic state estimation.

• The possibility of applying the KF to the dynamic state estimation of modern power grid systems has always seemed appealing, however it has proven challenging given the **highly complex and dynamic** nature of the state in modern power systems, and the relatively **low measurement rate** of traditional Remote Terminal Units (**RTU**s) from the Supervisory Control and Data Acquisition (SCADA) systems (intervals of several seconds).

• However, given new phasor measurement technologies the KF once again seems promising for estimating dynamic power system states, with **high frequency and synchronized data** provided by Phasor Measurement Units (**PMU**s).




- Traditional Remote Terminal Units (RTUs)
- Data not synchronized, about 5 seconds per sample
- Traditional State Estimation: updated every 2~3 minutes

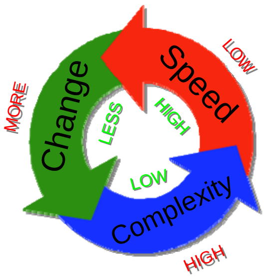
- Novel Phasor Measurement Units (PMUs)
- Data synchronized by GPS techniques, about 30 samples per second
- Real-time Estimation?

## Challenges

• **Computational burden with large-scale data processing**

• **Unknown system dynamics and erroneous measurements**

## How to handle large-scale data processing with limited computational resource?

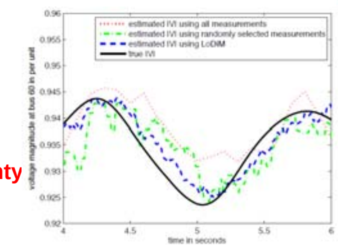


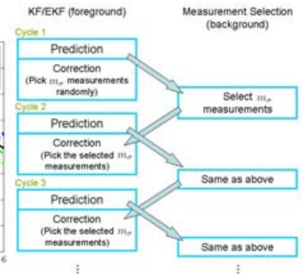

• When the number of measurements ($m$) to be processed per cycle is large, calculating the **Kalman gain** is expensive (**$O(m^3)$**)

• We proposed the Lower Dimensional Measurement-space (**LoDiM**) state estimation algorithm

• The **LoDiM** algorithm we proposed has a background-running **measurement selection procedure,** which analyzes the error covariance matrix per cycle using **Principal Component Analysis** (PCA), then create a "**ranking vector**" for all measurements

• LoDiM selects only a **subset of measurements** per cycle with most "value" --- largest **sensitivity-to-uncertainty** ratio




## How to deal with unknown system dynamics and erroneous measurements?

*"All models are wrong, but some are useful"*

*---George Box*

• Kalman filters achieve optimal performance when system noise characteristics have known statistical properties (zero-mean, Gaussian, and spectrally white…)

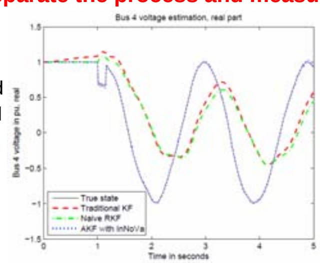
• Estimates using traditional Kalman filters can deviate from truth fast when facing **unknown system dynamics** and/or **erroneous measurements**

• We developed Adaptive Kalman Filter with Inflatable Noise Variances (**AKF with InNoVa**)

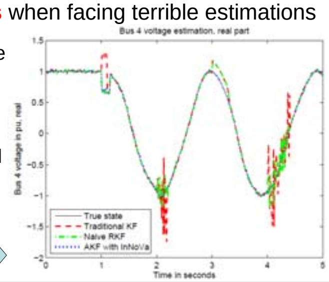
• **AKF with InNoVa** employs a **normalized a priori innovation test** and a **normalized a posteriori innovation test**, to adjust process/measurement noise cov. separately on the fly

• It can **separate the process and measurement factors** when facing terrible estimations

Performance with wrong modeling and a mulfunctioned device




Performance with several noise interfered devices




## Expected Contributions

• When the massive measurement data processing and limited computational resources become obstacles in real-time state estimation, **LoDiM has the potential to strategically reduce measurement dimension, and dynamically adjust the filter to available computational resources**

• If hypothetical models do not match actual models, and/or the measurements contains significant errors, **AKF with InNoVa can help identify and reduce the impact of incorrect system modeling and/or erroneous measurements**

• AKF with InNoVa adjusts noise covariances, making it possible to **incorporate AKF with InNoVa into the LoDiM algorithm, so that it will focus on the faster changing state subspace and avoid selecting potentially bad measurements**

## Contact

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