Sensitivity Analysis of Sensor Networks for Distribution Grids

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Sensor Coverage in Electricity Networks

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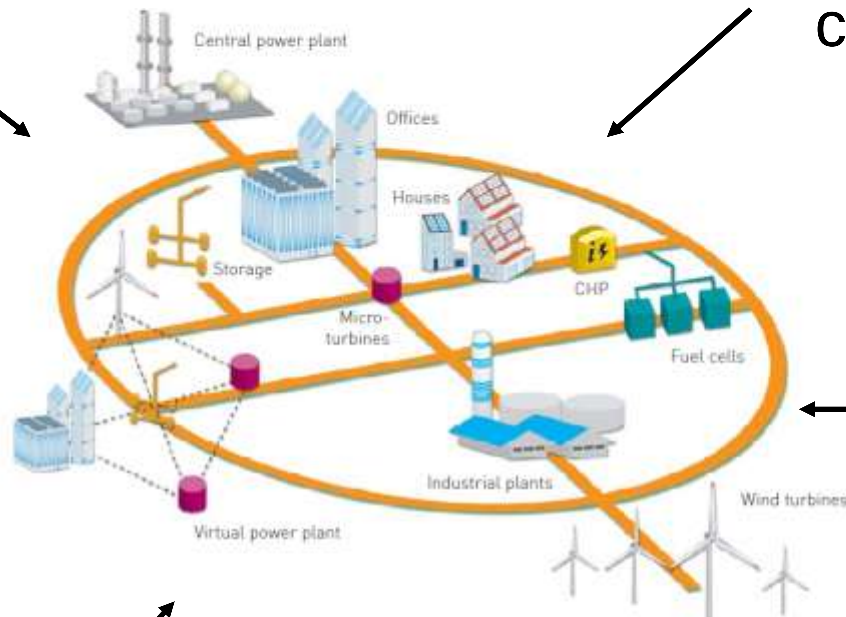
How to handle
Too much data ?

Which sensors
can be removed ?

How many
Sensors are
Needed ?



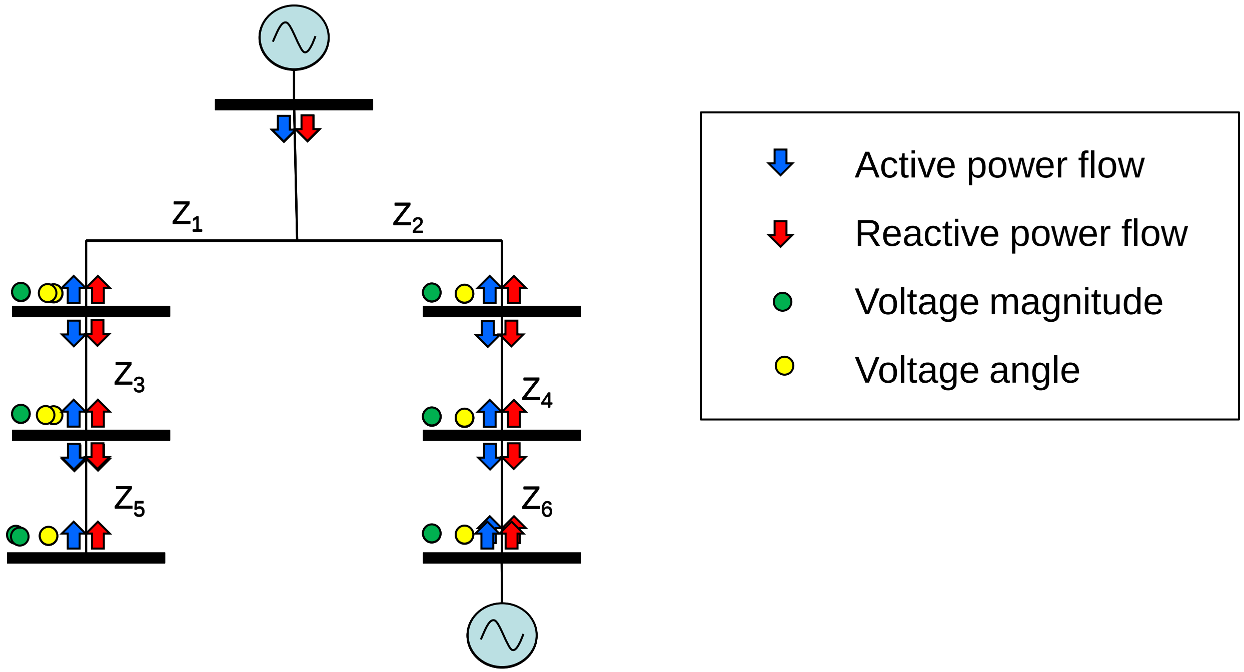
What
happens
when a given
sensor fails ?

Estimate unknown
Cable impedances

How accurate
Should a given
Sensor be ?

State estimation

- From limited power flow and voltage measurements derive voltage magnitudes and angles at each bus
- Derive power flow at every node in the network from estimated impedances and calculated voltages.



Sensitivity Analysis

Suppose the state estimation problem is given as

$$\min_{\mathbf{x}} (\mathbf{z} - H\mathbf{x})^{\mathrm{T}} (\mathbf{z} - H\mathbf{x}) \qquad \text{Subject to:} \quad E\mathbf{x} = \mathbf{y}$$

Where:
x are the parameters to be estimated
H is a (linearized) observation matrix
E is a constraint matrix
z and **y** are vectors storing measured data values

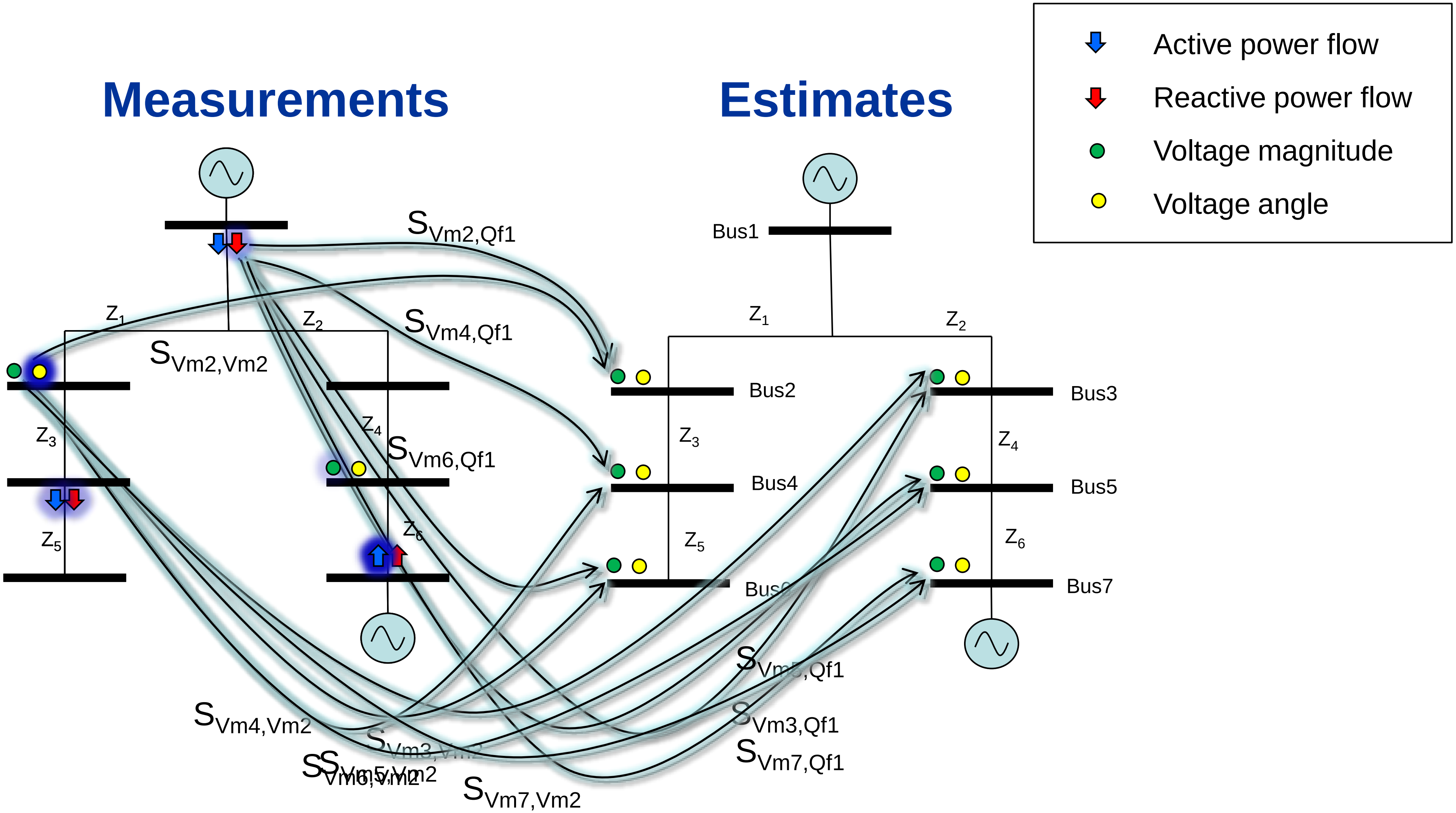
The solution depends linearly on **y** and **z:** $\mathbf{x} = S_{\mathbf{z}}\mathbf{z} + S_{\mathbf{y}}\mathbf{y}$

And the variance matrix is:
(**z** and **y** supposed uncorrelated)

$$V_{\mathbf{x}} = S_{\mathbf{z}} V_{\mathbf{z}} S_{z}^{\mathrm{T}} + S_{\mathbf{y}} V_{\mathbf{y}} S_{\mathbf{y}}^{\mathrm{T}}$$

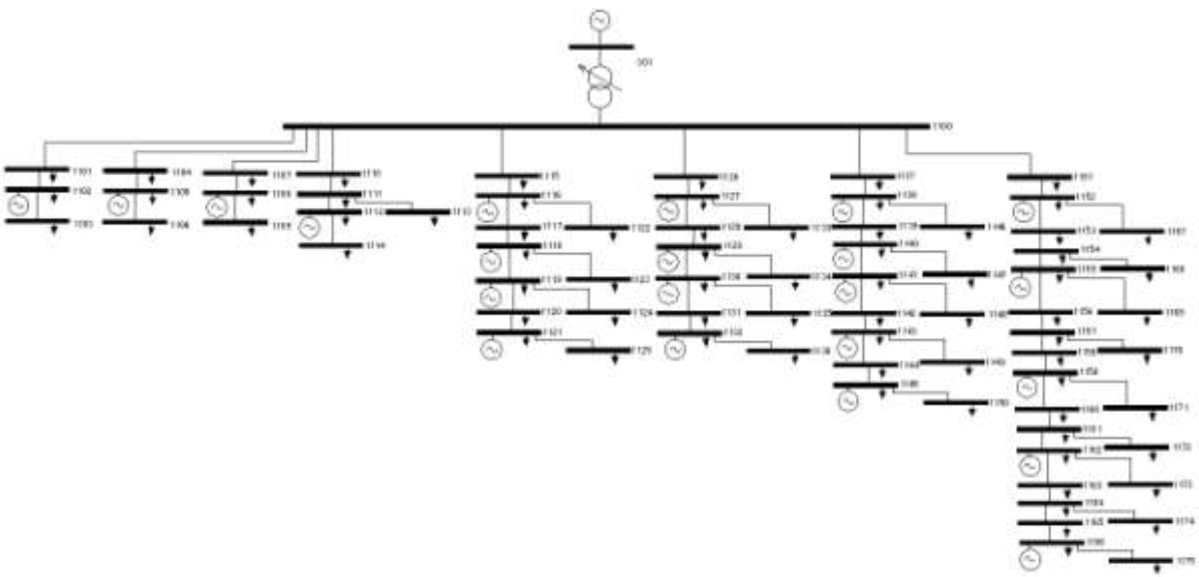
The matrices S_z and S_y show precisely how the uncertainties associated with the data vectors **z** and **y** contribute to the uncertainties associated with the parameter estimates **x**.

Sensitivity analysis

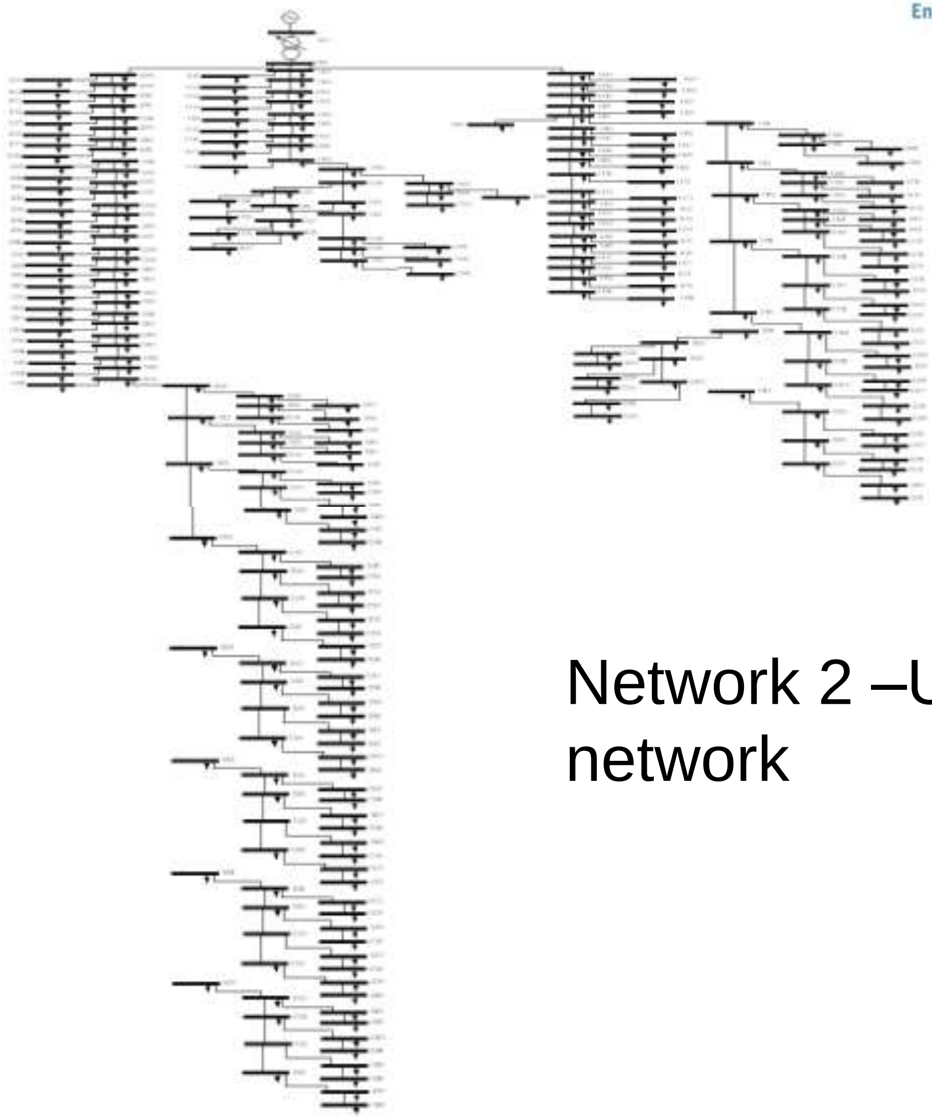


Example simulated networks

Network 1 – United Kingdom Generic Distribution System (UKGDS) 77 bus network



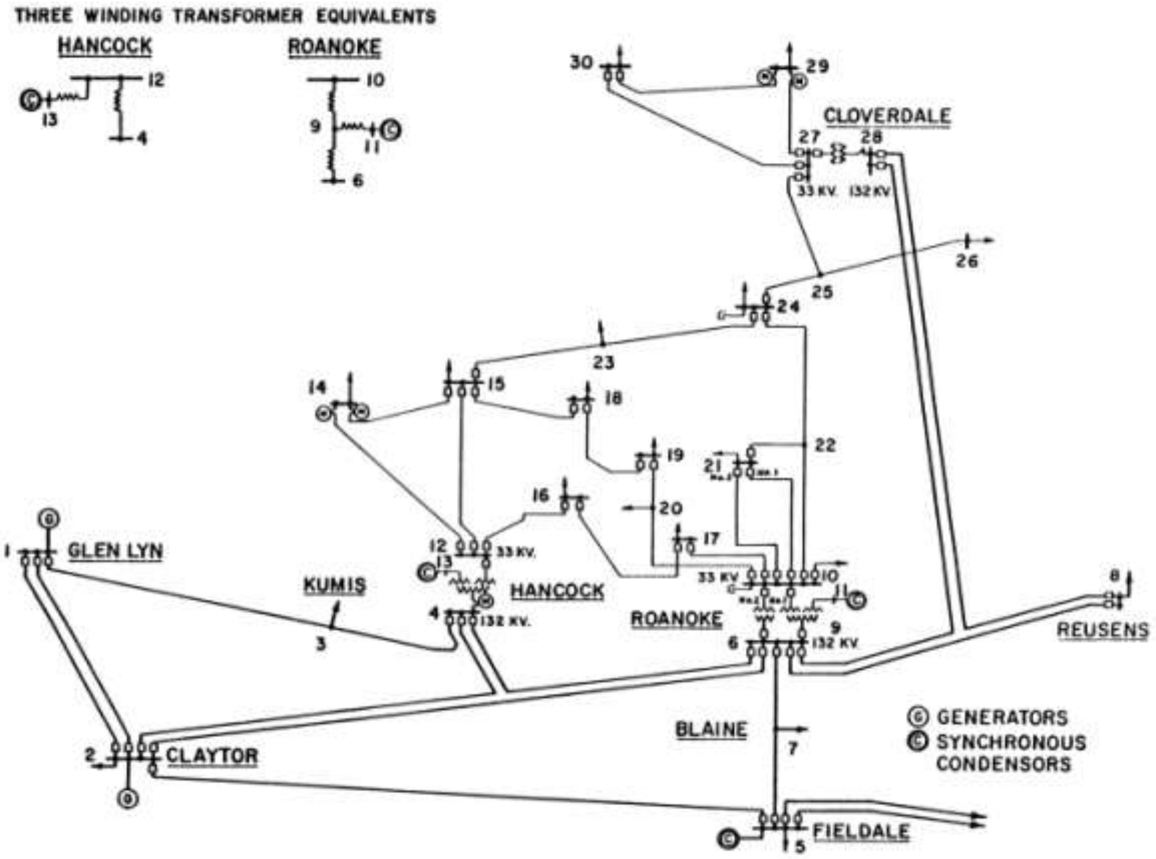
Example simulated networks



Network 2 –UKGDS 290 bus network

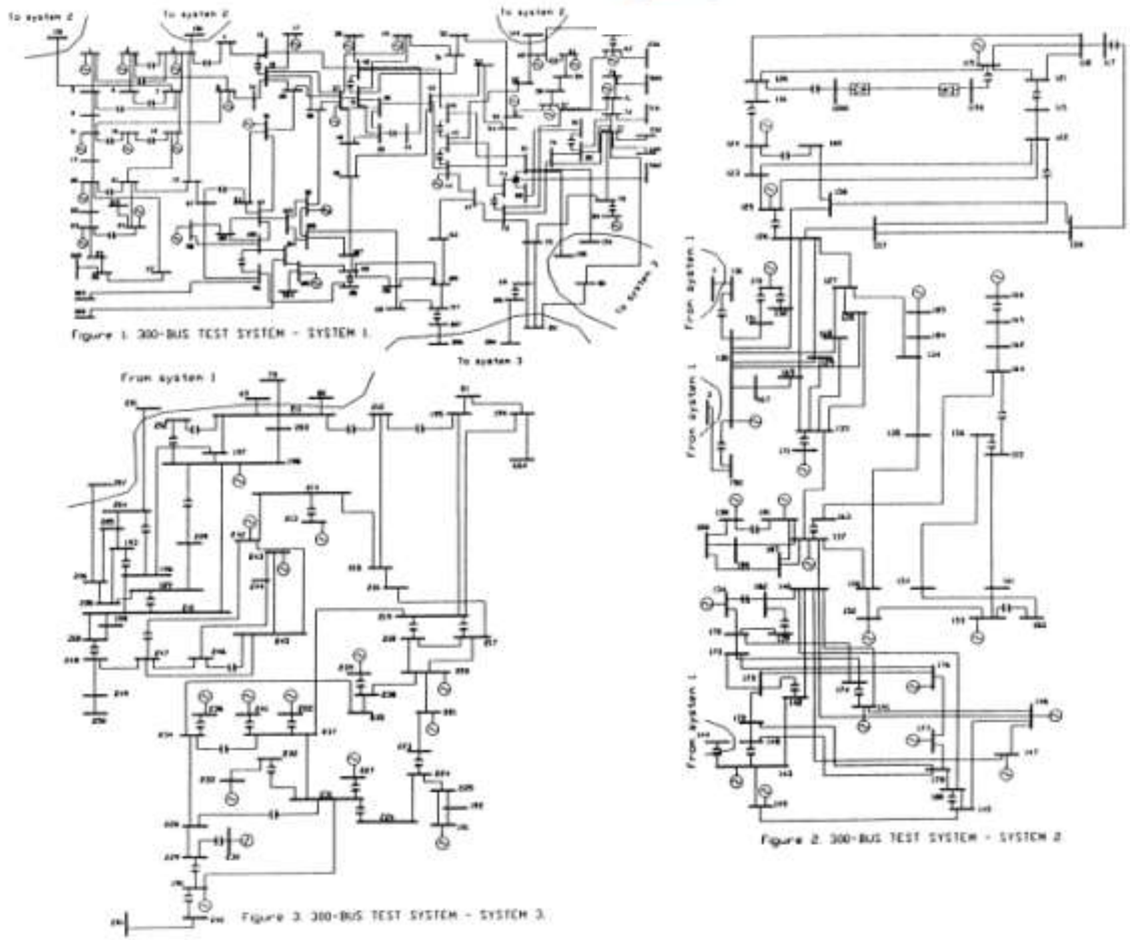
Example simulated networks

Network 3 – IEEE 30 bus system



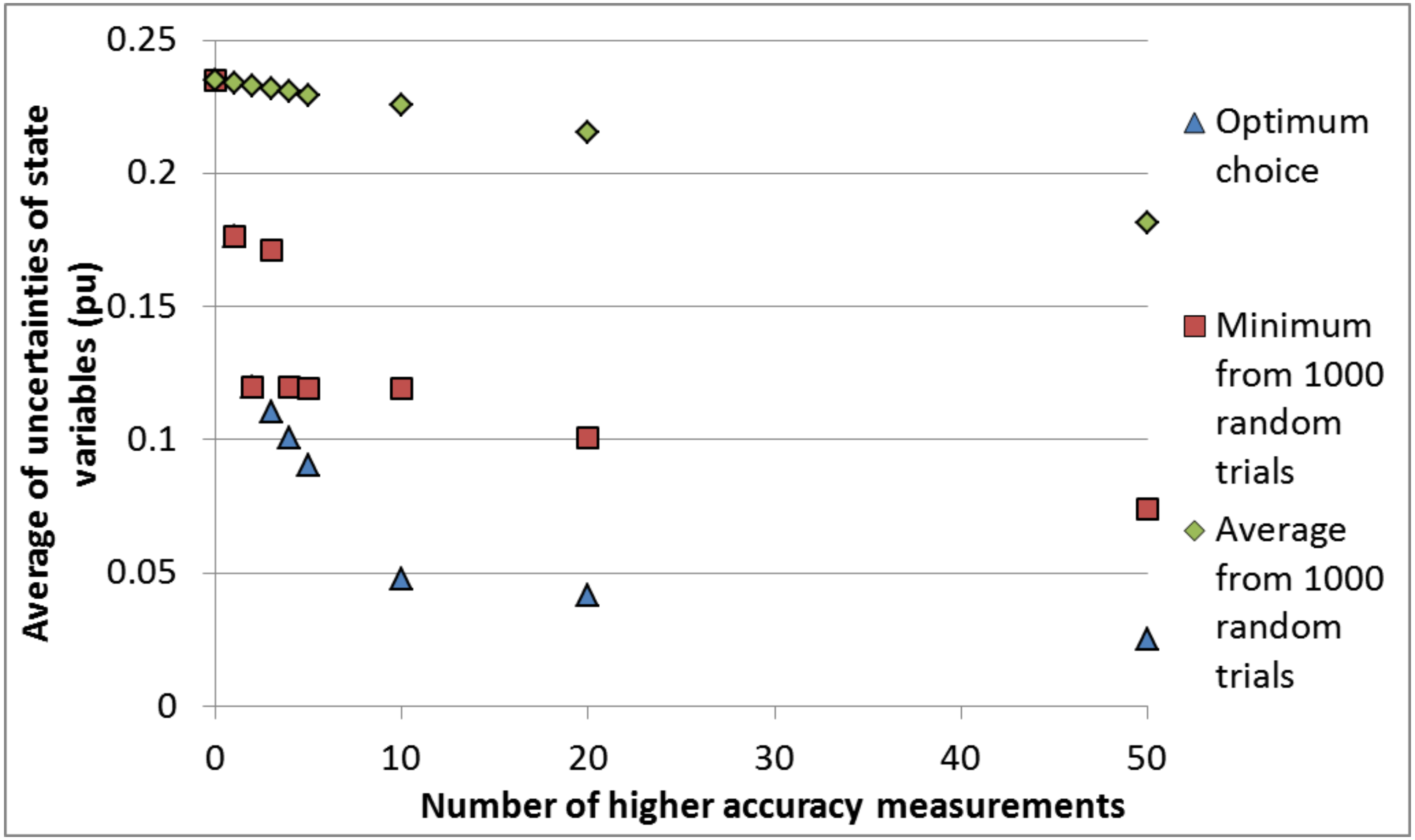
Example simulated networks

Network 4 – IEEE 300 bus system



Choosing optimum measurement locations using sensitivity analysis

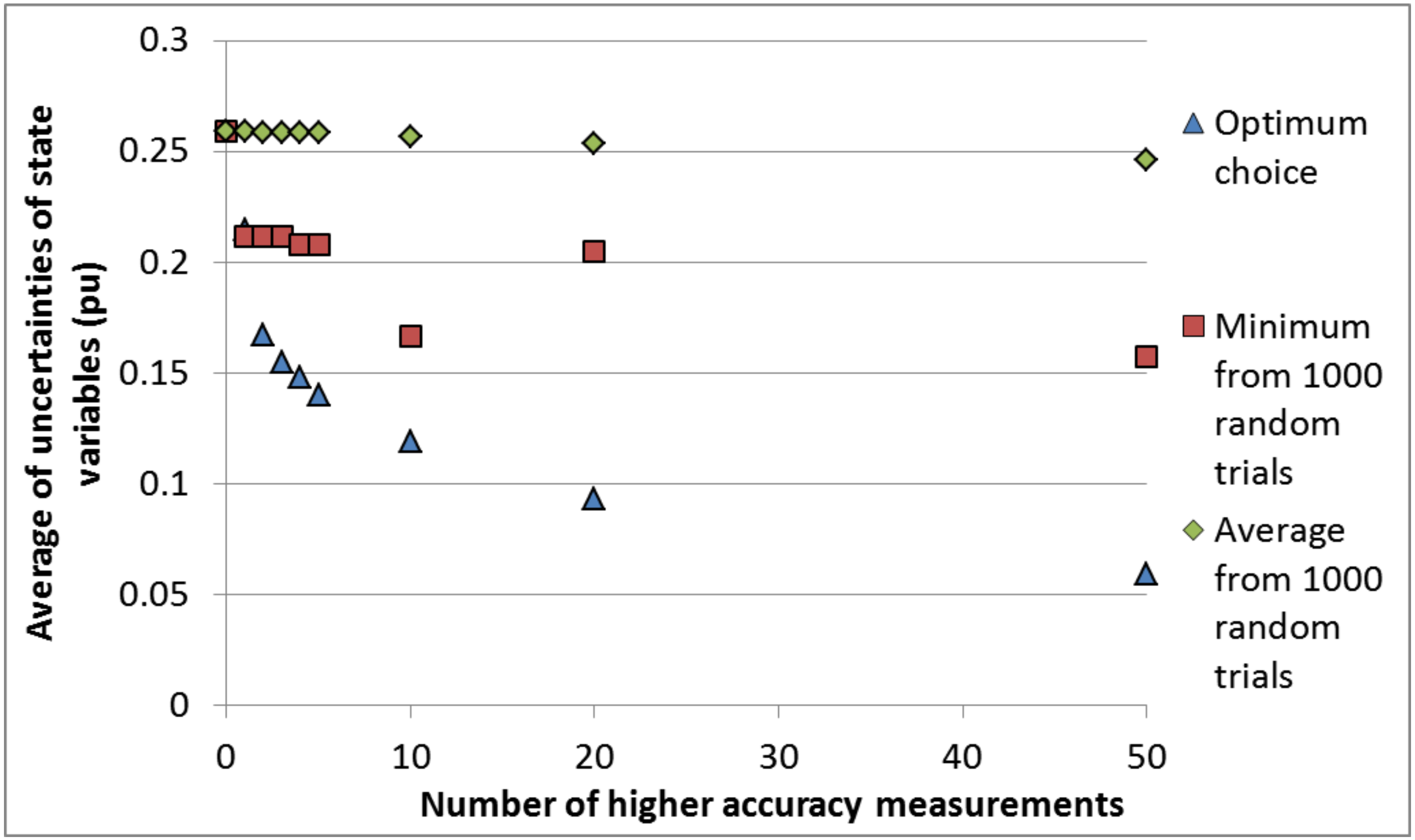
Network 1



Choose positions of high accuracy "real" measurements and low accuracy "pseudo" measurements

Choosing optimum measurement locations using sensitivity analysis

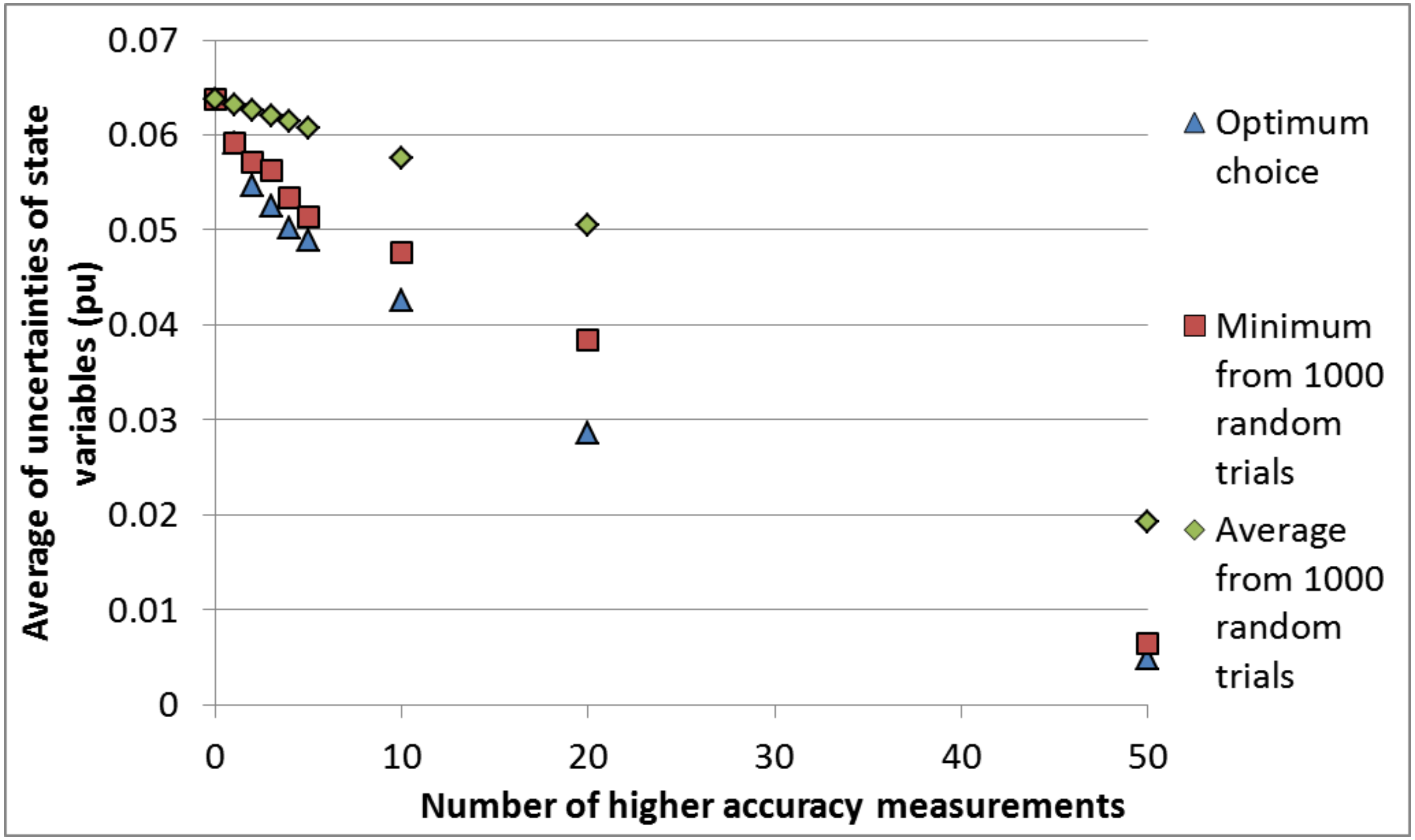
Network 2



Choose positions of high accuracy "real" measurements and low accuracy "pseudo" measurements

Choosing optimum measurement locations using sensitivity analysis

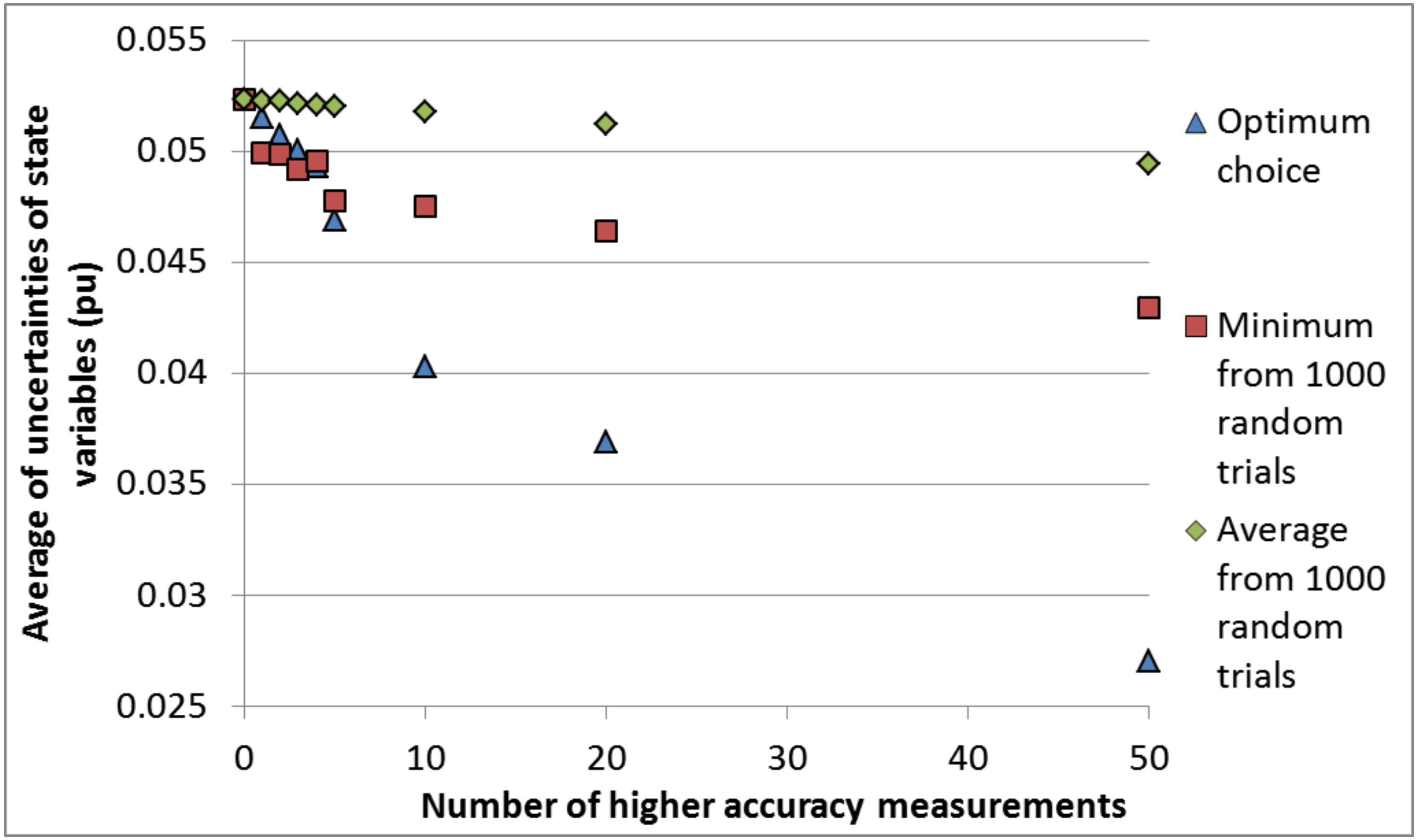
Network 3



Choose positions of high accuracy "real" measurements and low accuracy "pseudo" measurements

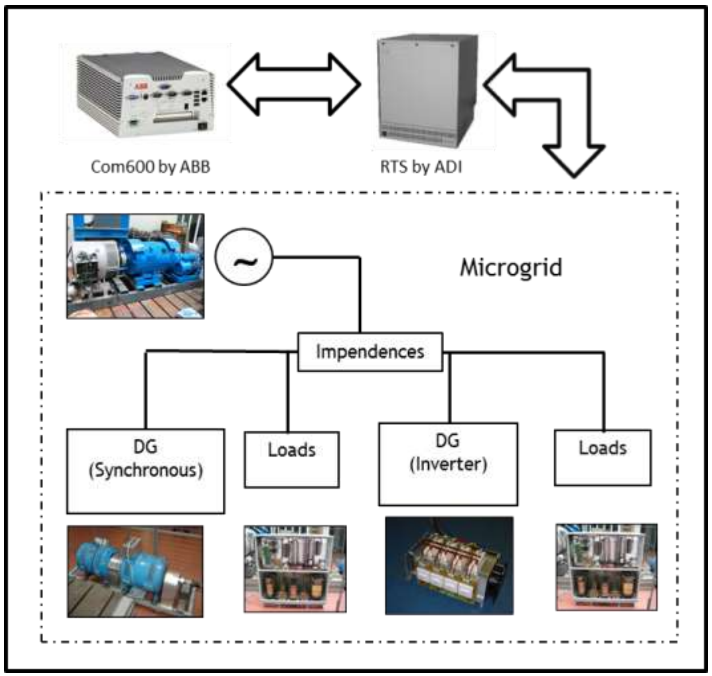
Choosing optimum measurement locations using sensitivity analysis

Network 4

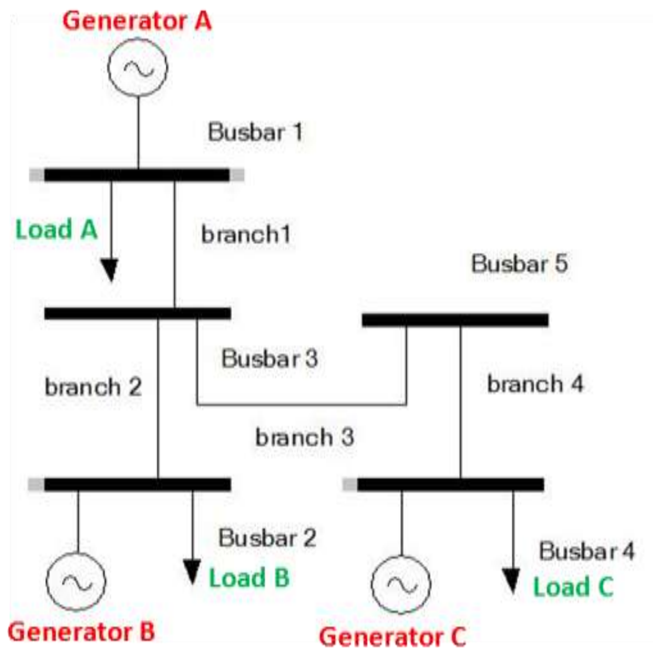


Choose positions of high accuracy “real” measurements and low accuracy “pseudo” measurements

University of Strathclyde experimental smart-grid

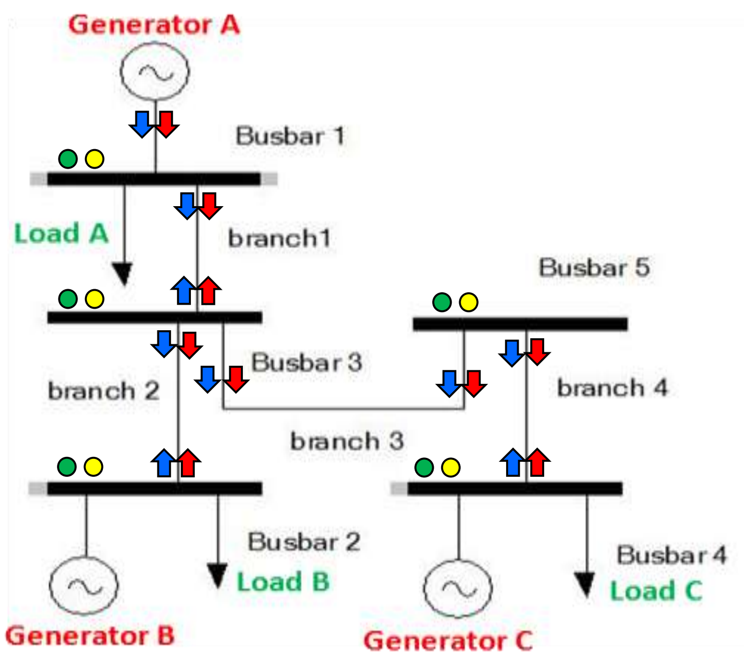


Control system



Network model

Testing on microgrid



Start with fully instrumented grid

- Active power flow
- Reactive power flow
- Voltage magnitude
- Voltage angle

Apply state estimation → Measurement error

Apply sensitivity analysis → Measurement uncertainty

Testing on microgrid

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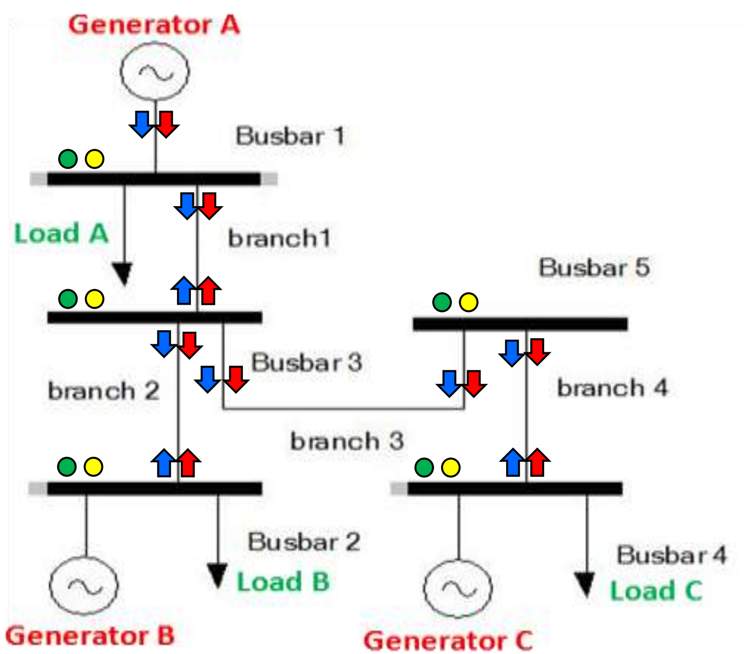


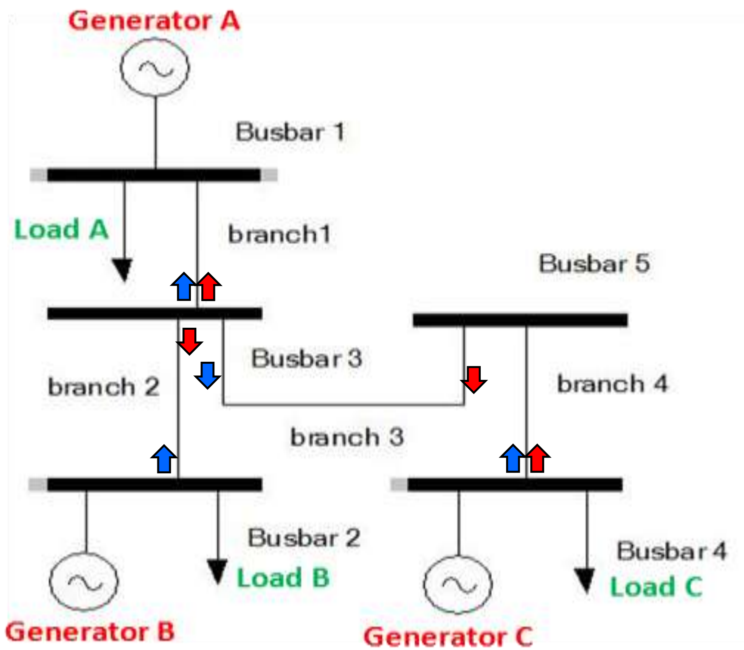
Start with fully instrumented grid

- Active power flow
- Reactive power flow
- Voltage magnitude
- Voltage angle

Average measurement error of 1.7 %

Average state variable uncertainty of 0.4 %

Testing on microgrid



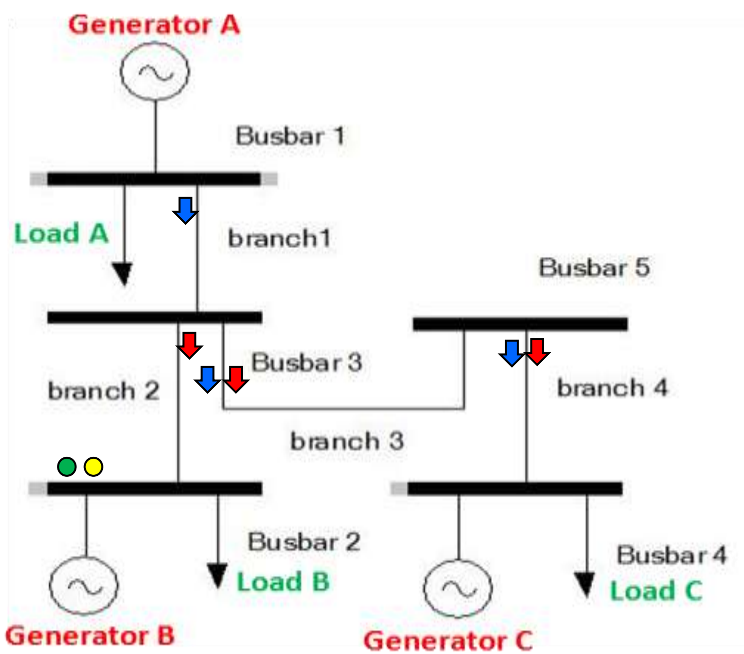
Apply algorithm to find optimum minimum measurement set

- Active power flow
- Reactive power flow
- Voltage magnitude
- Voltage angle

Average measurement error of 1.0 %

Average state variable uncertainty of 0.7 %

Testing on microgrid



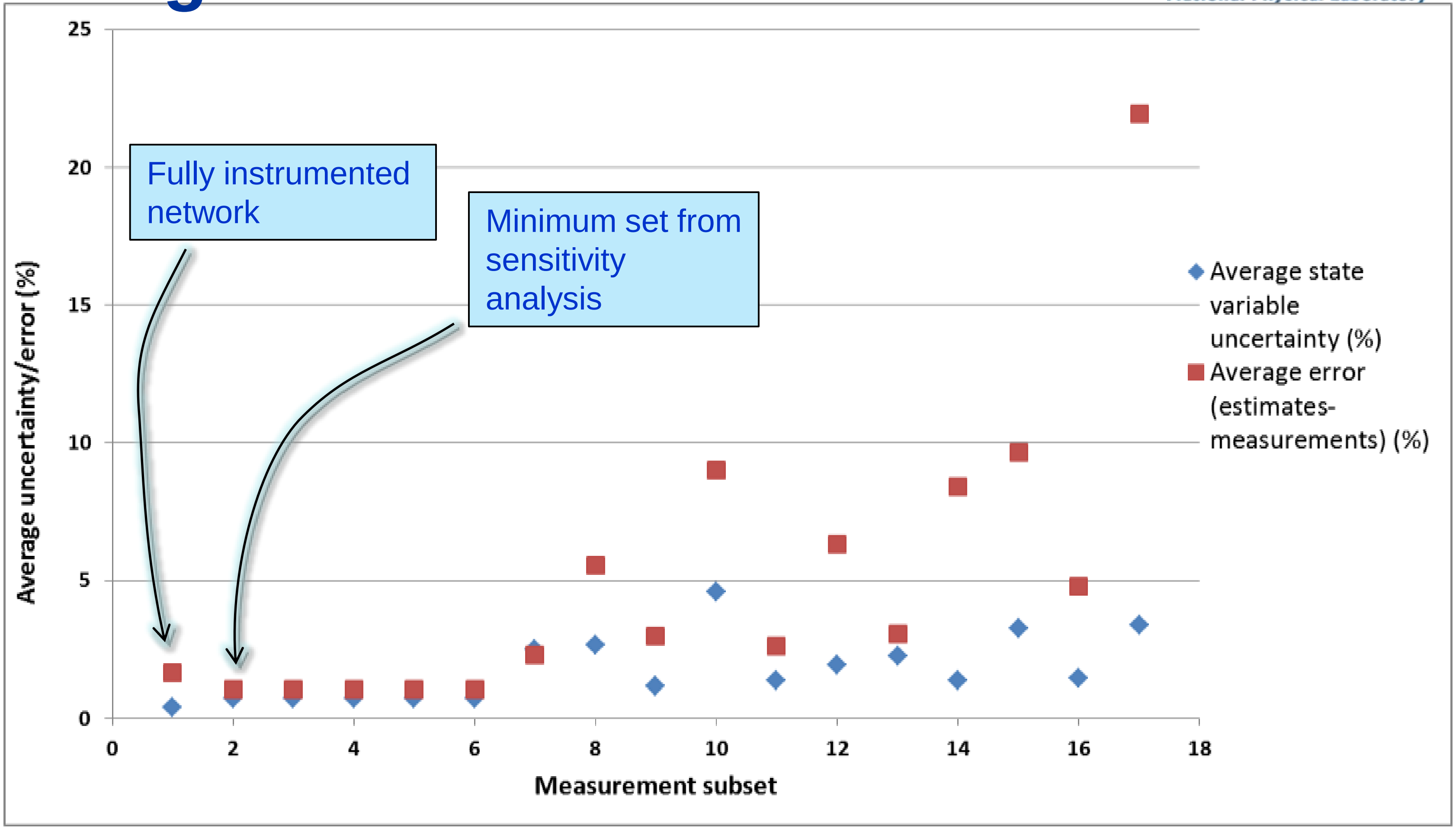
Compare with random selection of measurements

- Active power flow
- Reactive power flow
- Voltage magnitude
- Voltage angle

Average measurement error of 3.1 %

Average state variable uncertainty of 2.2 %

Microgrid measurement errors



Comparison of measurement error and state variable uncertainty

Summary

- Successfully modelled Strathclyde microgrid in MATLAB
- Applied state estimator to Strathclyde microgrid and larger simulated networks
- Verified uncertainty calculations against monte-carlo calculations
- Expanded state estimator to include uncertain impedances in the network interconnections
- Verified state variable uncertainty calculations against real measurements

Next steps

- Improve speed of optimal measurement placement algorithm
- Sensitivity analysis with cable impedances included
- Apply techniques to estimate line impedances
- Expand to include unbalanced networks
- Test with distributed generation included
- Investigate use of PMU and smart meter data.
- Try on full size real networks – need to engage with DNO