

# Mapping Low Voltage Networks Using AMI Data



MONASH  
University



THE UNIVERSITY OF  
MELBOURNE



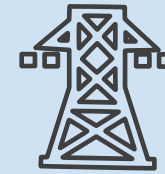
# Project Overview



**Smart Meters  
Data**



**Phase Grouping**



**Topology/Impedance  
Estimation**



**Applications**

## Research Team



Dr Reza Razzaghi



Dr Lachlan Andrew



Abu Pengwah



David Flynn

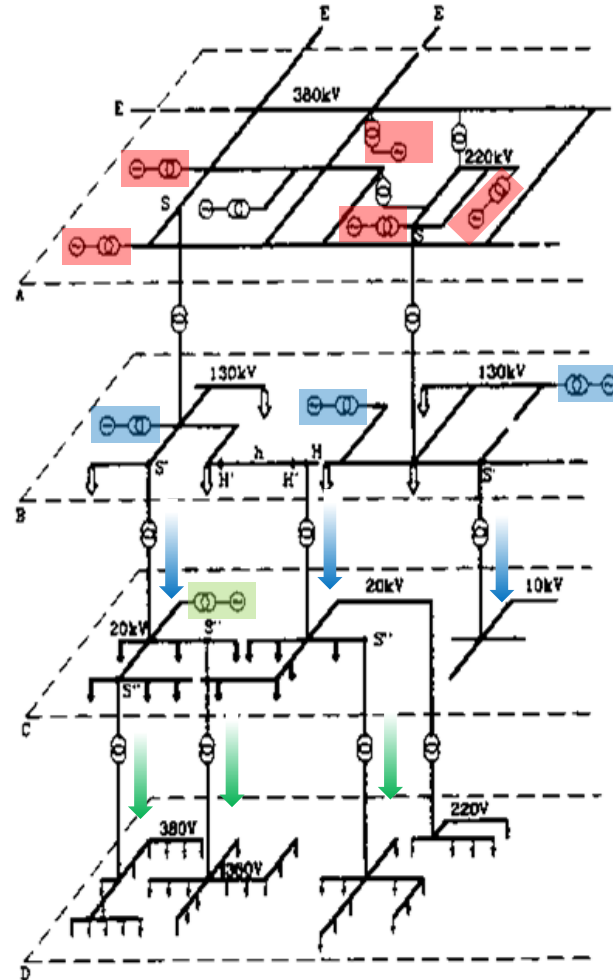
# Challenge- Visibility of LV Networks

**Transmission**

**Sub-transmission**

**Distribution (HV)**

**Distribution (LV)**



In traditional power systems, the main **sources of uncertainties** are represented by the **loads**.



Majority of the control and operational problems are solved in the **planning** or **dispatching** stages.



**LV Network visibility was not necessary**

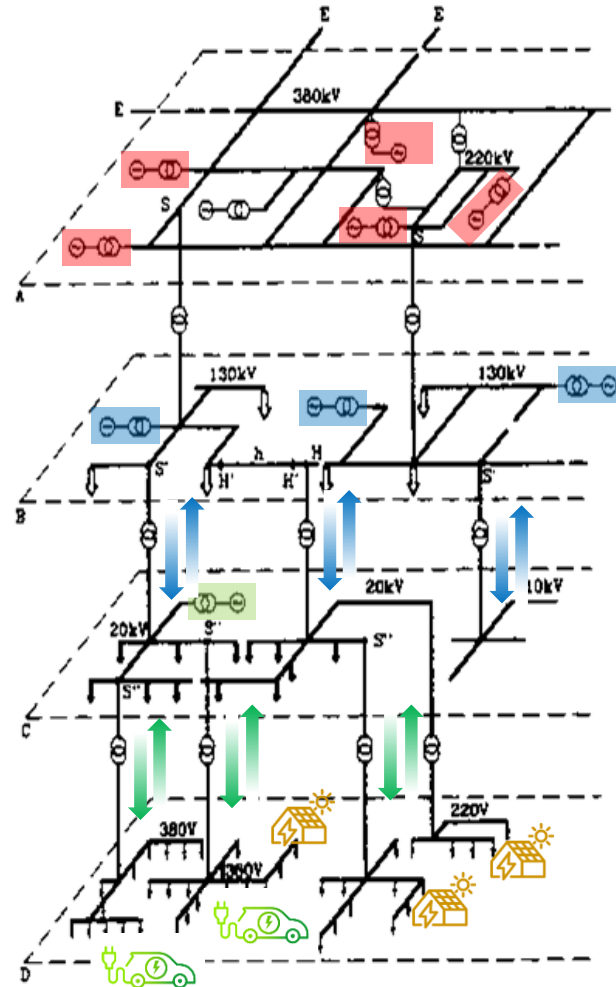
# Challenge- Visibility of LV Networks

**Transmission**

**Sub-transmission**

**Distribution (HV)**

**Distribution (LV)**



Distributed energy resources (DER)



DER management and orchestration



Visibility and accurate models are needed

# Challenges – Electrical Models of LV Networks

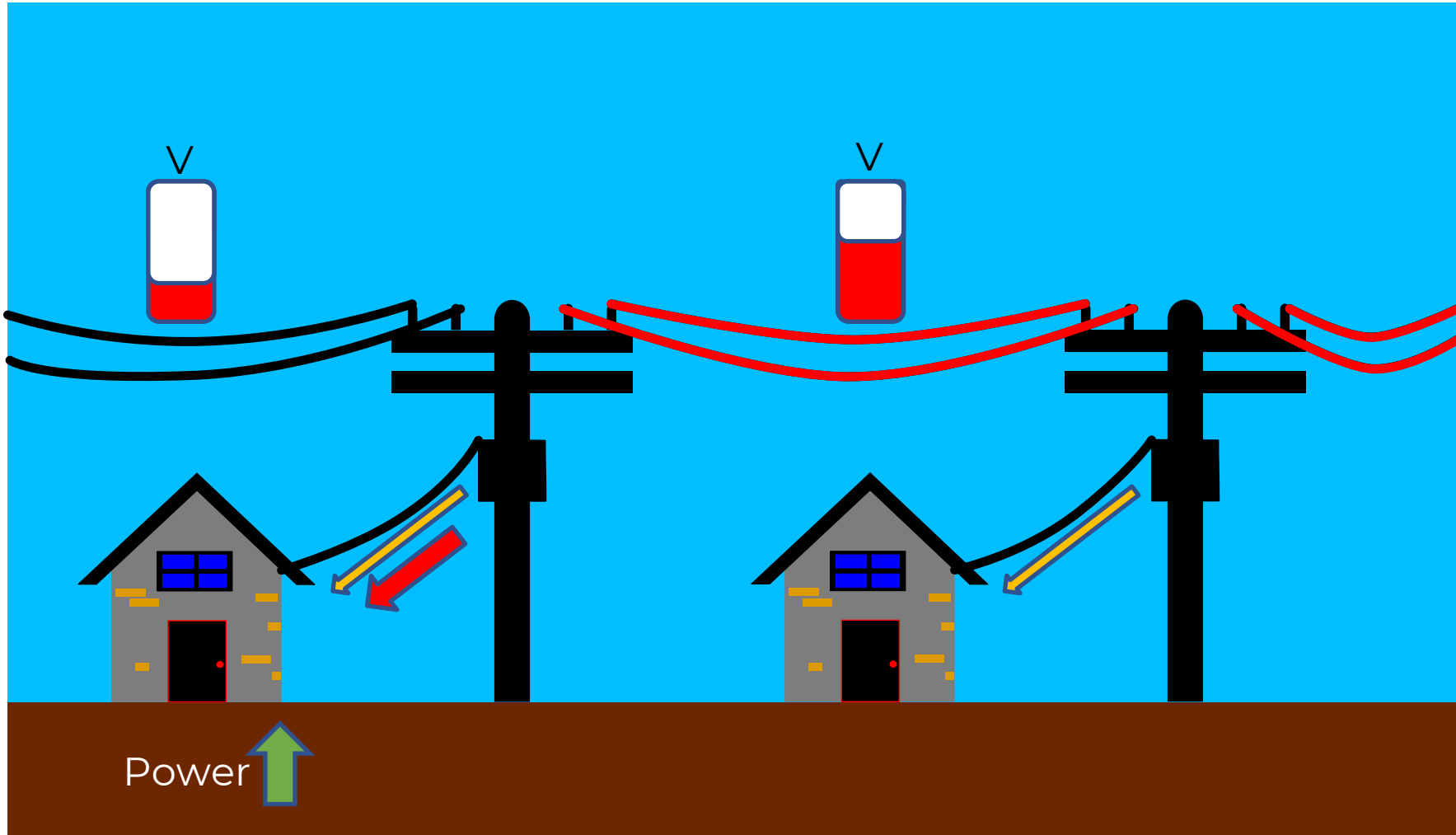
1 Incomplete assignment of customers to phases

2 Inaccurate location of customers on LV circuits

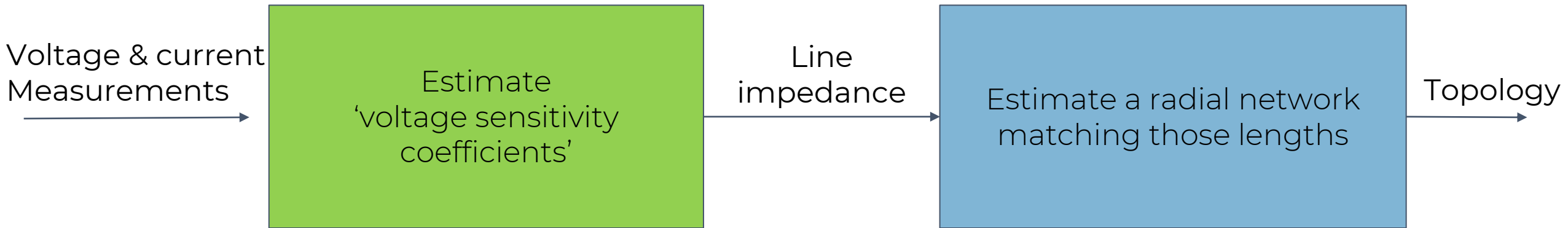
3 Incomplete records of network topology

4 Incomplete electrical parameters of LV lines

# Voltage Sensitivity Coefficients



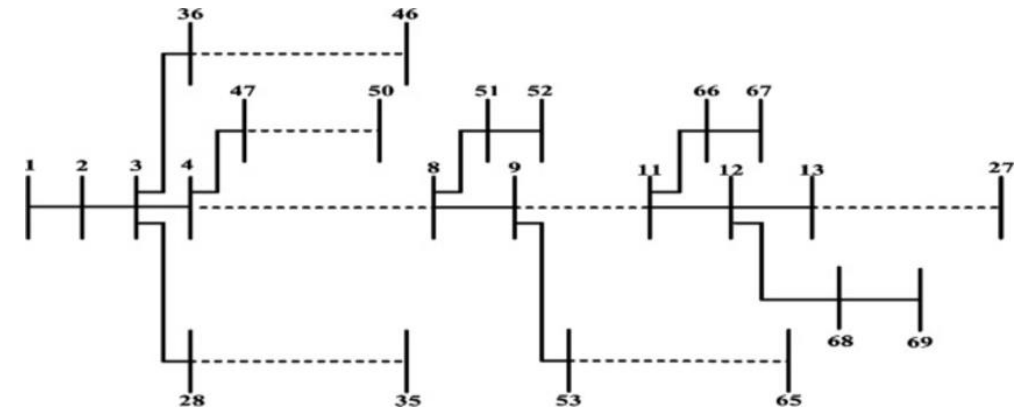
# Algorithm Outline



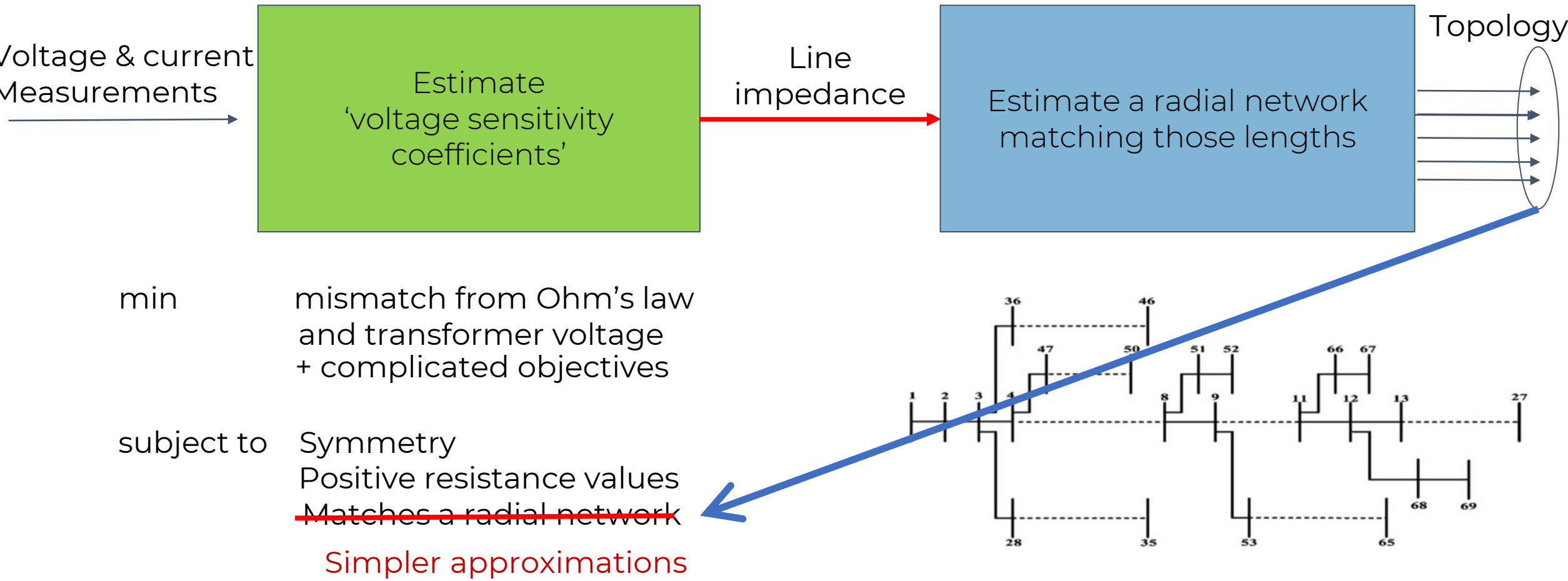
Ohm's law

Noisy data -- non-physical solutions

Want the "best" estimate satisfying physical constraints



# Algorithm Outline

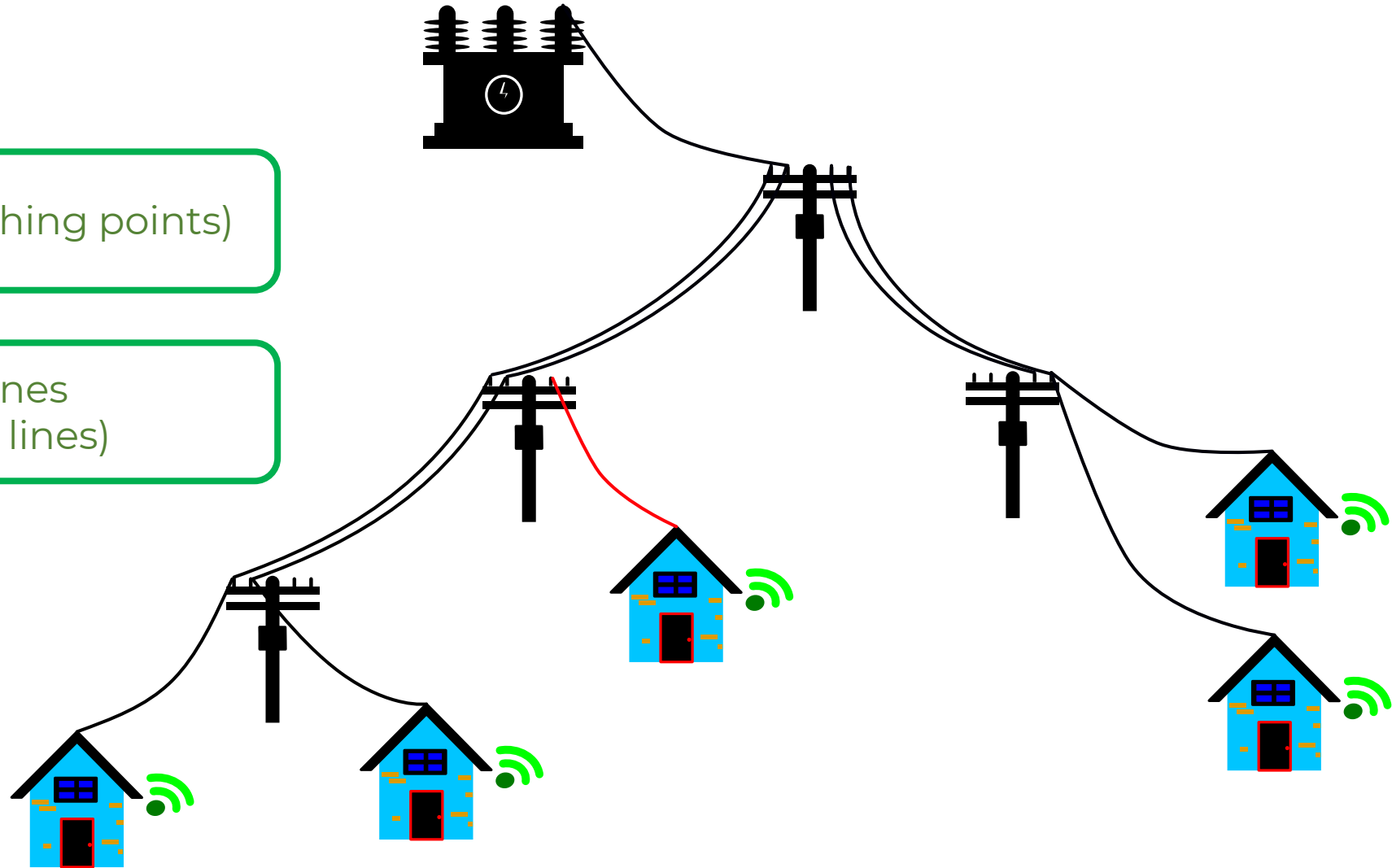




# Topology Learning Algorithm

1 Location of poles (branching points)

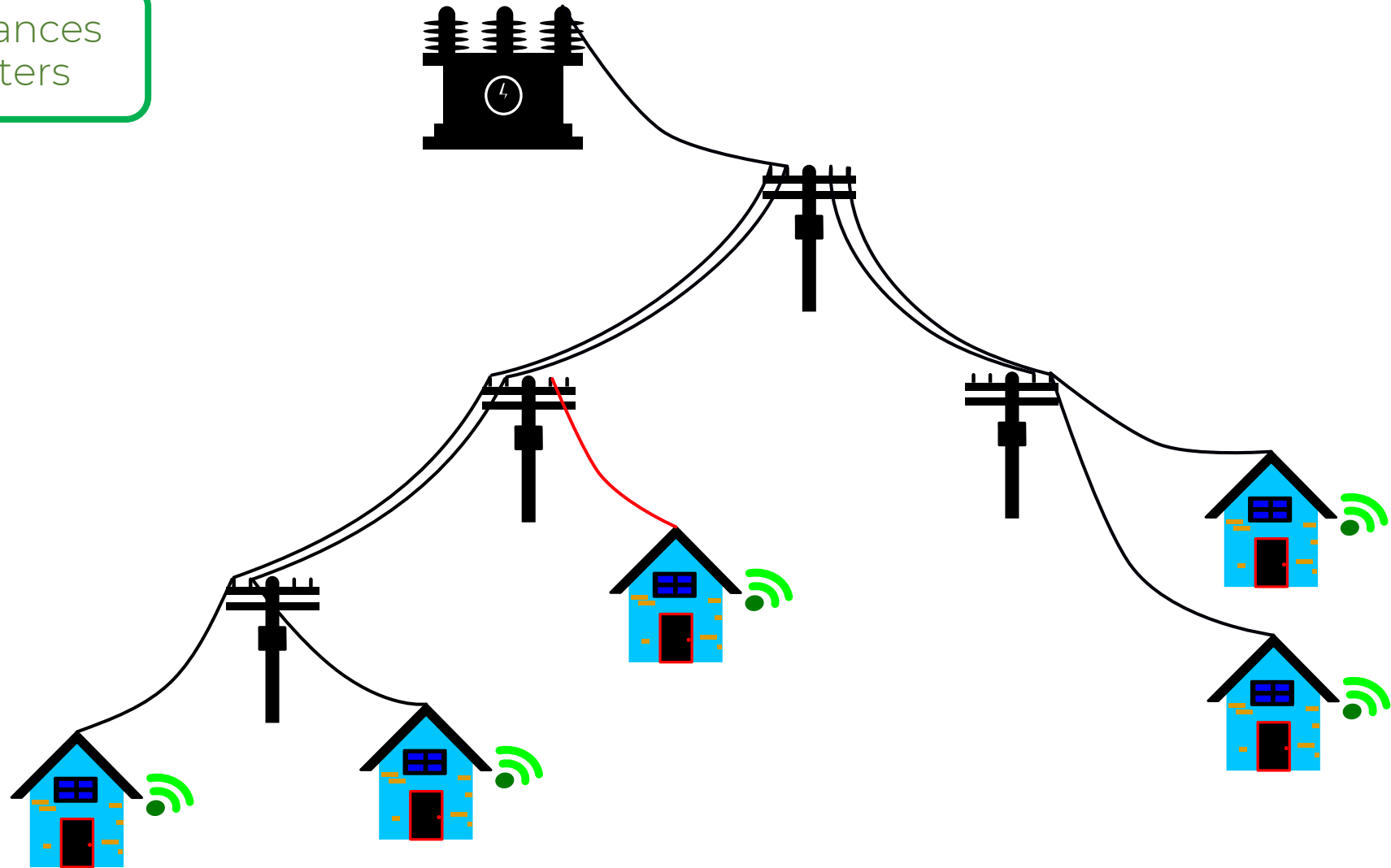
2 Impedance of lines  
(including service lines)



# Topology Learning Algorithm

1

Estimated electrical distances  
between customer meters



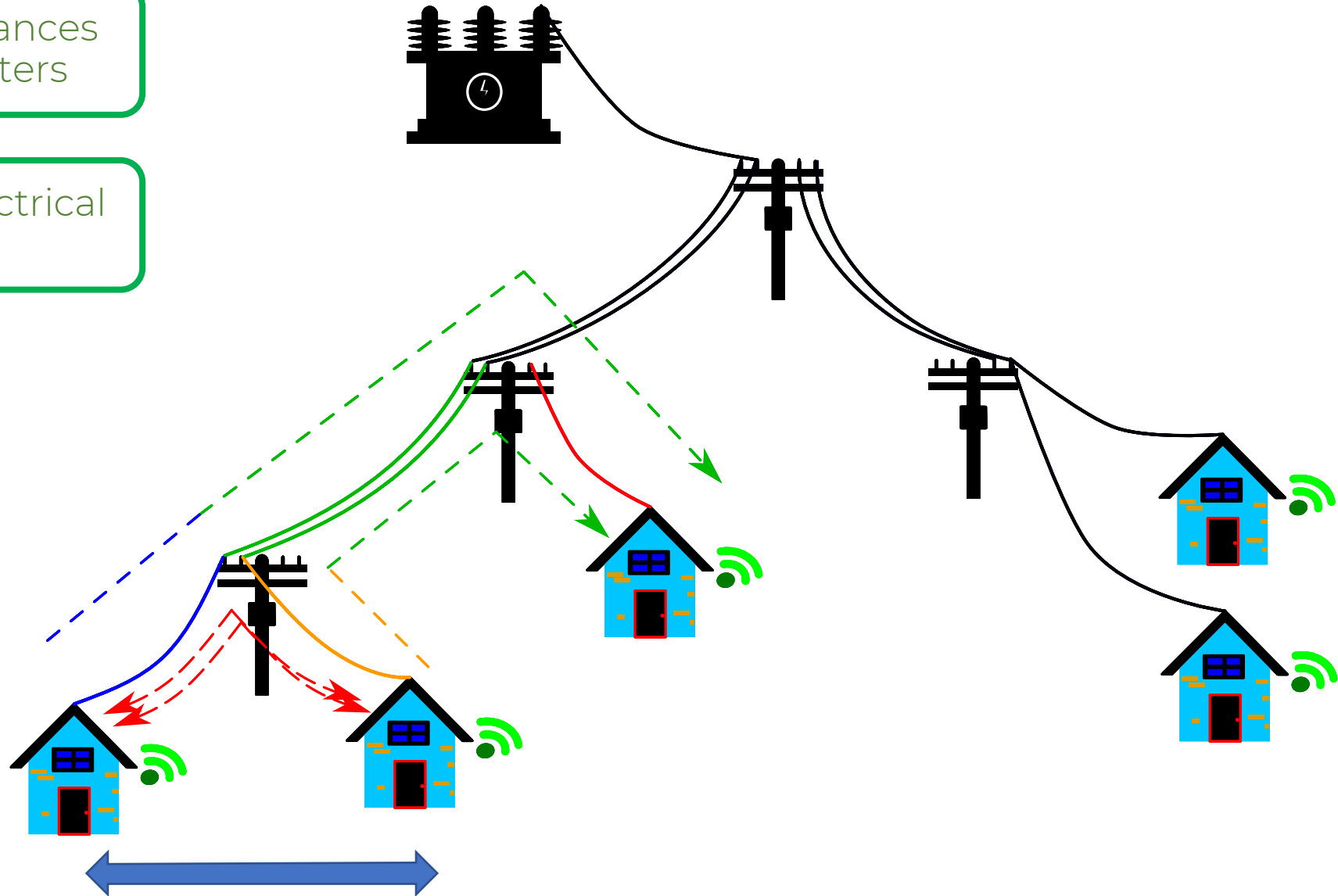
# Topology Learning Algorithm

1

Estimated electrical distances  
between customer meters

2

Differences between electrical  
distances



# Topology Learning Algorithm

1

Estimated electrical distances  
between customer meters

2

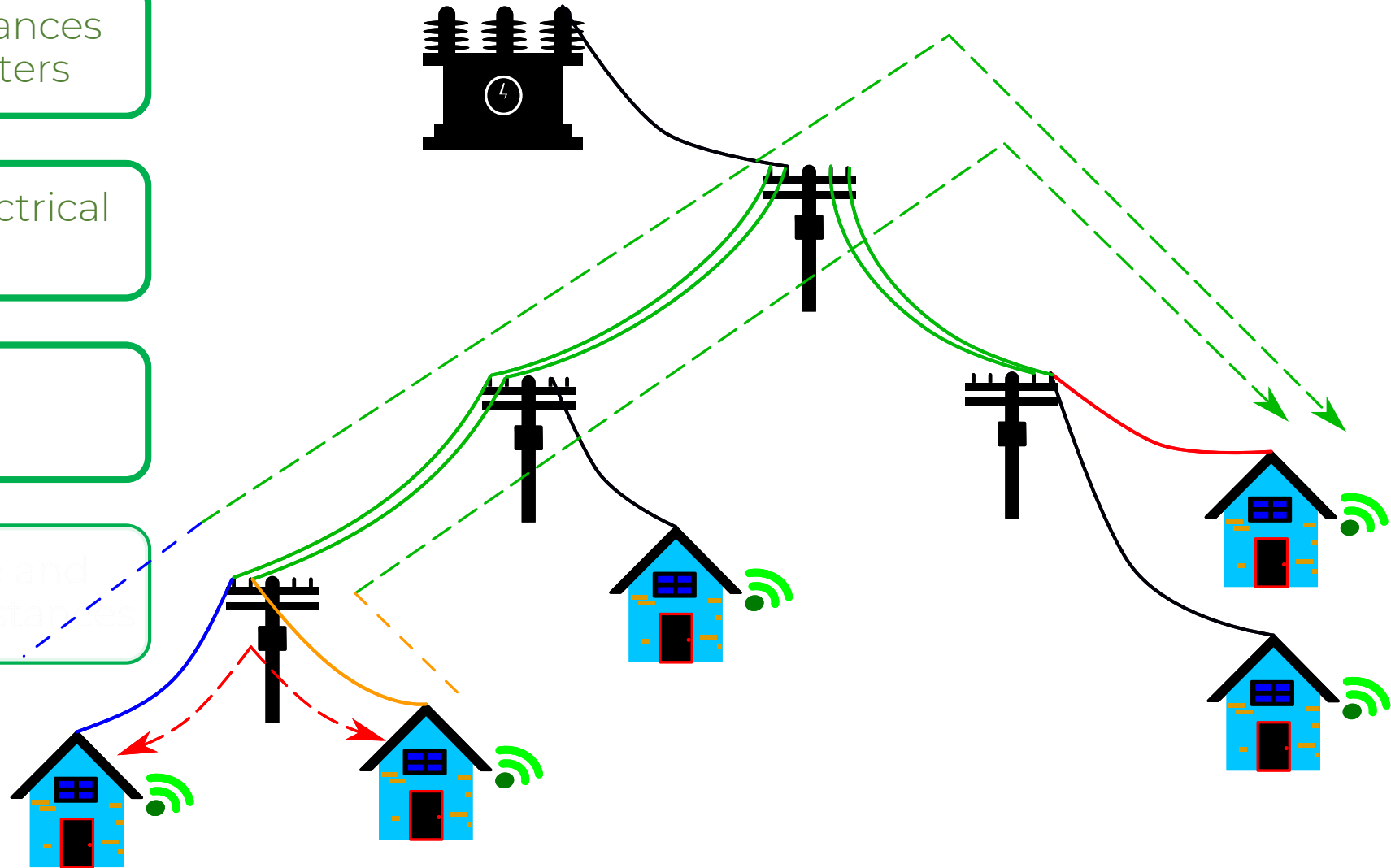
Differences between electrical  
distances

3

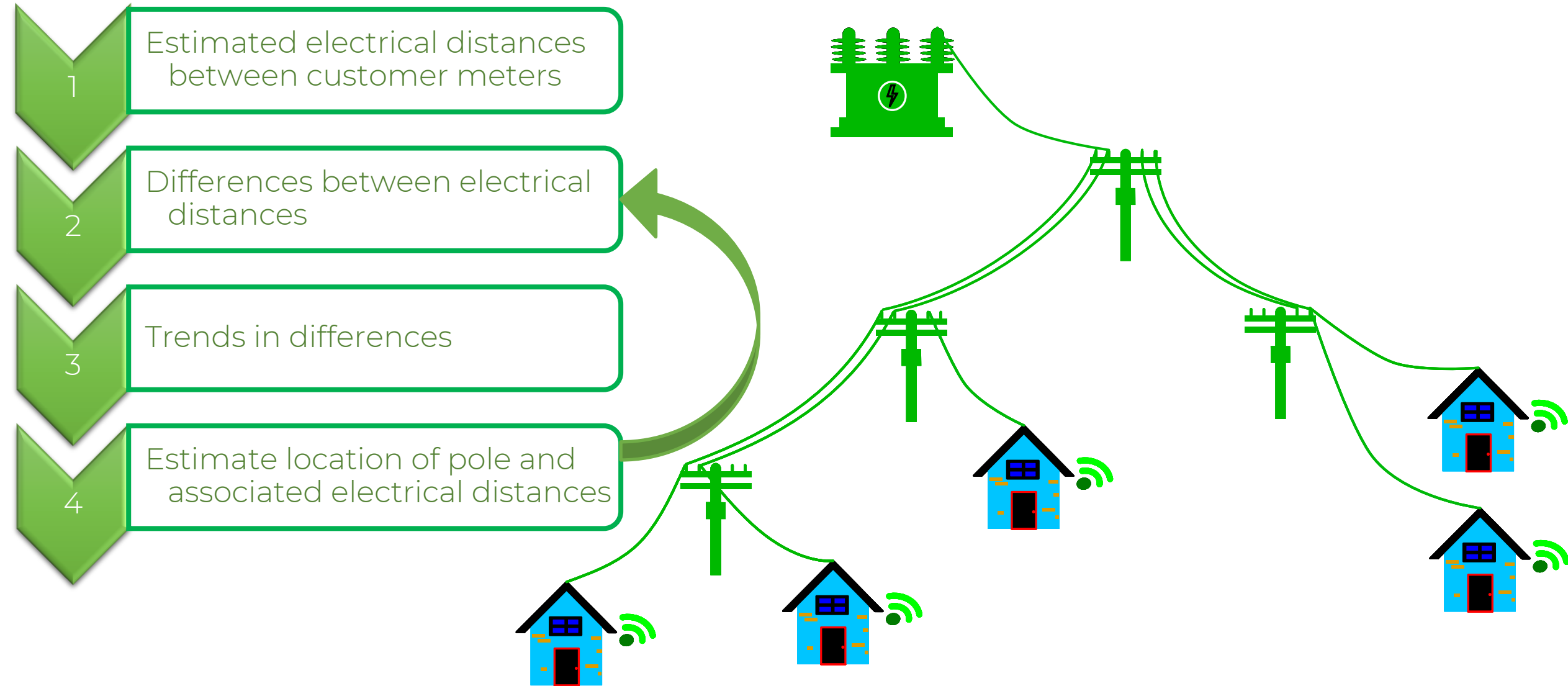
Trends in differences

4

Estimate location of pole and  
associated electrical distances

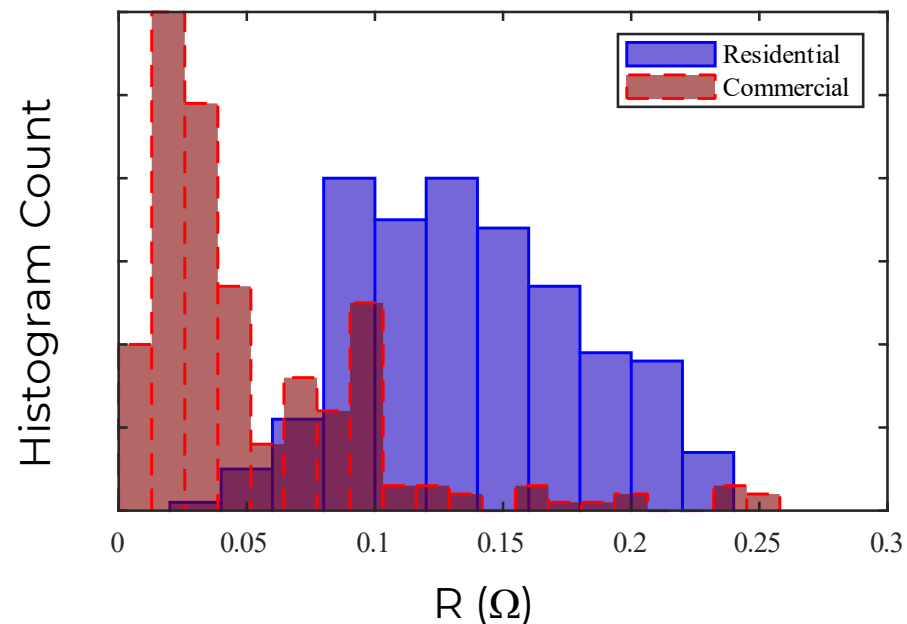
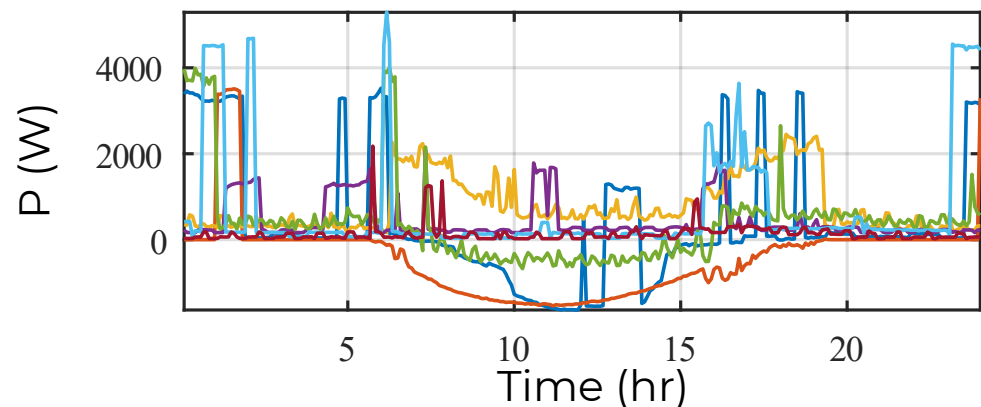


# Topology Learning Algorithm

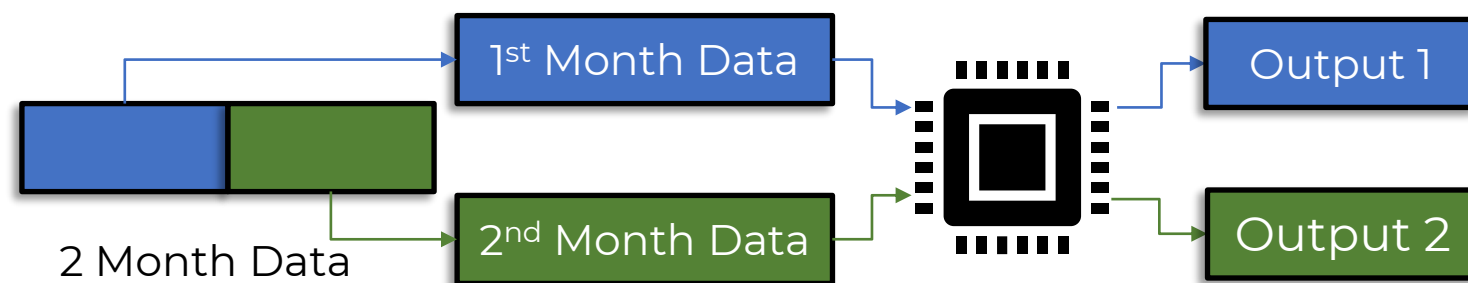
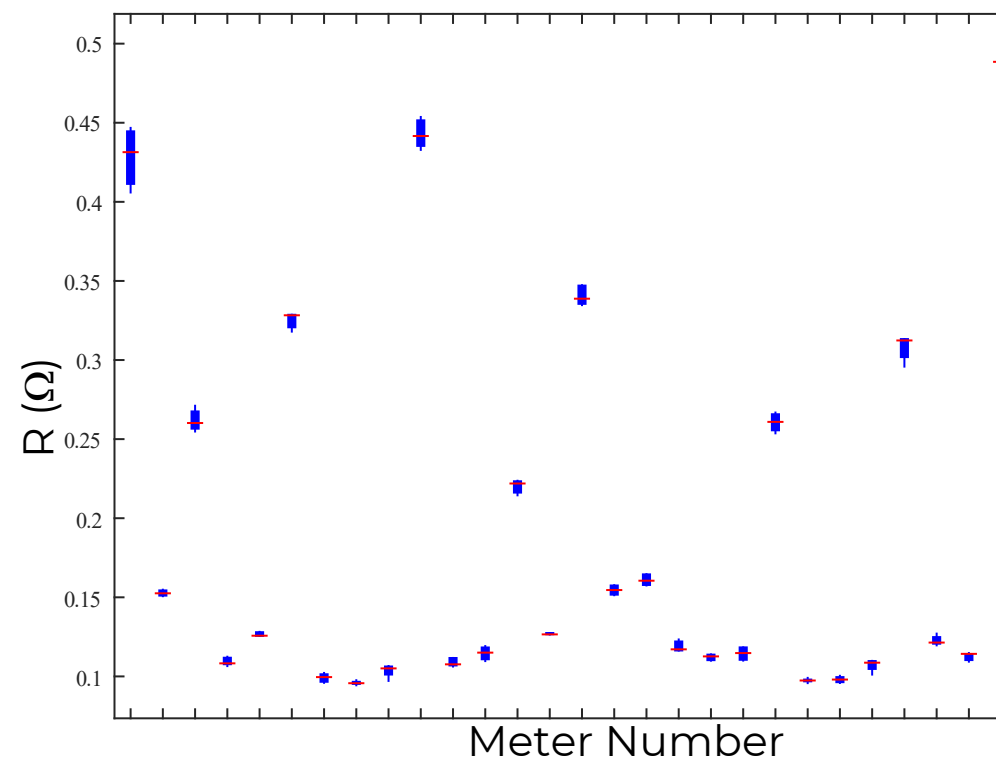


# Line Impedance Estimation

Typical load profile during a day

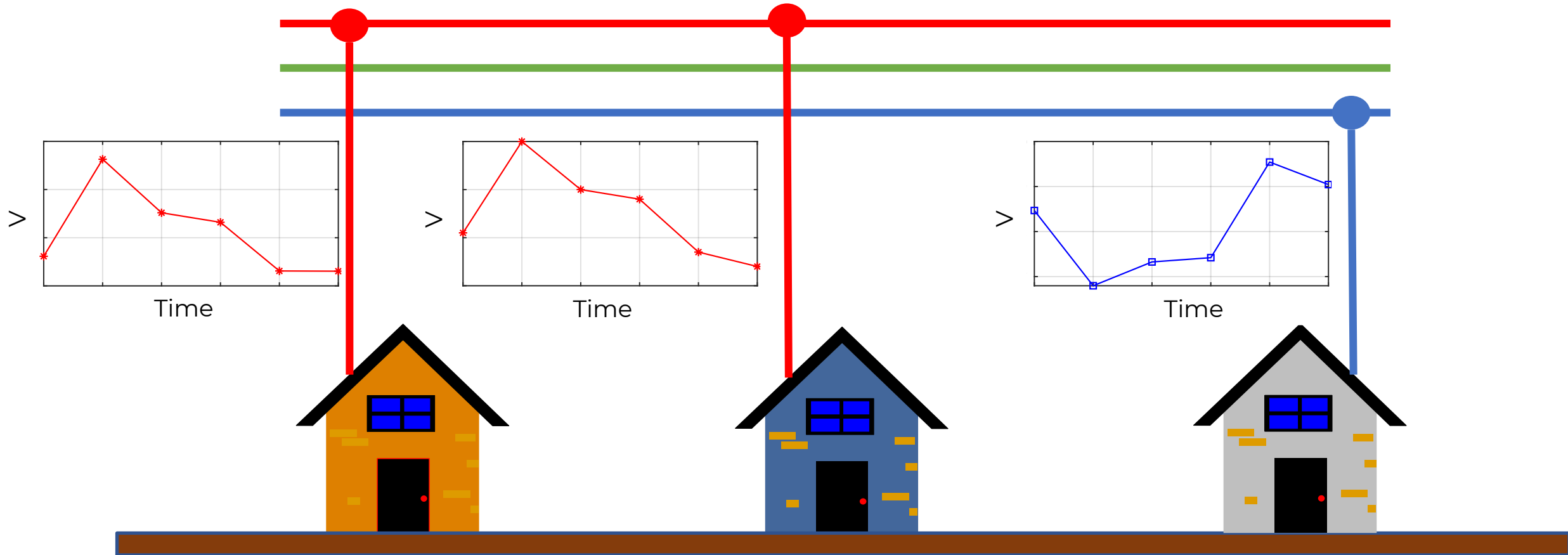


Variation in the estimated impedance using non-overlapping sets of measurements

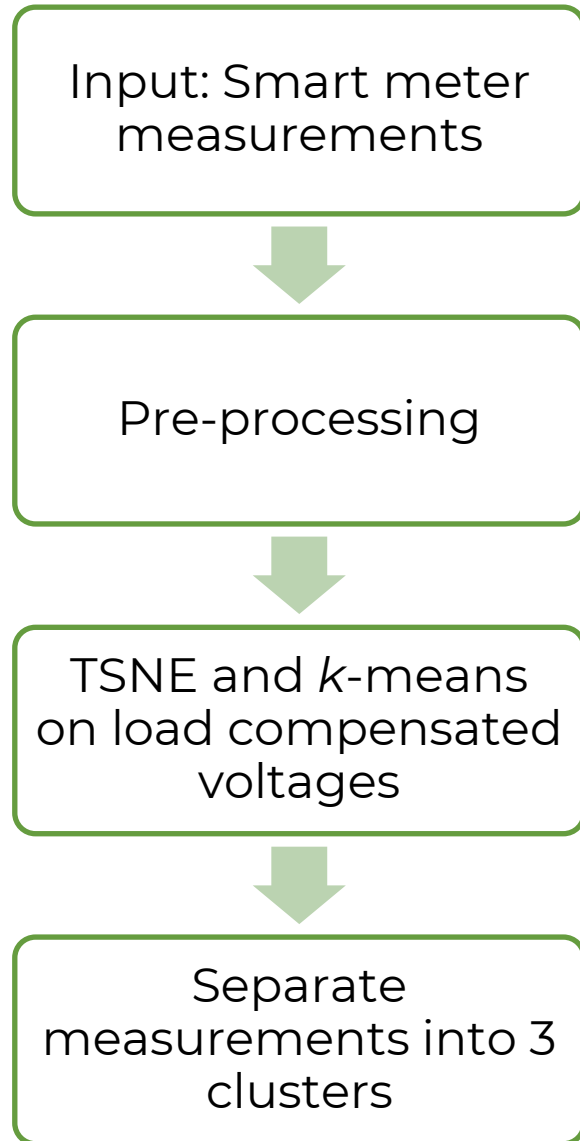


# Customer Phase Grouping

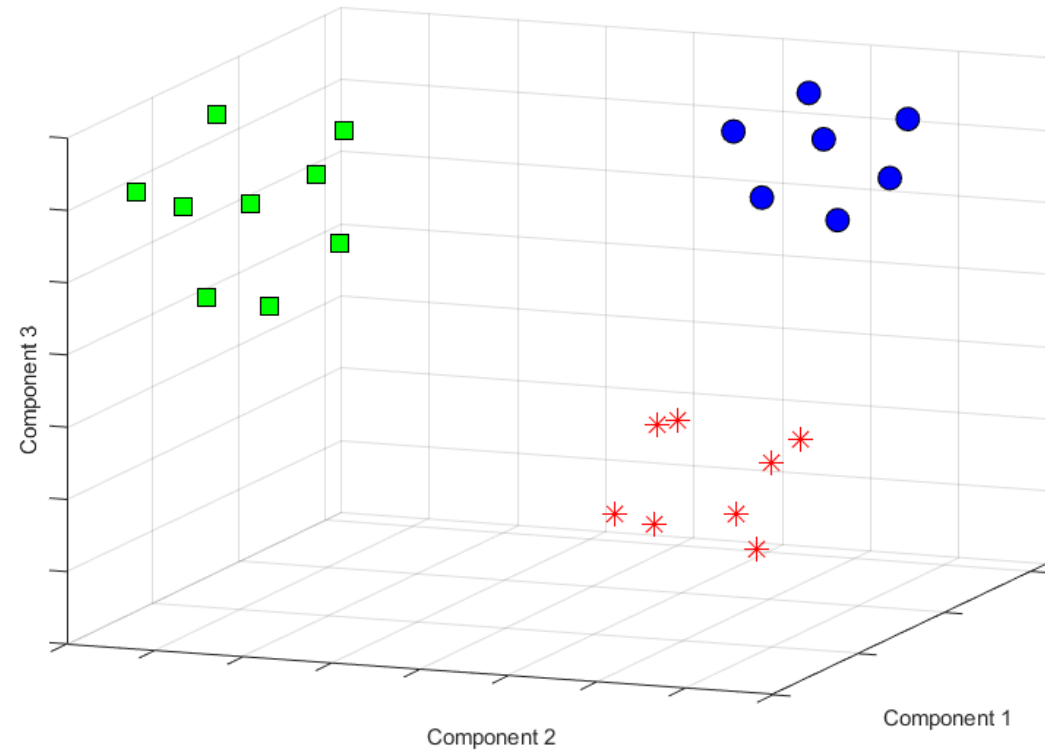
Voltage correlation-based techniques for phase grouping



# Customer Phase Grouping



Example of clusters





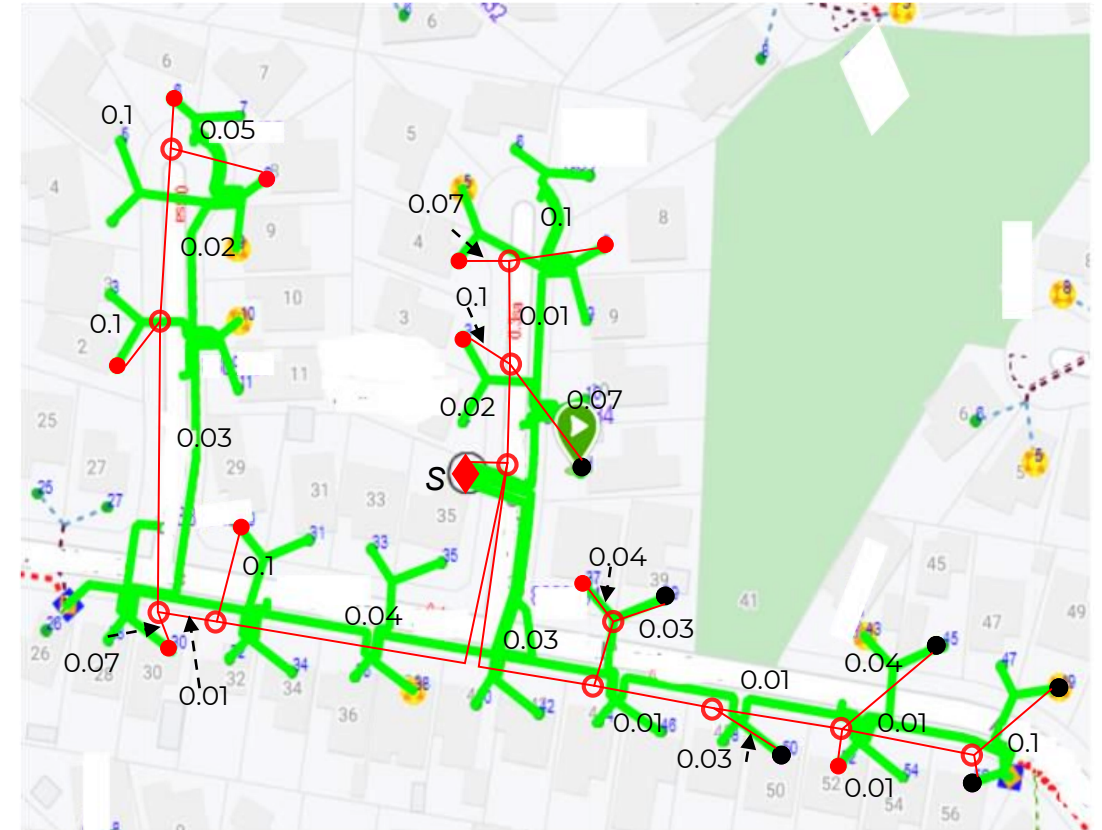
# Network Topology Estimation - Performance Evaluation

Tested on various LV networks:

- 6 transformers with residential customers
- 5 transformers with commercial customers

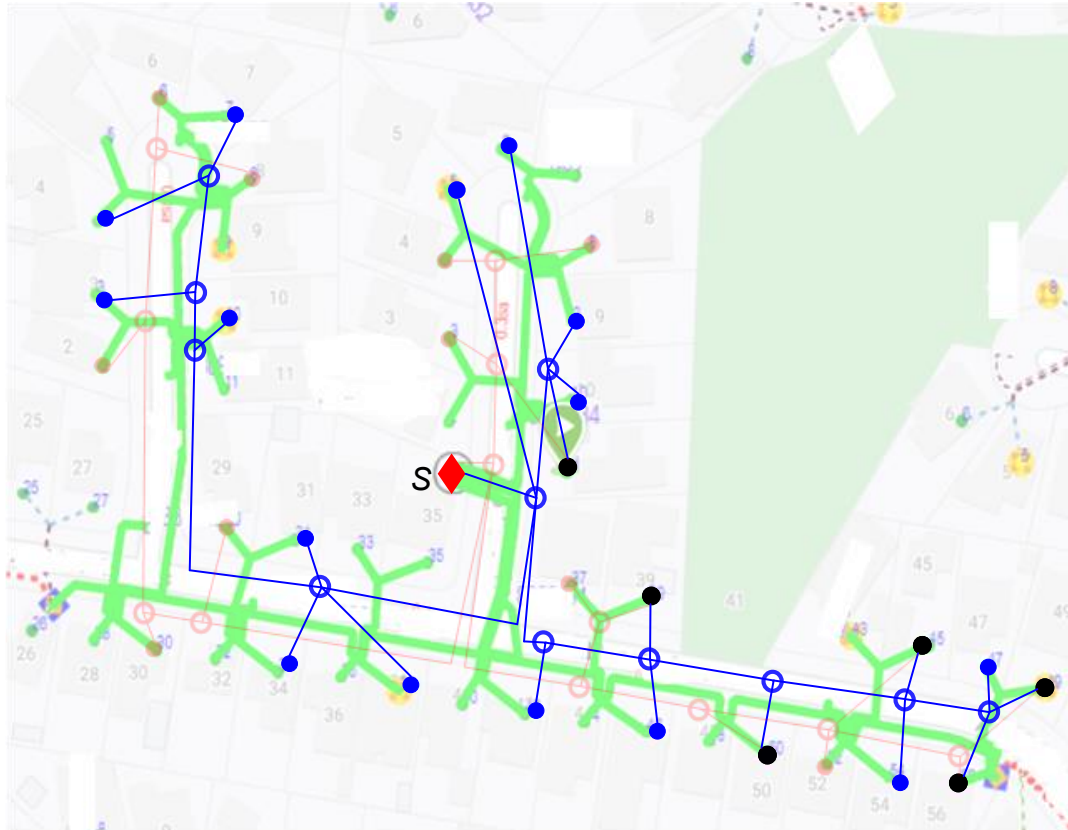
Consistency check using non-overlapping sets of measurements

Network 1- Phase R

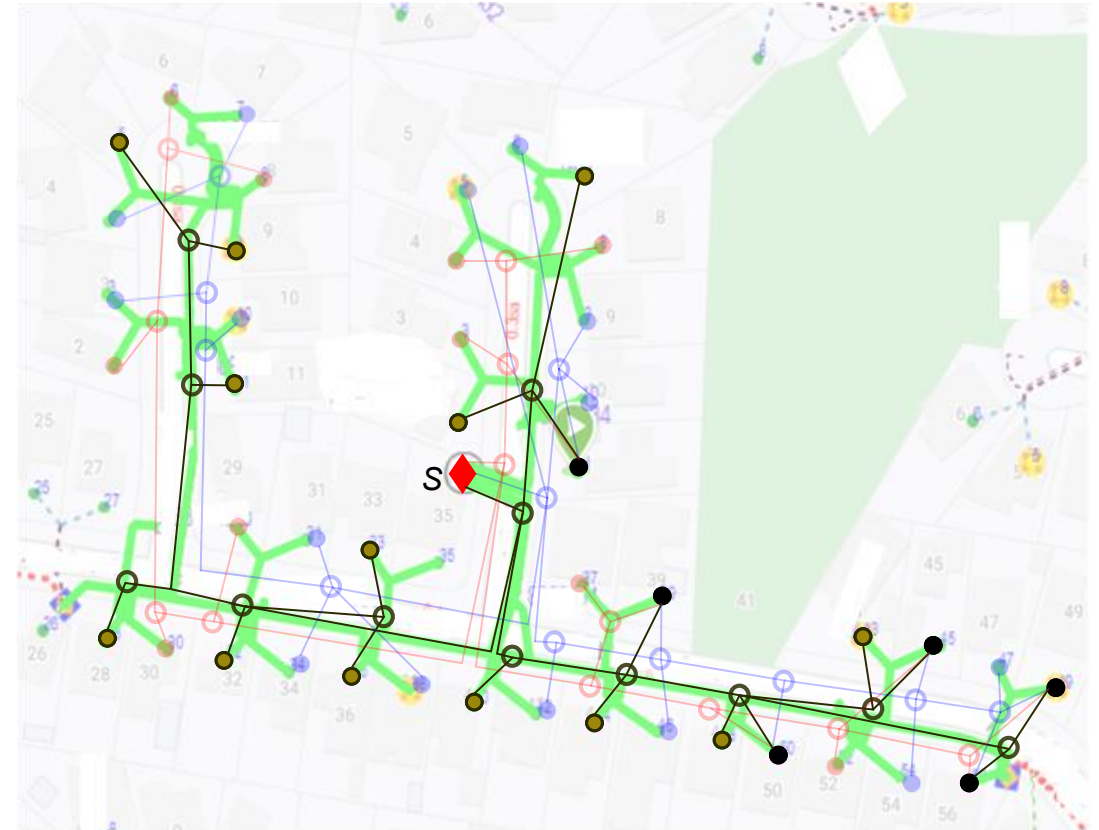


# Network Topology Estimation - Performance Evaluation

Network 1- Phase B



Network 1- Phase W



# Application 1 - Fault Detection

## Challenge:

Faults can occur throughout the network

Can be easy to fix, but require knowledge on where fault has occurred – not always obvious

Can we **detect** and **locate** these faults in a timely manner?



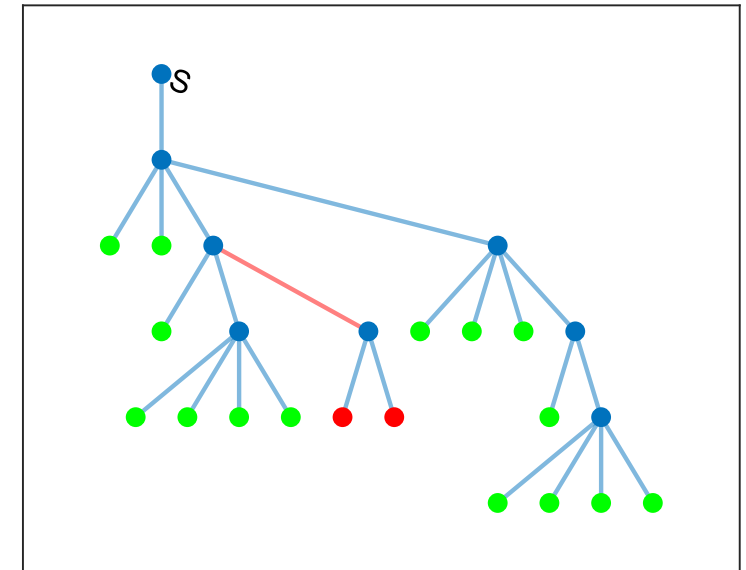
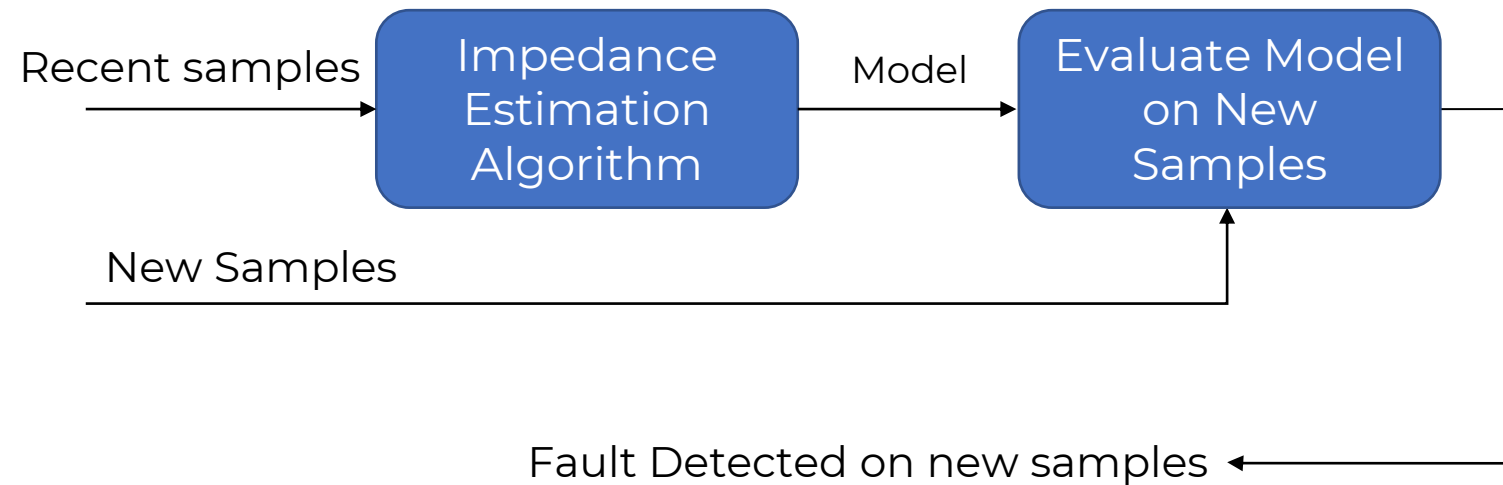
# Application 1 - Fault Detection

## Solution:

Build models of network before faults occur (keep models up to date)

When a fault occurs, observe a deviation from expected customer voltage values

Deviations occur for customers downstream from the fault





# Application 1 - Fault Detection

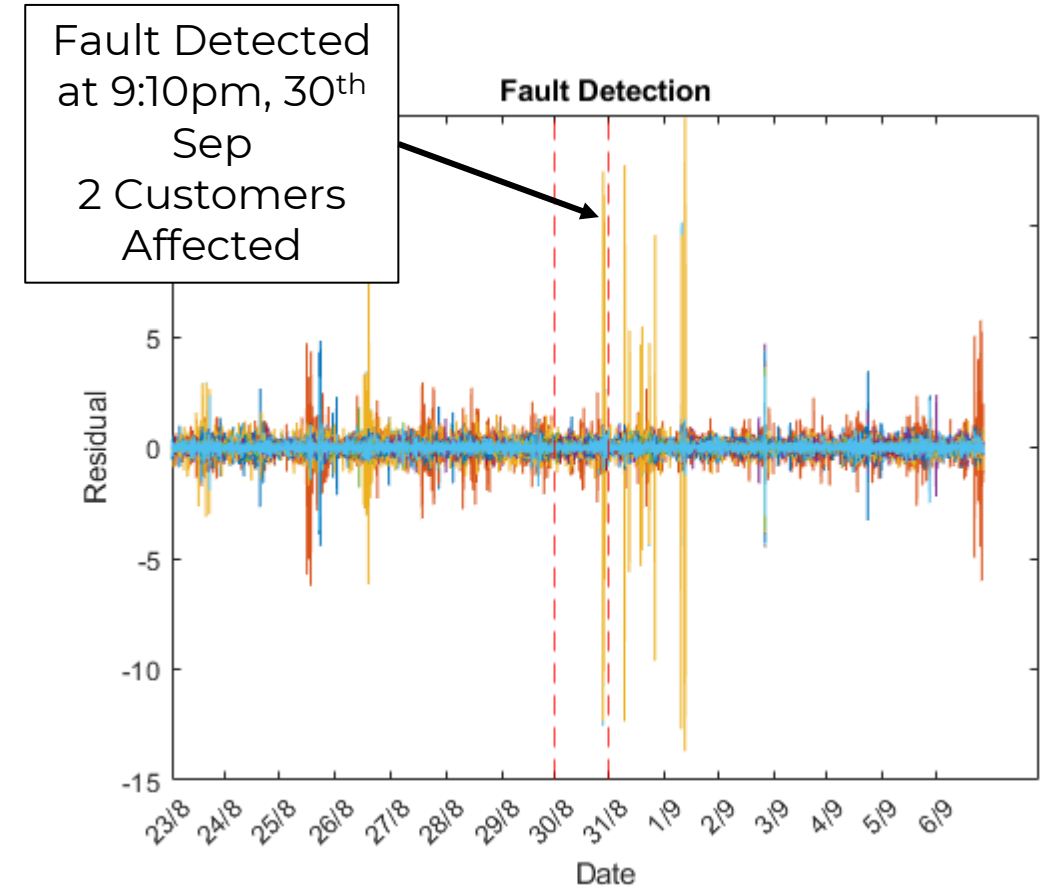
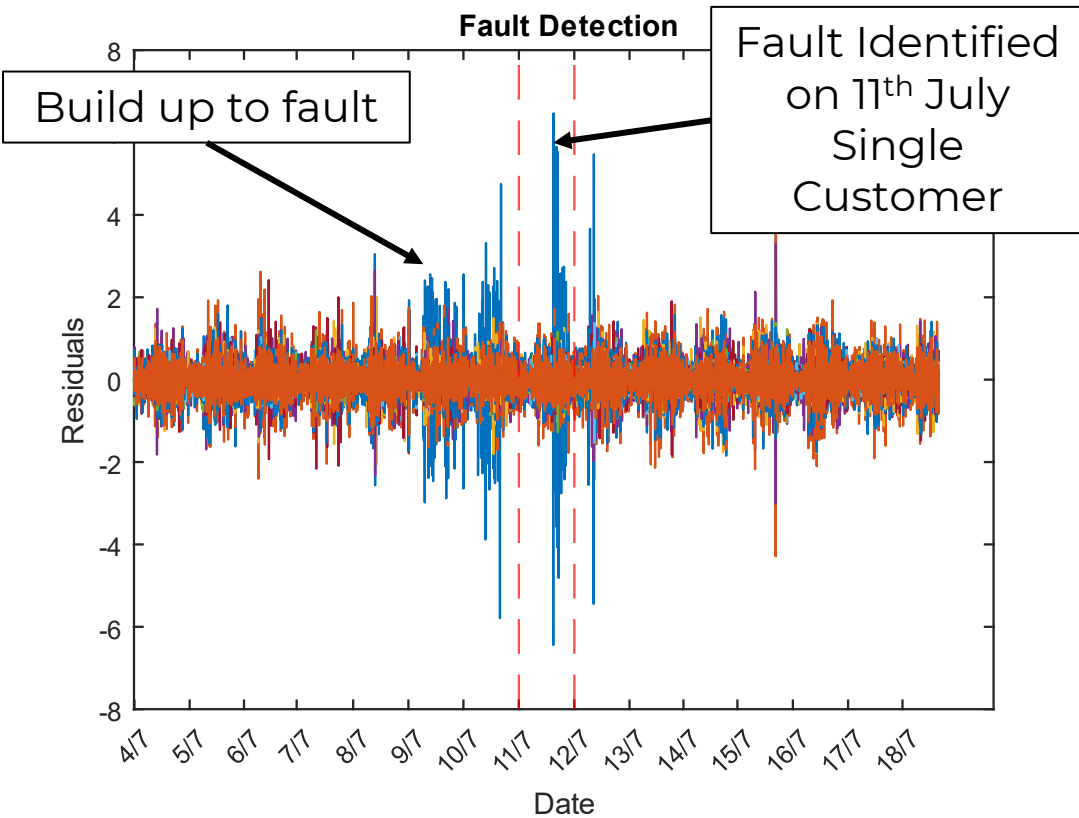
## Test Cases:

- High impedance fault
- Burned Fuse in pillar
- Rubbing caused by council tree

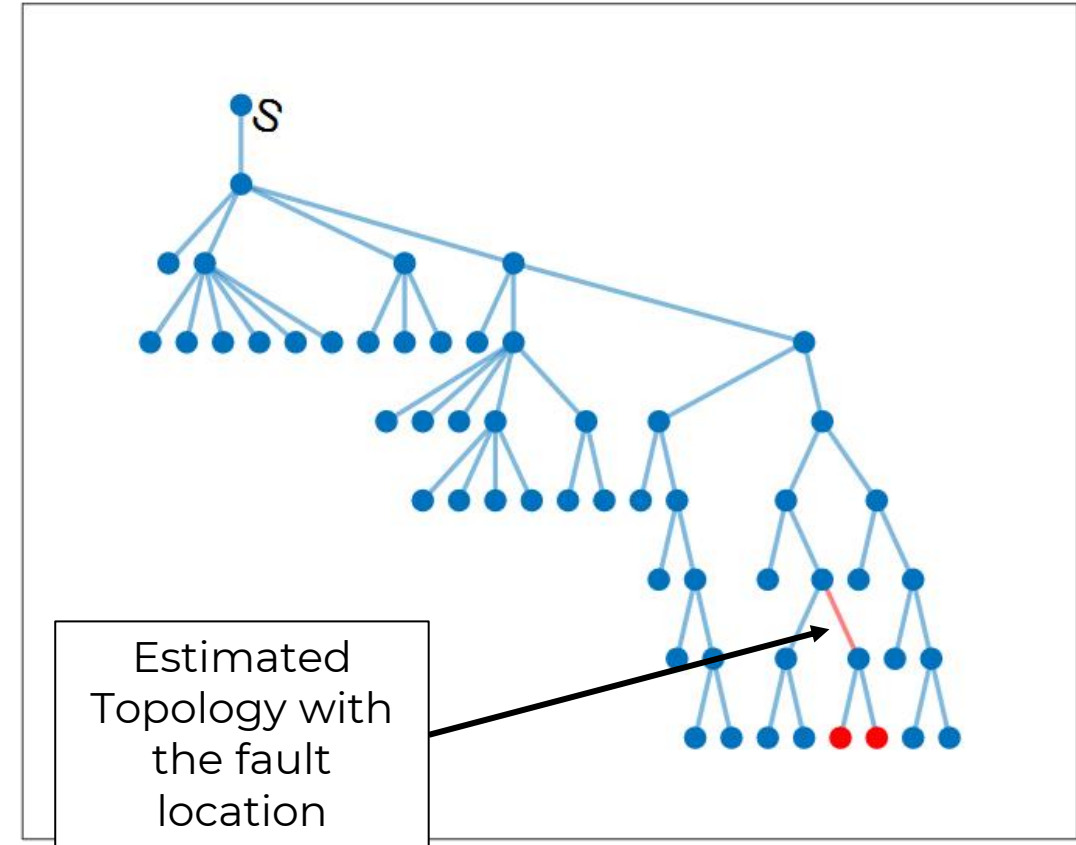
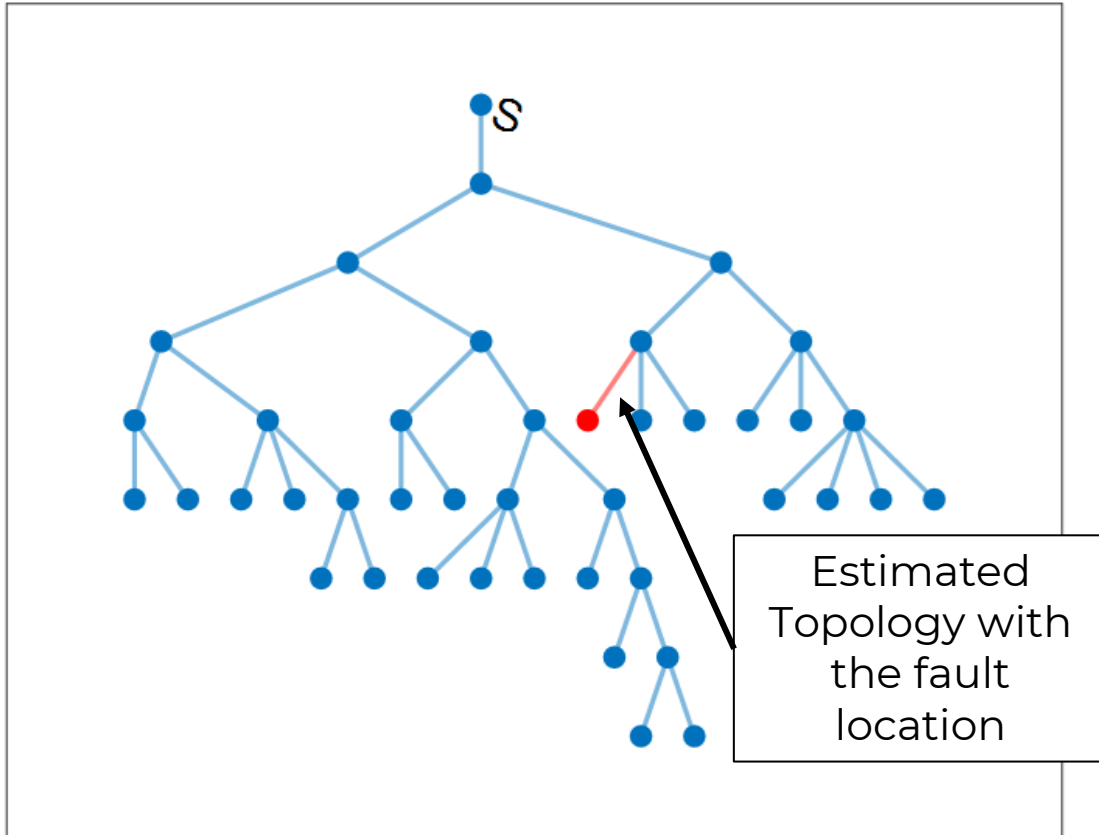
## Summary of Findings:

- Faults are identified for all test cases
- Fault signatures can be seen within 2 samples (typical 10 minutes)
  - Longer times will allow for more confidence
- In some cases, able to **detect build up to the fault**

# Application 1 - Fault Detection



# Application 1 - Fault Detection



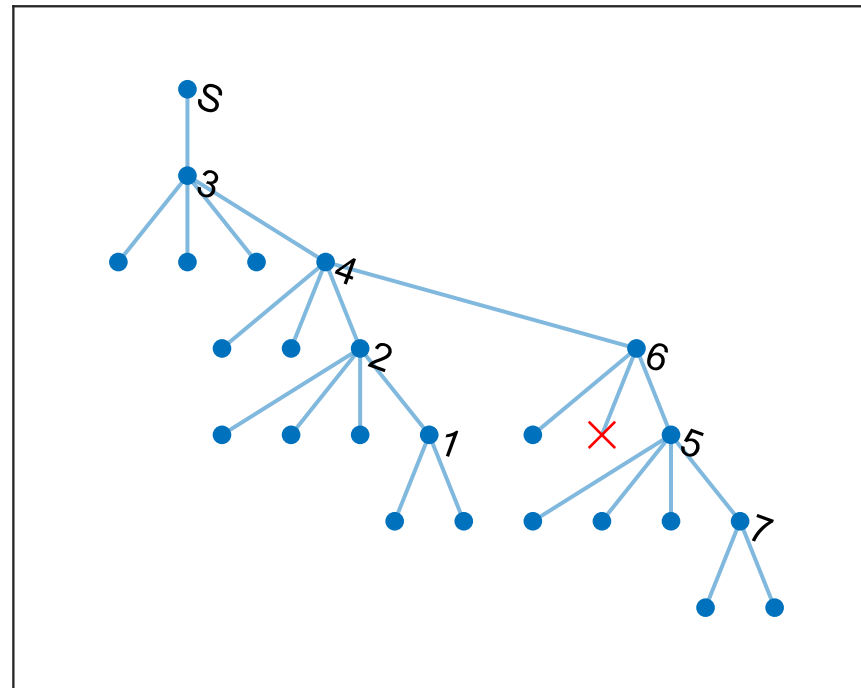
# Application 2 - Unmetered Load detection



Source: Ausgrid

## Problem:

- Some loads aren't metered (streetlights, theft)
- Assuming high smart meter coverage, with only 1-2 unmetered customers
- **Where are these loads?**



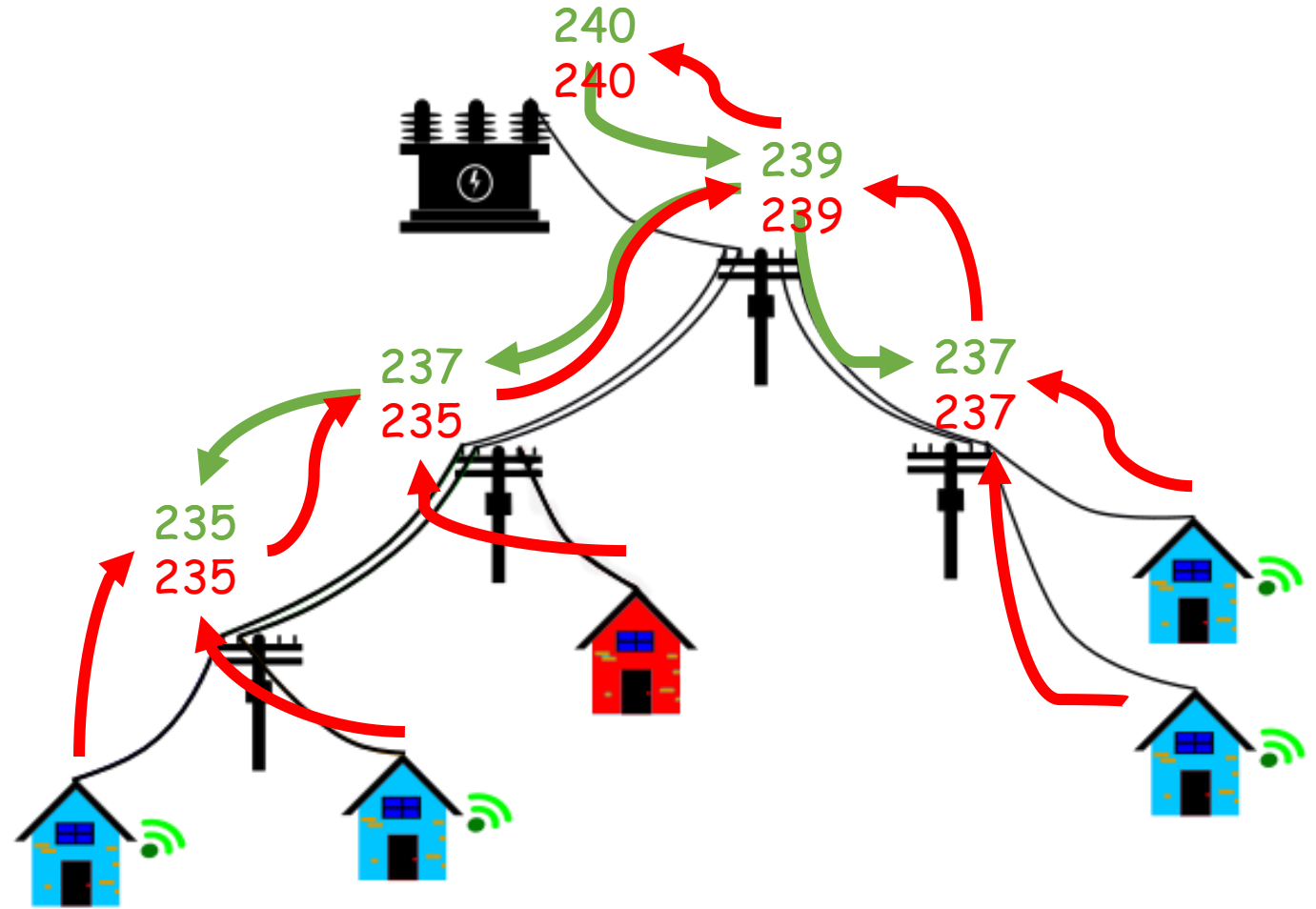
YES  
Node 6



# Application 2 - Unmetered Load detection

## Solution:

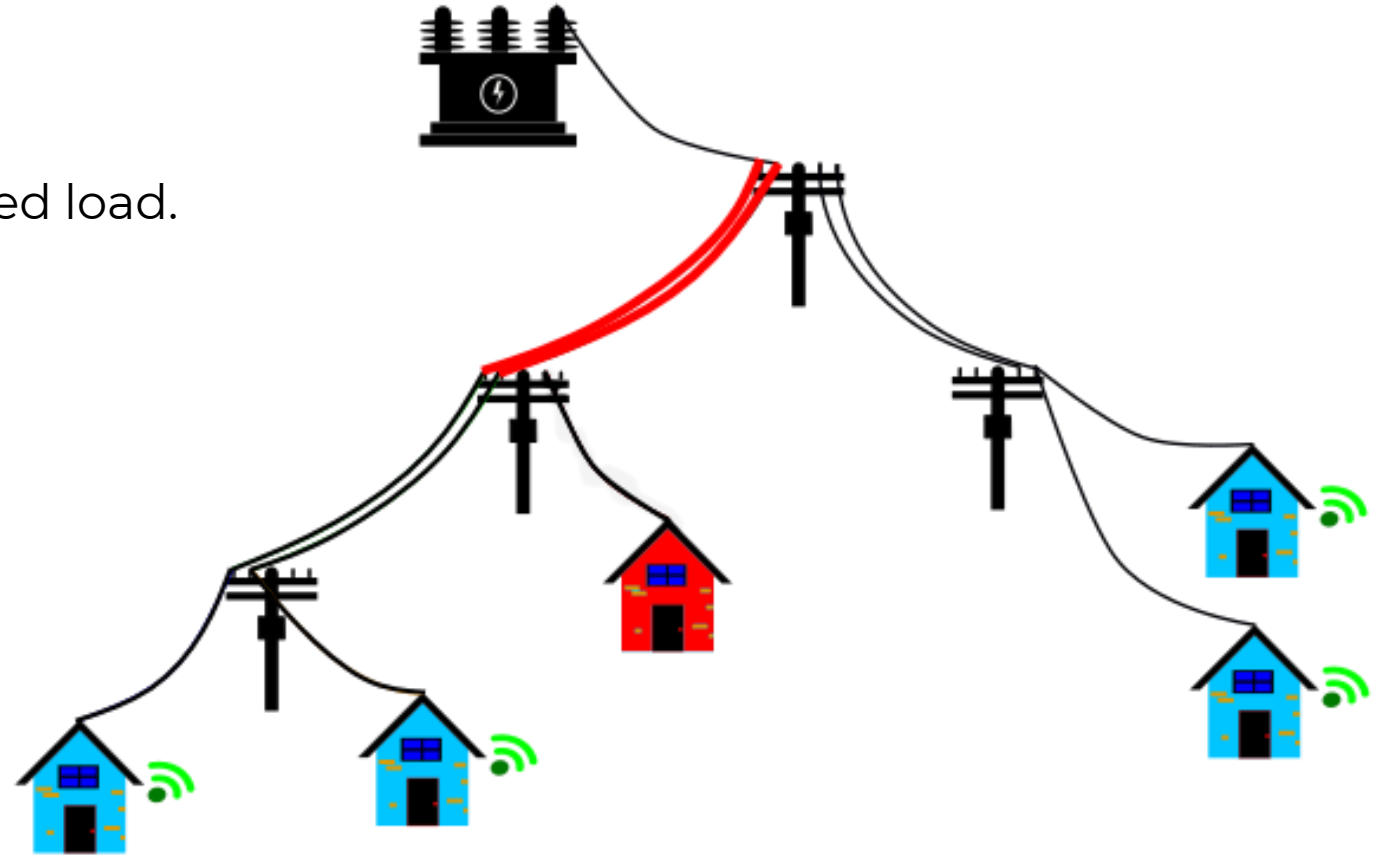
- Estimate voltage at poles in 2 ways:
  - From **Transformer (Estimated)**
  - From **Customers (Measured)**
- Difference in voltage estimates can indicate if unmetered load is present and where it is



# Application 2 - Unmetered Load detection

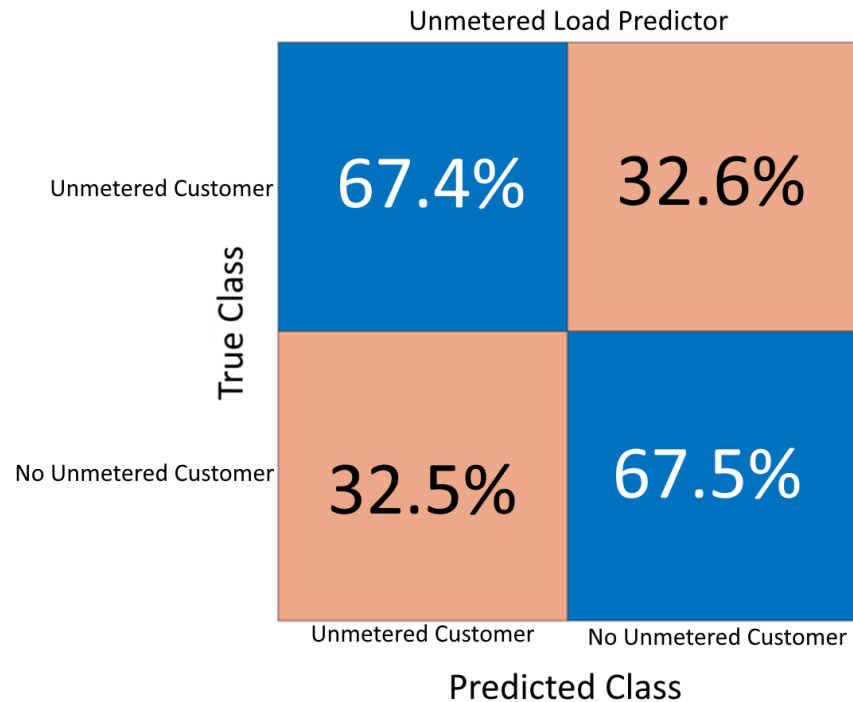
## Implementation:

- Utilize peak current draw of unmetered load.
- Topology estimation can disguise the “average” effect of unmetered load.
- Heavy unmetered loads are more pronounced - easier to detect.
- Detect during these times.



# Application 2 - Unmetered Load detection

- 67% accuracy for detecting unmetered loads
- 45% accuracy for locating unmetered load (to within nearby area)
- See significant improvement in accuracy for exact location of unmetered customer



	Exact Guess	Nearby Node	Approximate Accuracy
Random Selection	10.0%	19.1%	29.1%
Algorithm	33.3%	11.9%	45.2%

# Summary

## Algorithms for:

- Clustering algorithms for phase grouping of customers
- Mapping low voltage networks using AMI data
- Estimating impedance values

## Applications:

- Fault detection in LV grids
- Unmetered load and electricity theft detection
- Accurate DER hosting capacity assessment
- Better informed regulatory and asset investment decisions

# Mapping Low Voltage Networks Using AMI Data

Dr Reza Razzaghi  
reza.razzaghi@monash.edu

