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Improving Distribution System Model Accuracy by Leveraging Ubiquitous Sensors

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Outline

1. Motivation
2. Parameter Estimation
3. Topology and Parameter Estimation
4. Conclusions

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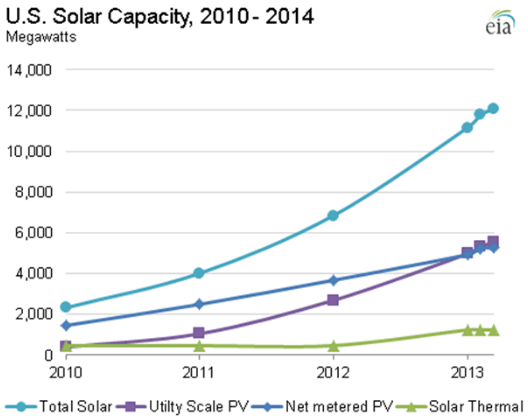
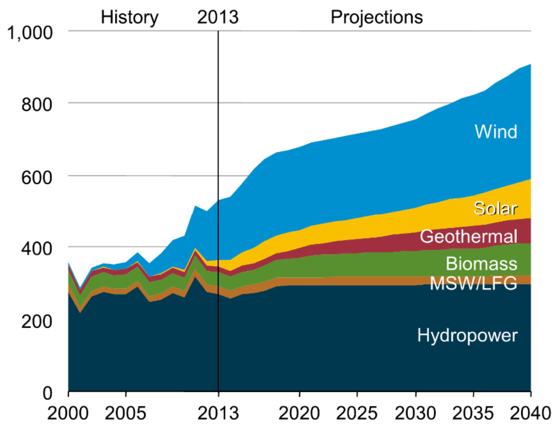
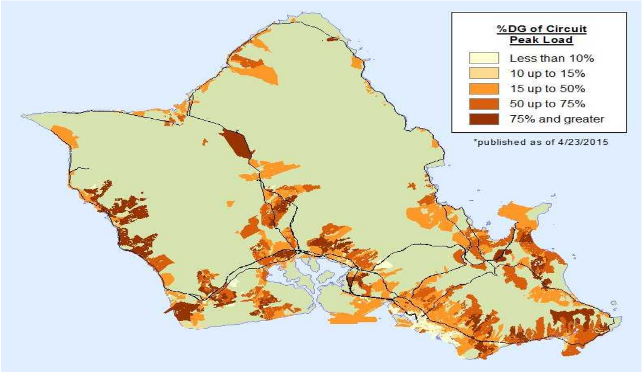
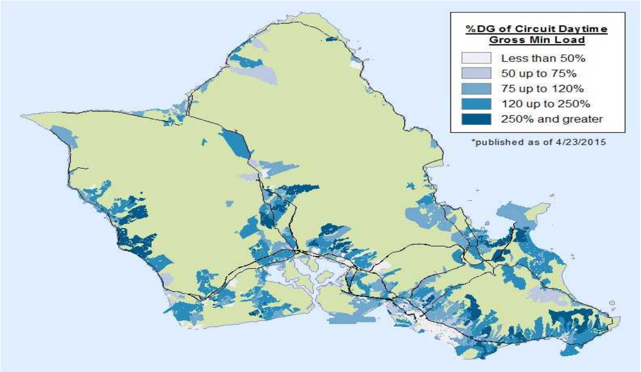
Strong Growth of PV





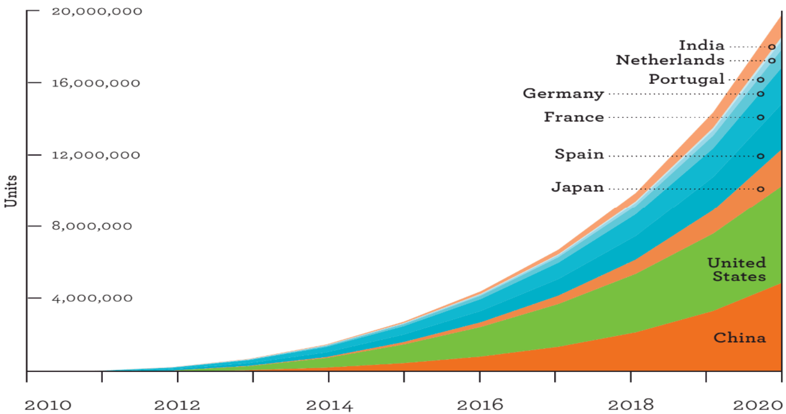




- www.eia.gov/
- www.hawaiianelectric.com

Other Types of Distributed Energy Resources (DERs)

- Electric mobility
- Battery storage



- "Global EV Outlook", International Energy Agency, Apr. 2013
- http://www.teslamotors.com/powerwall

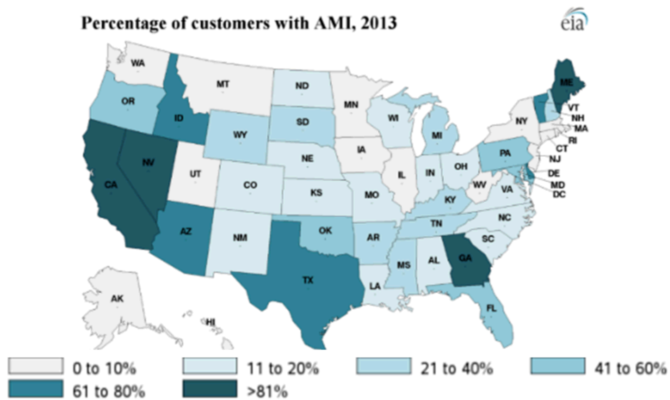
Unprecedented Changes

- Increasing locational and time-dependent impacts
  - Bi-directional and ever stronger fluctuating power flows
  - Increasing component loadings leading to reduced expected equipment lifetime
  - …
- To maintain a high-quality and reliable distribution system operation with high penetration of DERs, there is an increasing need for
  - Accurate understanding of these impacts
  - New level of situational awareness(?)

Accurate distribution system models are required for smart distribution systems

Ubiquitous Distribution System Measurements

- In the past, limited visibility in the distribution systems
- Smart meters have already radically increased the number of measurements
- PV micro inverters offer a new level of measurement and control
- These modern distribution system measurements have the potential to provide enough information to support the new situational awareness needs



Can Microinverters Stabilize Hawaii's Shaky Grid?

Enphase's systems are connected to an estimated 140 MW of peak power solar generation capacity in Hawaii.

- www.eia.gov
- www.greentechmedia.com

Leveraging Measurement Data for Model Calibration

- This project will heavily utilize the PV micro inverter measurements received from the Enphase Energy
- CRADA established with Sandia[1]
- The dataset consists of up to 5 years of instantaneous AC voltages and currents collected every 5 minutes from thousands of PV microinverters all across the country
- The data set grows by 400GB/week

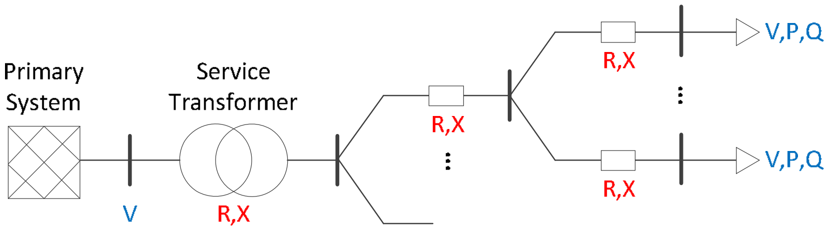
1. Talk to Matthew Reno or Robert Broderick

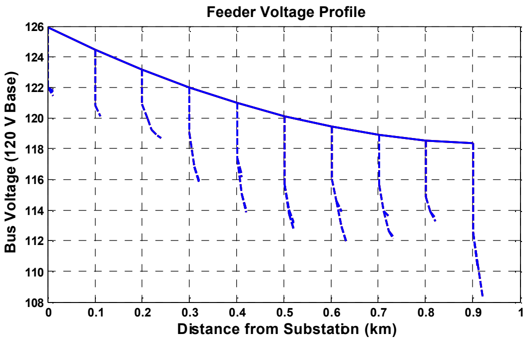
Limitations of Distribution System Models

- Much of distribution system planning and operation relies on analyses performed on models (and data) that are assumed to be accurate
- Currently, **they typically are not accurate**
  - Due to the large number of components and parameters, there is a lot of uncertainty w.r.t. the accuracy and quality of current utility models
  - Limited model verification has been performed
  - Human errors, inaccurate manufacturing data, unrecorded network changes, incorrect tap information...
  - Incorrect component parameters are among the most common errors in Geographical Information System (GIS)

Secondary Circuit Models, the Weakest Link?

- Secondary (low-voltage) circuits are typically either not been modeled at all or are modeled with a lower level of detail than the MV circuits
- However, it is becoming particularly important to have accurate secondary circuit models since
  - A large number of DERs are connected to the secondary circuits
  - A large portion of the per-unit voltage drop/raise occurs over the service transformers and lines that have large impedances and X/R-ratios





Need for Parameter Estimation

- The typical approaches to correct GIS errors, such as manual inspections and utilizing added measurements, require considerable man hours and extra resources
- These approaches are **not cost-effective**

There is a growing need for automated parameter estimation procedures to improve the accuracy of the distribution system (secondary circuit) models

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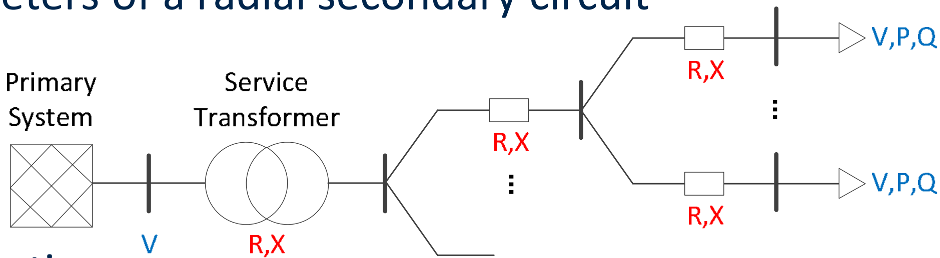
Distribution System Parameter Estimation

- Distribution system parameter estimation (DSPE) is a new research area
  - Motivated by the increasing DER (especially PV)
  - Has become possible with modern distribution system measurements (AMI / PV)
- Compared to transmission, DSPE challenges include:
  - No existing state estimator!
  - Faster changes in the system (load, PV, …)
  - Voltage controlling device operation
  - Lower measurement granularity, redundancy, accuracy, reliability
  - Modeling of unbalanced loads with various connections & characteristics, multi-phase asymmetric distribution systems, phase coupling of lines, phase errors in GIS, various transformer types & connections…

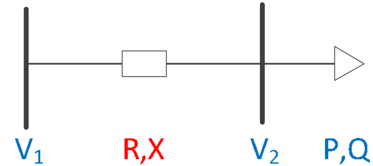
DSPE Problem Statement

- Goal: Estimate all positive sequence series impedance (R & X) parameters of a radial secondary circuit



- Assumptions
  1. Known radial circuit topology
  2. Balanced 3-phase circuit or 1-phase circuit (here work shown for 3-phase)
  3. Each leaf node of the tree has a meter (smart meter or PV micro inverter) that measures the voltage and either active and reactive power or current and power factor
  4. Voltage estimate (measured or simulated) at the medium-voltage bus of the service transformer

Estimating Branch Series Impedance Parameters



- Linearized voltage drop approximation

$$V_{drop} = |V_1| - |V_2| \approx (RP + XQ)/V_2 = RI_R + XI_X$$

- For K number of measurement samples

$$\Delta \boldsymbol{V} = \boldsymbol{V}_1 - \boldsymbol{V}_2 = R\boldsymbol{I}_R + X\boldsymbol{I}_X$$

- Denote $\boldsymbol{y} = \boldsymbol{V}_1 - \boldsymbol{V}_2$, $\boldsymbol{X} = [\boldsymbol{I}_R \quad \boldsymbol{I}_X]$, and $\boldsymbol{\beta} = [R \quad X]^T$
- Gives the linear equation $\boldsymbol{y} = \boldsymbol{X\beta}$
- Finding the best $\boldsymbol{\beta}$ in least-squares sense is equal to solving

$$\min_{\boldsymbol{\beta}} \|\boldsymbol{y} - \boldsymbol{X\beta}\|_2^2 = \min_{\boldsymbol{\beta}} \sum_{k=1}^{K} (y_k - \boldsymbol{x}_k\boldsymbol{\beta})^2 = \min_{\boldsymbol{\beta}} \boldsymbol{\beta}^T\boldsymbol{X}^T\boldsymbol{X\beta}$$

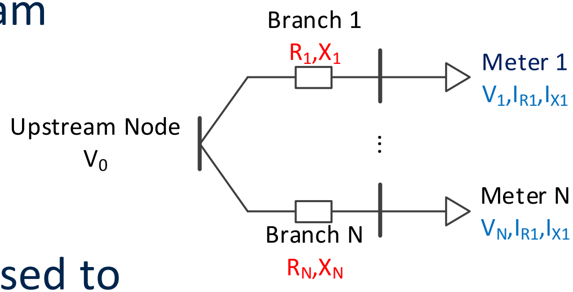
- If $\boldsymbol{X}$ has full column rank, the solution is the ordinary least squares estimator (OLS)

$$\widehat{\boldsymbol{\beta}} = [\hat{R} \quad \hat{X}]^T = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y}$$

Estimating Impedances of N Parallel Branches

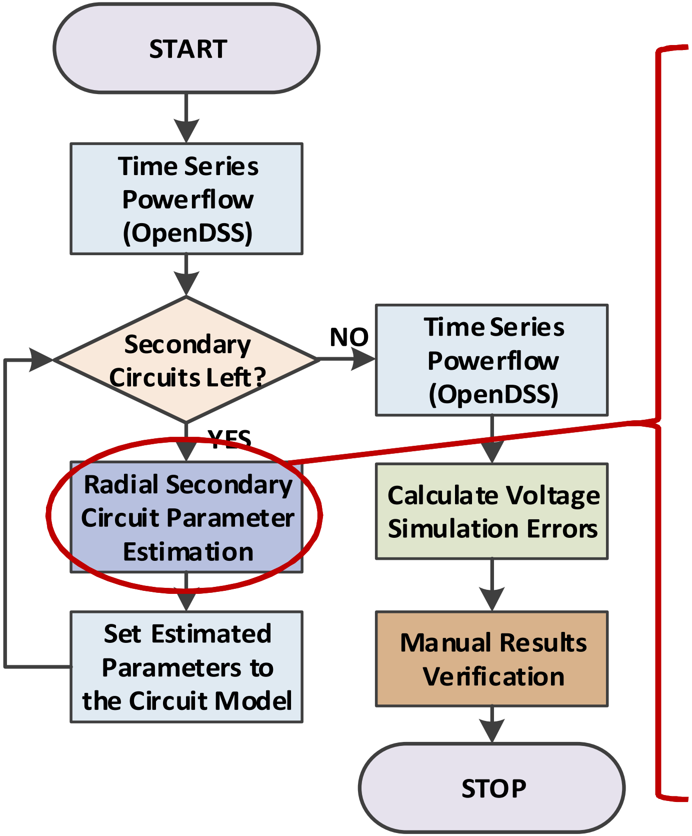
- Each of the N branches provides an approximate estimate the “Upstream Node” voltage

$$\begin{cases} V_0 = V_1 + R_1 I_{R1} + X_1 I_{X1} + \epsilon_1 \\ V_0 = V_2 + R_2 I_{R2} + X_2 I_{X2} + \epsilon_2 \\ \vdots \\ V_0 = V_N + R_N I_{RN} + X_N I_{XN} + \epsilon_N \end{cases}$$



- Each pair of two branches can be used to estimate the branch pair impedance parameters as shown above
- Results in “N choose 2” regression problems and N-1 estimates of each parameter
- Final parameter estimate taken as an average over the individual estimates

Hierarchical Radial Circuit Parameter Estimation

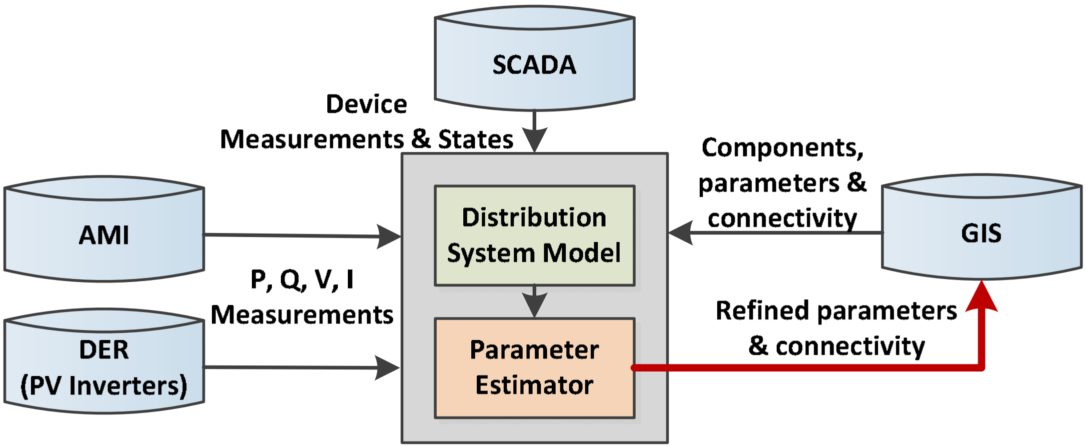


Algorithm for each secondary circuit

1. Search for a tree node whose downstream branch parameters are unknown and whose all immediate downstream buses have measured/estimated measurements, STOP if none is found
2. Estimate the parallel branch impedances
3. Estimate the upstream node voltage

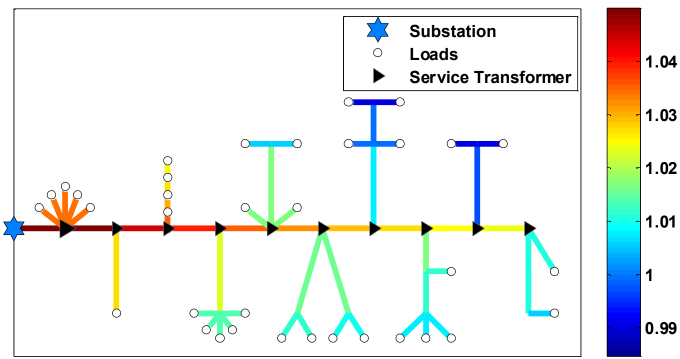
Necessary Flow of Data

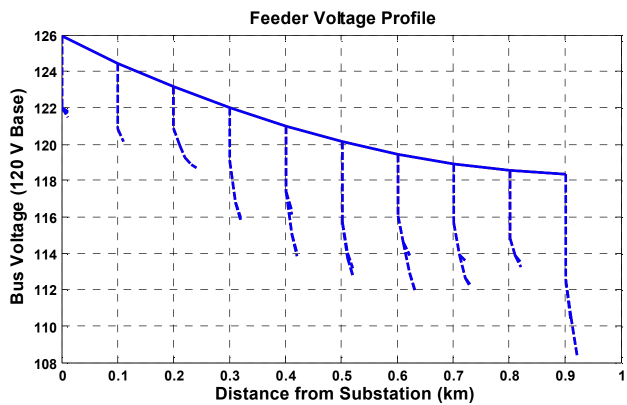
- Further software integration will be required…
- Ideally a semi-automated process



66-Node Three-Phase Test Circuit

Secondary Order from Substation	Load Connections
1	5 loads connected to a transformer
2	1 large load connected to a pedestal
3	5 loads connected in series on service line (without service drops)
4	5 loads connected to a pedestal
5	2 loads connected to a transformer, 2 loads connected to a pedestal
6	2 separate pedestals each with two loads
7	2 pedestals in series each with 2 loads
8	2 pedestals in series: first with one load, second with 3 loads
9	1 pedestal with two loads
10	1 load connected to the transformer, 1 pedestal with 1 load





Regression Model Selection

- Best linear regression model depends (among other things) on the true parameter values and the measurement error level
- Best results with simple model for small impedances (lines) and more complicated model for large impedances (transformers)

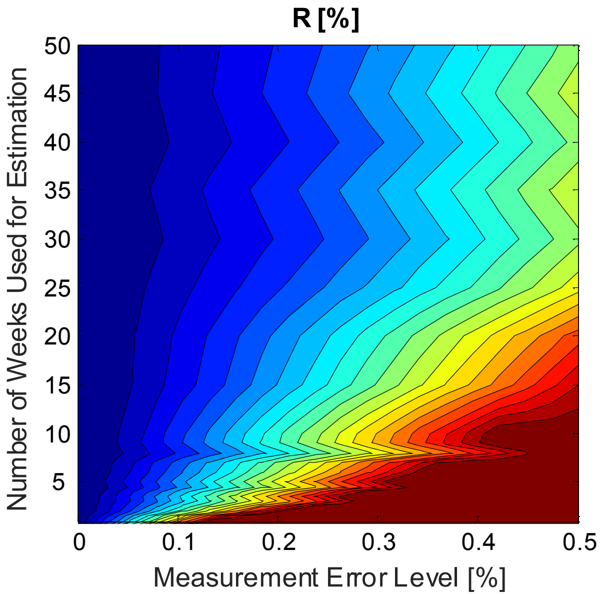
Predictor Variables in Regression Problems with Transformer Parameters (All Models Include I_R and I_X)				Avg. Abs. R_{err} [%]	Avg. Abs. X_{err} [%]	Model Order (Best to Worst)
Intercept	$I_R \times I_X$	I_R^2	I_X^2			
				3.761	3.095	4
		X		2.461	3.113	1
			X	4.665	4.683	6
		X	X	2.843	3.216	2
	X			3.774	4.122	5
	X	X	X	2.924	3.440	3

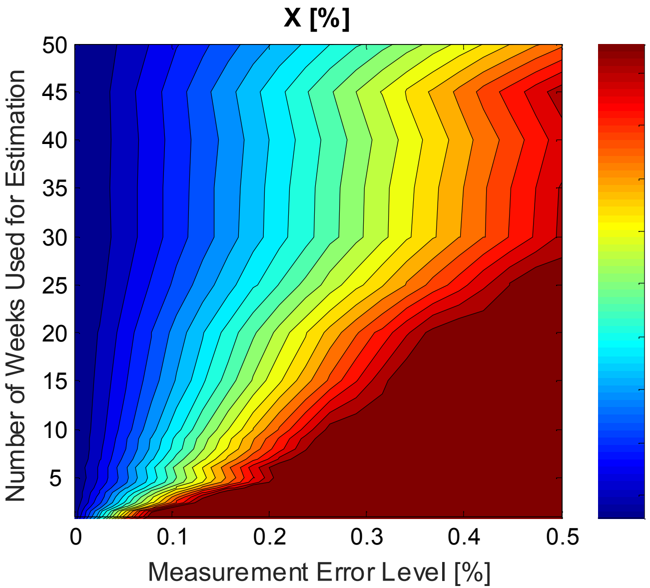
Parameter Estimation Results for 66-Node Circuit

- Results without measurement error
  - Relative errors of R: average 0.69%, maximum 2.64%
  - Relative errors of X: average 0.60%, maximum 2.78%
- Results with 1% P, 1% Q, and 0.2% V random uniform measurement error
  - Relative errors of R: average 2.05%, maximum 8.67%
  - Relative errors of X: average 2.73%, maximum 9.50%

Parameter Estimation Results for 66-Node Circuit

- Accuracy w.r.t. the number of measurement samples and (P,Q, and V) measurement error level



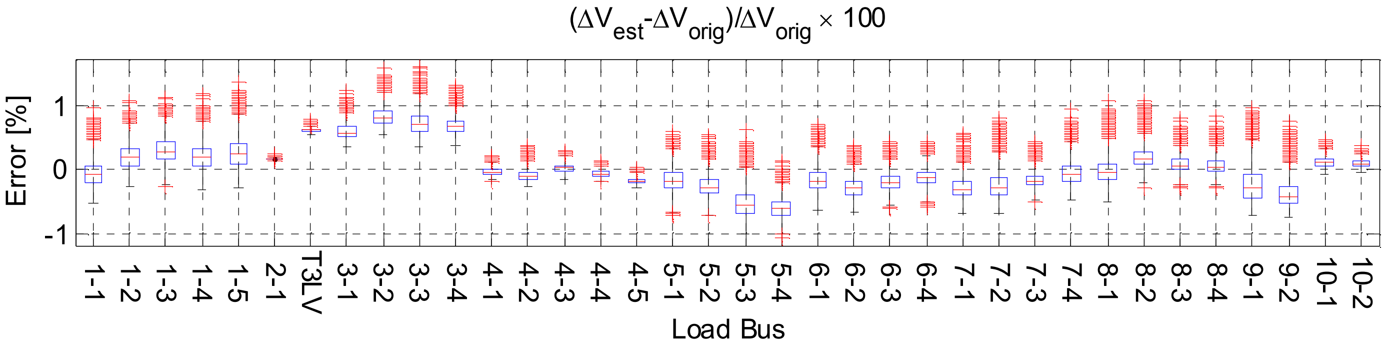


Dependency on Voltage Measurement Error

- Parameter estimation accuracy depends on voltage measurement error level
- Relative parameter estimation errors are relatively high already at 0.5% voltage measurement error level since this translates to high relative voltage error over short secondary circuit lines
- This is theoretical limitation, not a limitation of the presented method

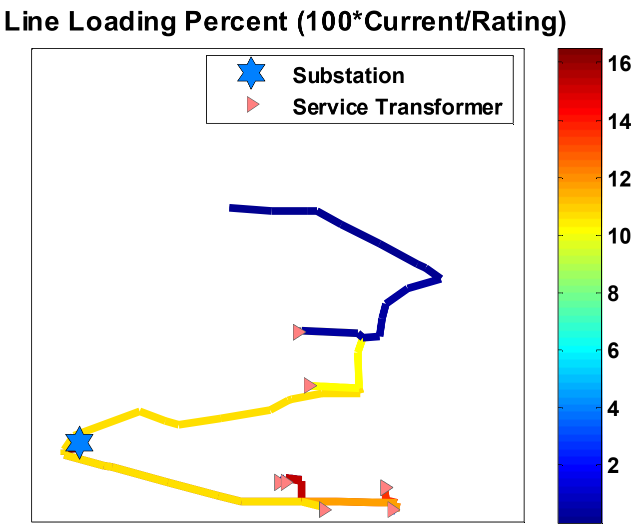
Parameter Estimation Results for 66-Node Circuit

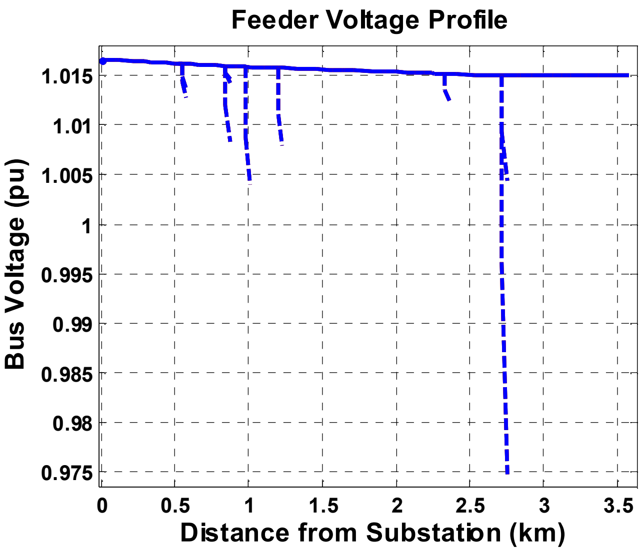
- These results for 1% P, 1% Q, and 0.2% V random uniform measurement error
- Very accurately simulated voltage drops



Georgia Tech Feeder

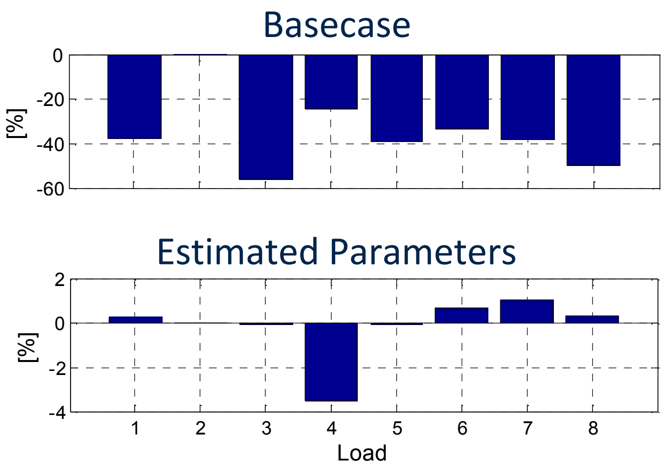
- Well-balanced 3-phase 19.8 kV feeder
- ~3.5 km long, peak load >0.90 MW





Georgia Tech Feeder Parameter Estimation Results

- Standard manufacturer parameters used for the secondary circuits
- Since the true parameters were unknown, the parameter estimation accuracy was measured with mean bias error of the simulated load voltages errors (MBE $= \frac{1}{n}\sum_{i=1}^{n}\frac{(V_{sim}-V_{meas})}{V_{meas}}$)



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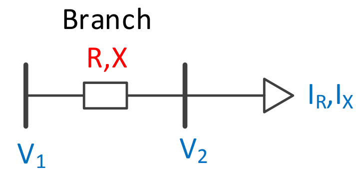
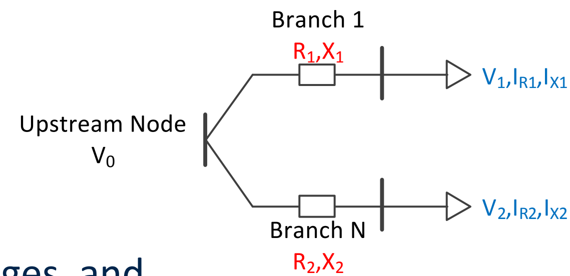
Joint Topology and Parameter Estimation

- Method based on iterative meter pairing
- At each iteration
  - Construct regression problems for all meter pairs for circuit type 1 and circuit type 2
  - Pair the two meters with the best regression fit
  - If best pair for circuit type 1, add downstream meter currents to the upstream meter and remove the downstream meter
  - If best pair for circuit type 2, create “Upstream Node”, estimate its voltages, and remove both meters
- The method can estimate all radial topology types

Circuit Type 1



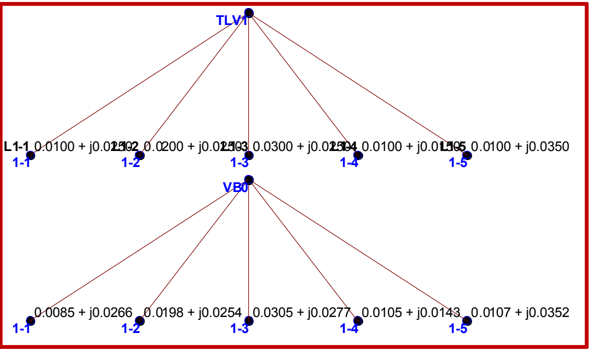
Circuit Type 2

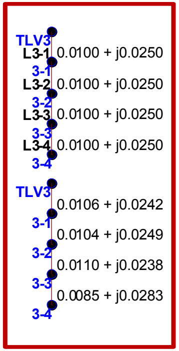


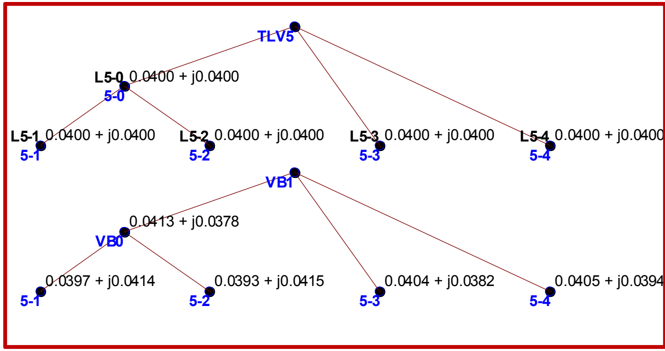
Results for the 66-Node Circuit

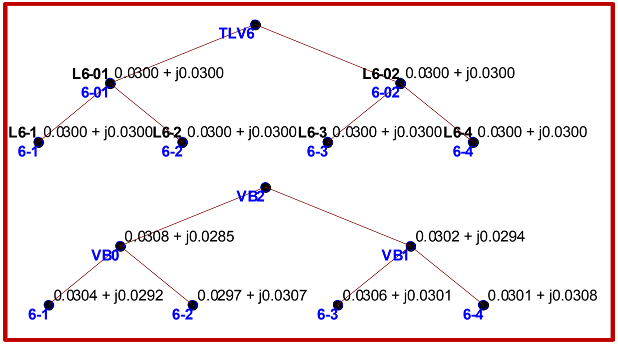
- All the secondary circuit topologies are correctly estimated both without and with measurement error
- As expected, parameter estimation accuracy is slightly worse when the topologies are unknown
- It is important to pair the meters in a correct sequence, otherwise some topology types cannot be reconstructed correctly
- Correct meter pairing can be challenging in the presence of measurement error

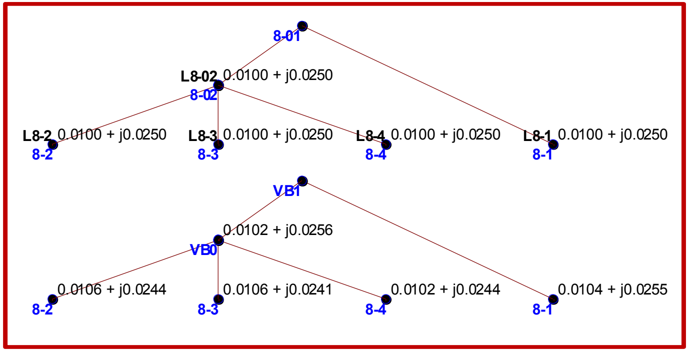
Results for the 66-Node Circuit

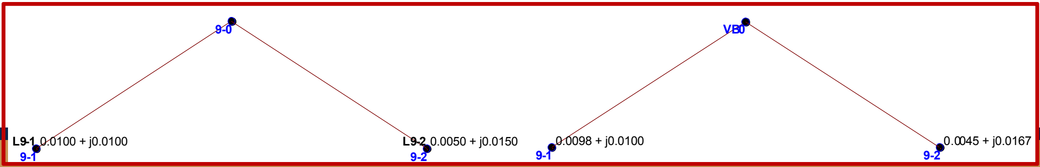






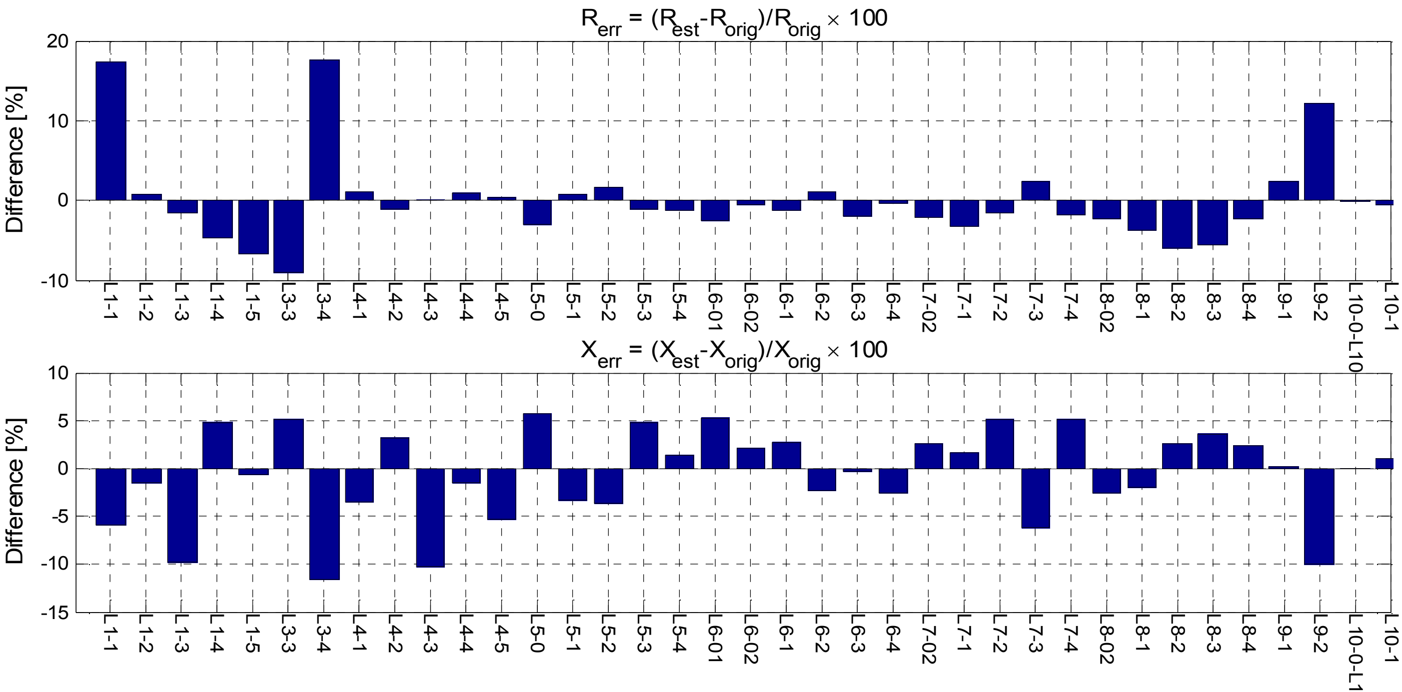






Results for the 66-Node Circuit

- 1% P, 1% Q, and 0.2% V measurement error



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Conclusions

- Future smart(er) distribution systems likely to require more accurate models
- Secondary circuit models are particularly poorly modeled circuit sections that have high influence on voltage levels
- Automated parameter and topology estimation can be used to improve the accuracy of (secondary circuit) model accuracies
- In our on-going work, we utilize these methods on utility feeder models with SCADA and PV microinverter measurements
- Many other modeling inconsistencies are expected to be found since utility models seldom verified with measurements

References

1. J. Peppanen, M. J. Reno, R. J. Broderick, and S. Grijalva., “Distribution System Secondary Circuit Parameter Estimation for Model Calibration”, Sandia National Laboratories, Albuquerque, New Mexico, 2015.
2. J. Peppanen, M. J. Reno, R. Broderick, S. Grijalva “Distribution System Model Calibration with Big Data from AMI and PV Inverters,” IEEE Transactions on Smart Grid, Short Paper Submitted February 2015.
3. J. Peppanen, M. J. Reno, M. Thakkar, S. Grijalva, and R. G. Harley, “Leveraging AMI Data for Distribution System Model Calibration and Situational Awareness,” IEEE Transactions on Smart Grid, 2015.
4. J. Peppanen, J. Grimaldo, M. J. Reno, S. Grijalva, and R. G. Harley, “Increasing distribution system model accuracy with extensive deployment of smart meters,” in IEEE Power and Energy Society General Meeting, Washington D.C., 2014.

END

Backup Slides Follow

Conventional Power System Parameter Estimation

- Parameter estimation problem consists of finding the most likely component parameters that may be known with varying accuracy
- This presentation focuses on line and transformer impedance parameters that can be considered time invariant and estimated offline
- Transmission system parameter estimation (TSPE) is a well-established field that has been studied since 1970s
- TSPE is typically integrated in the state estimation algorithm (residual sensitivity analysis vs. augmented state vectors)
- In TSPE, typically only few suspicious parameters are estimated
- High measurement quality and redundancy

Linearized Voltage Drop Approximation

- The proposed parameter estimation approach relies on the well-known linearized approximation of voltage drop magnitude over a series impedance
- The exact voltage drop is

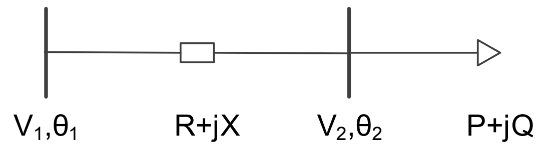
$$V_1 - V_2 = (R + jX)I$$

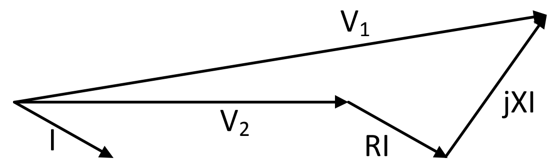
- In rectangular coordinates

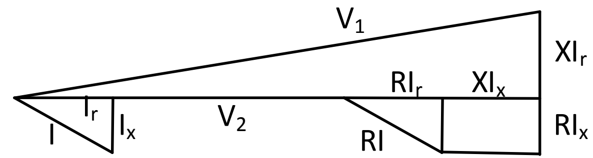
$$V_1 - V_2 = RI_X + XI_R + j(RI_X - XI_R)$$

- Usually $RI_R - XI_x \ll RI_r + XI_r$ and thus,

$$V_{drop} = |V_1| - |V_2| \approx (RP + XQ)/V_2 = RI_R + XI_X$$

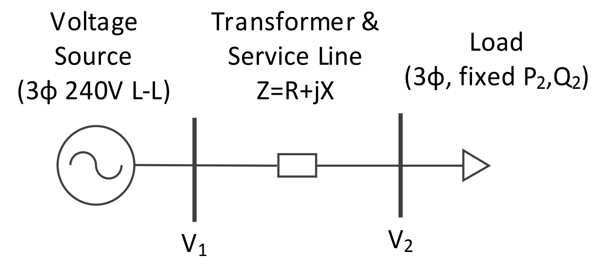


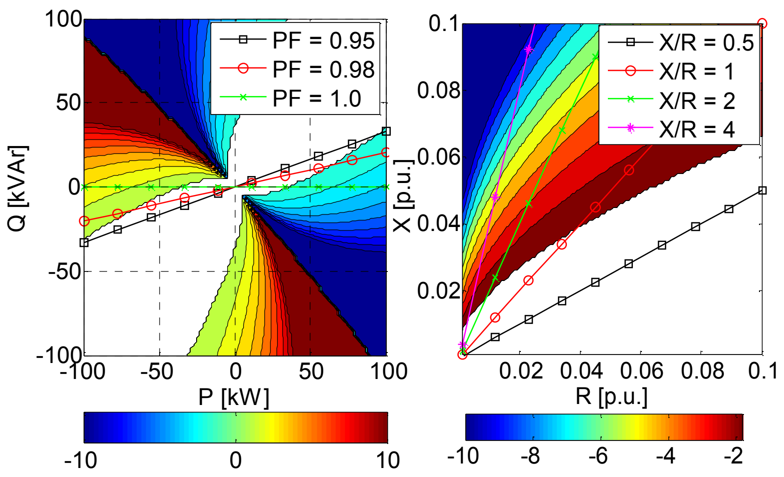




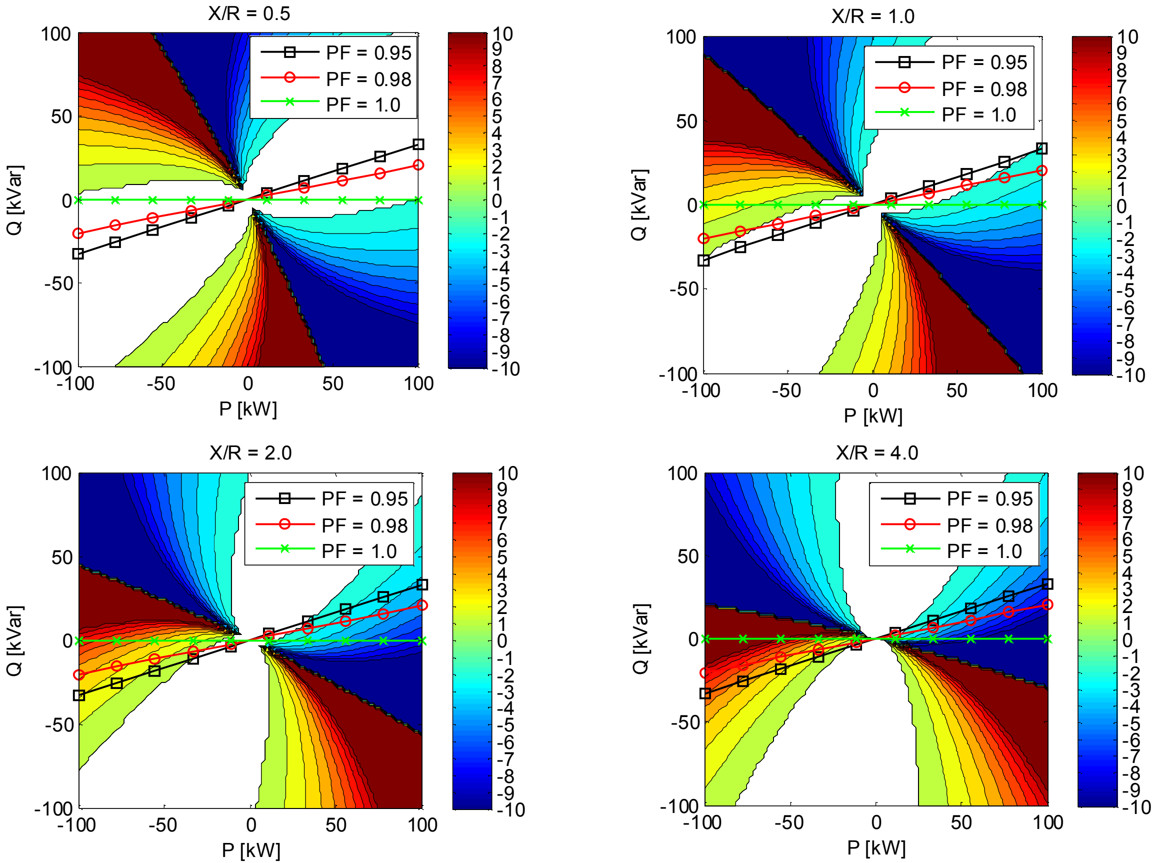
Linearized Voltage Drop Approximation Accuracy

- The linearized voltage drop approximation is known to be accurate in typical situations
- I evaluated the accuracy on a simple 2-bus test case with various P, Q, R, X values
- With typical P and Q values, the approximation error is < 1-2%
- Considerably larger errors can occur with
  1. Large pos. P & neg. Q
  2. Large neg. P and pos. Q

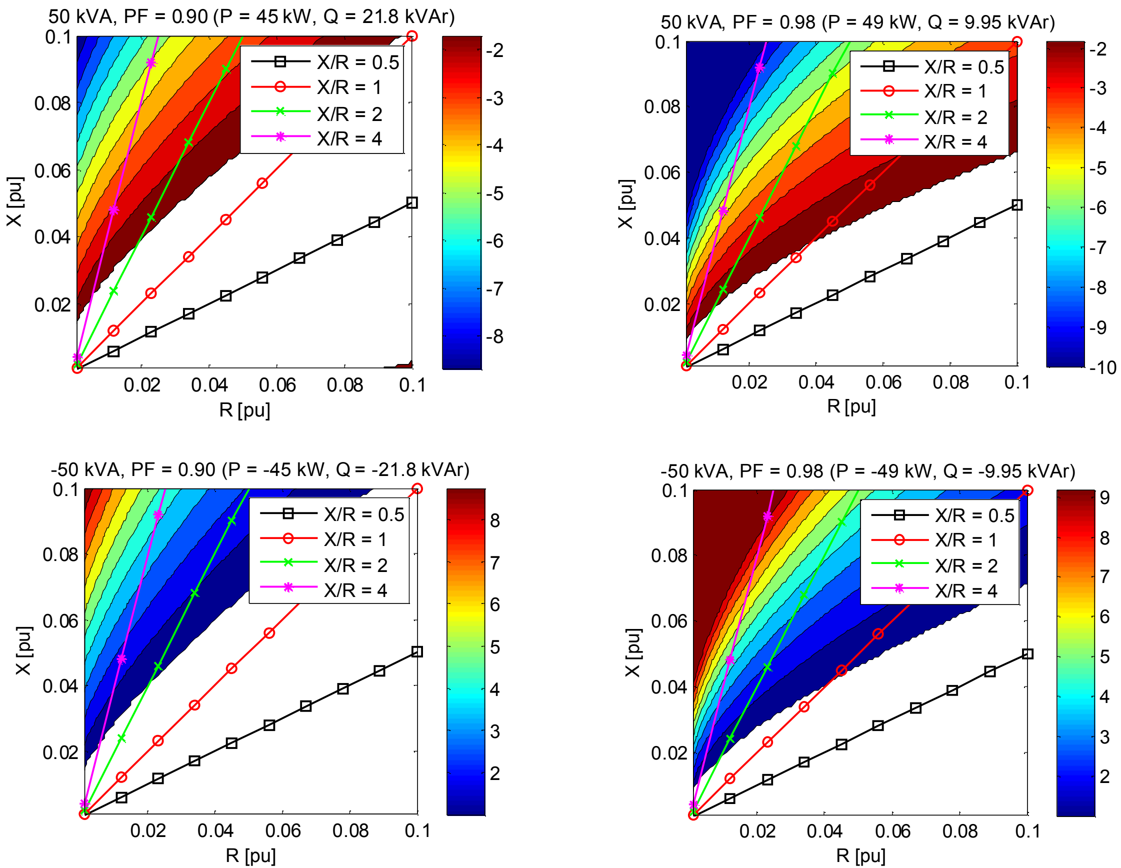




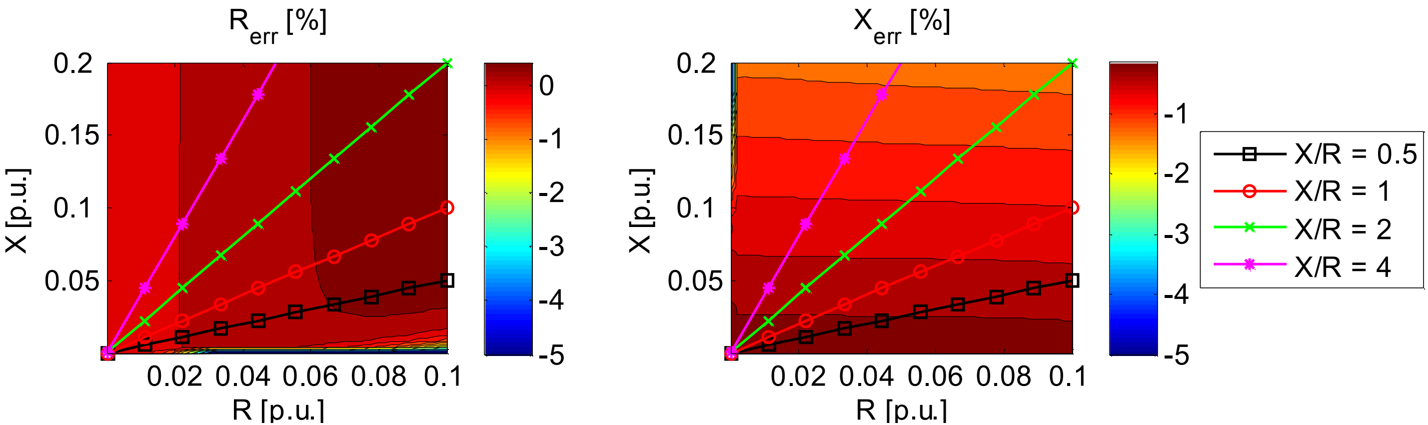
Linearized Voltage Drop Accuracy w.r.t P and Q



Linearized Voltage Drop Accuracy w.r.t P and Q

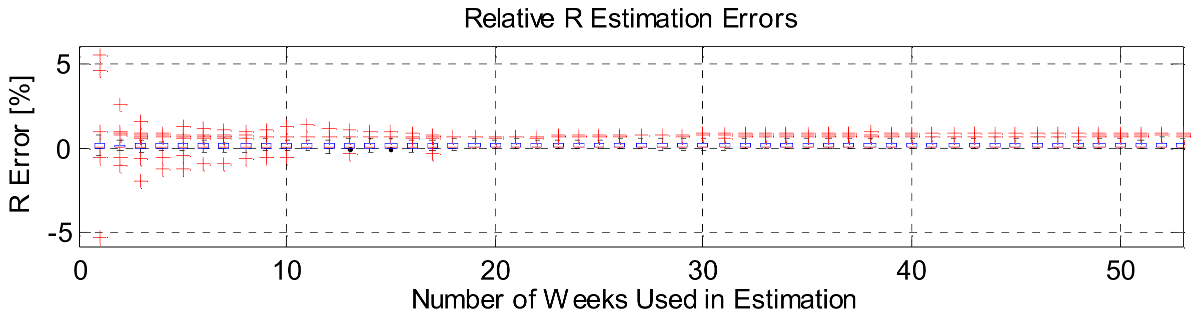


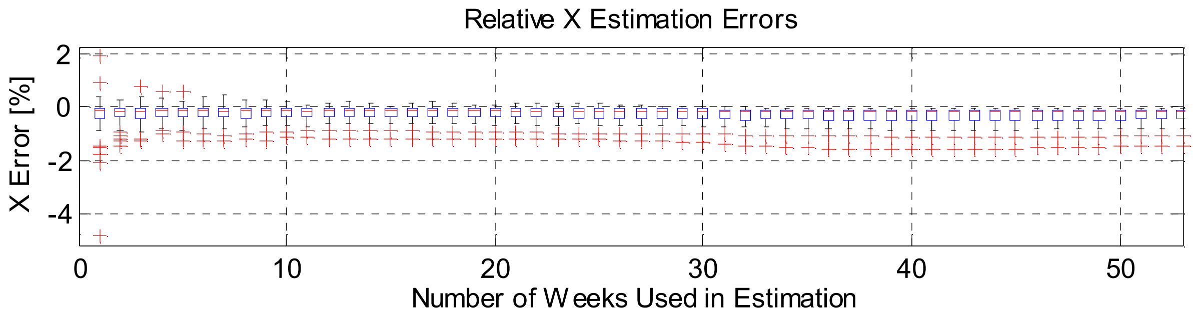
Model Accuracy w.r.t. R and X



Parameter Estimation Accuracy w.r.t. Sample Size

- How large sample size is needed without measurement error?





Georgia Tech Feeder Detailed Results

- Many peculiarities encountered
  - Meter 136E_ML1 records instantaneous measurements
  - Meter B149E_MH2 has an abnormal load shape due to large research equipment
  - Building B199E_MH1 has a lot of PV with negative power injections