Power Quality Data Analytics:

A new world of applications

Walmir Freitas
University of Campinas – UNICAMP
http://www.dsee.fee.unicamp.br/~walmir

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Acknowledgement

Part of these slides are based on a series of presentations done by Prof. Wilsun Xu, University of Alberta, the visionary and former chair of the IEEE/PES Working Group on Power Quality Data Analytics

Agenda

- ✓ Power Quality (Disturbance) Data Analytics: definition
- ✓ Potential data sources
- ✓ Data analytics
- ✓ Potential applications: smart meters – low resolution data
- ✓ Potential applications: power quality meter – high resolution data
- ✓ Final comments

Power Quality Data Analytics (Power Disturbance Analytics)

Power quality data analytics (or simply Power Disturbance Analytics) is the discipline specialized in collecting measurement-based power system data, extracting information from it, and applying the findings to solve several power system problems such as:

- ✓ Power quality
- ✓ Power system protection
- ✓ Equipment condition monitoring
- ✓ System condition monitoring
- ✓ Active risk-based asset management

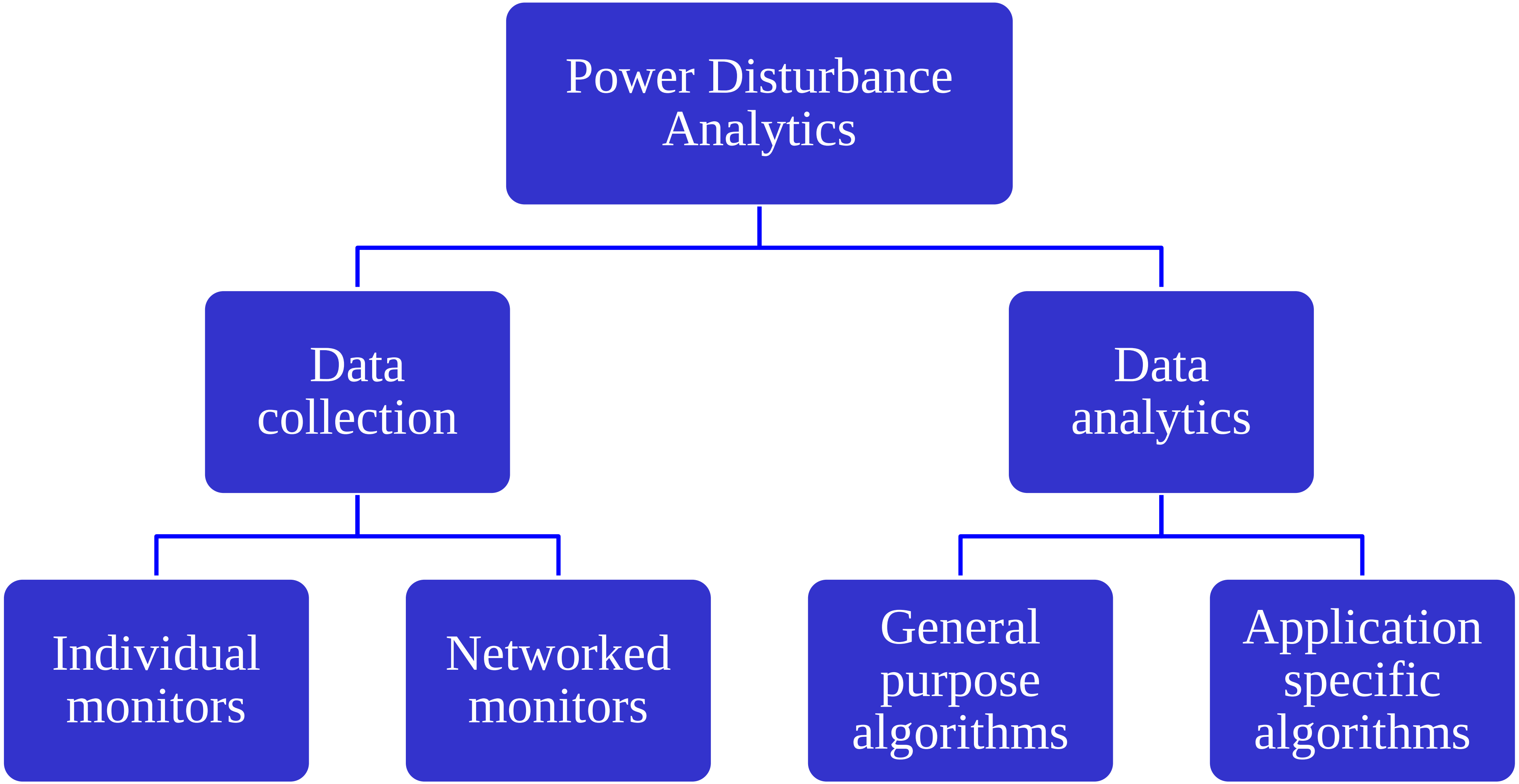
Walmir Freitas:

- ✓ One of the Working Group founders
- ✓ Chair: 2018-2020
- ✓ Vice-chair: 2016-2018
- ✓ Secretary: 2013-2016
- ✓ Received, as chair, the **IEEE PES T&D Committee Award for Outstanding Technical Report** – 2020

IEEE/PES has recognized the relevance of this emerging area by establishing the Working Group on Power Quality Data Analytics, which reports to the IEEE/PES Power Quality Subcommittee (active since 2013)

Adapted from: IEEE Working Group on Power Quality Data Analytics (http://grouper.ieee.org/groups/td/pq/data/)

Power Disturbance Data Analytics: components



Power Disturbance Analytics

Data collection

Data analytics

Individual monitors

Networked monitors

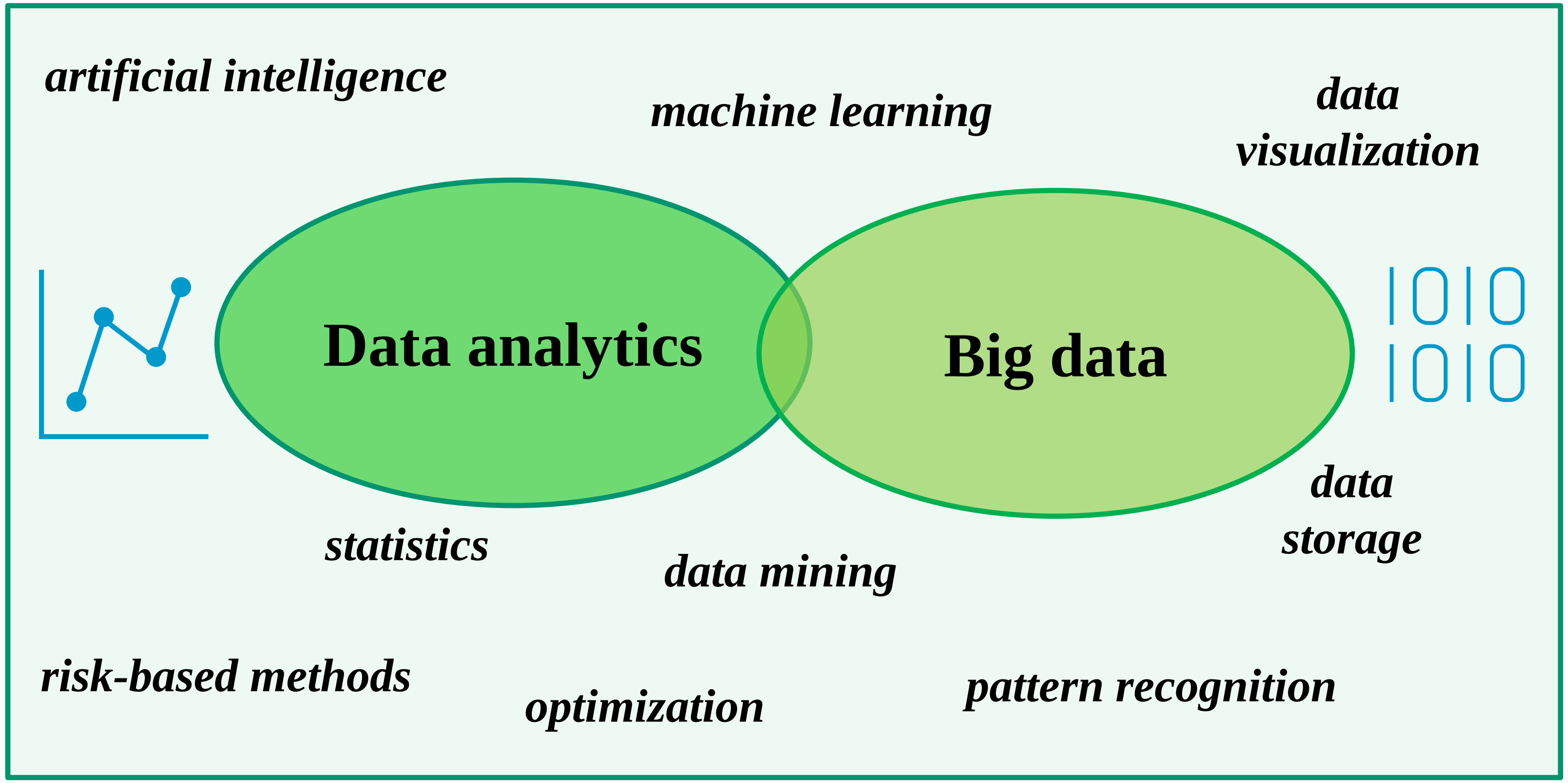
General purpose algorithms

Application specific algorithms

Data science and data analytics

Data science *is an interdisciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge (information) from noisy, structured and unstructured data, and apply it to a broad range of domains. Data science is related to data mining, machine learning, big data, computational statistics and analytics (Adapted from Wikipedia)*

Data Science



artificial intelligence

machine learning

data visualization

Data analytics

Big data

statistics

data mining

data storage

risk-based methods

optimization

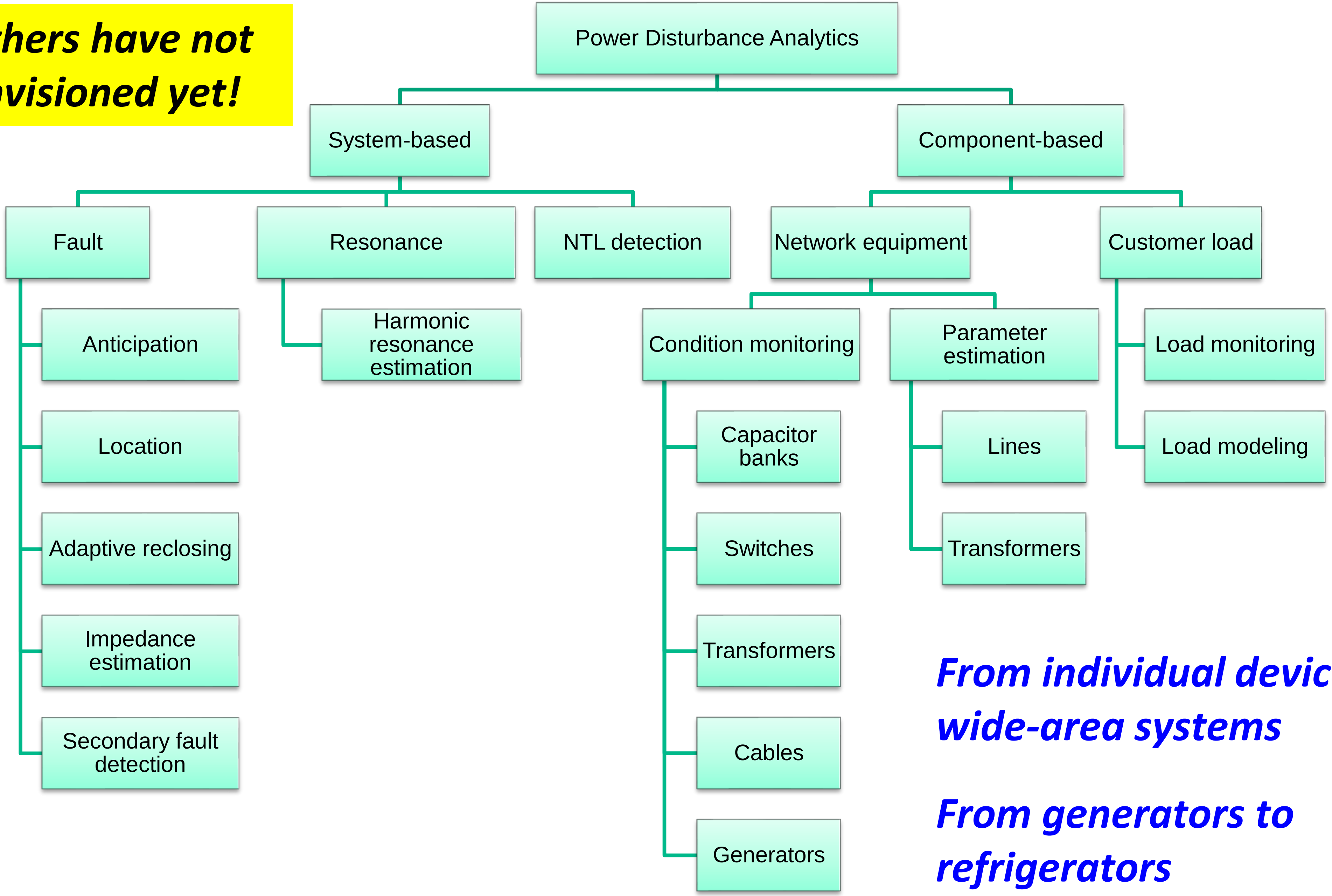
pattern recognition

Potential data sources

- AMI: E, P, Q, V and I data (billing and demand monitoring)
- SCADA: 60 Hz magnitude (P, Q, V and I) data
- PMU: voltage and current phasors
- PQ monitors: rms and event-triggered waveform data
- Waveform measurement units (WMU): gapless voltage and current waveforms (synchronized or unsynchronized)
- Other potential data sources:
  - ✓ Modern relays – mission critical, hard to access data
  - ✓ Digital fault recorders – specialized for fault recording
  - ✓ Condition monitors – specialized/customized devices

Potential applications

Many others have not been envisioned yet!



From individual devices to wide-area systems

From generators to refrigerators

Sample of potential applications

- ✓ Potential Applications (Smart Meter – low resolution data):
    - Automated management of GIS/asset and other related databases (BDGD)
    - Non-technical loss detection and location
    - Technical loss management and evaluation
    - Fault location
    - Load modeling
    - Customer load disaggregation
    - DER hosting capacity
- ✓ Potential Applications (Power Quality Meter – high resolution data):
    - Resonance detection and mitigation (wind and solar parks)
    - Fault anticipation
    - Detection and location of high impedance faults

Automated management of GIS (BDGD) and others related databases

Issue: Utilities GIS/Assets database presents errors and inconsistencies due to:

- ✓ wrong data registration
- ✓ absence of data or update
- ✓ Line/transformer parameter variations due to weather conditions and equipment aging
- ✓ manual procedures for database update from field crew

Relevance: these databases are the core for:

- ✓ technical decisions
- ✓ economic decisions
- ✓ regulatory decisions

Idea: Combine customer smart meter data and data analytics to automatically correct:

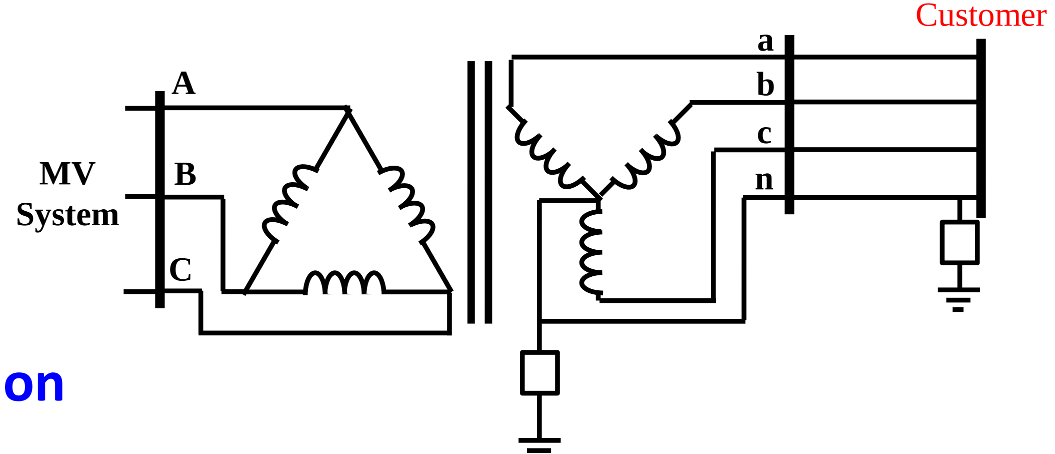
- ✓ MV and LV system topology
- ✓ line and transformer parameters
- ✓ customers phase connection
- ✓ status of switches
- ✓ regulators/compensators settings and parameters

GIS automated correction (BDGD): LV systems

Issue: how to correct

- ✓ system topology
- ✓ customers phase connection
- ✓ line parameters

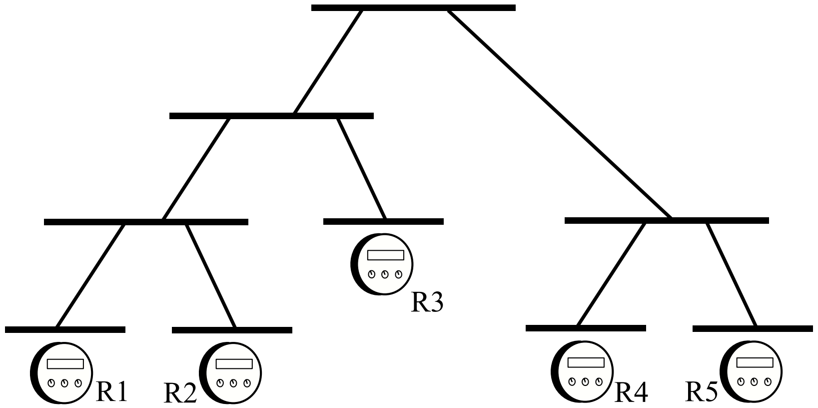
Idea: use **multiple linear regression** and **data from customers smart meters**:



$$\underbrace{\boldsymbol{V}_{\boldsymbol{an}1}-\boldsymbol{V}_{\boldsymbol{an}2}}_{\eta x1}=\underbrace{\left[1\;-\boldsymbol{I}_{\boldsymbol{R}1}{}^{T}\;\boldsymbol{I}_{\boldsymbol{X}1}{}^{T}\;\boldsymbol{I}_{\boldsymbol{R}2}{}^{T}\;-\boldsymbol{I}_{\boldsymbol{X}2}{}^{T}\right]}_{\eta x13}\underbrace{\begin{bmatrix}\beta_0\\ \boldsymbol{R}_1{}^{T}\\ \boldsymbol{X}_1{}^{T}\\ \boldsymbol{R}_2{}^{T}\\ \boldsymbol{X}_2{}^{T}\end{bmatrix}}_{13x1}\backslash$$

$$R_1^{+}\approx\beta_1-(\beta_2\ or\ \beta_3)\approx R_{aa1}-(R_{ab1}\ or\ R_{ac1})$$
$$X_1^{+}\approx\beta_4-(\beta_5\ or\ \beta_6)\approx X_{aa1}-(X_{ab1}\ or\ X_{ac1})$$
$$R_{n1}\approx(\beta_2\ or\ \beta_3)\approx R_{nn1}-R_{an1}$$

line parameters



Topology is built from the bottom (customers) up (transformer) approach to the transformer, by pairing meters (real meters and virtual meters)

Step 1 ⟶

Phase identification: highest R^2_{CM}
Meter connection: $R^2_{CM} \approx 1$ connection correct
$R^2_{CM} < 1$ connection incorrect

Step 2 ⟶

Phase identification: highest R^2_{CM}
Meter connection: $R^2_{CM} \approx 1$ connection correct
$R^2_{CM} < 1$ connection incorrect

Step 3 ⟶

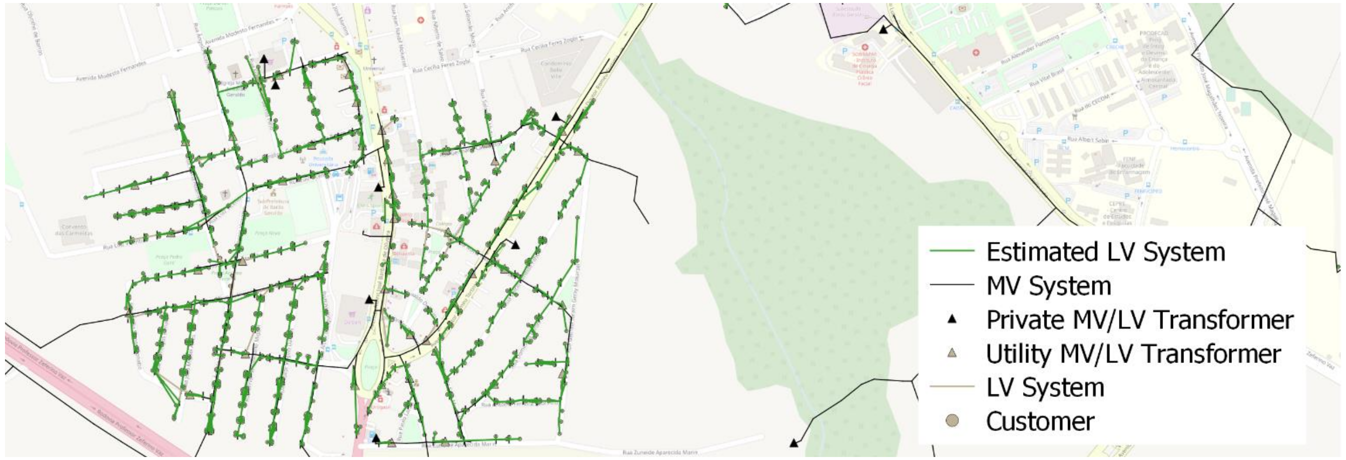
Phase identification: highest R^2_{CM}
Meter connection: $R^2_{CM} \approx 1$ connection correct
$R^2_{CM} < 1$ connection incorrect

system topology and customer phasing

Source: V. C. Cunha, W. Freitas, F. C. L. Trindade, and S. Santoso, "Automated determination of topology and line parameters in low voltage systems using smart meters measurements," IEEE Transactions on Smart Grid, vol. 11, pp. 5028-5038, 2020 - © IEEE 2020

GIS automated correction (BDGD): LV systems

Real case: MV/LV systems: 2,175 buses; 2,000$^+$ customers (87% residential); 76 MV/LV transformers



Low resolution:

- ✓ Metering error: 1.0%
- ✓ Measurement desynchronization: 10 sec
- ✓ 30 days of sample size

High resolution

- ✓ Metering error: 0.2%
- ✓ Measurement desynchronization: 0 sec
- ✓ 30 days of sample size

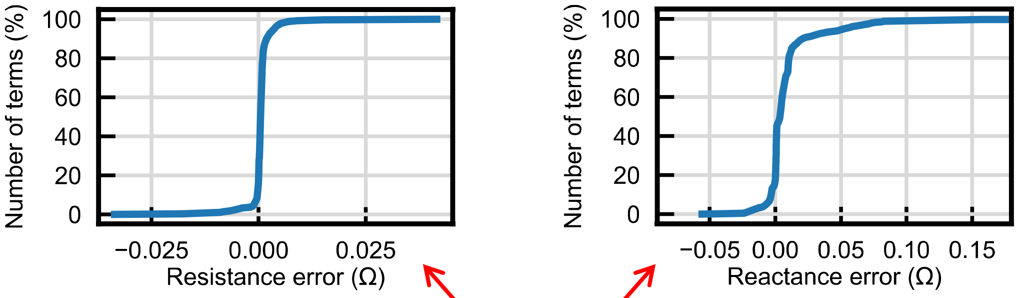
Topology and phasing

Metric	High-Precision Scenario (%)			Low-Precision Scenario (%)		
Resolution (min)	15	30	60	15	30	60
Branch	92	92	91	33	48	58
Line length	87	88	87	31	41	49
Phasing	100	100	100	100	100	100

High success rate

Phasing estimation still has high success rate

Line parameters



Line parameters successfully estimated (more than 90% of the parameters estimated accurately)

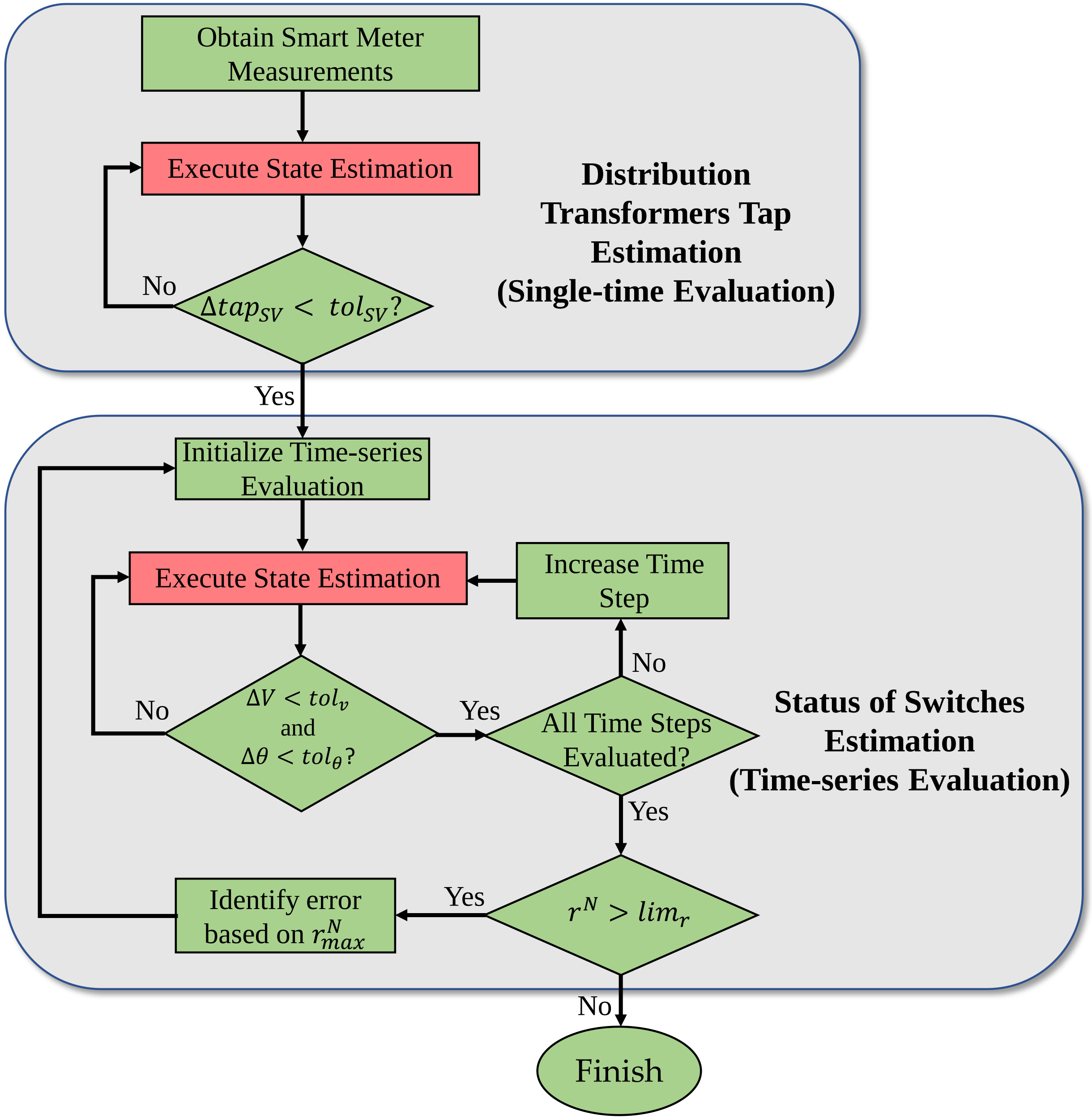
Source: V. C. Cunha, W. Freitas, F. C. L. Trindade, and S. Santoso, "Automated determination of topology and line parameters in low voltage systems using smart meters measurements," IEEE Transactions on Smart Grid, vol. 11, pp. 5028-5038, 2020 - © IEEE 2020

GIS correction: tap position of service (MV/LV) transformers and status of switches

Issue: Utilities GIS Database presents errors, missing data, and inconsistencies on MV systems regarding to:

- ✓ Tap position of service transformers (MV/LV transformers)
- ✓ Status of switches

Idea: Combine **customer smart meter data** and a **generalized state estimation** formulation to correct this equipment

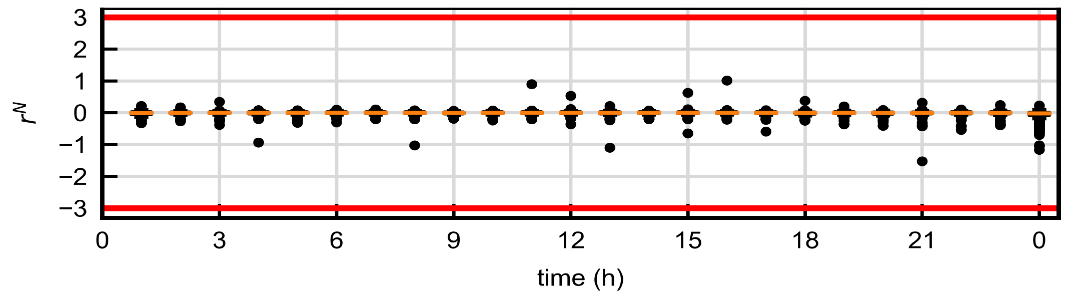


Source: V. C. Cunha, W. Freitas, and S. Santoso, "Determination of tap position of transformers and status of switches in distribution systems using a generalized state estimator," submitted to IEEE Transactions on Power Systems

GIS correction: tap position of service (MV/LV) transformers and status of switches

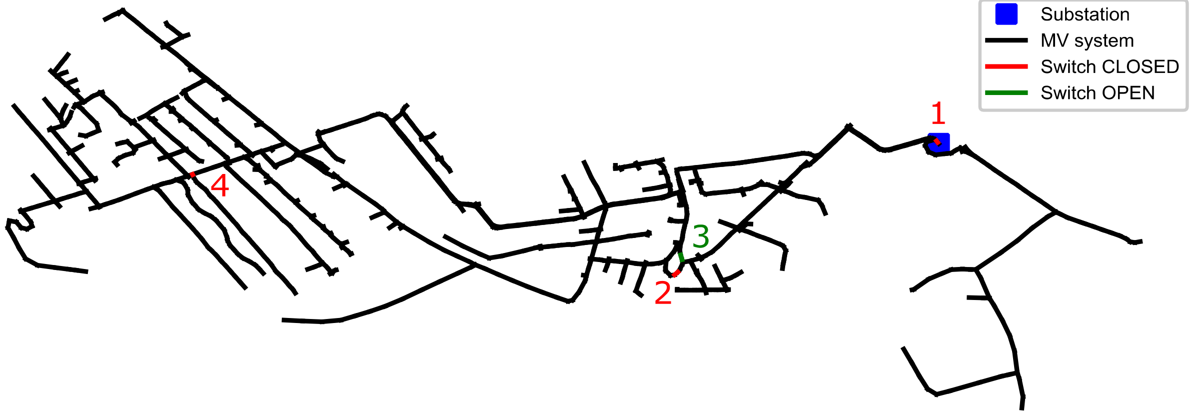
Real case: MV/LV system with 5,000+ customers (87% residential) and 190 MV/LV transformers

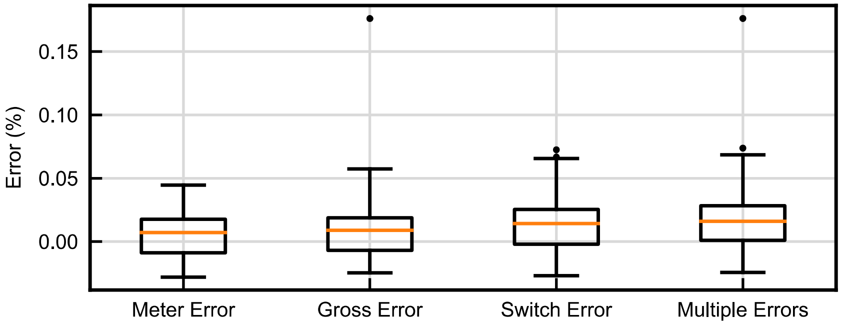
Bus/Switch	Phase	r_P^N	r_Q^N	r_V^N	r_θ^N	Iteration
2794	c	12.52	12.56	-12.65	-	1
S2	a	0.22	-5.07	-	-	2
S3	b	-	-	8.59	-0.19	3
S1	c	-	-	-0.01	-1.53	4



Status of switches: 100% accurate – 24 hours of operation

Source: V. C. Cunha, W. Freitas, and S. Santoso, "Determination of tap position of transformers and status of switches in distribution systems using a generalized state estimator," submitted to IEEE Transactions on Power Systems





MV/LV transformer tap: 100% accurate

The method is robust against:

- ✓ Meter Errors (precision class and clock desynchronization of meters)
- ✓ Gross Errors (*e.g.*, incorrect power measurements)
- ✓ Switch Errors (incorrect status of switches)

GIS correction: estimation of physical status and control settings of voltage regulators and capacitor banks

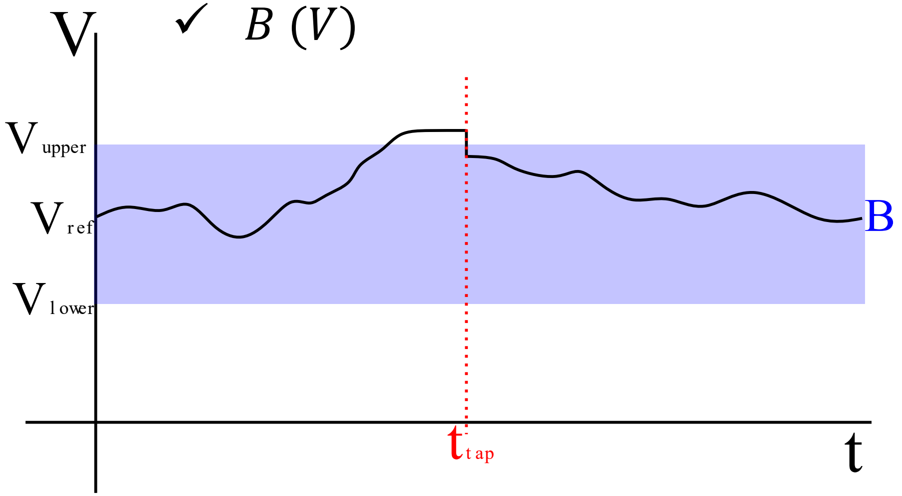
Issue: Control settings of voltage regulators and capacitor banks are constantly updated on field, but this information is often not updated on the database

Idea: Combine **customer smart meter data** and a **generalized state estimation formulation** to estimate the physical status of capacitor banks and voltage regulators, and the control settings of this equipment

Voltage regulator: what is to be estimated

Control settings:

- ✓ $V_{\text{sup}}\ (V)$
- ✓ $V_{\text{inf}}\ (V)$
- ✓ $V_{ref}\ (V)$
- ✓ $B\ (V)$



Capacitor bank: what is to be estimated

Control mode:

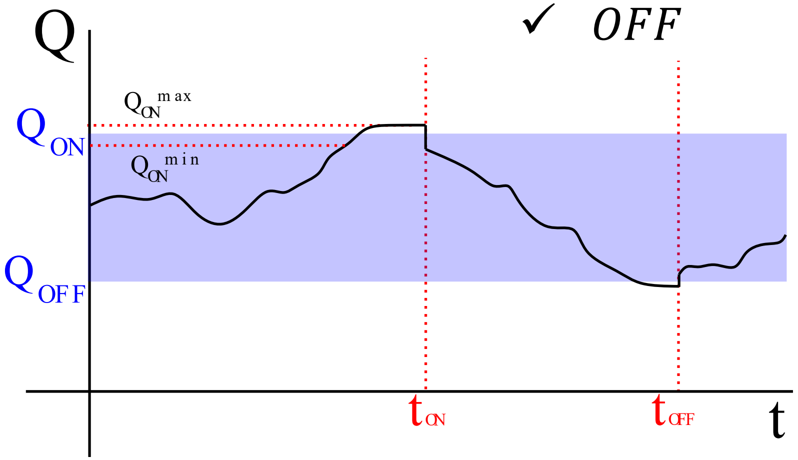
- ✓ reactive power
- ✓ power factor
- ✓ time
- ✓ current

Control settings:

- ✓ Q_{ON}
- ✓ Q_{off}

Operation period (status):

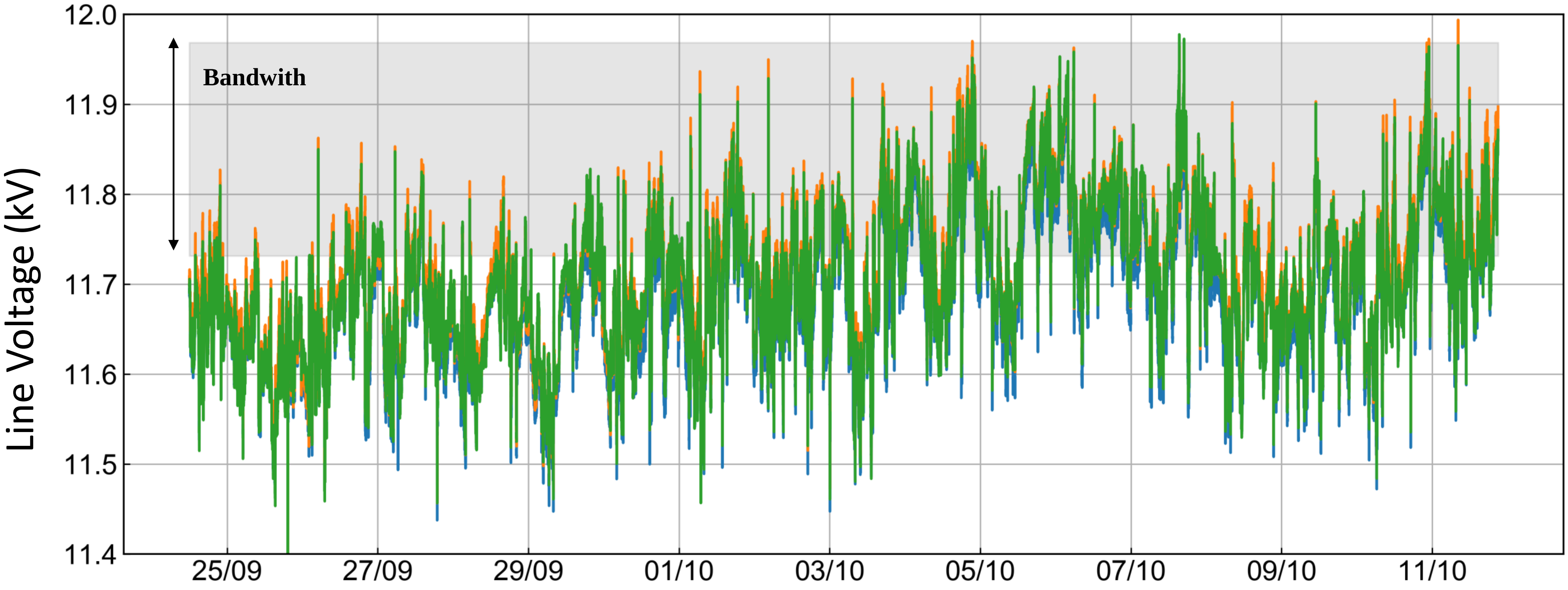
- ✓ ON
- ✓ OFF



Source: V. C. Cunha, Integration of new Methods into Distribution Management Systems in the Presence of Distributed Energy Resources and Smart Meters, Ph.D. Dissertation, UNICAMP, 2022

GIS correction: estimation of physical status and control settings of voltage regulators and capacitor banks

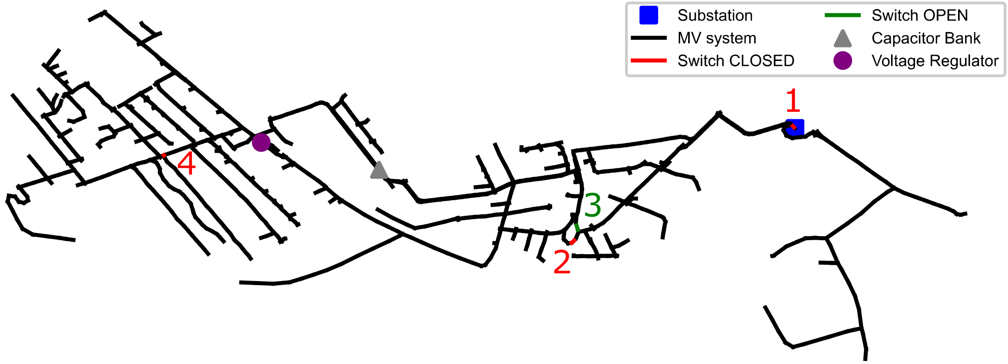
Real case 1: Why estimate the control settings of voltage regulators?

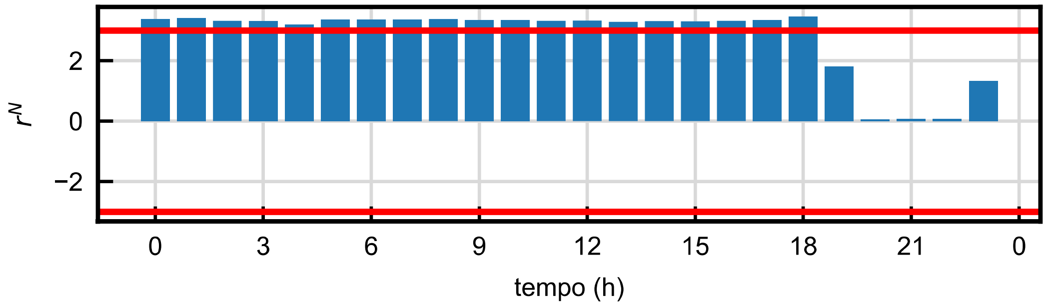


Real case 2: Existence of a 1.2 MVA capacitor bank from a disactivated industry without the knowledge by the utility

GIS correction: estimation of physical status and control settings of voltage regulators and capacitor banks

Real case: MV/LV system with 5,000+ customers (87% residential) and 190 MV/LV transformers




Determine Capacitor Bank Status

Estimate Control Settings – Average Values

Setting	Original	Resolution (15 min)			Resolution (60 min)		
		Days			Days		
		1	3	7	1	3	7
V_{sup} (V)	11,775	11,787	11,791	11,790	11,795	11,787	11,792
V_{inf} (V)	11,625	11,609	11,617	11,612	11,596	11,606	11,607
V_{ref} (V)	11,700	11,698	11,704	11,701	11,695	11,697	11,700
B (V)	1.5	1.77	1.73	1.77	1.98	1.8	1.84
Q_{ON} (kvar)	1,200	1,196<Q<1,208	1,202<Q<1,189	1,202<Q<1,187	869<Q<1,131	869<Q<1,117	1,144<Q<1,126
Q_{OFF} (kvar)	800	801	805	807	819	832	866

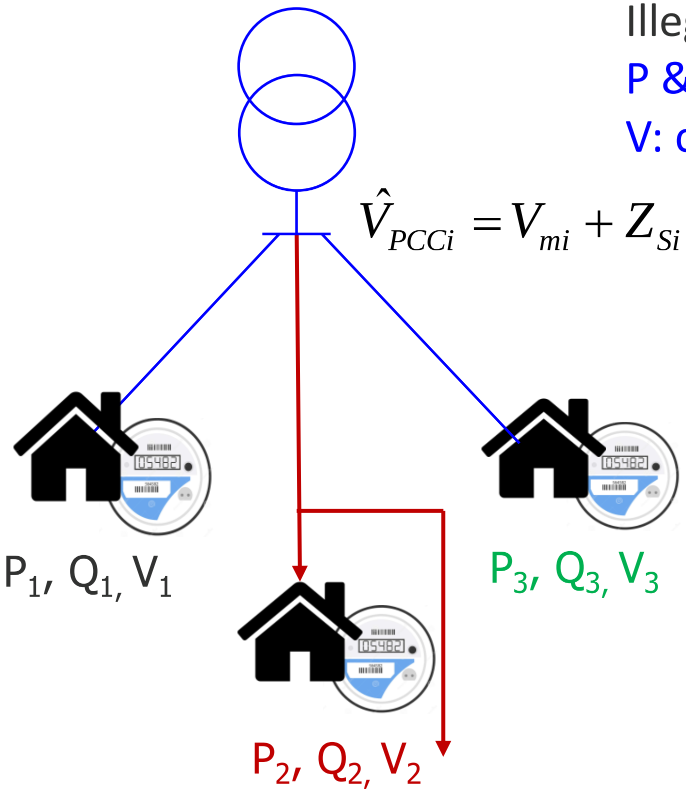
The control settings and operation period are properly estimated

Source: V. C. Cunha, Integration of new Methods into Distribution Management Systems in the Presence of Distributed Energy Resources and Smart Meters, Ph.D. Dissertation, UNICAMP, 2022

Non-Technical Losses: detection and location (Idea 1)

✓ Issue: Illegal load connection (NTL) tampers active and reactive power measurements, but no voltage measurement. **Power flows, voltage does not**

✓ Idea 1: By using P, Q and V measured by the **smart meter** in each customer, one can estimate the V_{PCC}. The lowest estimated value indicates potential NTL

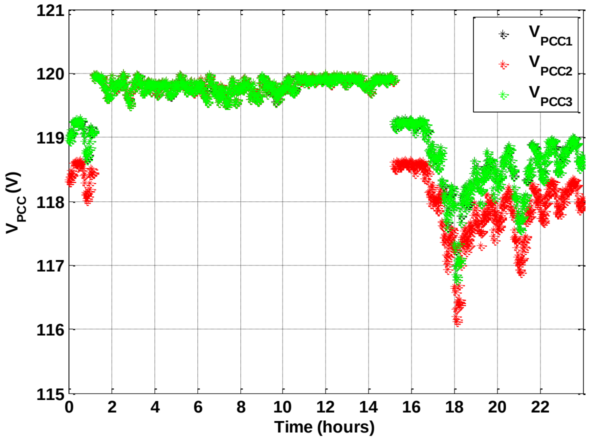


$$\hat{V}_{PCCi} = V_{mi} + Z_{Si} \cdot \hat{I}_i$$

Illegal load connection

P & Q: tampered data

V: correct data



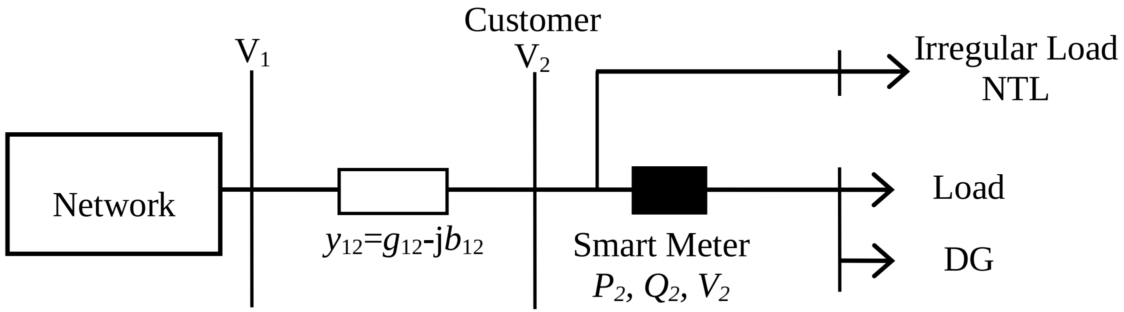
Volt drop method:

V_{PCC} is estimated by using data from each customer smart meter connected to the same MV/LV transformer. Estimated values different (lower) indicated NTL

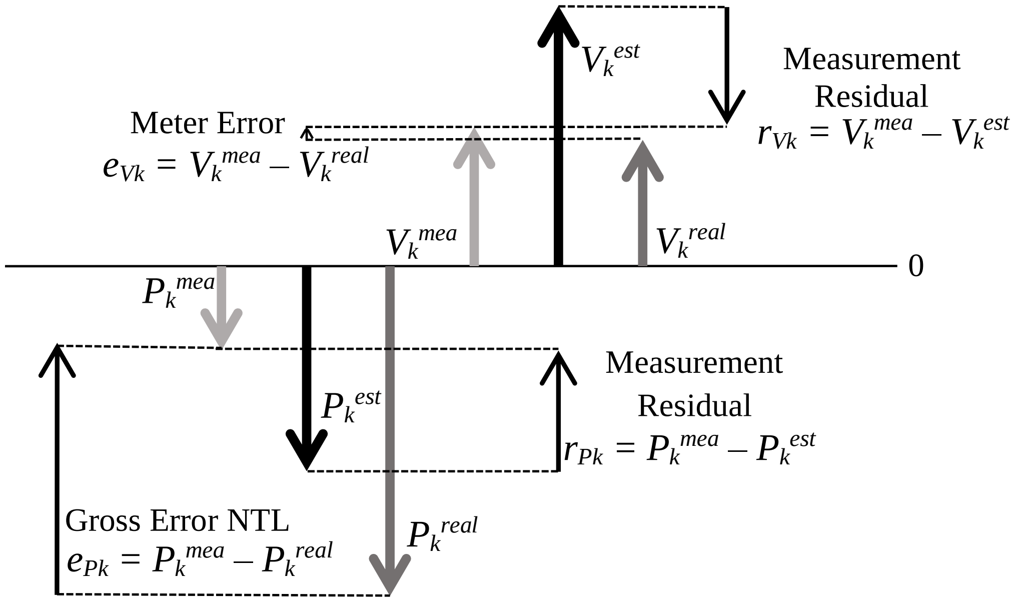
Source: F. C. L. Trindade, J. C., M. Vieira, W. Freitas, W. Xu: proof of concept applied to BC hydro (smart meter database: 2013)

Non-Technical Losses: detection and location (Idea 2)

Issue: Energy theft by the connection of irregular loads



Idea 2: Use data from **customer smart meters** to run a **state estimation process**, as active and reactive power measurements are tampered, but voltage is not



Method can typically detect and locate NTL as small as 2 kW for LV illegal loads and 23 kW for MV illegal loads

Source: L. Raggi, F. Trindade, V. C. Cunha, W. Freitas, “Non-technical loss identification by using data analytics and customer smart meters,” IEEE Transactions on Power Delivery, v. 35, p. 2700-2710, 2020 - © IEEE 2020

Non-Technical Losses: detection and location (Idea 2)

Case study:

- ✓ 13.8-kV feeder (real): 55 LV systems + 64 MV customers – 1,682 buses.
- ✓ LV–NTL: magnitude from 1 kW to 10 kW (~1,000 occurrences)
- ✓ MV–NTL: magnitude from 20 kW to 200 kW (56 occurrences)

LV-NTL

NTL (kW)	Successful Cases (%)				e) N_{NTL} (percentile)	
	a)	b)	c)	d)	50th	90th
1	24.8	19.6	19.6	23.9	1	1
2	86.9	71.8	70.7	81.5	1	1
3	97.3	88.3	85.1	92.8	1	2
4	99.3	95.3	91.0	96.9	1	2
5	99.3	97.7	94.6	97.8	2	3
6	99.5	98.6	95.9	98.8	2	3
7	99.5	98.9	96.6	98.9	2	3
8	99.5	99.1	97.0	99.3	2	3
9	99.5	99.1	97.7	99.3	2	4
10	99.5	99.1	98.4	99.5	2	4

a) NTL is detected; b) NTL bus is among the suspect buses; c) NTL bus is indicated with the maximum Err_{NTLk}(%) value; d) NTL bus or a first neighbor bus is indicated with the maximum Err_{NTLk}(%) value; e) Number of buses indicated as suspects of NTL.

MV-NTL

NTL (kW)	Successful Cases (%)				e) N_{NTL} (percentile)	
	a)	b)	c)	d)	50th	90th
20	0	0	0	0	0	0
21	0	0	0	0	0	0
22	39.6	39.6	39.6	39.6	1	1
23	96.9	96.9	96.9	96.9	1	1
24/25/50/100/150	100	100	100	100	1	1
200	100	100	100	100	1	2

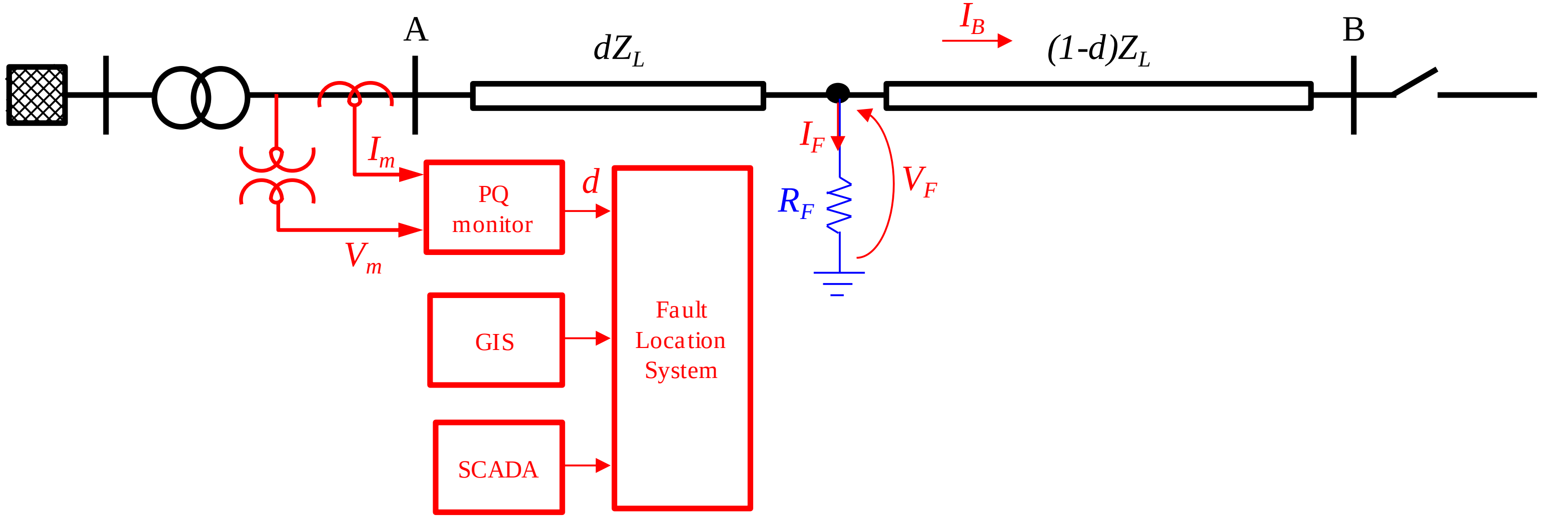
a) NTL is detected; b) NTL bus is among the suspect buses; c) NTL bus is indicated with the maximum Err_{NTLk}(%) value; d) NTL bus or a first neighbor bus is indicated with the maximum Err_{NTLk}(%) value; e) Number of buses indicated as suspects of NTL.

Source: L. Raggi, F. Trindade, V. C. Cunha, W. Freitas, "Non-technical loss identification by using data analytics and customer smart meters," IEEE Transactions on Power Delivery, v. 35, p. 2700-2710, 2020 - © IEEE 2020

Fault location: distribution systems (idea 1)

Idea 1:

- ✓ Collect V&I at feeder terminal
- ✓ Calculate downstream Z using V&I
- ✓ Estimate fault distance using Z
- ✓ PQ monitor is used to collect data



Basic idea of impedance-based fault location technique

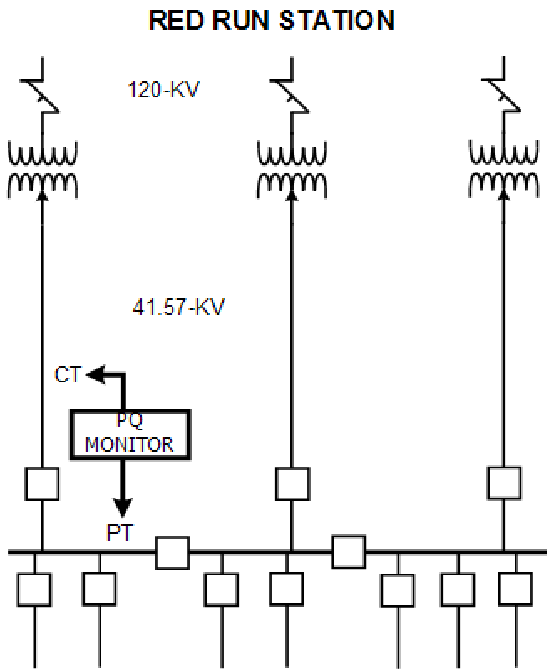
Examples of Algorithms for Single-Phase Fault Location

- Positive-Sequence and Zero-Sequence
  - Loop Impedance (Z_L)
  - Loop Resistance (R_L)
  - Loop Reactance (X_L)
- Positive-Sequence Algorithms
  - Resistance-to-Fault (RTF)
  - Impedance-to-Fault (ZTF)
  - Reactance-to-Fault (XTF)
- RMS Voltage and RMS Current Only
  - Absolute Impedance (Z)

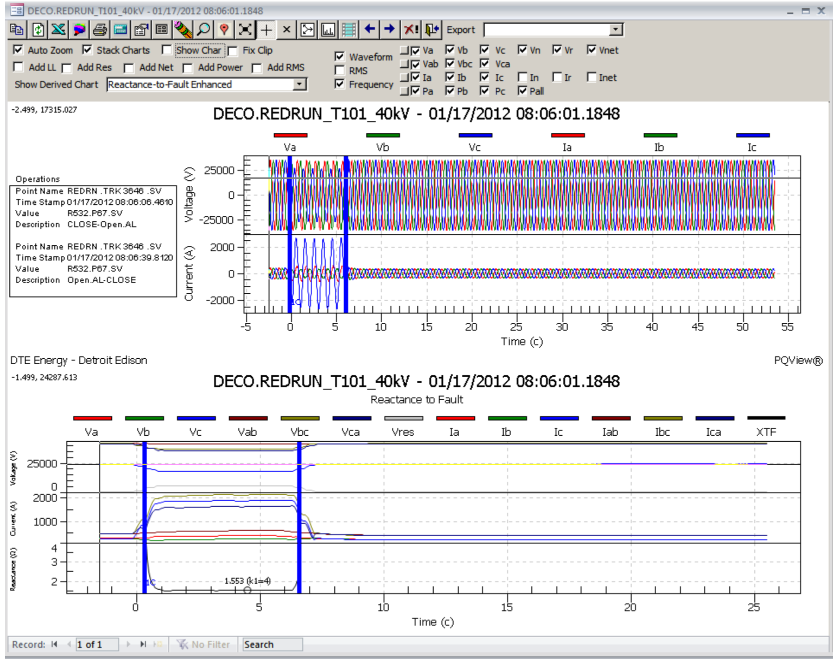
Fault location: distribution systems (idea 1)

Case:

DTE Energy - Detroit Edison (DECo)



PQ monitor installation at HV/MV substation for fault location - © 2012 IEEE

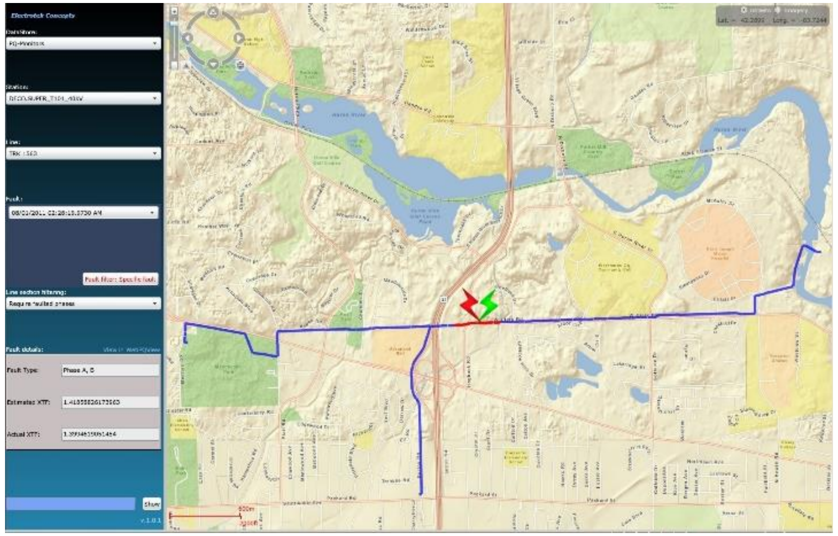


Operations

Point Name REDRN .TRK 3646 .SV
Time Stamp 01/17/2012 08:06:06.4610
Value R532.P67.SV
Description CLOSE-Open.AL

Point Name REDRN .TRK 3646 .SV
Time Stamp 01/17/2012 08:06:39.8120
Value R532.P67.SV
Description Open.AL-CLOSE

Single-line-to-ground fault measured by the PQ monitor - © 2012 IEEE



Example Street View Map of estimated (green lightning) and actual (red lightning) fault location - © 2012 IEEE

Source: D. D. Sabin, and A. R. Dettloff, “Overview of an Automatic Subtransmission Fault Location System at DTE Energy,” IEEE/PES General Meeting 2012 - © 2012 IEEE

Fault location: distribution systems (idea 2)

Issue:

- ✓ How to avoid identification of multiple locations?

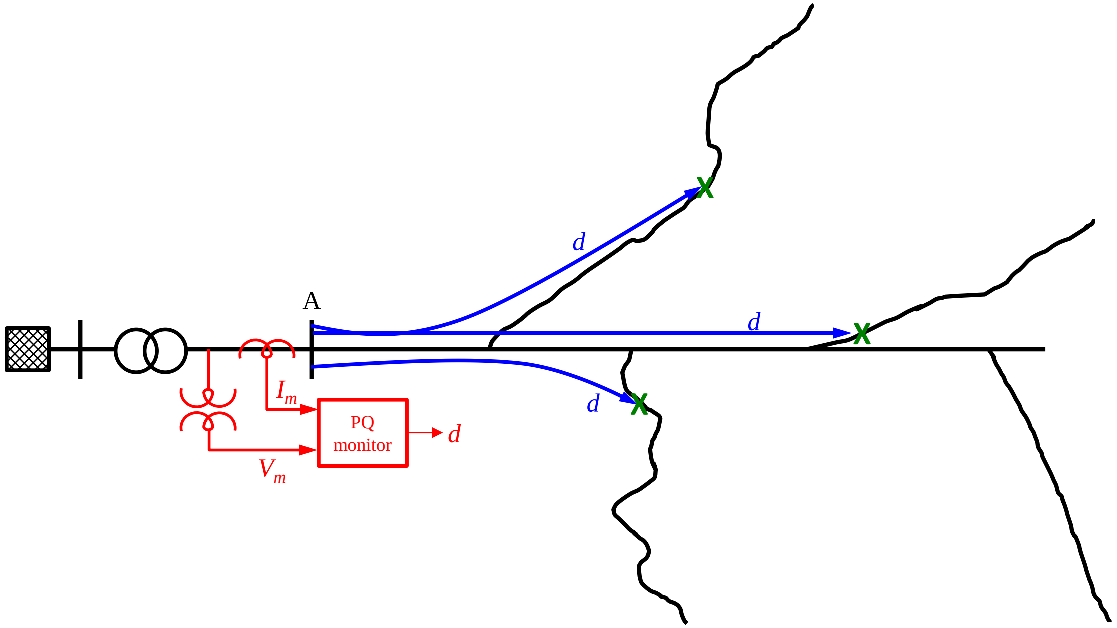
Idea 2:

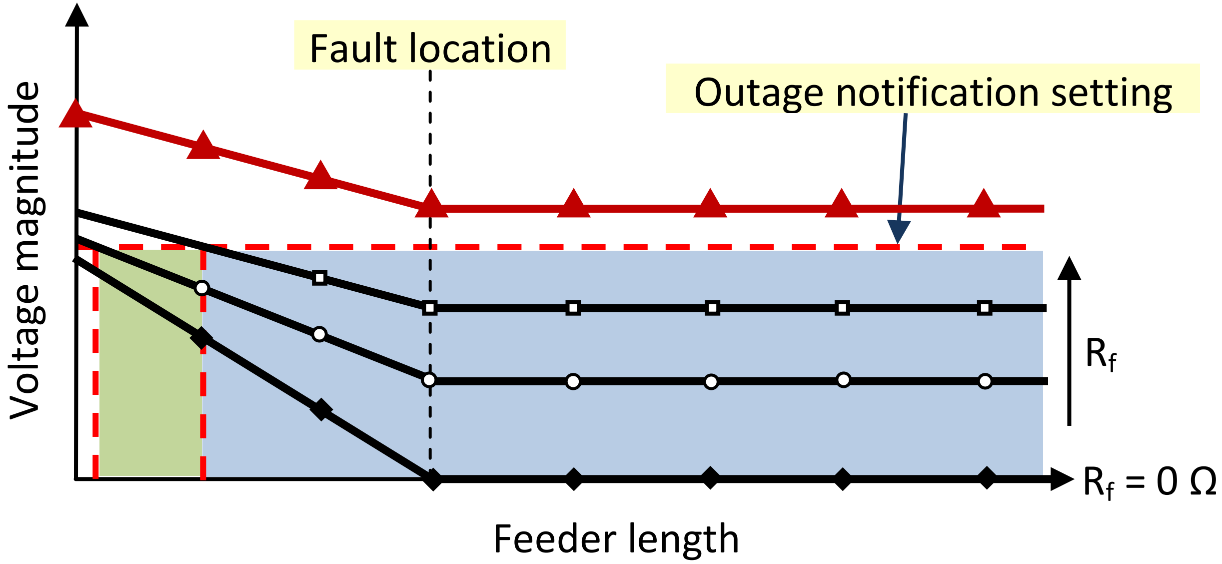
Use information from **customer smart meters**:

- ✓ Outage mapping (might not be sufficient)
- ✓ Voltage magnitude (concept of low voltage zone)

Functionalities:

- ✓ Outage mapping: simpler and lower accuracy
- ✓ Voltage measurement: more complex and higher accuracy

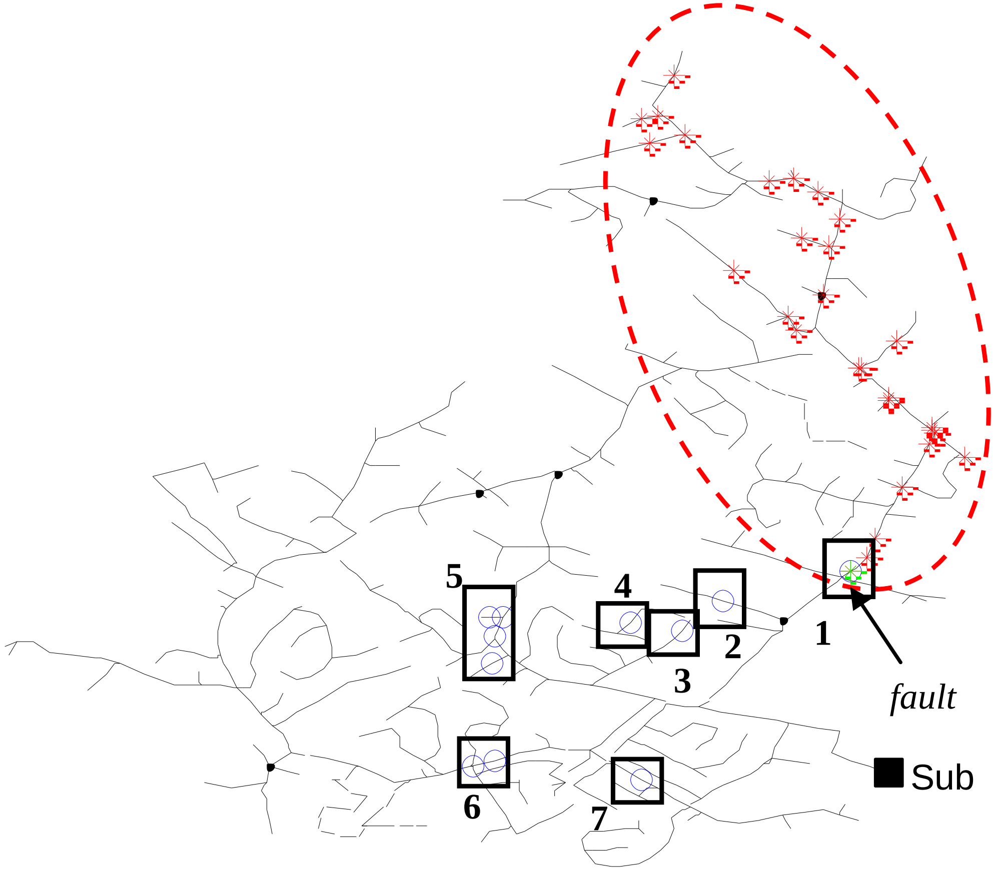




Source: F. C. L. Trindade, W. Freitas, “Low voltage zones to support fault location in distribution systems with smart meters” IEEE Transactions on Smart Grid, v. 8, p. 2765-2774, 2017 - © 2017 IEEE

Fault location: distribution systems (idea 2)

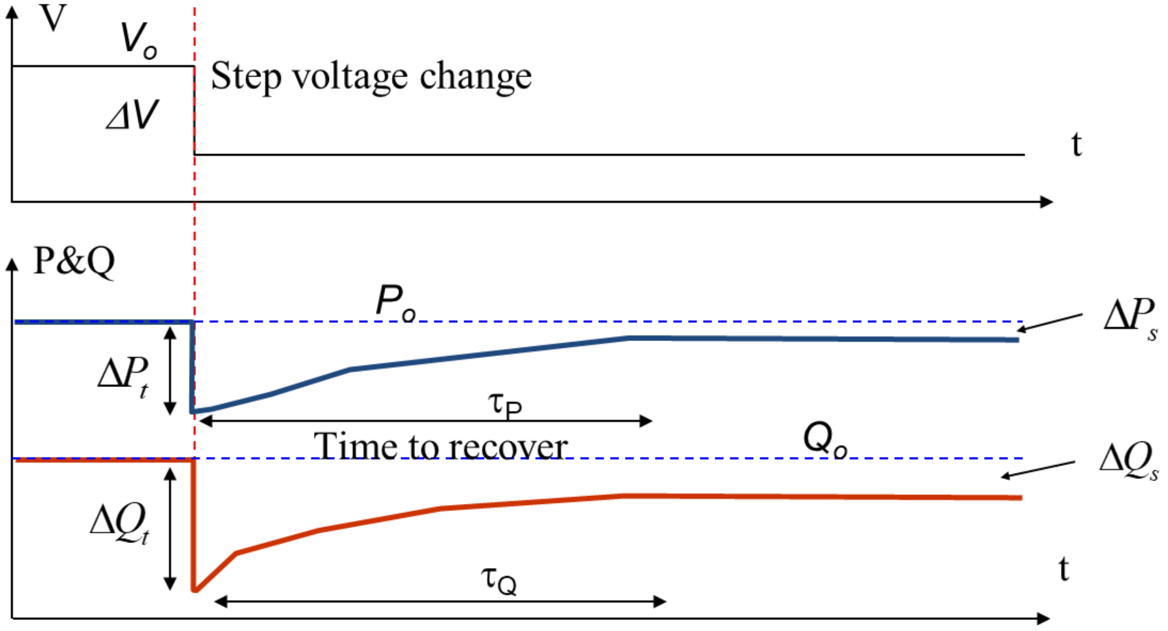
Results of fault location for a **single-phase** fault with $\boldsymbol{R_f = 0.5\ \Omega}$.



Estimated fault location	**Voltage magnitude (pu)**
1	0.171
2	0.236
3	0.365
4	0.365
5	0.363
6	0.365
7	0.365

Source: F. C. L. Trindade, W. Freitas, “Low voltage zones to support fault location in distribution systems with smart meters” IEEE Transactions on Smart Grid, v. 8, p. 2765-2774, 2017 - © 2017 IEEE

Load modeling: what are to be modeled?



Load parameters for loads with the above responses:

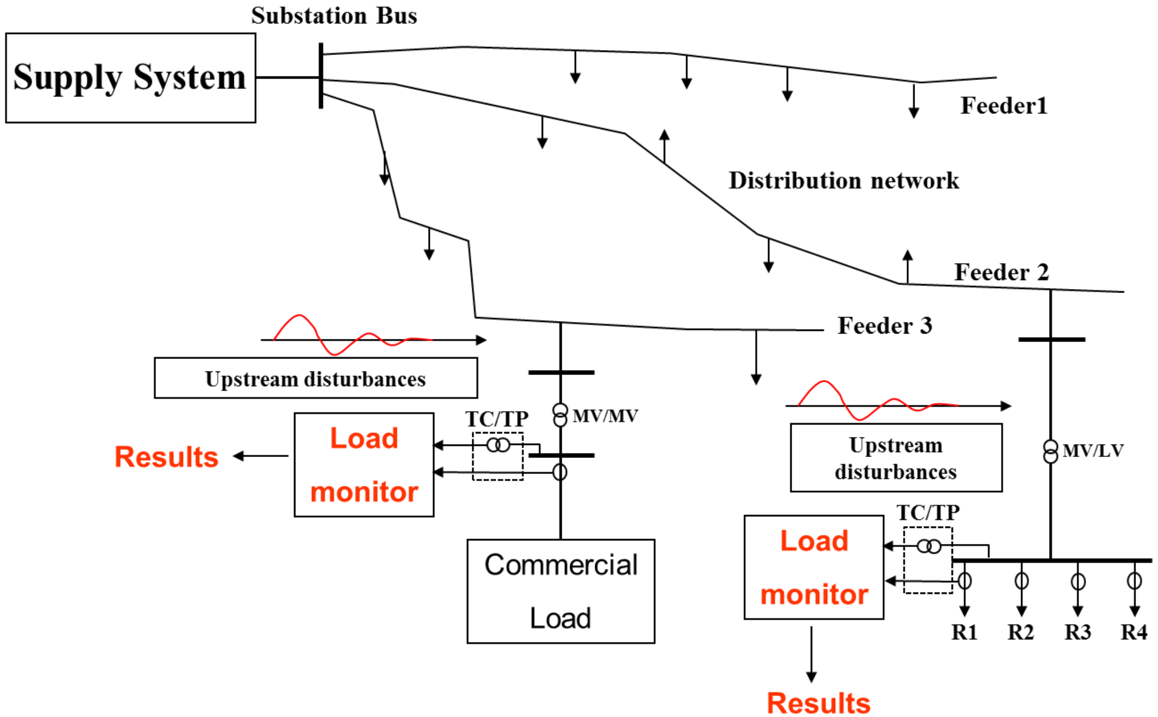
- Transient load responses: ΔP_t and ΔQ_t
- **Steady-state load responses: ΔP_s and ΔQ_s**
- Time to recover: τ_P and τ_Q

Why is it important to correctly model the steady-state load responses?

- ✓ Determination of technical and non-technical losses
- ✓ Allocation of capacitor banks and voltage regulators
- ✓ Decision-making of strategies for voltage regulation and var compensation
- ✓ Ampacity calculations
- ✓ Expansion studies

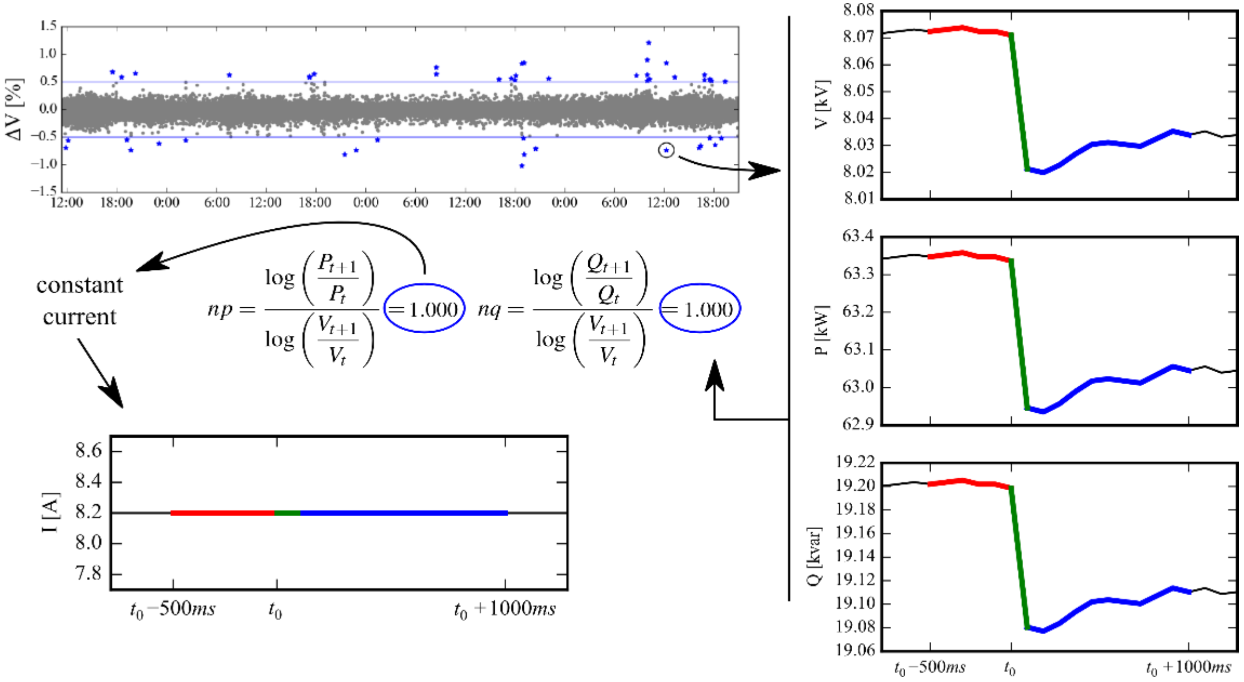
Source: W. Freitas and L. C. P. da Silva, Distribution System Load Modeling Based on Detection of Natural Voltage Disturbances, IEEE/PES General Meeting, 2012 - © 2012 IEEE

Load modeling: parameter estimation



$$P = P_0\left(\frac{V}{V_0}\right)^{np} \text{ and } Q = Q_0\left(\frac{V}{V_0}\right)^{nq}$$

Exponential model



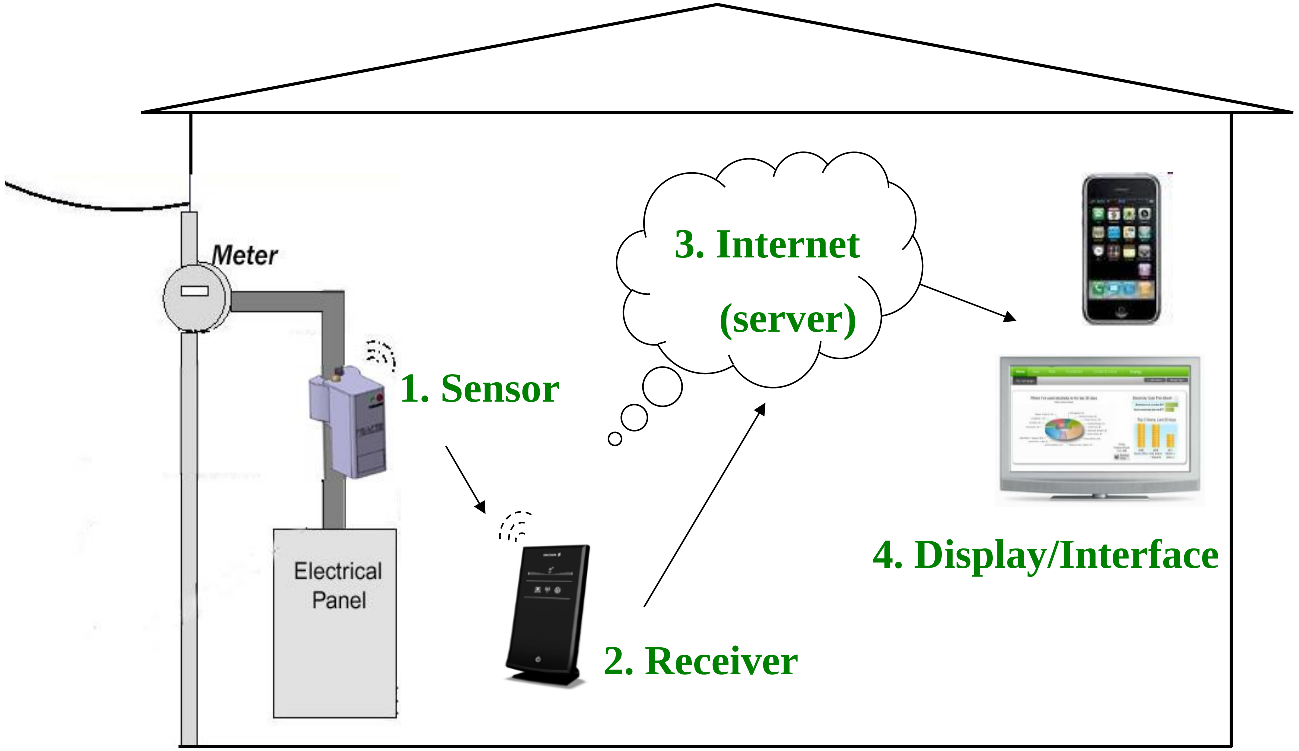
- Which model should be used?
- Which signals should be monitored?
- How to automatically detect (select) a voltage disturbance useful for load monitoring? (Upstream versus downstream disturbance)
- Which level of voltage variation should be detected?
- How large should the measurement window be?
- Is the number of events enough to be representative?

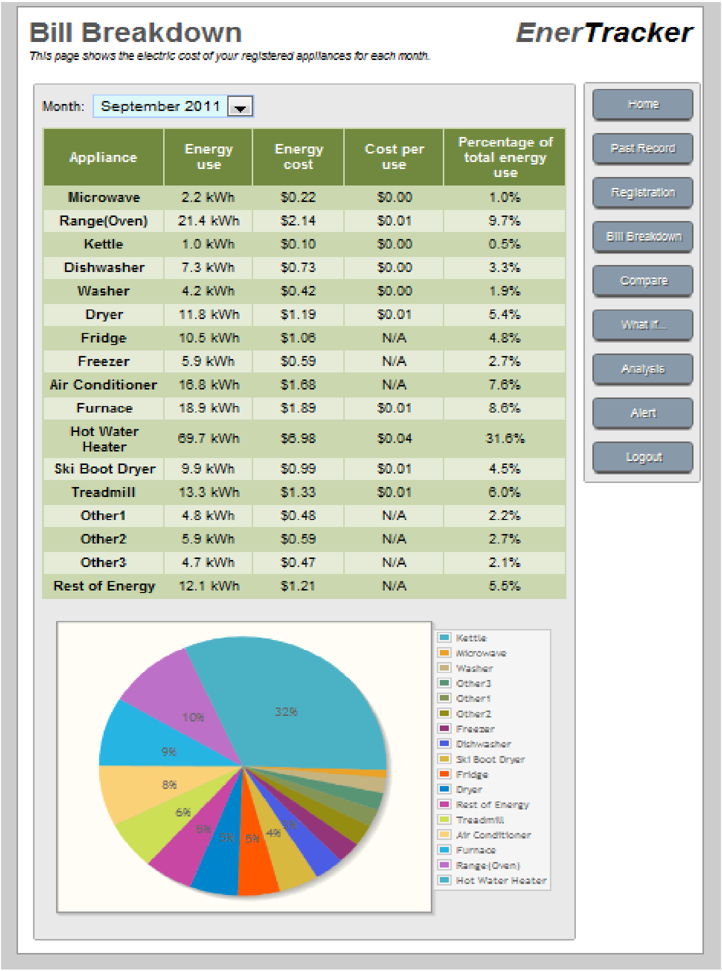
Case study: In a pilot project, measurements were carried out for 3 and 1/2 days (82 consecutive hours)

Source: W. Freitas and L. C. P. da Silva, Distribution System Load Modeling Based on Detection of Natural Voltage Disturbances, IEEE/PES General Meeting, 2012 - © 2012 IEEE

Customer appliance monitoring

Issue: How to use V&I current from a single sensor to monitor individual home appliances consumption?





Bill Breakdown

EnerTracker

This page shows the electric cost of your registered appliances for each month.

Month: September 2011

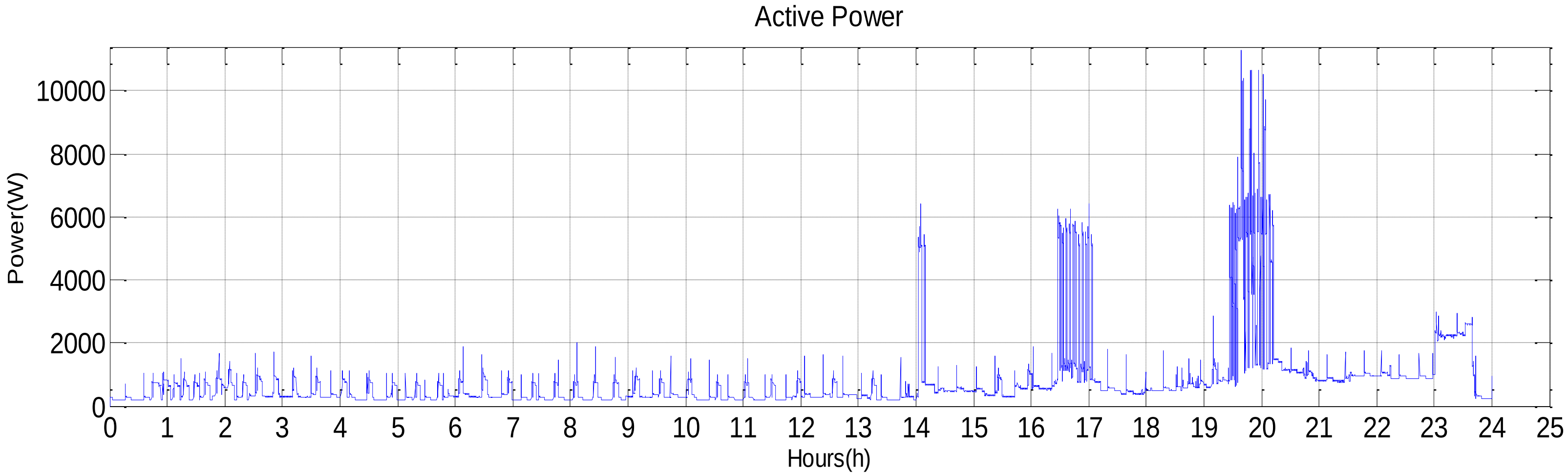
Appliance	Energy use	Energy cost	Cost per use	Percentage of total energy use
Microwave	2.2 kWh	$0.22	$0.00	1.0%
Range(Oven)	21.4 kWh	$2.14	$0.01	9.7%
Kettle	1.0 kWh	$0.10	$0.00	0.5%
Dishwasher	7.3 kWh	$0.73	$0.00	3.3%
Washer	4.2 kWh	$0.42	$0.00	1.9%
Dryer	11.8 kWh	$1.19	$0.01	5.4%
Fridge	10.5 kWh	$1.06	N/A	4.8%
Freezer	5.9 kWh	$0.59	N/A	2.7%
Air Conditioner	16.8 kWh	$1.68	N/A	7.6%
Furnace	18.9 kWh	$1.89	$0.01	8.6%
Hot Water Heater	69.7 kWh	$6.98	$0.04	31.6%
Ski Boot Dryer	9.9 kWh	$0.99	$0.01	4.5%
Treadmill	13.3 kWh	$1.33	$0.01	6.0%
Other1	4.8 kWh	$0.48	N/A	2.2%
Other2	5.9 kWh	$0.59	N/A	2.7%
Other3	4.7 kWh	$0.47	N/A	2.1%
Rest of Energy	12.1 kWh	$1.21	N/A	5.5%

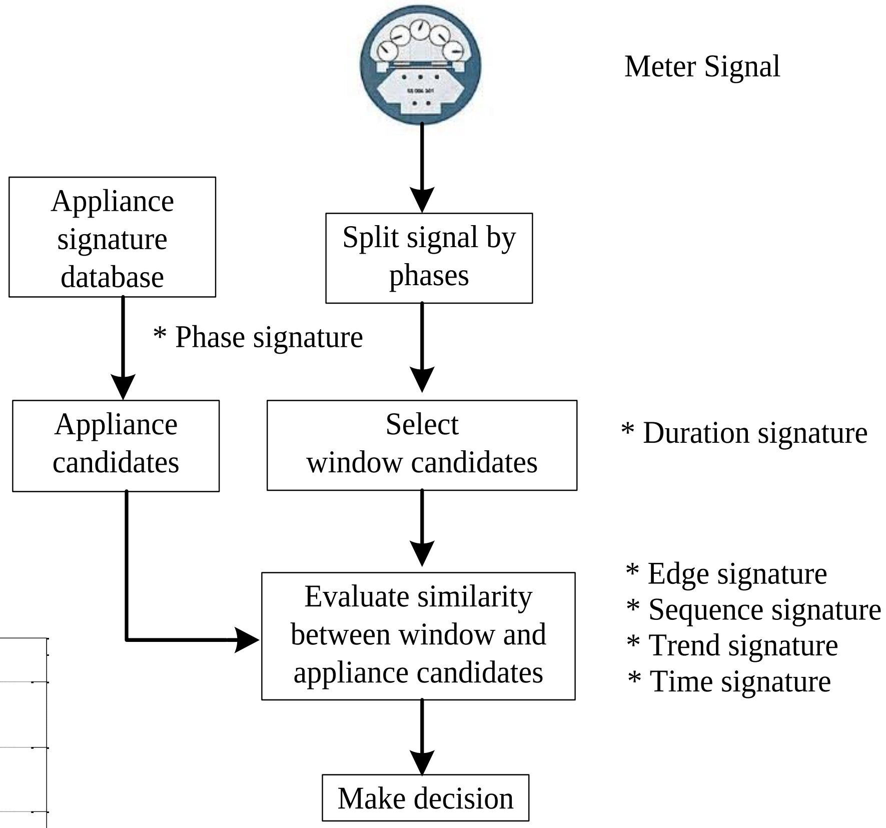
Source: M. Dong, P. C. M. Meira, W. Xu, W. Freitas, "An event window-based load monitoring technique for smart meters", IEEE Transactions on Smart Grid, v. 3, p. 787-796, 2012 - © 2012 IEEE

Customer appliance monitoring

Idea: Develop an event-window-based approach using unique characteristics (signatures) of typical appliances such as:

- edge signatures
- sequence signatures
- trend signatures
- time/duration signatures
- phase signatures
- power signatures
- harmonic signatures




Meter Signal

Appliance signature database

Split signal by phases

* Phase signature

Appliance candidates

Select window candidates

* Duration signature

Evaluate similarity between window and appliance candidates

* Edge signature
* Sequence signature
* Trend signature
* Time signature

Make decision

Source: M. Dong, P. C. M. Meira, W. Xu, W. Freitas, “An event window-based load monitoring technique for smart meters", IEEE Transactions on Smart Grid, v. 3, p. 787-796, 2012 - © 2012 IEEE

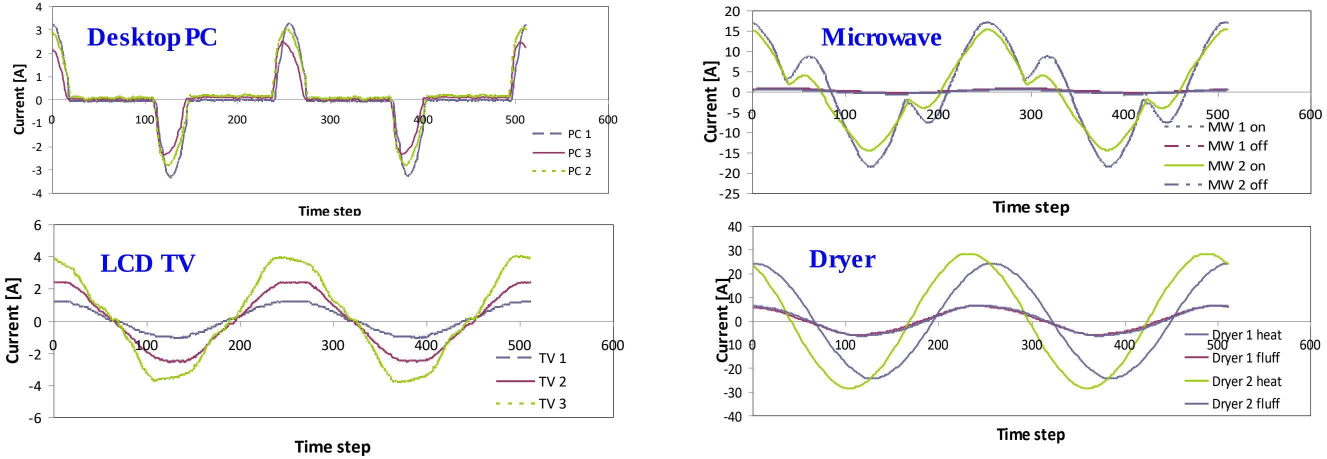
Customer appliance monitoring

Appliance characteristics (signatures)

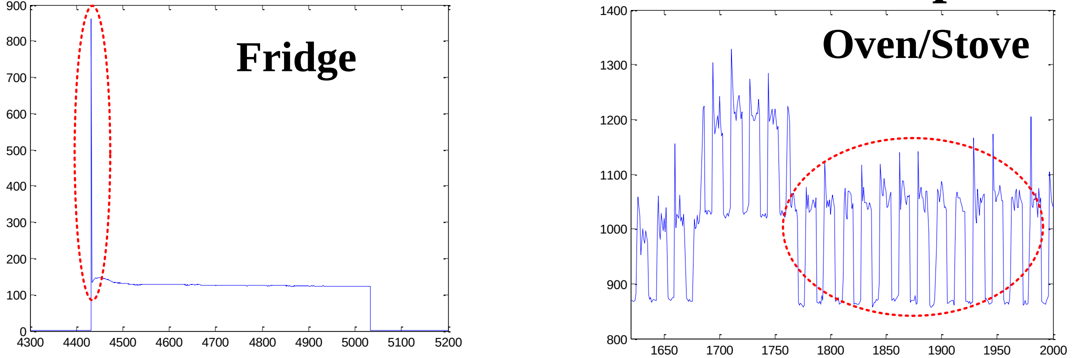
Characteristic 1: Power levels

- A microwave oven draws about 1000W when turned on
- A fridges draws about 100W when turned on

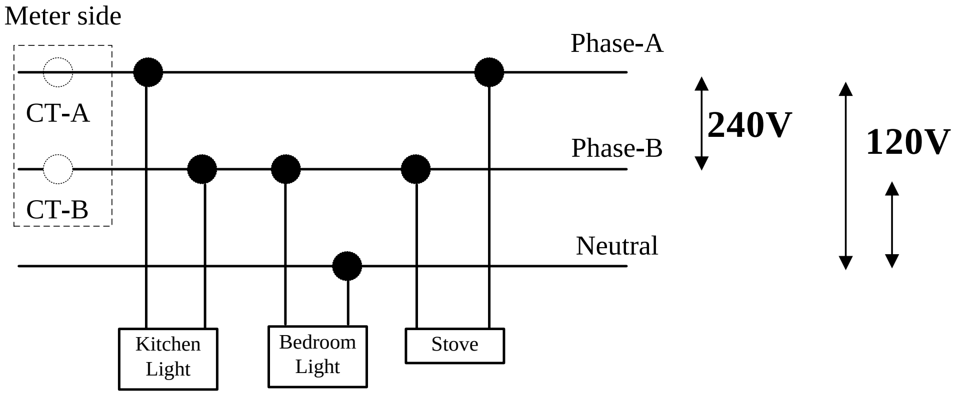
Characteristic 2: Current waveforms



Characteristic 3: Turn on transients and operating cycles

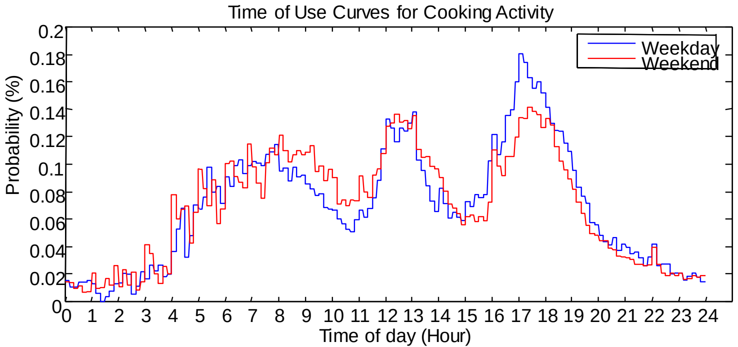


Characteristic 4: “Electrical location”



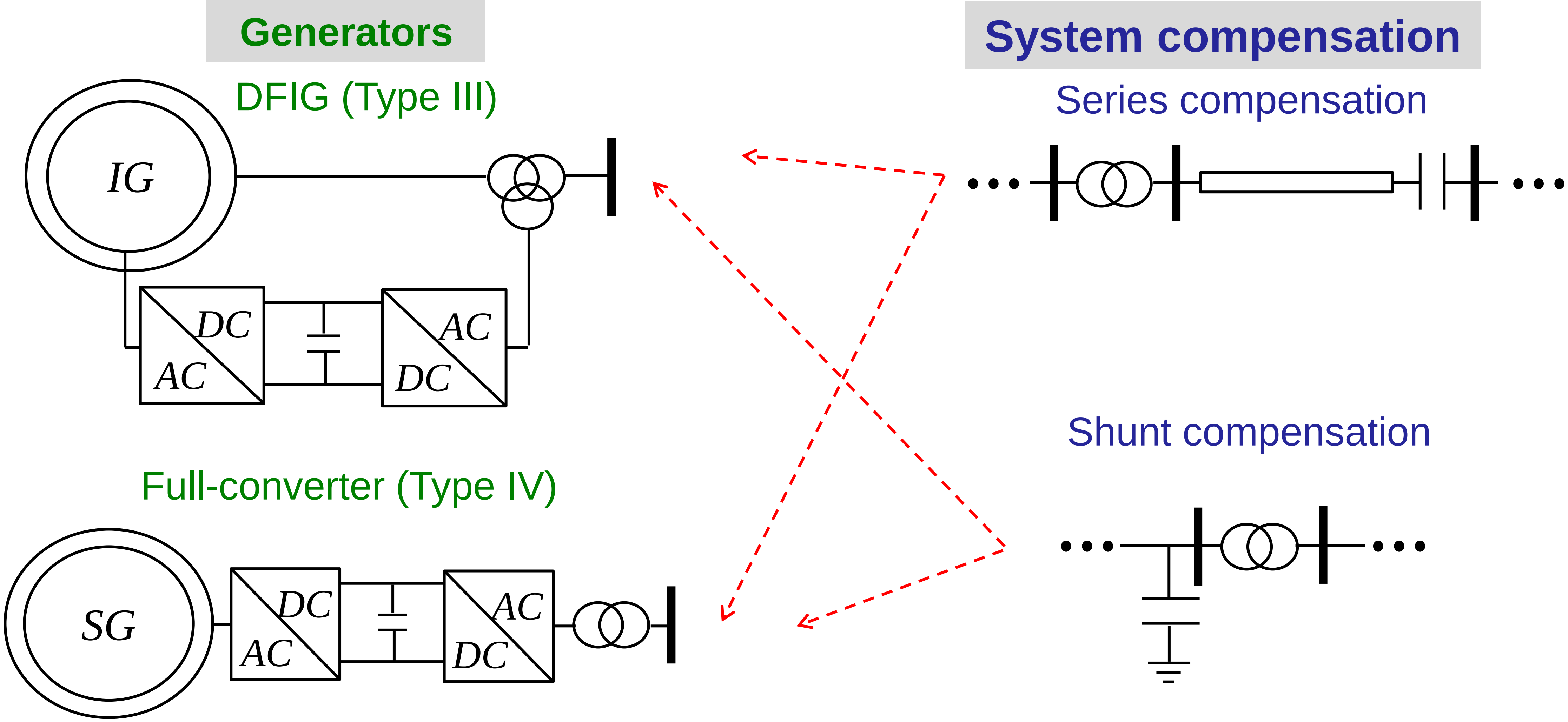
Characteristic 5: Duration and time of use

Load name	Min length	Max length
Fridge(cycle)	>10 mins	<40 mins
Freezer(cycle)	>10 mins	<40 mins
Furnace(cycle)	>5 mins	<30 mins
Stove	>3 mins	<45 mins
Kettle	>3 mins	<15mins
Washer	>20 mins	<90 mins
Dryer	> 20 mins	<75 mins
Bedroom light	>0 min	<5 hrs
Living room light	>0 min	<8.5 hrs
TV	>0 min	<10 hrs



Source: M. Dong, P. C. M. Meira, W. Xu, W. Freitas, “An event window-based load monitoring technique for smart meters", IEEE Transactions on Smart Grid, v. 3, p. 787-796, 2012 - © 2012 IEEE

Wind generation: resonances



Generators

DFIG (Type III)

Full-converter (Type IV)

System compensation

Series compensation

Shunt compensation

Issue: interactions among the wind farms and the system capacitances and inductances can produce sub-synchronous resonances (series compensation) and harmonic resonances (shunt compensation), which can be weakly damped or unstable (high frequency)

Wind generation: resonances – real cases

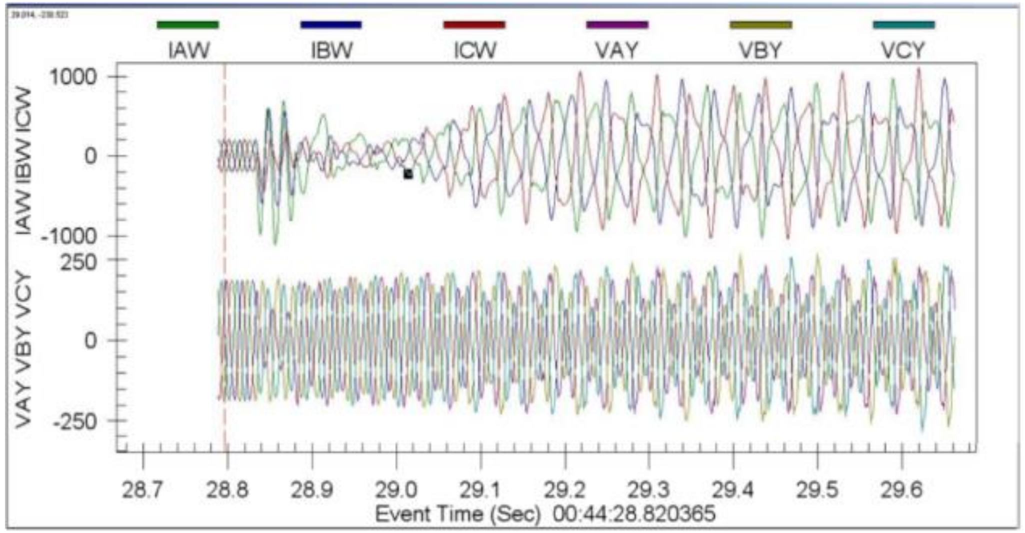
✓ Texas, USA: installed capacity: 200 MW (345 kV, Type III generators)

✓ Unstable resonance was caused by a short-circuit, followed by a transmission line being tripped close to the wind park

✓ Sub-synchronous currents reached 4.0 pu in 1 s

✓ Sub-synchronous voltages reached 2.0 pu in 3 s

✓ The event damaged the crowbar circuit of several wind park generators, and the series capacitor of a transmission line close to the wind park

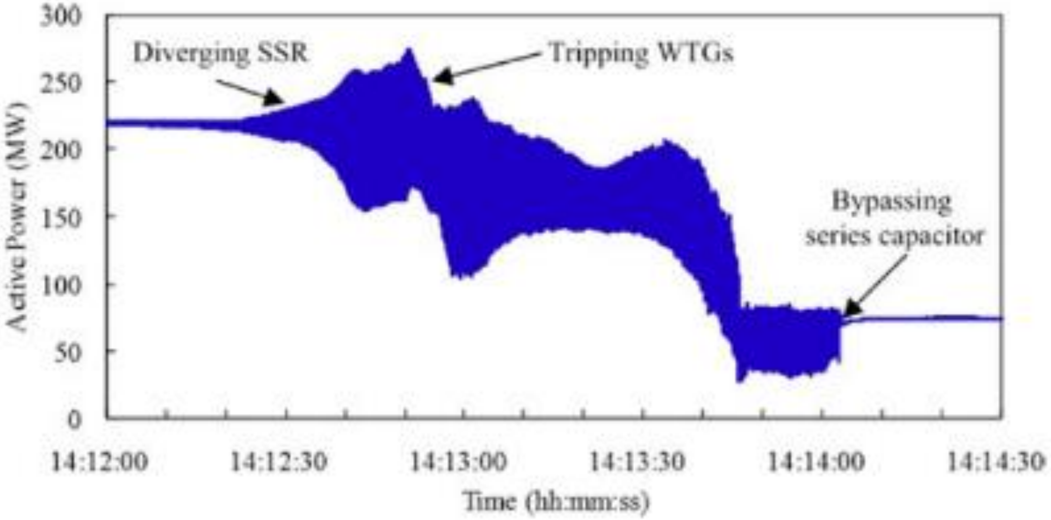


Source: D. Kidd, P. Hassink, “Transmission operator perspective of sub-synchronous interaction,” IEEE PES T&D, 2012 - © 2012 IEEE

✓ Heibei, China: installed capacity: 3.4 GW (220 kV, 82.5% - Type III, 15.4% - Type IV and 1.8% Type II generators)

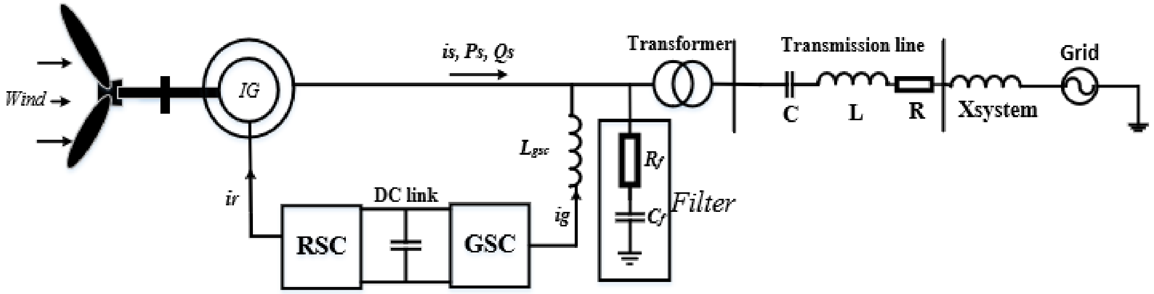
✓ 58 events of unstable sub-synchronous resonance were detected from Dec. 2012 to Dec. 2013

✓ Event (Mar. 19th, 2013): power generation was 219.5 MW. 30 s after the start, the oscillation magnitude reached 25% of the average power generation. A total of 66% of the generation was lost during the event



Source: X. Xie et. al., “Characteristic Analysis of Subsynchronous Resonance in Practical Wind Farms Connected to Series-Compensated Transmissions,” IEEE Trans. on Energy Conversion, 2017 - © 2017 IEEE

Wind generation: protective methods for mitigation (real-time)



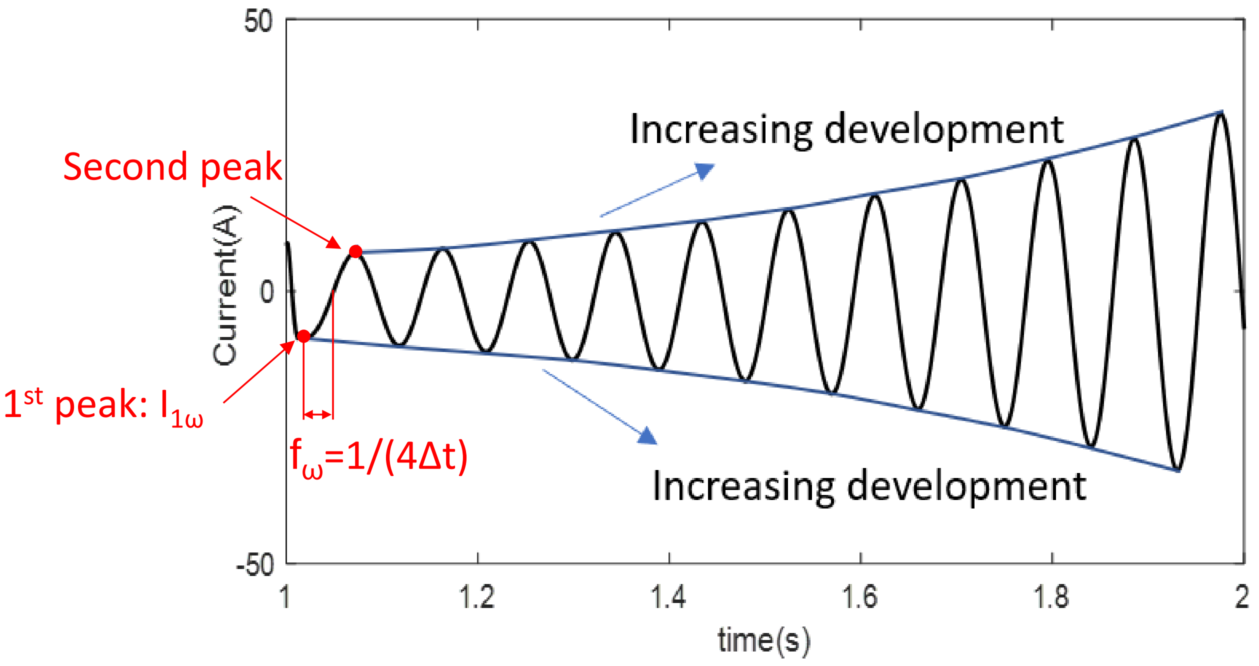
(a)

Issue:

SSR events in series compensated transmission lines connected close to DFIG-based wind farms have been reported

SSR currents can become significant in less than 1 second, causing equipment damages

Early detection of SSR characteristics is critical to avoid equipment damages and implement mitigation actions

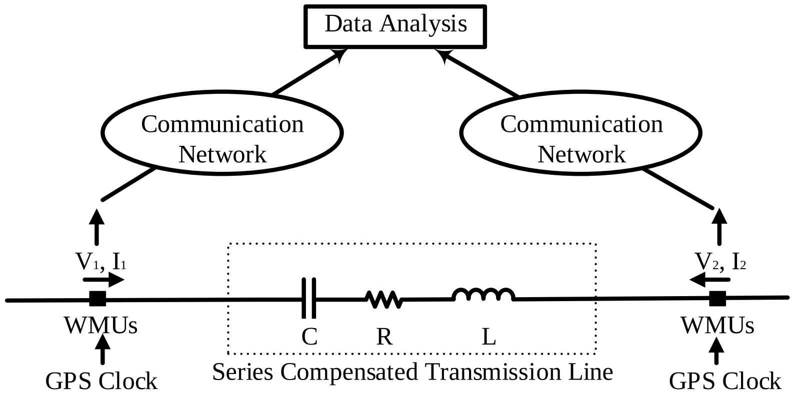


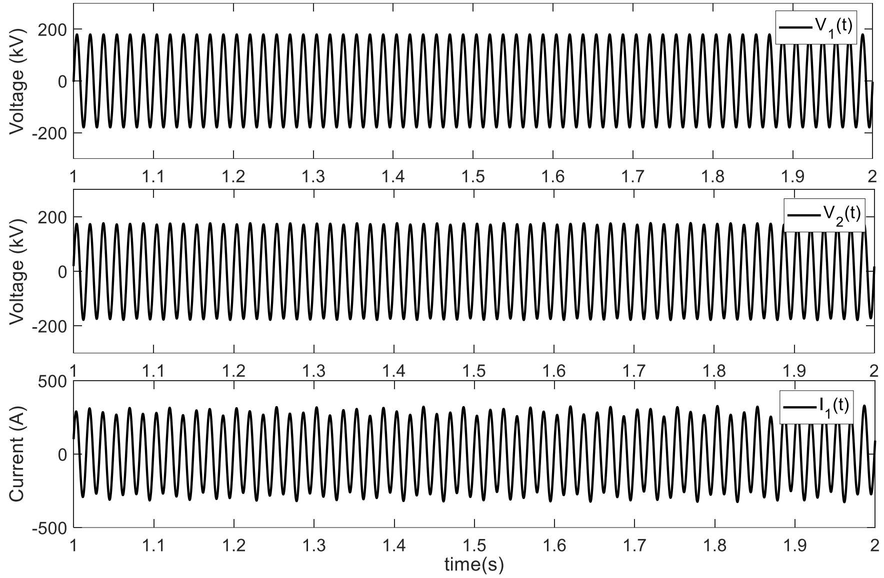
With 1^{st} and 2^{nd} peaks, one can obtain the damping ratio *a*

Challenge: obtain SSR current, with unknow frequency, with high speed and accuracy

Source: B. Gao, R. Torquato, W. Xu, W. Freitas, "Waveform-based method for fast and accurate identification of subsynchronous resonance events," IEEE Transactions on Power Systems, v. 34, p. 3626-3636, 2019 - © 2019 IEEE

Wind generation: protective methods for mitigation (real-time)

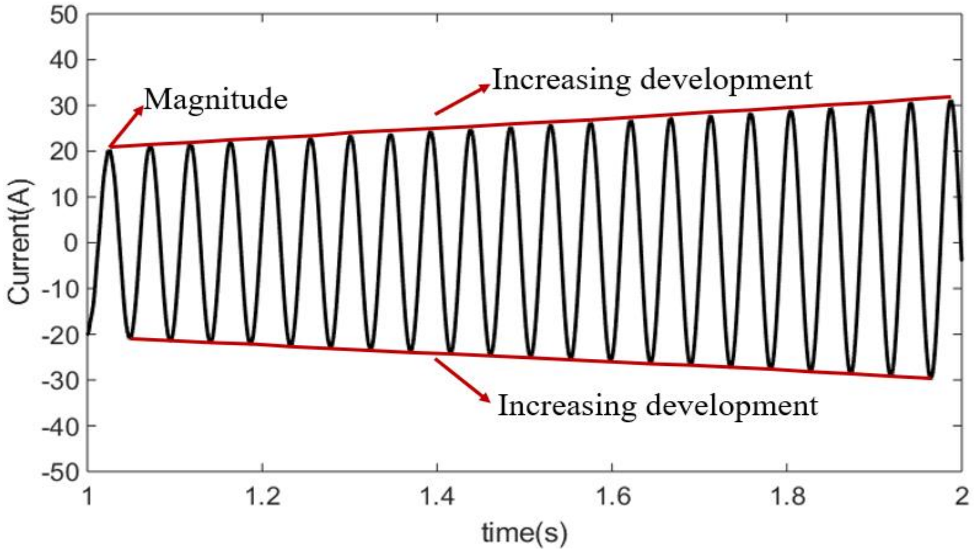




Synchronized waveforms

Idea: voltage and current waveforms at the line terminals can be collected to extract the sub-synchronous current by using the line as a natural analog filter

SSR characteristics can be obtained in ~1 SSR cycle



Extracted sub-synchronous component

Depend on line parameters

$$\Delta V_{line}(t) - \Delta V_{aux}(t) = A\underbrace{I_{1\omega} e^{-at} \cos(2\pi f_{\omega} t + \gamma_{1\omega}}_{\text{SSR current}} + \theta)$$

Source: B. Gao, R. Torquato, W. Xu, W. Freitas, “Waveform-based method for fast and accurate identification of subsynchronous resonance events," IEEE Transactions on Power Systems, v. 34, p. 3626-3636, 2019 - © 2019 IEEE

Incipient fault detection (fault anticipation)

Issue: Several faults in distribution systems are preceded by incipient faults, especially if the faults are related to equipment failures:

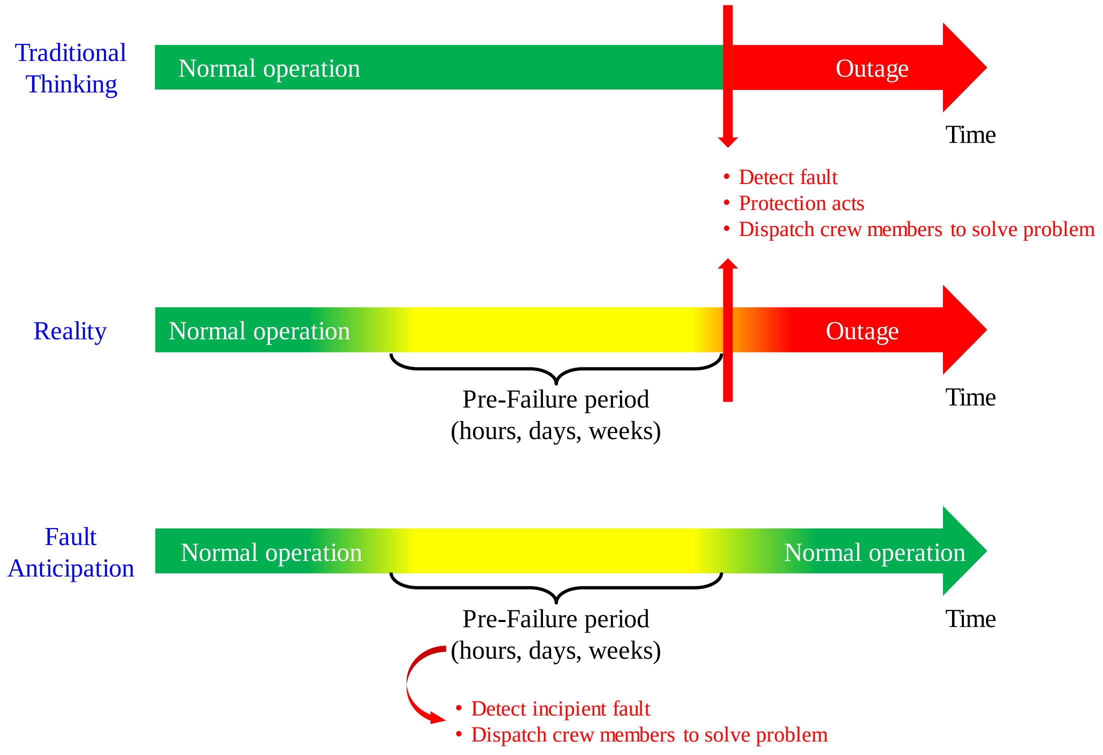
- overgrown trees under power lines
- insulation failure
- failure of transformer tap

Detection of incipient faults allows the adoption of predictive actions, avoiding the occurrence of a permanent fault

Characteristics of incipient faults:

- Small magnitude not enough to trigger relays
- Short duration not enough to trigger relays
- Distorted waveforms

Idea: detect abnormal voltage and current waveforms (PQ monitors)

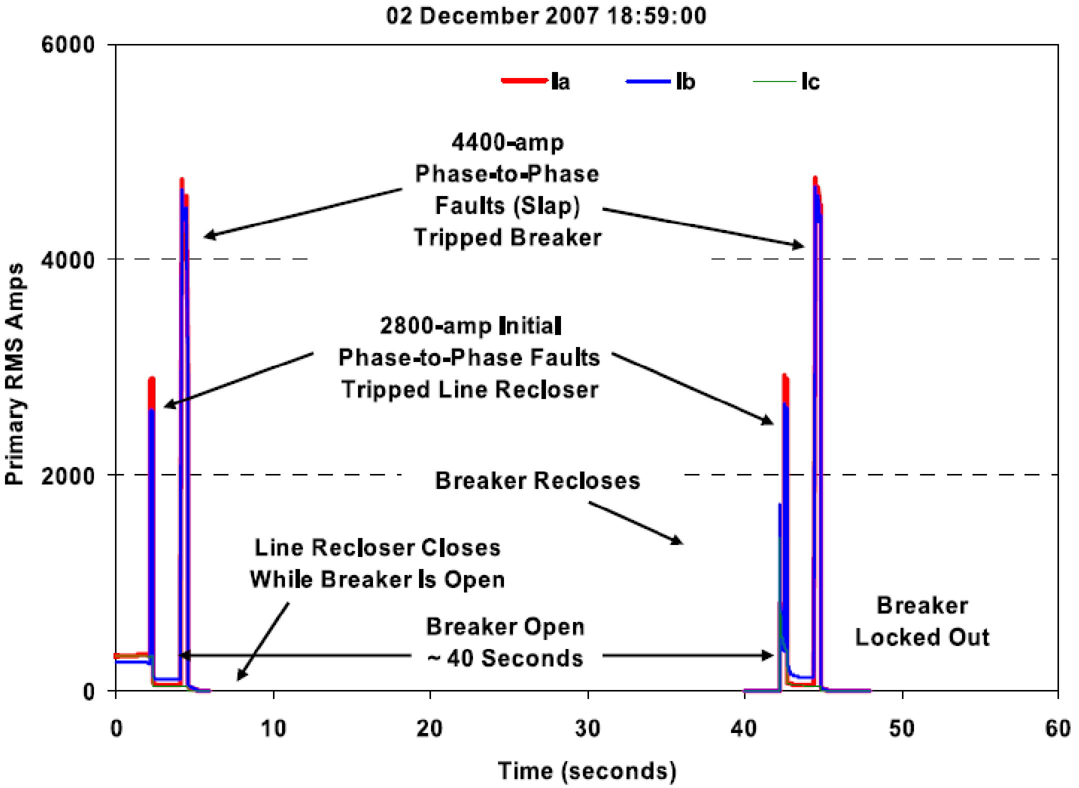


Concept of incipient fault detection (or fault anticipation)

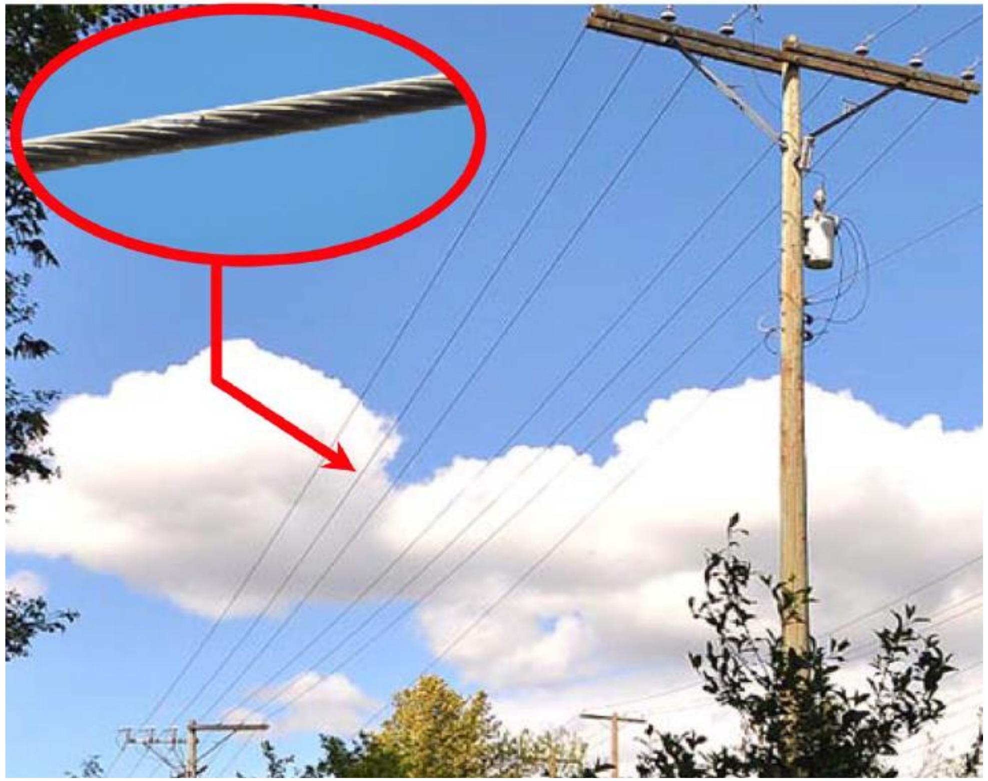
Adapted from: J. A. Wischkaemper, C. L. Benner, B. D. Russell, and K. Manivannan, “Application of Waveform Analytics for Improved Situational Awareness of Electric Distribution Feeders,” *IEEE Trans. on Smart Grid*, vol. 6, pp. 2041-2049, 2015

Incipient fault detection (fault anticipation)

Real case 1: Fault-induced conductor slap (FICS): occurs when magnetic forces from an initial fault cause movement in upstream conductors sufficient to cause contacts, resulting in a second, higher magnitude fault closer to the substation



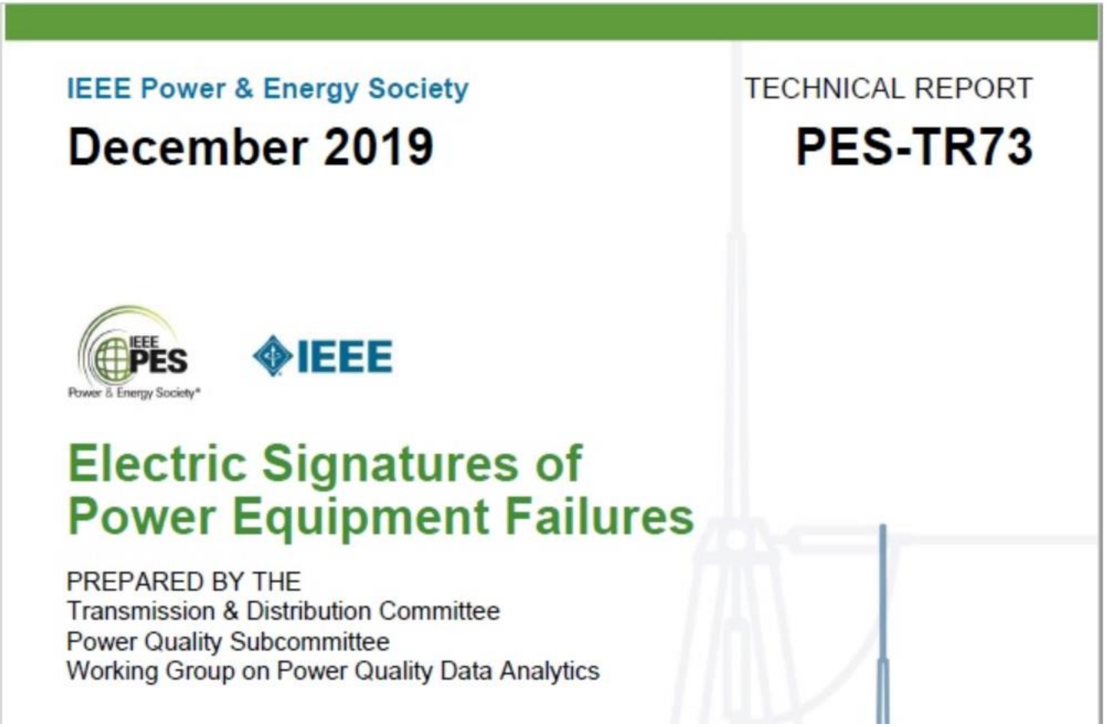
RMS current waveforms for FICS sequence - © 2015 IEEE



Span with multiple FICS events - © 2015 IEEE

Source: J. A. Wischkaemper, C. L. Benner, B. Don Russell, and K. Manivannan, “Application of waveform analytics for improved situational awareness of electric distribution feeders” IEEE Transactions on Smart Grid, vol. 6, pp. 2041-2774, 2049 - © 2015 IEEE

More information: Electric signatures of power equipment failure (PES-TR73)



IEEE Power & Energy Society

December 2019

TECHNICAL REPORT

PES-TR73

Electric Signatures of Power Equipment Failures

PREPARED BY THE
Transmission & Distribution Committee
Power Quality Subcommittee
Working Group on Power Quality Data Analytics

1. Failure signatures of equipment
    - Underground cables
    - Overhead lines
    - Transformers & tap changers
    - Switches
    - Capacitors
    - Lightning and surge arresters
    - Potential transformers
2. Review of waveform abnormality detection methods
3. Discussions on how to move forward

https://resourcecenter.ieee-pes.org/technical-publications/technical-reports/PES_TP_TR73_TD_122019.html

IEEE PES T&D Committee Award for Outstanding Technical Report: *“For Advancing the Power Quality Data Analytics Domain by Demonstrating Techniques for Prediction and Analysis of Electric Power Equipment Failure” – 2020*

Comments

- ✓ Due to uncertainties, variabilities and unpredictability of demand and generation, economic and environmental concerns, the electrical energy systems of the future will be planned and operated based more and more on risk-based methods, stochastic approaches and active (predictive) philosophies
- ✓ Data analytics will be essential for the future of the electrical energy systems
- ✓ Smart meters (and other sensors) are one of the core technologies to promote this paradigm change (more killer applications can make this solution a business case)
- ✓ Models and methods must be developed considering the availability and quality of data

worse than make a decision with no data, it is to make a decision with bad data

Thank you

Walmir Freitas

http://www.dsee.fee.unicamp.br/~walmir