IRP 4.3: Advanced Monitoring and Controls of the Electrical Distribution Network

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Controls Lab in GE Global Research

Myself

- Diplomas in Mathematics + Industrial Engineering at UPC Barcelona, Master Thesis at ETH Zurich
- M.S. from Stanford University, focusing on Optimization and Statistical Learning
- Professional experience as Data Scientist at Accenture Analytics and Arcvi (founder)

Supervisors

- Adolfo Anta (Research Engineer at GE Global Research, PhD UCLA)
- Bart De Schutter (Full Professor at TU Delft)

GE Global Research

- R+D division of General Electric. Diversified across all business: Power, Oil & Gas, Renewable Energy, Energy Connections, Aviation, Healthcare, Transportation
- Over 3,000 scientists, engineers and researchers
- Headquartered in Niskayuna, NY; sites in the US, Germany, India, China, Brazil
- **Europe Center**: near Munich, Germany, on the high-tech campus Garching, together with TU Munich and other research institutions. 200 employees, 11 labs
- **Controls Europe Lab:** Part of Electrical Systems Europe, linked to the global Controls, Electronics and Signal Processing (CESP) organization. 13 researchers.

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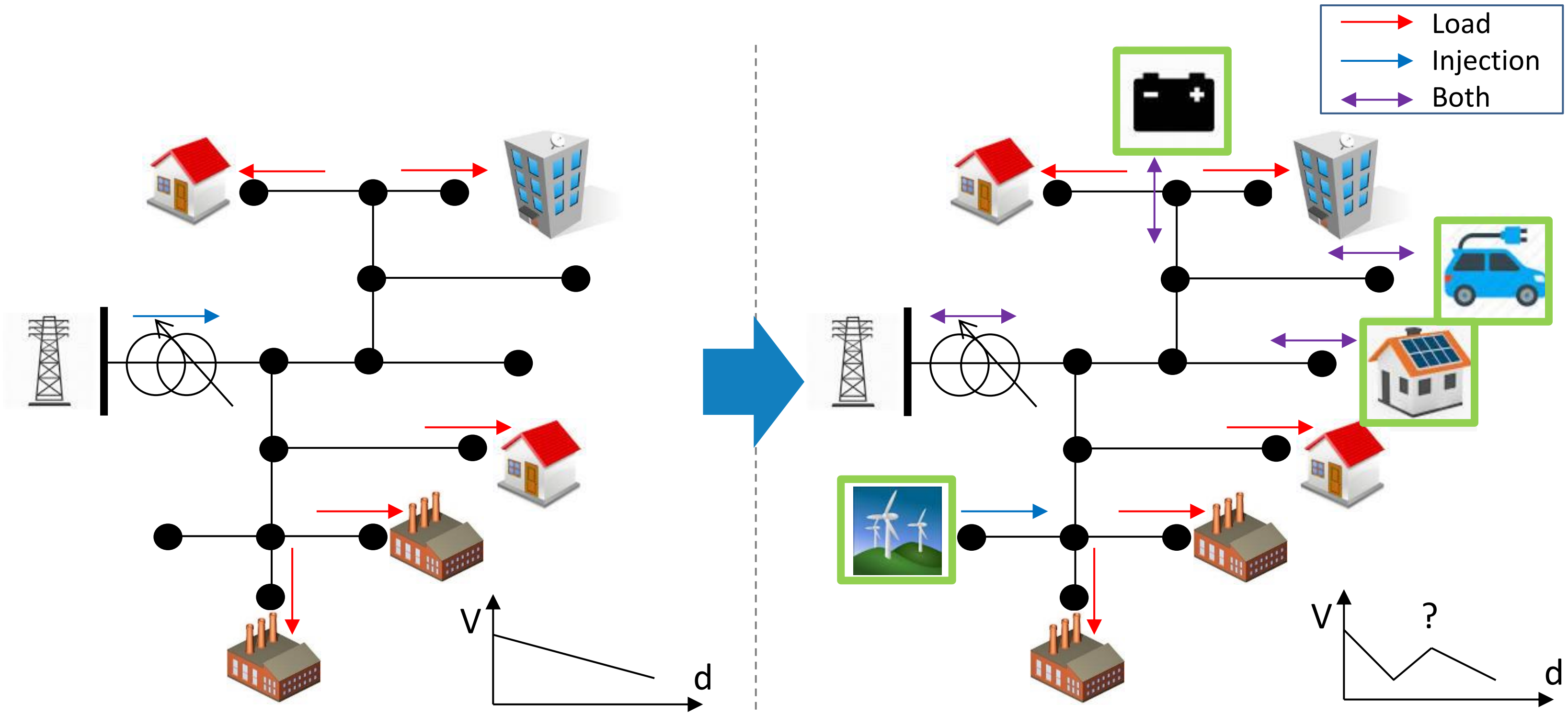
Towards a new distribution grid



- Only passive loads
- Oversized for peak loads
- Few real-time measurement (substation)

→ No need for monitoring, not possible

- Passive loads + Distributed generation
- Reverse power flow, fast changing
- Real-time measurements (PMU, SM)

→ Need accurate estimation, now possible

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My research topic

Monitoring problems in distribution networks

- Large number of buses and loads, but **few measurements available**. Not observable. (opposite to transmission)
- **Expensive** to install all sensors.
- **Coupled 3-phases** and **unbalanced loads**. More complex power flow.
- Simple load allocation methods based on **estimations produce large inaccuracies.**
- **Not prepared** for Distributed Energy Generation (PV, Wind, Electrical Vehicles, etc.).

State Estimation solution

1. State Estimation methods **for distribution networks** (coupled and unbalanced phases)
2. Prior knowledge (loads capacities and forecasts) **+ real-time information** (PMU & SM) → improve robustness and accuracy
3. Minimum **number** and optimal **location of sensors**: +performance, -cost
4. State Estimation for a **better control** of the grid: Voltage regulator, frequency, distributed generation, batteries, etc.

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State Estimation – state of the art

Definitions

Network state variables x:

- Vector of **voltage phasors of all buses,** $x = [V_1, \dots , V_N] \in \mathbb{C}^{2N-1}$.
- Polar coordinates, **magnitude and angle**, $x = [|V_1|, |V_2|, \dots , |V_N|, \theta_2, \dots, \theta_N]^T \in \mathbb{R}^{2N-1}$, $\theta_1 = 0$.

Measurement vector z:

- Loads **estimations,** voltage and current **measurements**, etc.
- **Measurement function** $h()$, from states to measurements: $z = h(x) + \omega$.
- **Measurement noises** $\omega \sim N(0, \sigma)$.

Standards steps in Energy Management Systems

Topology Processor

- Checks state of switches, transformers, etc.
- Network structure & function $h()$

Observa-bility Analysis

- Checks system observability with available measurements
- At least: $\#measurements > 2N - 1$.

Weighted Least Squares Solution

- Optimal estimator: $\hat{x} = argmin_x [z - h(x)]^T W^{-1} [z - h(x)]^T$, W^{-1} covariance matrix of measurement noises.
- Iteratively (Newton-Raphson): $\hat{x}_{k+1} = \hat{x}_k + \left[H_k^T W^{-1} H_k\right]^{-1} H_k^T W^{-1} [z - h(\hat{x}_k)]$, where $H_k = \nabla_x h(x) \,|_{x=\hat{x}_k}$.

Bad Data Process

- Excess of measurements to determine corrupted or malicious data.
- Check statistical outliers

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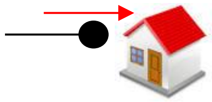
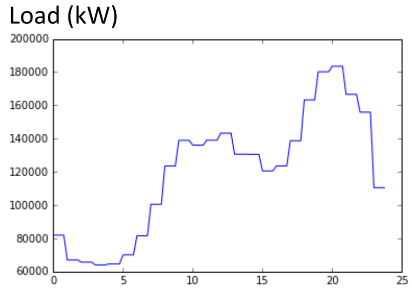
Sources of measurements

Hourly load estimations S_{pseudo}:

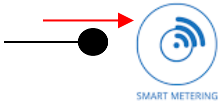
- Based on forecasts and known installed load capacities at every bus.
- **Pseudo-measurements**, not actual measurements. Noise with **large standard deviation**.

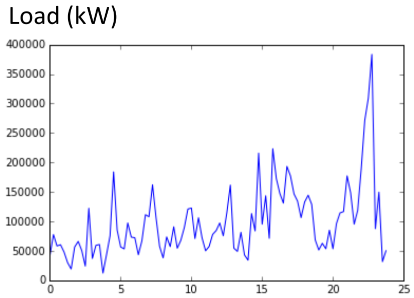




Real-time Measurements VI_{meas}:

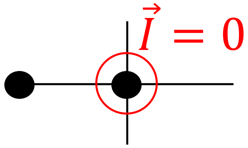
- Real-time information from sensors, **Phasor Measurement Units** or **Smart Meters**.
- Precise, measurement noise with **low standard deviation**.

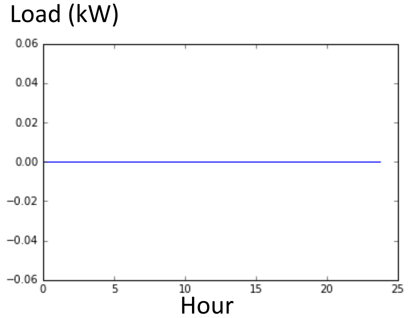




Connection buses (no load):

- Buses with no load. Called **virtual-measurements**.
- Modelized as **physical constraints** to the solution of the problem.





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Methods developed - contributions

① **Include equality constraints through dimension reduction:**

- Instead of Lagrange multipliers for equality constraints.
- **Optimization in sub-space**: $V \in \{V | V = Fx + V_0\}$, with V_0 a particular solution and F the kernel of the matrix with rows of the admittance matrix of connection buses.

② **Split problem into offline + online** (extending Schenato et al., 2014[1]**):**

1. **Prior solution:**
   - Using load pseudo-measurements and virtual-measurements
   - Solve the **Power Flow** problem: $V_{prior} = PowerFlow(S_{pseudo})$
   - **Offline** with iterative method
2. **Updated solution:**
   - Update prior solution with real-time measurements:

   $V_{post} = V_{prior} + K(VI_{meas} - C_{meas}V_{prior})$, C_{meas} is mapping $VI_{meas} = C_{meas}V + \omega$
   - Optimal Bayesian gain K, **minimizing expected covariance** of error:

   $$\Sigma_{post} = E[(V - V_{post})^* (V - V_{post}) | S_{pseudo}, VI_{meas}]$$
   - **Online**. No iterations, low computational cost $O(N^3)$.

Note[1]: L. Schenato, G. Barchi, D. Macii, R. Arghandeh, K. Poolla, and A. Von Meier, "Bayesian linear state estimation using smart meters and pmus measurements in distribution grids," in Smart Grid Communications (SmartGridComm), 2014 IEEE International Conference on.

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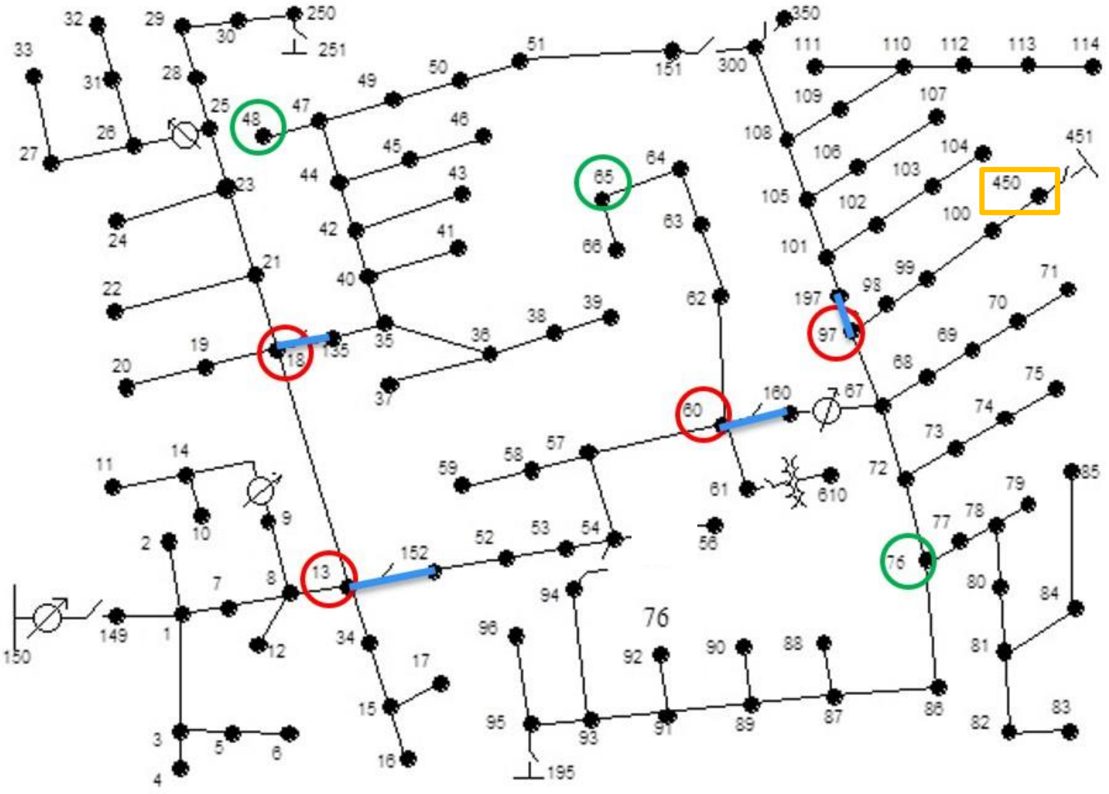
123-bus test feeder + load profile

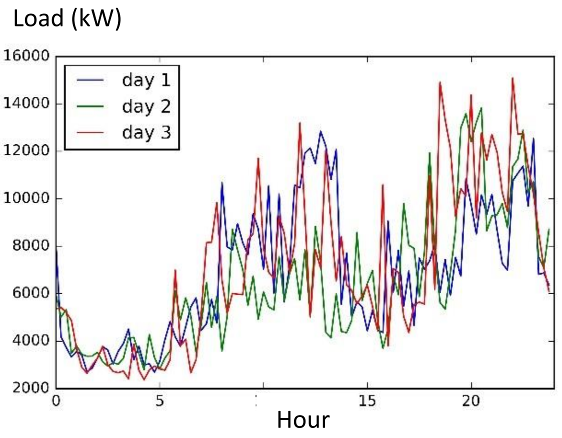
Test feeder[1]



Measurements & DG

○ Voltage meas.
○ Current meas.
— Branch current meas.
▭ Solar Injection

Load profiles



Note[1]: From the IEEE PES Distribution Systems Analysis Subcommittee's Radial Test Feeders.
URL: http://www.ewh.ieee.org/soc/pes/dsacom/testfeeders/index.html

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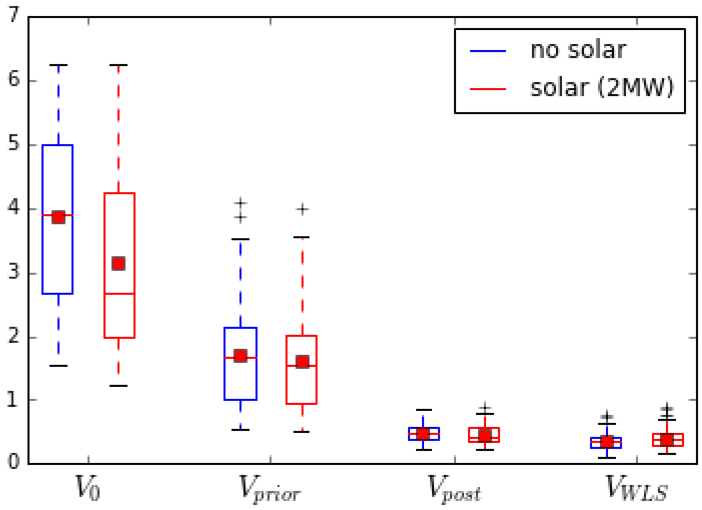
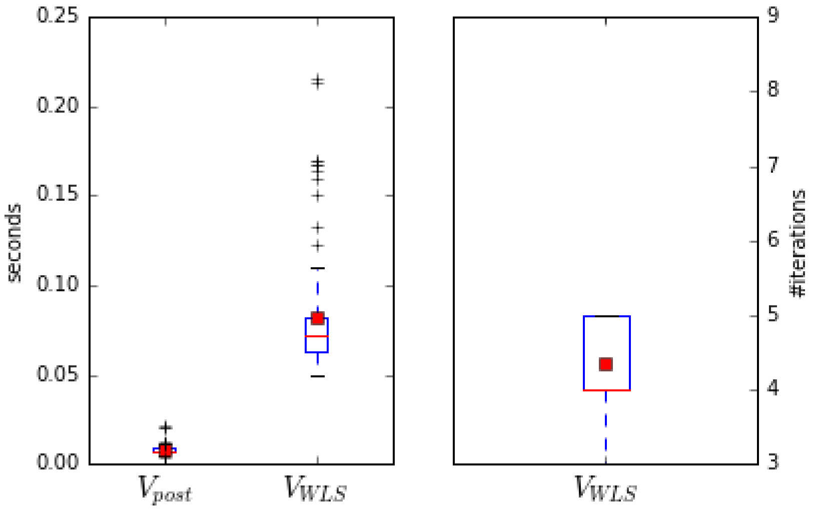
Results & Conclusions

Performance (in MAPE(%)[1])



Execution complexity



Conclusions

- V_{post} almost as good as V_{WLS}
- V_{post} less computation time
- V_{post} more robust
- Both robust to distributed generation

Ongoing & future work

- Include dynamics to account for past information in the sensors
- Optimal cost-efficient sensor placement

Note[1]: Mean Absolute Percentage Error: $MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|x_i - \hat{x}_i|}{|x_i|}$

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Sensor placement

Combinatorial optimization:

- Choose the set M of optimal k sensors:

$$M = argmin_M \left(tr\left(\Sigma_{post}\right)\right) s.t. |M| < k \text{ (| | means cardinality of the set)}$$

- NP-hard problem, approximations: greedy forward selection, evolutionary algorithms, combinations, etc.

Convex optimization approximation:

- Assume all buses with sensors, with noise standard deviations as variables: $\sigma_{meas,i} \in \{1\%, \infty\%\}$
- Problem still combinatorial:

$$\sigma_{meas} = argmin_{\sigma_{meas}} \left(tr\left(\Sigma_{post}\right)\right) s.t. |(\sigma_{meas})_{1\%}| < k,\ \sigma_{meas,i} \in \{1\%, \infty\%\}\ \forall i$$

- Relaxations:
  - Use change of variables $y_i = {}^{1}/_{\sigma^2_{meas,i}}$ → $tr\left(\Sigma_{post}\right)$ convex objective function on y
  - Use variable space $y_i \in (0{,}10000]$ → continuous optimization
  - Use l_1-norm approximation for cardinality operator: $\|y - 1\|_1 < k$ → convex constraint
- Convex problem:

$$y = argmin_y \left(tr\left(\Sigma_{post}\right)\right) s.t. \|y\|_1 < k, y_i \in (0{,}10000]\ \forall i$$

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Thanks, questions?

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