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FNSNF

New Adaptive Kalman Filter for Step-Varying Processes: Application to Smart Grid State Estimation

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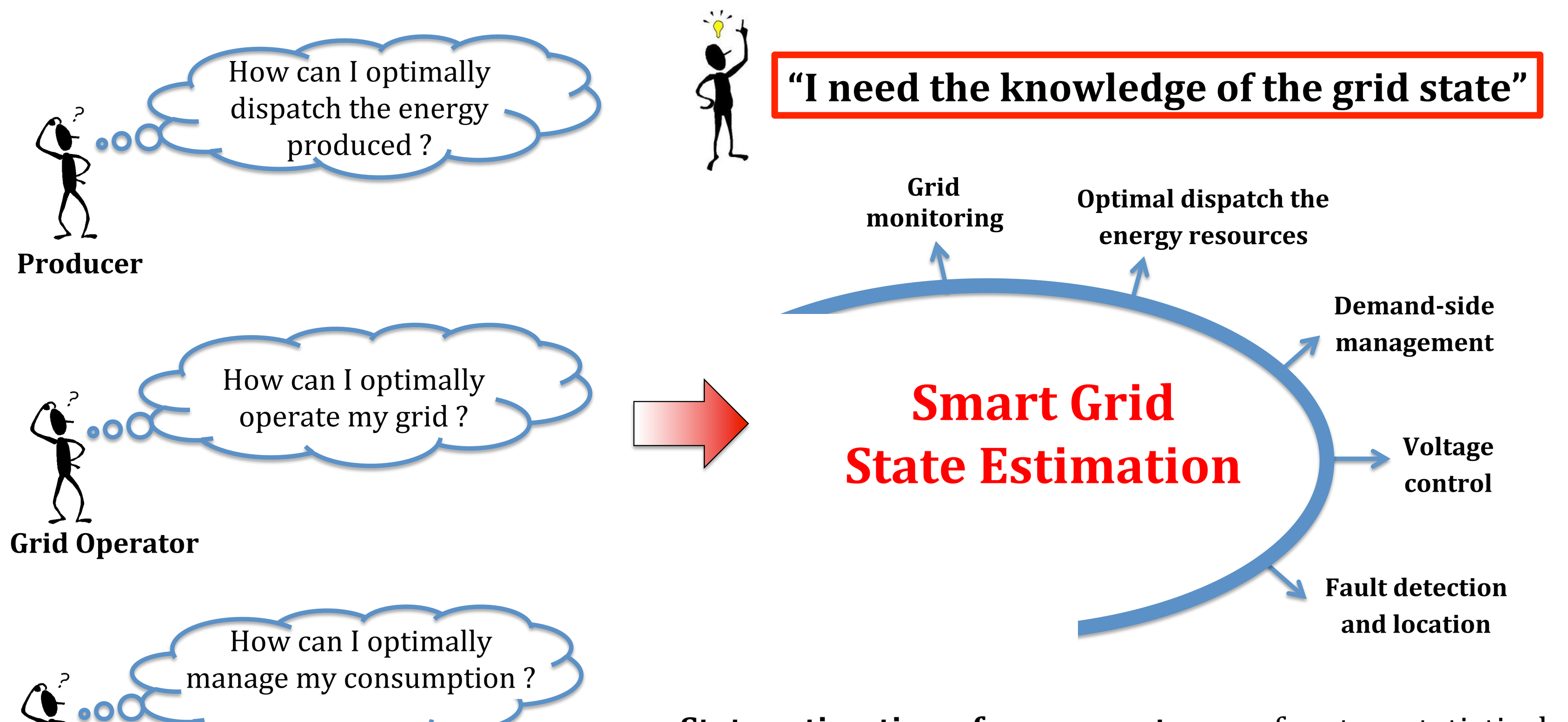
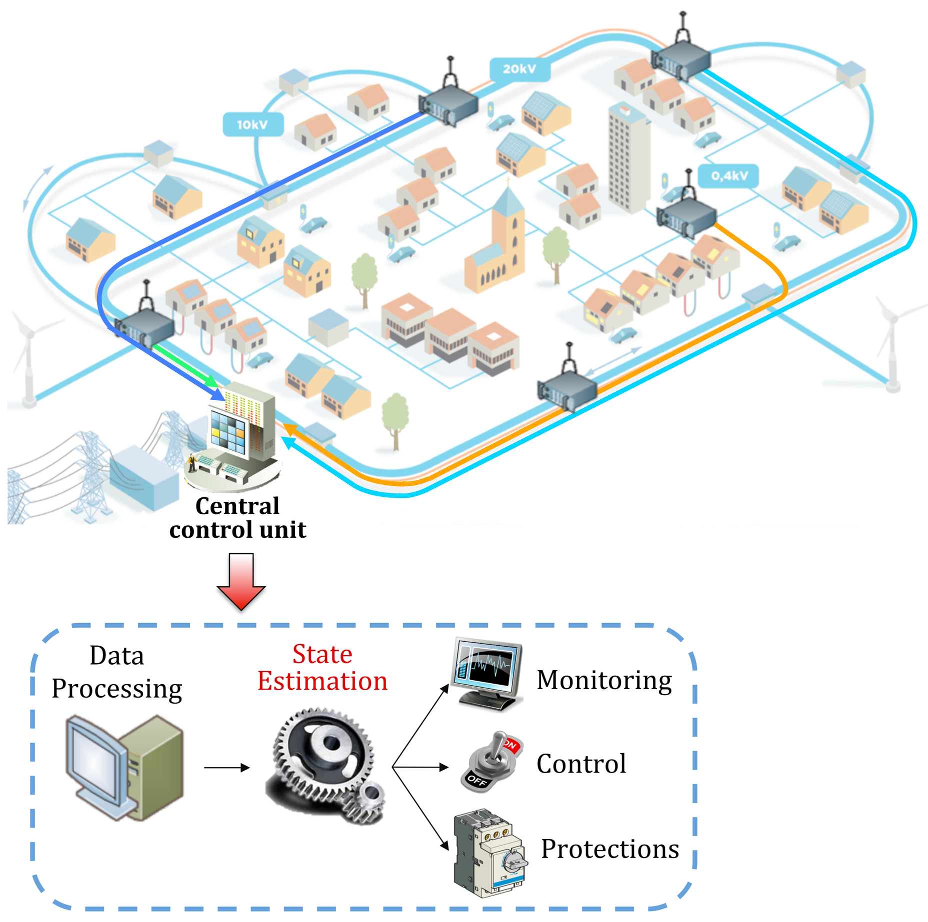
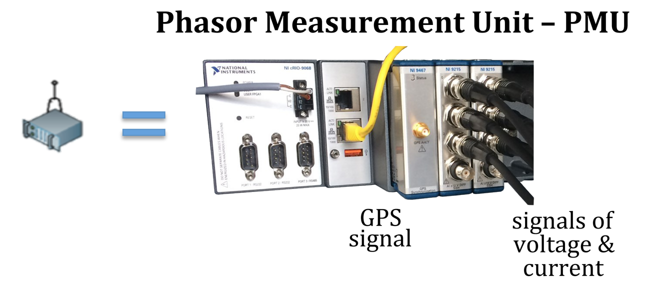
Why State Estimation in Smart Grids

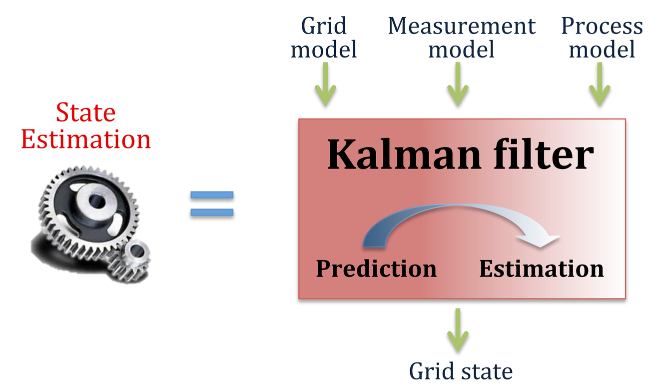


State estimation of power systems refers to a statistical procedure that processes the measurements in order to provide the most likely grid state (i.e. voltages, currents, power flows, etc.).

The Concept







Adaptive Kalman Filter for Step-varying Processes

The challenge

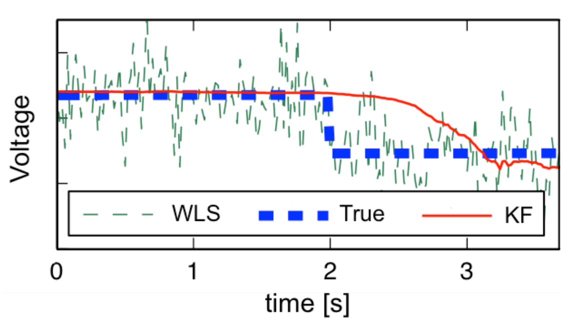
Measurement model
(known, linear, exact)

$$\underset{\text{meas. set}}{\mathbf{z}_k} = \mathbf{H}\underset{\text{state}}{\mathbf{x}_k} + \underset{\text{meas. noise}}{\mathbf{v}_k} \sim N(0,\mathbf{R})$$

Process model
($\mathbf{Q}_k$ is unknown !)

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \underset{\text{process noise}}{\mathbf{w}_k} \sim N(0,\mathbf{Q})$$

Grid state step-variation



Problem:
the KF is not able to track state step-variations if the process model uncertainty remains unchanged !

The new PECE method to cope with state step-variations

Kalman filter equations

Prediction

$$\tilde{\mathbf{x}}_k = \hat{\mathbf{x}}_{k-1}$$
$$\tilde{\mathbf{P}}_k = \hat{\mathbf{P}}_{k-1} + \mathbf{Q}_k$$

Innovation

$$\mathbf{y}_k = \mathbf{z}_k - \mathbf{H}\mathbf{x}_k$$
$$\mathbf{S}_k = \mathbf{H}\tilde{\mathbf{P}}_k\mathbf{H}^T + \mathbf{R}$$

Estimation

$$\mathbf{K}_k = \tilde{\mathbf{P}}_k\mathbf{H}^T + \mathbf{S}_k^{-1}$$
$$\hat{\mathbf{x}}_k = \tilde{\mathbf{x}}_k + \mathbf{K}_k\mathbf{y}_k$$
$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H})\tilde{\mathbf{P}}_k$$

The PECE method
(Prediction Error Covariance Estimation)

Convex optimization problem

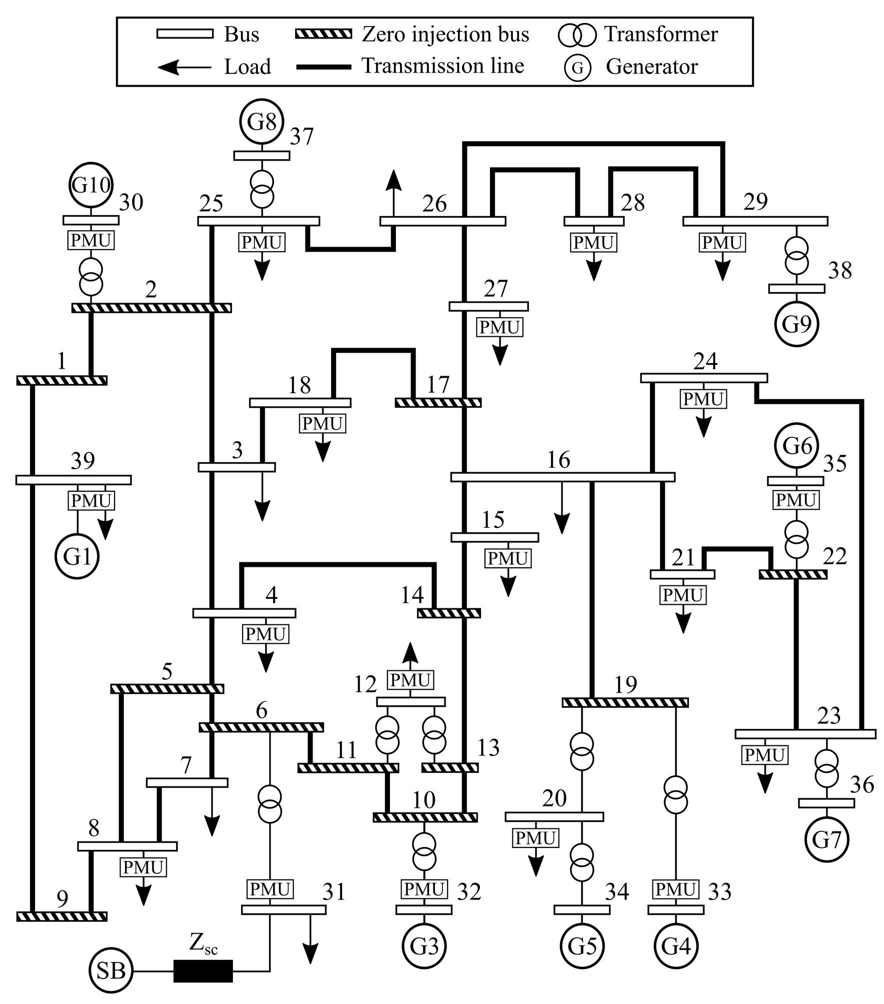
$$\min_{\Sigma_k}\left\{-\log\left(\det\Sigma_k\right) + trace\left(\Sigma_k\mathbf{C}_k\right)\right\}$$
$$\text{subject to:}\quad \Sigma_k \geq 0$$
$$\mathbf{R}^{-1} - \Sigma_k \geq 0$$

$$\mathbf{C}_k = \mathrm{cov}(\mathbf{y}_k,\ldots,\mathbf{y}_{k-N+1}) \qquad \hat{\mathbf{C}}_k = \Sigma_k^{-1}$$

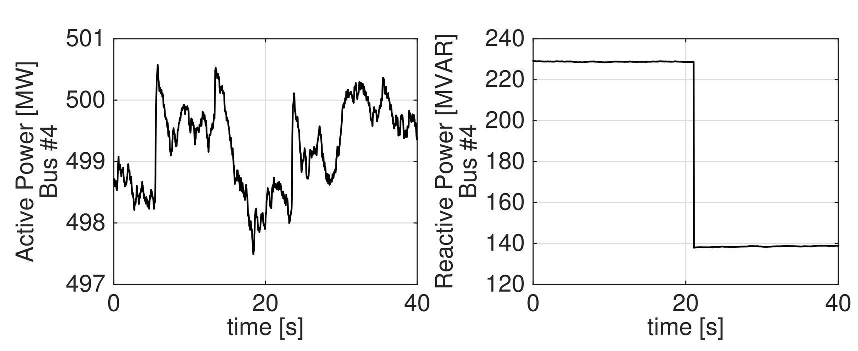
$$\hat{\mathbf{C}}_k = \mathbf{H}\tilde{\mathbf{P}}_k\mathbf{H}^T + \mathbf{R} \;\rightarrow\; \tilde{\mathbf{P}}_k \text{ estimated}$$

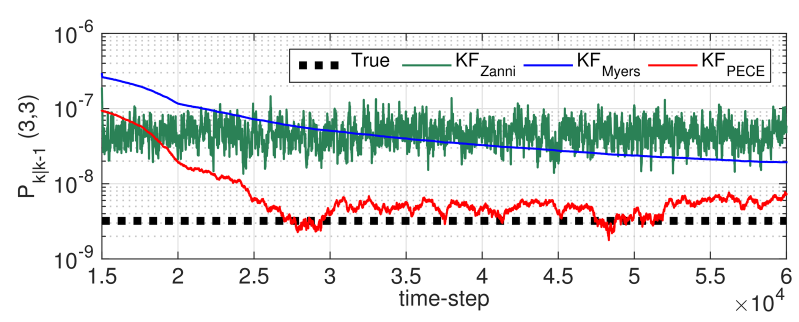
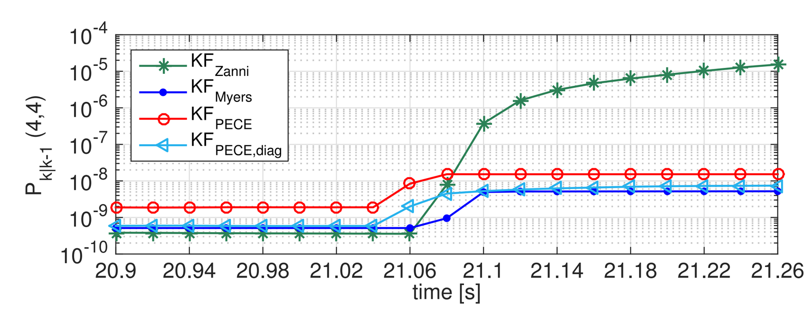
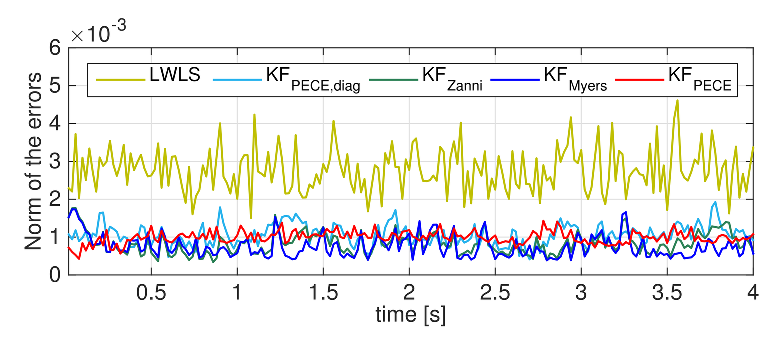
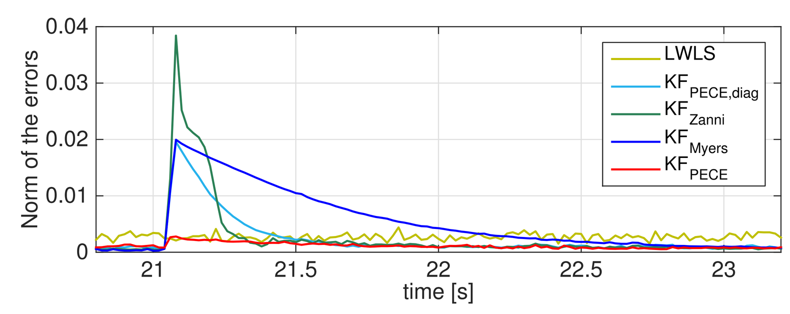
Numerical validation: application to smart grid state estimation

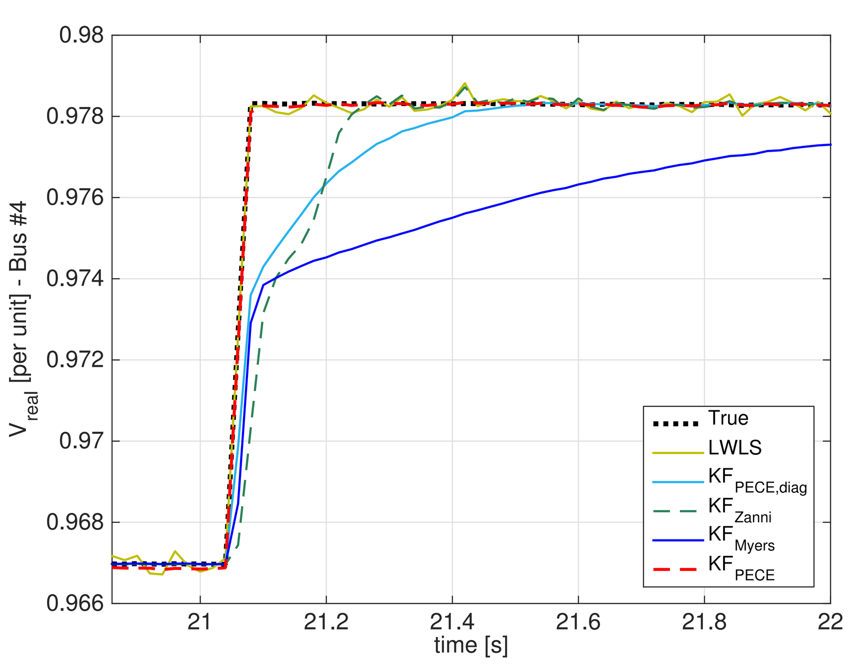
New England 39-bus test system



Simulated step-variation of reactive power at bus #4



	Stationary	Step-variation
Estimated $\tilde{\mathbf{P}}_k$		
Estimation error		



Conclusions:

- For the first time in the literature we have proposed a method that
  - correctly estimates the true value of $\mathbf{P}_k$ for processes characterized by constant noise covariances, and
  - rapidly tracks the system state subject to large state step-variations.
- **Convex optimization problem** to ensure the **symmetry and positive semidefiniteness** of $\mathbf{P}_k$.
- **Setting of a single parameter** N, so that the parameter tuning for specific applications is simplified.
- **Off-diagonal entries** of $\mathbf{P}_k$ play an important role for the proper tracking of state step-variations.
- **Drawback**: computationally expensive for high-dimensional systems.