nano-tera.ch
swiss scientific initiative in health / security / environment systems

SmartGrid RTD 2013

Real-Time State Estimation of Active Distribution Grids using the Kalman Filter

L. Zanni, R. Cherkaoui, and M. Paolone

EPFL

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Why State Estimation in Smart Grids

Producer: How can I optimally dispatch the energy produced ?

Grid Operator: How can I optimally operate my grid ?

Consumer: How can I optimally manage my consumption ?

"I need the knowledge of the grid state"

Real-Time State Estimation

- Accurate
- fast (sub-second)
- Reliable

Grid monitoring · Optimal dispatch the energy resources · Demand-side management · Voltage control · Fault detection and location

State estimation is a statistical procedure that processes the measurements in order to get the most likelihood state of the grid (voltages, currents, power flows, etc.).

Main Features of our State Estimator

PMU Measurements: **voltage** and **current synchrophasors** (amplitude and phase):

very accurate · very frequent (every 20 milliseconds) · synchronized

The use of PMU measurements leads to an **exact measurement model**, therefore the **state estimation algorithm is not iterative (increasing speed and accuracy).**

Kalman Filter algorithm: recursive state estimator that processes the measurements, but also **predicts the state of the grid**.

Phasor Measurement Unit – PMU

Grid parameters → Measurement model → Prediction model → **Kalman Filter** ("Prediction" Time Update, "Estimation" Measurement Update) → Grid state

Kalman Filter state estimator adapted to active distribution grids

Background and Challenge:

State Estimation is performed only in **transmission grids** using the well-known **Weighted Least Squares (WLS) algorithm**.

Kalman Filter, although in principle can provide better results, **has never been applied** to power grids because of:

- **its computational complexity and implementation;**
- **difficulty to define an exact prediction model including its covariance matrix.**

Adopted Prediction Model:

Kalman Filter prediction:

$\hat{\mathbf{x}}_k, \hat{\mathbf{P}}_k$ — Estimated state and its covariance at time-step k → $\tilde{\mathbf{x}}_{k+1}, \tilde{\mathbf{P}}_{k+1}$ — Predicted state and its covariance for the next time-step $k+1$

The adopted Prediction Model is:

ARIMA (0,1,0)

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

simple (no parameters) · suitable for high-rate state estimators

The covariance matrix $\mathbf{Q}$ represents the uncertainty of the prediction.

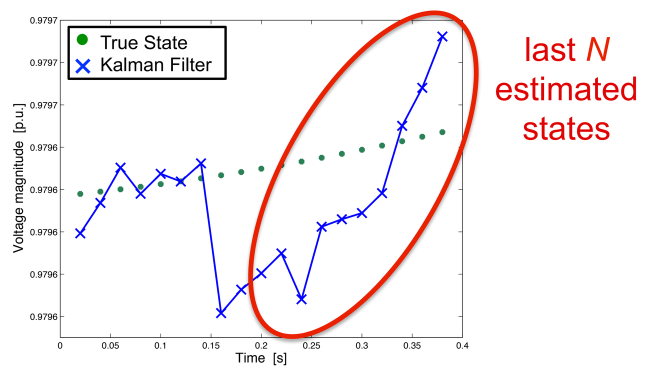
Proposed Q Assessment Method:

We assess the matrix $\mathbf{Q}$ on-the-fly using the last N estimated states:

$$\mathbf{y}_j = \hat{\mathbf{x}}_{k-j} - \hat{\mathbf{x}}_{k-N} \quad (j = 1, \ldots, N)$$

$\mathbf{Q}$ is the sample variance of the vector of the residuals $\mathbf{y}$:

$$\mathbf{Q}_k = \mathrm{var}(\mathbf{y}_1, \ldots, \mathbf{y}_N)$$



Kalman filter vs. WLS:

As long as the true state $\mathbf{x}_k$ satisfies the adopted prediction model

the **Kalman filter always outperforms the Weighted Least Squares (WLS)**, as shown in the theorem below:

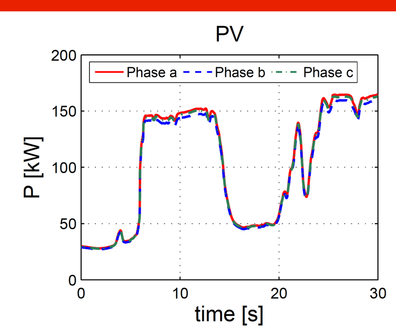
Theorem.

$$\mathbb{E}\left(\|\mathbf{x}_k - \hat{\mathbf{x}}_{k,LWLS}\|^2\right) = \mathbb{E}\left(\|\mathbf{x}_k - \hat{\mathbf{x}}_{k,DKF}\|^2\right) + \mathbb{E}\left(\|\hat{\mathbf{x}}_{k,LWLS} - \hat{\mathbf{x}}_{k,DKF}\|^2\right)$$

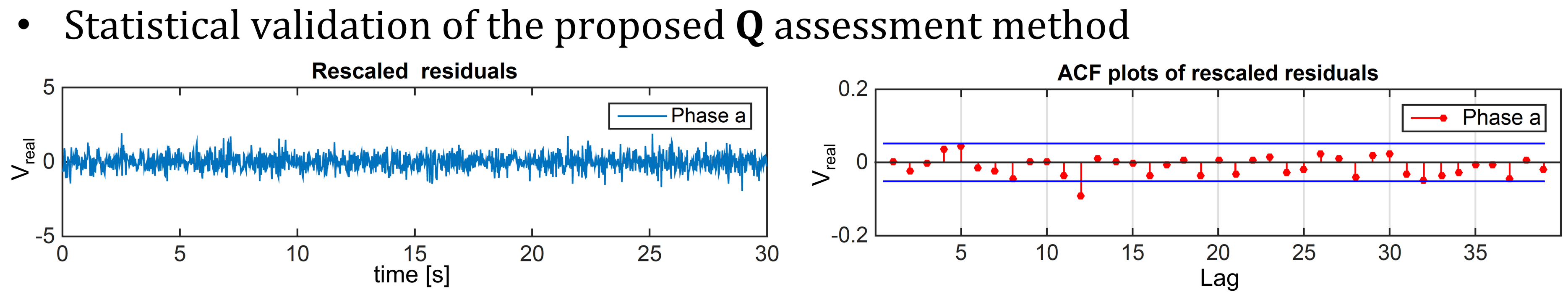
Achievements

Validation
- using several IEEE benchmark grids (13-bus, 34-bus, 123-bus)
- using measurements taken in real distribution grids

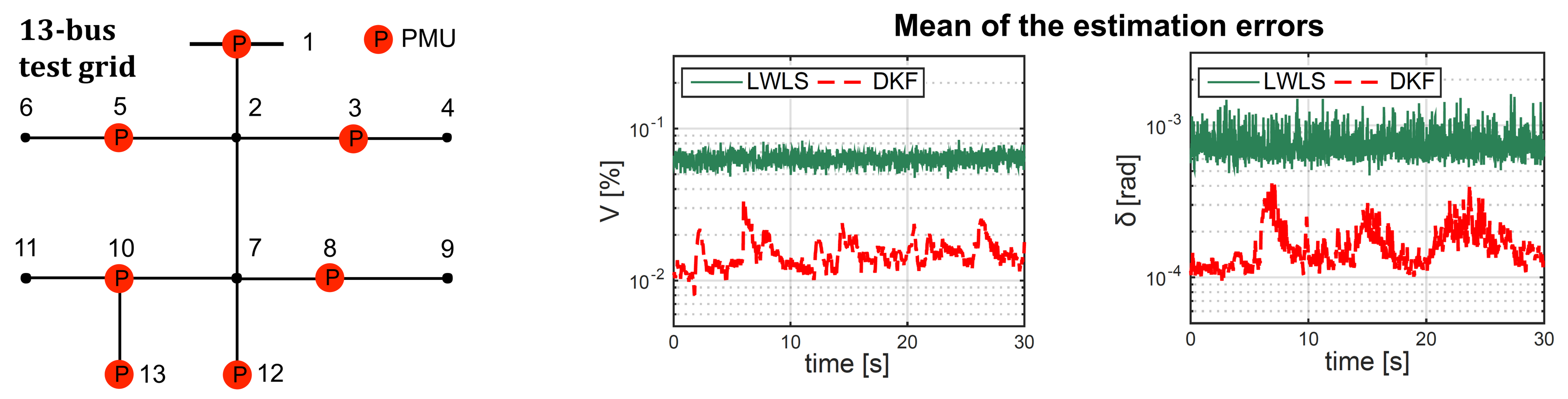
Example: real measurements of the power injected by photovoltaic panels



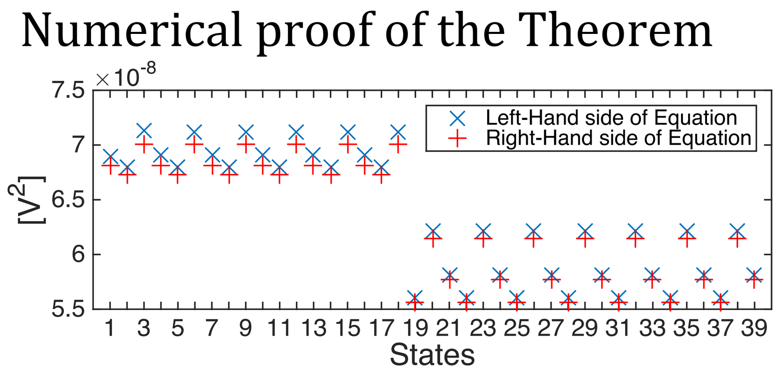
- Statistical validation of the proposed **Q** assessment method



- Accuracy performance: Kalman Filter vs. Weighted Least Squares



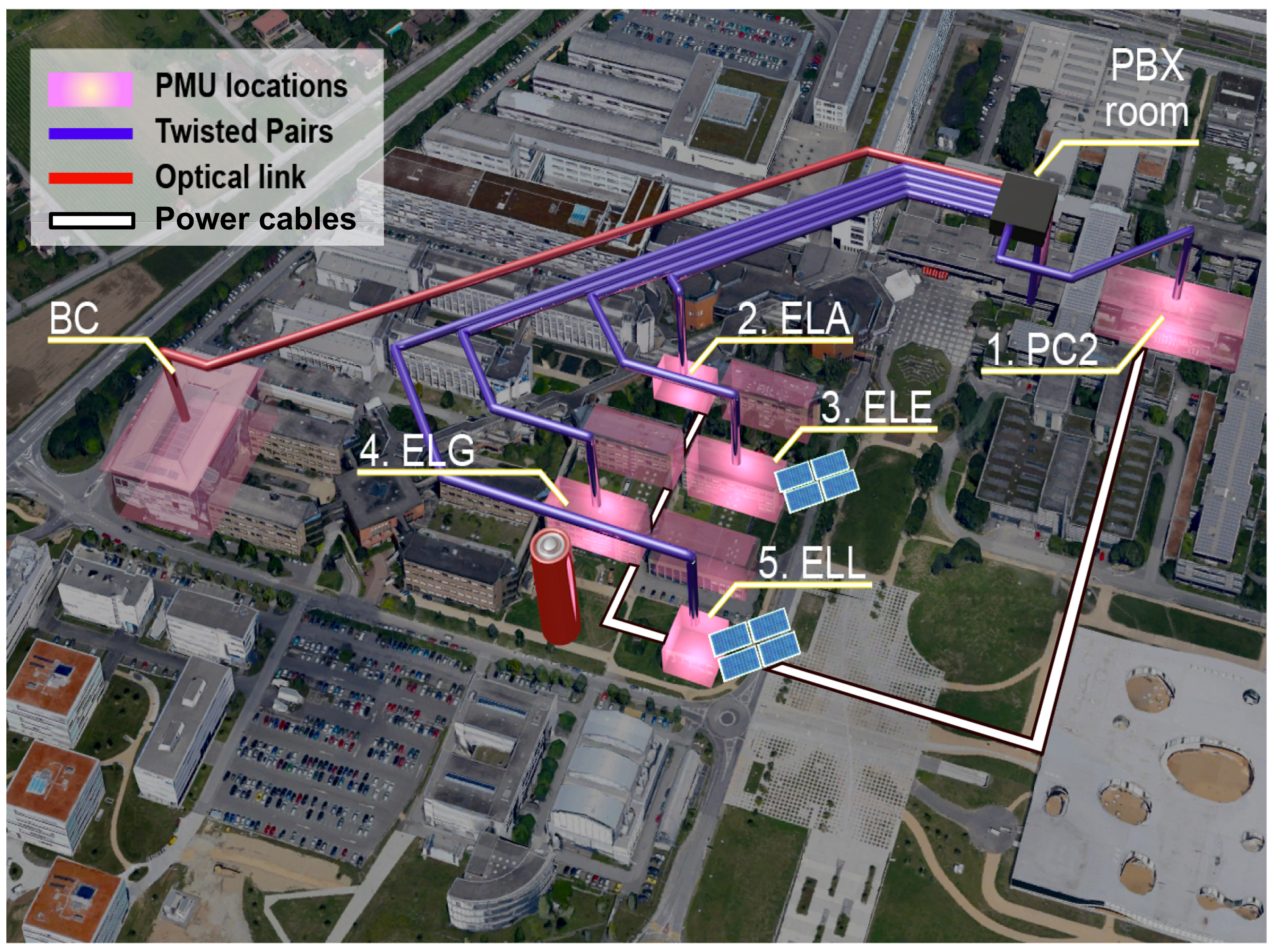
- Numerical proof of the Theorem



- Kalman filter computation time

Grid	Mean ± std [ms]
IEEE 13-bus	0.53 ± 0.065
IEEE 34-bus	4.0 ± 0.40
IEEE 123-bus	100 ± 2.6

Validation using the EPFL power grid



References

L. Zanni, S. Sarri, M. Pignati, R. Cherkaoui, and M. Paolone, "Probabilistic assessment of the process-noise covariance matrix of discrete Kalman filter state estimation of active distribution networks," in *Proc. Intern. Conf. Probabilistic Methods Applied to Power Systems (PMAPS)*, Durham, UK, July 7-10, 2014.

M. Pignati, M. Popovic, S. Barreto Andrade, R. Cherkaoui, German Dario Flores, Jean-Yves Le Boudec, Maaz Mohiuddin, Mario Paolone, Paolo Romano, Styliani Sarri, Teklemariam Tesfay, Dan-Cristian Tomozei, and Lorenzo Zanni, "Real-time state estimation of the EPFL-Campus medium-voltage grid by using PMUs," in *Proc. Conf. Innovative Smart Grid Technologies* (ISGT 2015), Washington, DC, USA, 2015.