Applications of Smart Meter Data to State Estimation

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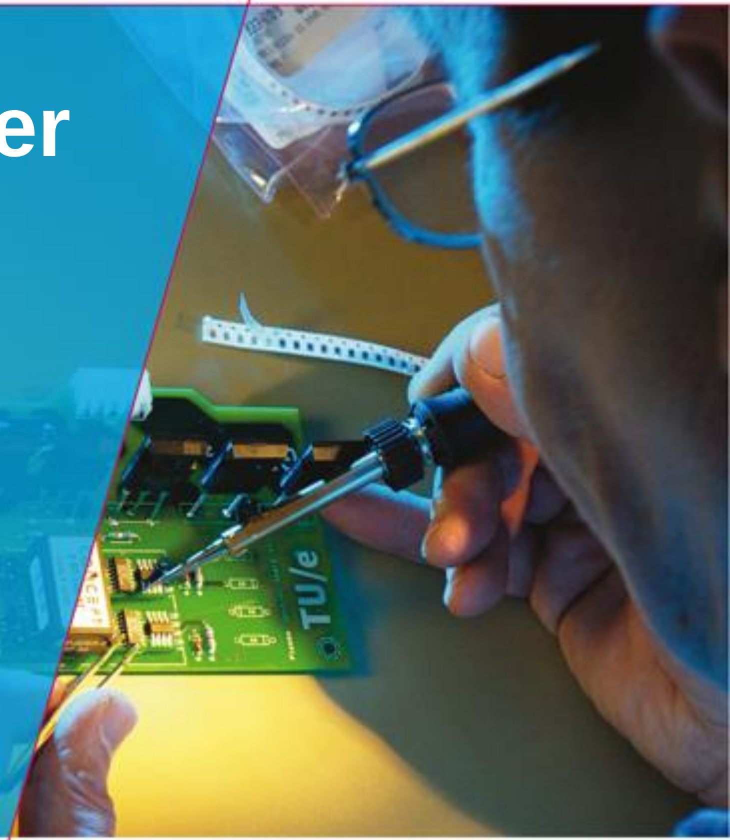

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Where innovation starts

Outline

- Introduction
- Implementation Procedure
  - Phase Identification
  - Data Aggregation
  - Uncertainty Estimation
- Case Study
  - Test Setup
  - Test Result
- Conclusions

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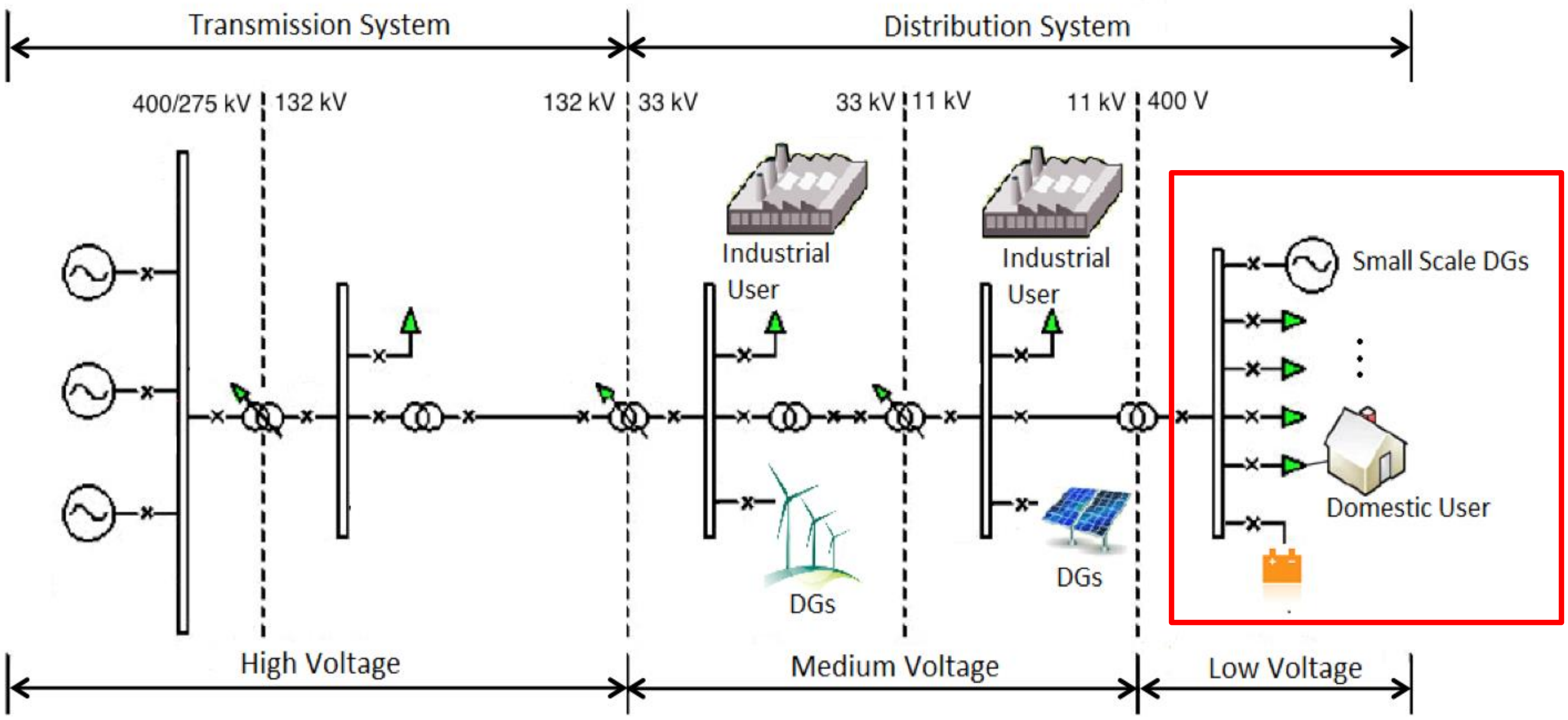
Introduction (1/3)

- **Since the last few years, distributed energy resources and storage devices are widely installed, which have made the power flow pattern more complicated;**
- **Distribution system state estimation (DSSE), which provides the control centers with the state information, plays a significant role in the grid operation;**
- **Most distribution networks are unobservabel due to a limited number of supervisory control and data acquisation (SCADA) devices are installed;**

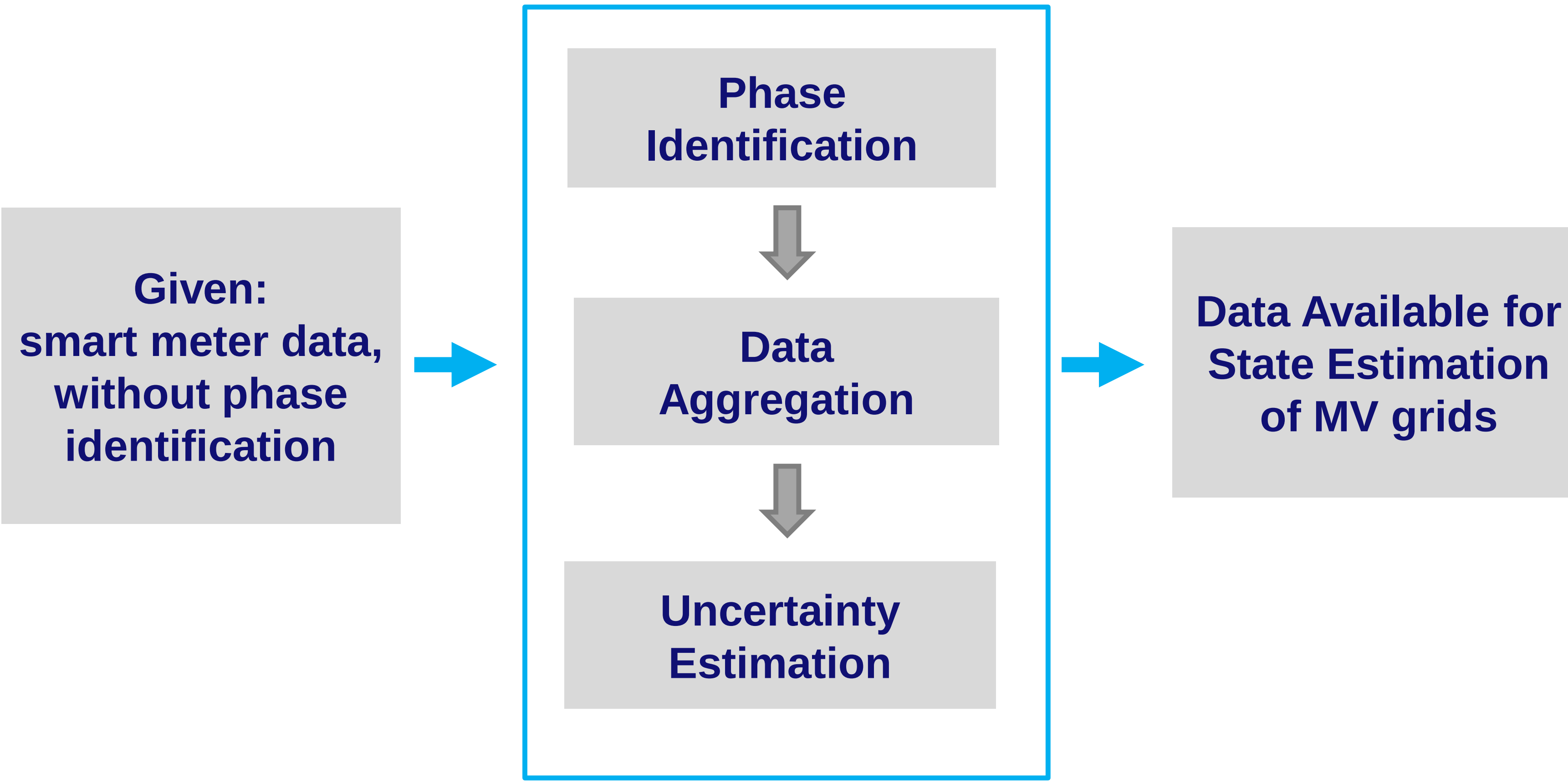
Introduction (2/3)



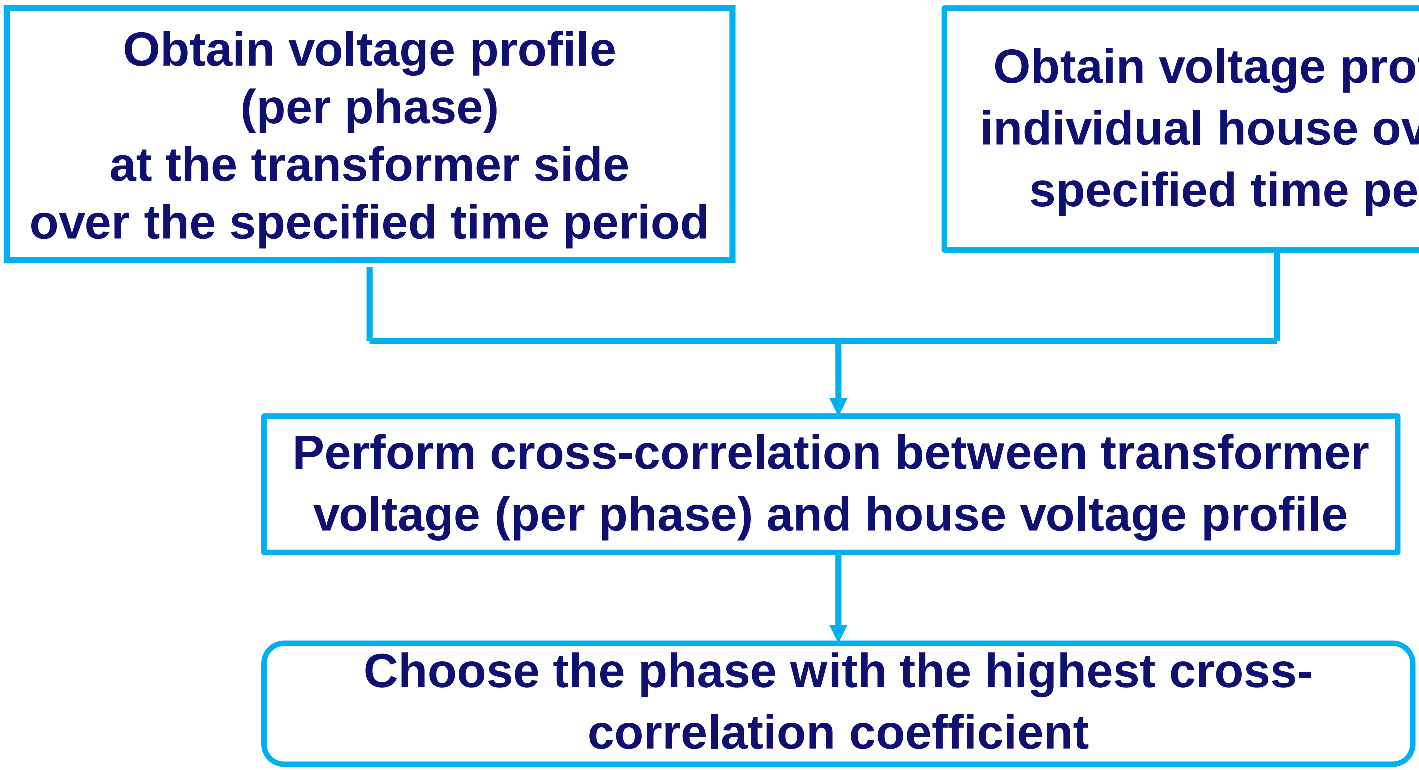
Introduction (3/3)

- **To make the network artificially observable, pseudo measurements are used, which decrease the accuracy of DSSE;**
- **Smart meters provide interval demand and generation data, also report voltage data and service interruption information of end-users of LV grids;**
- **Phase allocation information at the LV grid end-user side is often incomplete or missing.**

Implementation Procedure



Phase Identification



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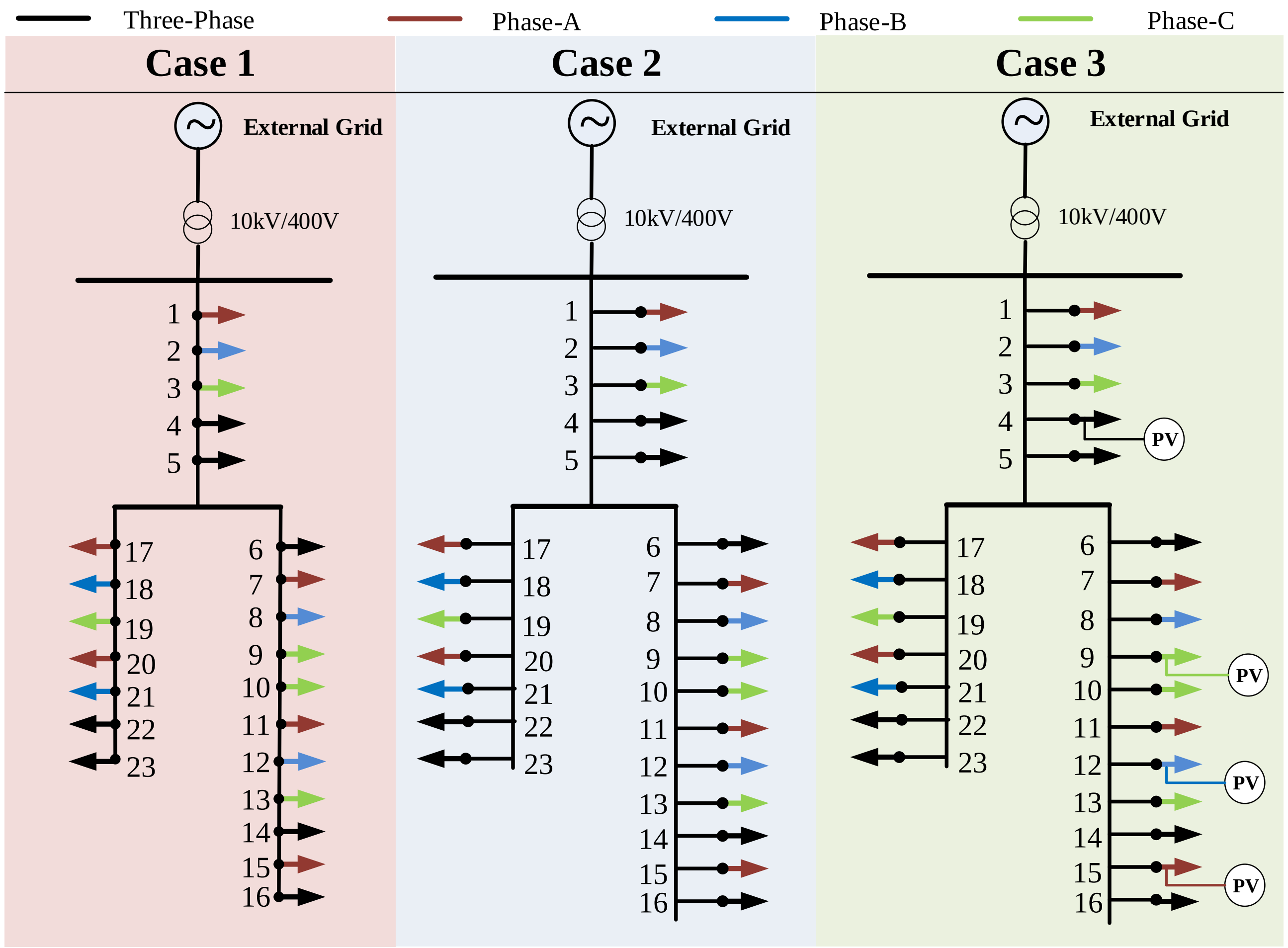
Example (1/2)

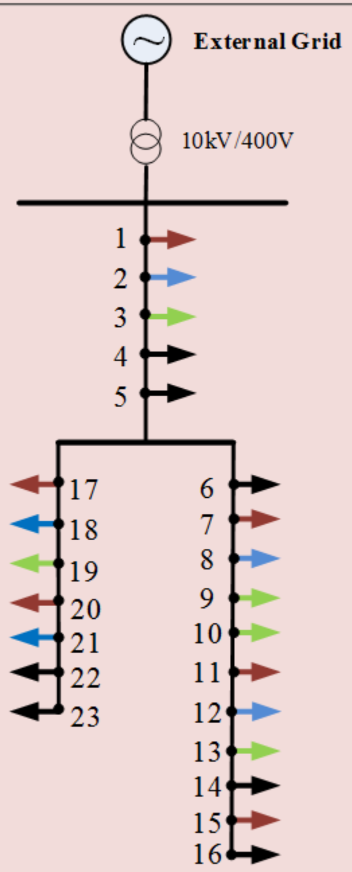


Three-Phase
Phase-A
Phase-B
Phase-C
Case 1
Case 2
Case 3
External Grid
10kV/400V
PV
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23

Example (2/2)

Node No.	Case 1			Case 3		
	Phase A	Phase B	Phase C	Phase A	Phase B	Phase C
1	**0.9090**	0.4059	0.5795	**0.9159**	0.4198	0.5473
2	0.5521	**0.9211**	0.5024	0.5226	**0.8962**	0.4713
3	0.3846	0.5821	**0.8682**	0.3969	0.6244	**0.8901**
4						
5						
6						
7	**0.8788**	0.3678	0.5416	**0.8809**	0.3675	0.5221
8	0.4450	**0.8331**	0.3640	0.4043	**0.7936**	0.3217
9	0.2803	0.4855	**0.7932**	0.3453	0.5615	**0.8505**
10	0.2667	0.4785	**0.7841**	0.3214	0.5646	**0.8396**
11	**0.8713**	0.3914	0.5237	**0.8738**	0.3938	0.5013
12	0.3292	**0.6905**	0.1722	0.2434	**0.5778**	0.0514
13	0.2420	0.4568	**0.7660**	0.2980	0.5332	**0.8230**
14						
15	**0.8703**	0.4017	0.5239	**0.8697**	0.3961	0.4989
16						
17	**0.8793**	0.3604	0.5461	**0.8774**	0.3544	0.5047
18	0.5285	**0.8834**	0.4460	0.5211	**0.8599**	0.4195
19	0.3288	0.5403	**0.8331**	0.3489	0.5922	**0.9616**
20	**0.8766**	0.3600	0.5485	**0.8803**	0.3618	0.5161
21	0.5407	**0.8859**	0.4568	0.5472	**0.8668**	0.4407
22						
23						

Case 1



100%

Data Aggregation (1/2)

In principle, power at the transformer is equivalent to the sum of the load consumptions and the power losses of the circuit, that is,

$$\begin{cases} P_t^b = \sum_{i=1}^{n} p_{t,i}^b + P_{t,loss}^b \\ Q_t^b = \sum_{i=1}^{n} q_{t,i}^b + q_{t,loss}^b \end{cases} \quad (1)$$

- ***b*---the index of a transformer**
- ***n*---the total number of the households connecting with the transformer**
- ***i*---the index of a household**
- **P_t^b---the active power of transformer *b* at time *t***

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Data Aggregation (2/2)

Generally, there are three ways to deal with the power losses:

- **Neglected roughly, considering the relatively smallness comparing with loads of the LV feeder and computational difficulties;**
- **Assumed as a percentage of the summed power $\sum_{i=1}^{n} p_{t,i}^{b}$, according to the transformer efficiency;**
- **Adopt other methods to evaluate.**

Uncertainty Estimation (1/3)

- **There is a hypothesis in Equation (1):**
  - ➢ **all households are equipped with smart meter devices;**
  - ➢ **all the measurements are perfectly synchronized;**
  - ➢ **each reading of an individual smart meter has intrinsic uncertainty;**
- **All contributing uncertainties should be expressed at the same confidence level, by converting them into standard uncertainties.**

Uncertainty Estimation (2/3)

- **There are two approaches to estimating uncertainties:**

  'Type A' and 'Type B' evaluations

- **The combined standard uncertainty for the aggregated data would be found by,**

$$\text{Combined uncertainty} = \sqrt{a^2 + b^2 + c^2 + \ldots etc.}$$

- **A particular value of coverage factor *k* gives a particular confidence level for the expanded uncertainty.**

Uncertainty Estimation (3/3)

Step 1. **Aggregate the smart meter data by phase;**

***Step 2*. Estimate each aspect of uncertainty;**

***Step 3*. Decide the dependency of each uncertainty;**

***Step 4*. Find the combined standard uncertainty from all the individual aspects;**

***Step 5*. Express the uncertainty in terms of a coverage factor;**

***Step 6*. Write down the aggregated result and the uncertainty.**

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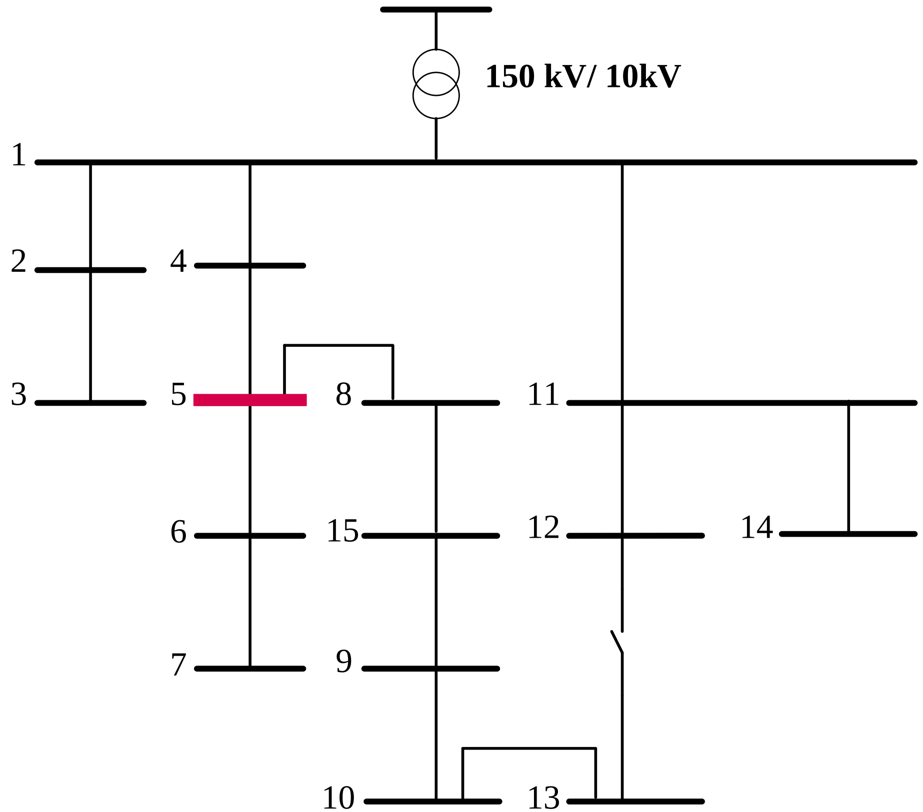
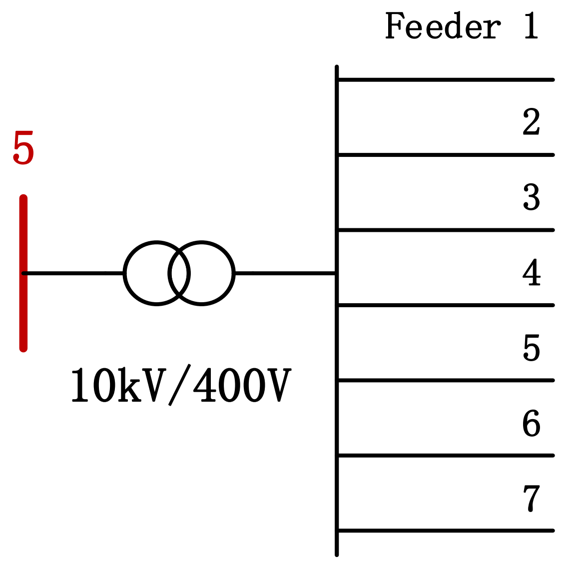
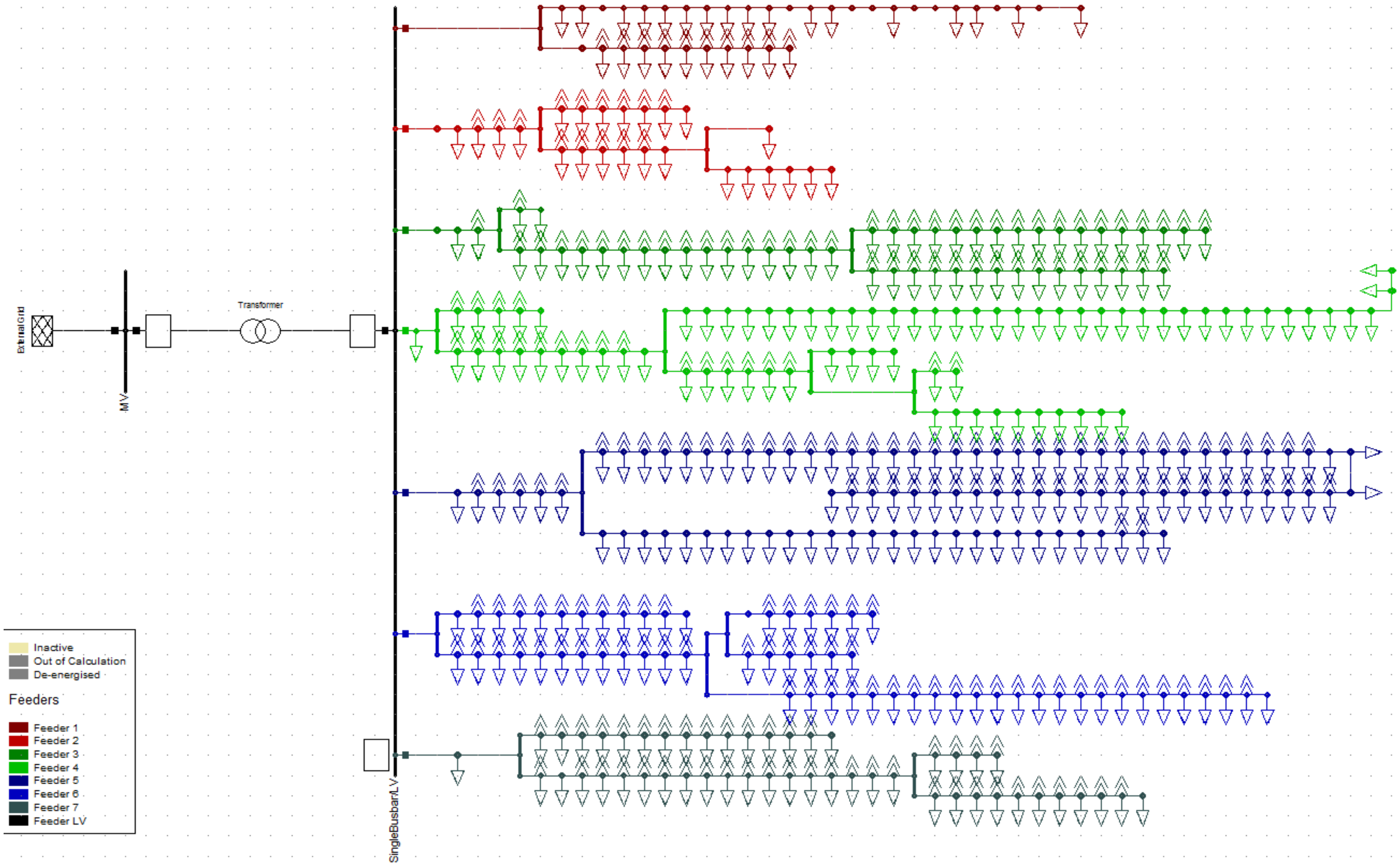
Test Setup (1/3)

The Zaltbommel MV network is a 10 kV network, connected to the HV grid at a single primary substation.





Test Setup (2/3)



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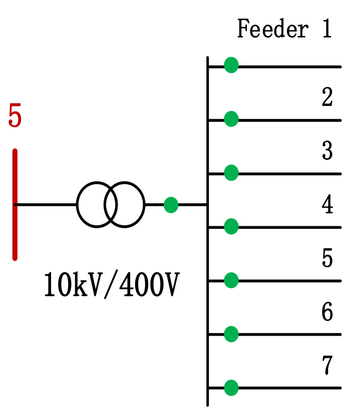
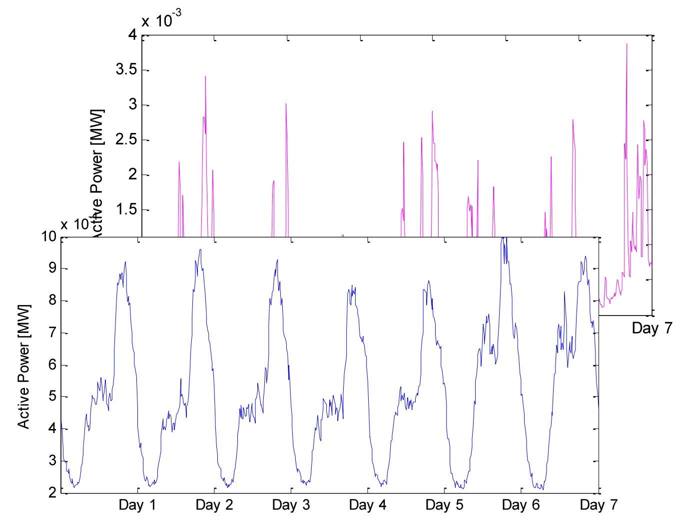
Test Setup (3/3)

- 15-minute average active power are measured at LV side of the transformer and the beginning of each feeder.
- 190 single households' load profiles over one week are obtained from smart meters, in every 15 minute.



	1	2	3	4	5	6
1	4.3275e-04	8.1200e-04	2.2000e-04	3.8000e-04	2.1600e-04	7.6800e-
2	3.9937e-04	5.3600e-04	1.2400e-04	4.3200e-04	1.7600e-04	7.0400e-
3	3.3574e-04	2.0800e-04	1.0800e-04	3.1600e-04	1.3600e-04	7.1600e-
4	3.1358e-04	1.8000e-04	1.0800e-04	4.9200e-04	2.0400e-04	7.2800e-
5	3.0024e-04	1.4000e-04	1.0800e-04	4.9600e-04	1.8000e-04	7.0000e-
6	2.9588e-04	1.2400e-04	1.6000e-04	4.0000e-04	1.2800e-04	3.2000e-
7	2.9073e-04	1.7200e-04	2.2000e-04	6.0400e-04	1.9600e-04	2.9600e-
8	2.6818e-04	1.6800e-04	1.0800e-04	3.9600e-04	2.1200e-04	2.9200e-
9	2.6840e-04	1.3600e-04	1.7600e-04	4.2000e-04	2.1200e-04	3.3600e-
10	2.6190e-04	1.2800e-04	1.0800e-04	4.8400e-04	2.0800e-04	3.0000e-
11	2.7382e-04	1.4800e-04	2.5600e-04	3.8000e-04	1.5200e-04	3.6800e-
12	2.4677e-04	1.2400e-04	2.9200e-04	4.6400e-04	1.2400e-04	3.1200e-
13	2.3349e-04	1.6000e-04	2.9600e-04	3.5200e-04	1.2800e-04	3.0000e-
14	2.2824e-04	2.2000e-04	2.8400e-04	2.5200e-04	1.9200e-04	3.1200e-
15	2.4507e-04	1.4400e-04	2.9200e-04	3.1200e-04	2.6400e-04	2.9600e-



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Test Results (1/5)

Actual Situation			
Total phase A	Total phase B	Total phase C	Total buses
135	122	126	383

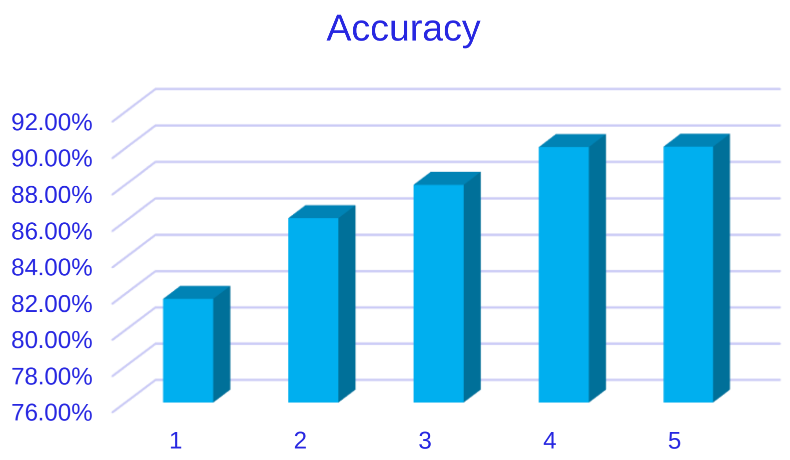
1 day in Summer			
Total phase A	Total phase B	Total phase C	Total buses
141	136	106	383

2 days in summer			
Total phase A	Total phase B	Total phase C	Total buses
132	141	110	383

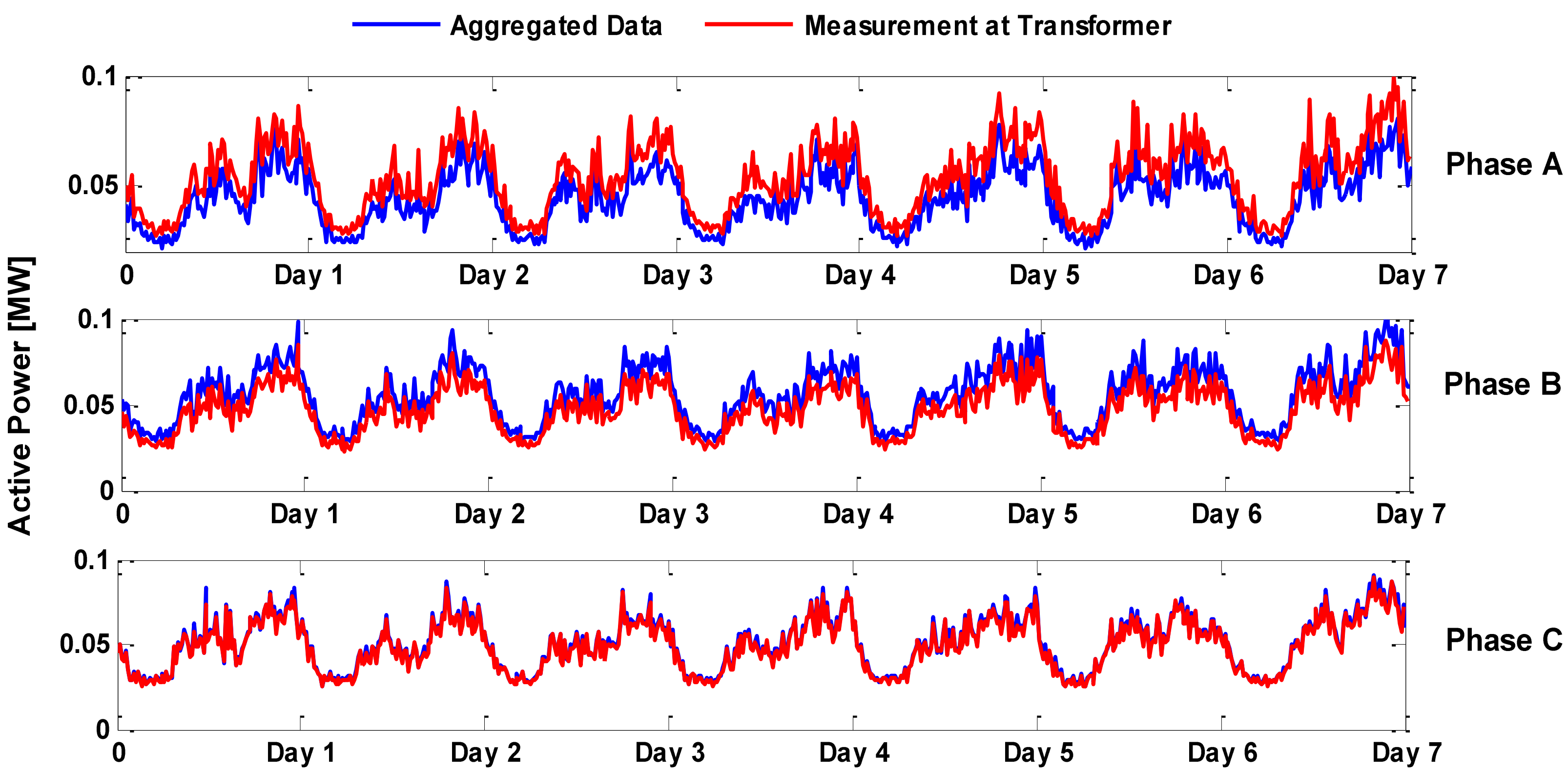
3 days in summer			
Total phase A	Total phase B	Total phase C	Total buses
128	147	108	383

4 days in summer			
Total phase A	Total phase B	Total phase C	Total buses
128	127	128	383

5 days in summer			
Total phase A	Total phase B	Total phase C	Total buses
132	141	110	383



Test Results (2/5)



Test Results (3/5)

- **Measurement devices *Esm***
  - ➢ **Type B error**
  - ➢ **For each smart meter *e_sm* : 0.1%-1%**
  - ➢ **The aggregated error (independent case)**

$$Esm = \sqrt{\sum_{i=i}^{N} (e\_sm_i)^2}$$

- **Missing data *Emd***
  - ➢ **Type A error**
  - ➢ **0.1%-5%**

Test Results (4/5)

- **Unsynchronization error *Eue***
  - ➢ **Type A error**
  - ➢ **0.1%-0.6%**
- **Phase identification error *Eid***
  - ➢ **Type B error**
  - ➢ **10%-15%**
- **Power loss error *Epl***
  - ➢ **Type B error**
  - ➢ **0.5%-2%**

Test Results (5/5)

- **The combined standard uncertainty for the aggregated data is:**

$$u=\sqrt{(Esm)^2+(Emd)^2+(Eue)^2+(Eid)^2+(Epl)^2}$$

- **Take the coverage factor *k*=2, which gives a particular confidence level 95%;**
- **The aggregated data available for state estimation is given by,**

$$\widetilde{P_t^b}=\sum_{i=1}^{n} p_{t,i}^{b}+u$$

- **The calculated *u* = (20%~40%)*$\sum_{i=1}^{n} p_{t,i}^{b}$, with confidence level 95%.**

Conclusions

- Smart meter data is beneficial to transformer load modeling and management;
- Aggregated smart meter data can be used for state estimation of both LV and MV networks;
- The uncertainty of aggregated smart meter data is lower than the pseudo- measurement which is always assumed 50%;
- The uncertainty of aggregated smart meter data could be reduced to some degree, by taking high-quality device and more precise phase identification method.

Thanks for your attention!

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State Estimation Introduction

State estimation algorithm is commonly based on the weighted least square method [4] , where the state variables (voltage magnitude and phase angle) are determined by the minimisation of the square of the error of all measurements. The basic equation which relates the measurements with the state variables is:

$$z = h(x) + e$$

Where
z is the measurement vector
x is the state variable vector
h is the nonlinear power flow equations
e is the measurement error vector

The state vector x can be estimated using different estimator techniques [7]:

1- Weighted Least Squares Estimator.
2- Least Absolute Value Estimator.
3- Reweighted Least Squares Estimator.

Weighted Least Squares Estimator will be used in this paper as it gives a consistent performance under Gaussian assumptions for known noise characteristics [9].

a. WLS estimator

Weighted least square method deals with minimisation of the error e, which is done by minimising the cost function $J(x)$ as follows :

$$J(x) = [z - h(x)]^T W [z - h(x)]$$

Where W is the weighting matrix, which is chosen to be the inverse of the covariance matrix of the measurement error vector.

Standard Uncertainty Calculation

7.1.1 Calculating standard uncertainty for a Type A evaluation

When a set of several repeated readings has been taken (for a Type A estimate of uncertainty), the mean, $\bar{x}$, and estimated standard deviation, s, can be calculated for the set. From these, the estimated standard uncertainty, u, of the mean is calculated from:

$$u = \frac{s}{\sqrt{n}}, \qquad (2)$$

where n was the number of measurements in the set. (The standard uncertainty of the mean has historically also been called the standard deviation of the mean, or the standard error of the mean.)

7.1.2 Calculating standard uncertainty for a Type B evaluation

Where the information is more scarce (in some Type B estimates), you might only be able to estimate the upper and lower limits of uncertainty. You may then have to assume the value is equally likely to fall anywhere in between, i.e. a rectangular or uniform distribution. The standard uncertainty for a rectangular distribution is found from:

$$\frac{a}{\sqrt{3}}, \qquad (3)$$

where a is the semi-range (or half-width) between the upper and lower limits.

Rectangular or uniform distributions occur quite commonly, but if you have good reason to expect some other distribution, then you should base your calculation on that. For example, you can usually assume that uncertainties 'imported' from the calibration certificate for a measuring instrument are normally distributed.

Table 1. Spreadsheet model showing the 'uncertainty budget'

Source of uncertainty	Value ±	Probability distribution	Divisor	Standard uncertainty
Calibration uncertainty	5.0 mm	Normal	2	2.5 mm
Resolution (size of divisions)	0.5 mm*	Rectangular	√3	0.3 mm
String not lying perfectly straight	10.0 mm*	Rectangular	√3	5.8 mm
Standard uncertainty of mean of 10 repeated readings	0.7 mm	Normal	1	0.7 mm
Combined standard uncertainty		Assumed normal		6.4 mm
Expanded uncertainty		Assumed normal ($k = 2$)		12.8 mm

*Here the (±) half-width divided by √3 is used.

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