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State Estimation in the Power Distribution System

Towards a Data-Driven Application in the Low Voltage Grid

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University of Passau

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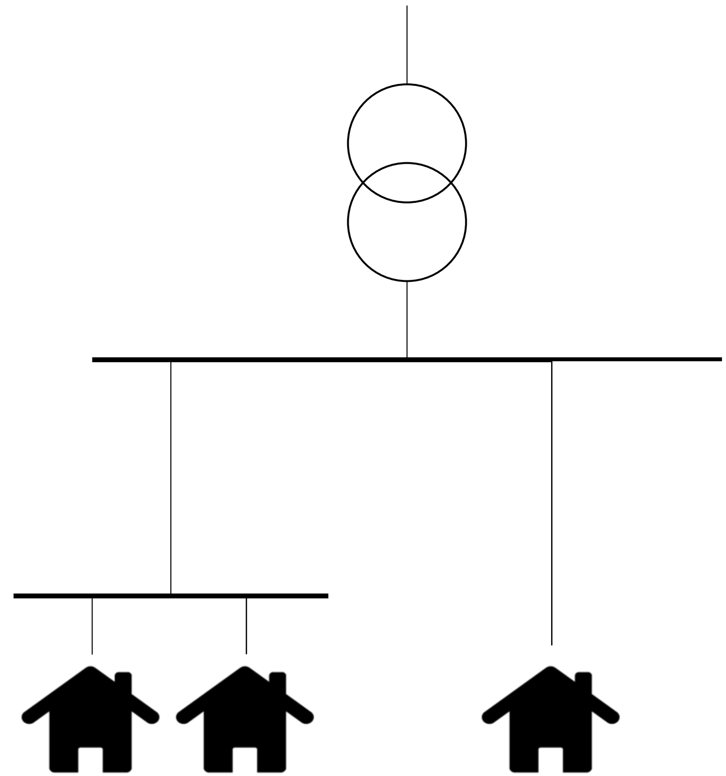
University of Passau

Computer Networks & Communications
Prof. Hermann de Meer

6th of December 2018

1. Motivation



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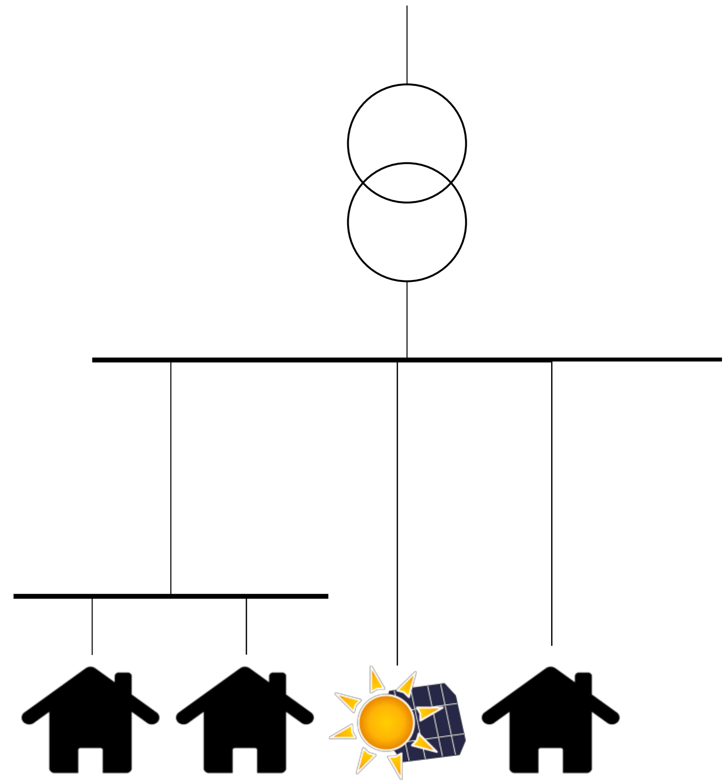

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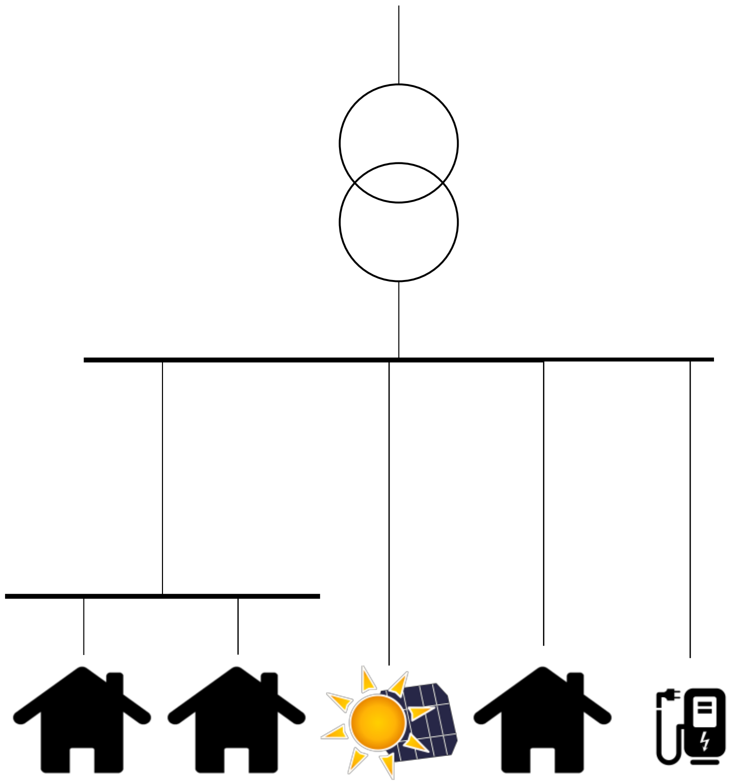
- New types of load, e.g., charging station



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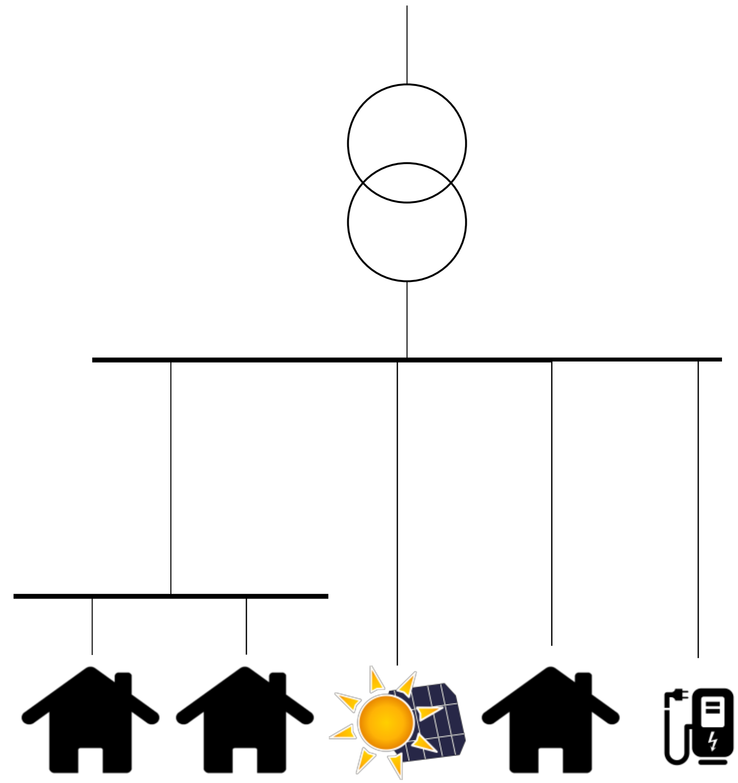
- Distributed generation
- New types of load, e.g., charging station
- Increasing “smartness” at prosumers



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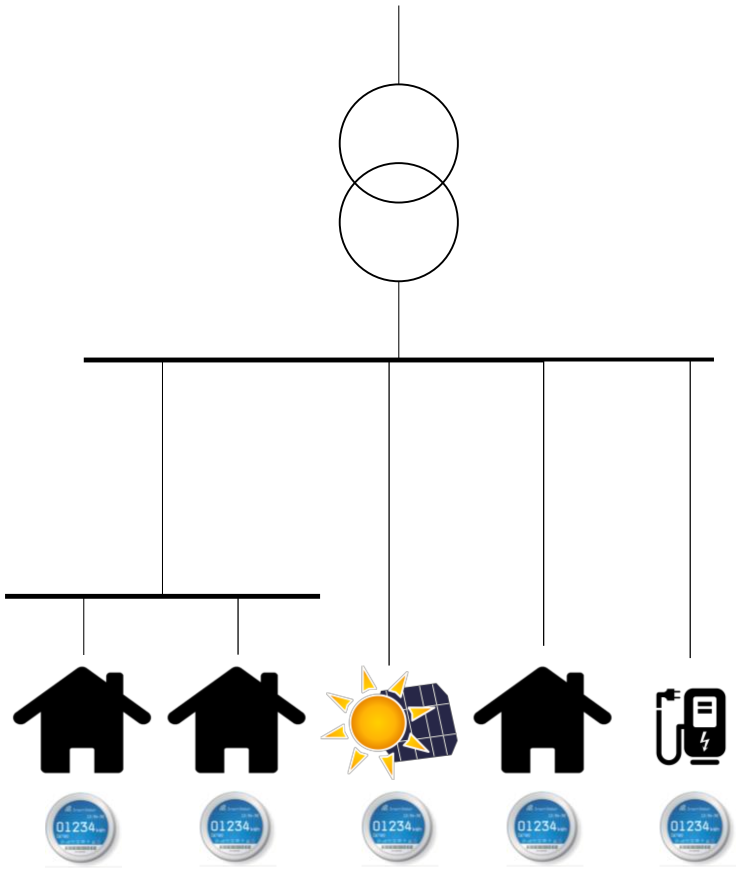
- *Special case:* Low voltage grid
  - Data available via smart metering devices, but high communication effort



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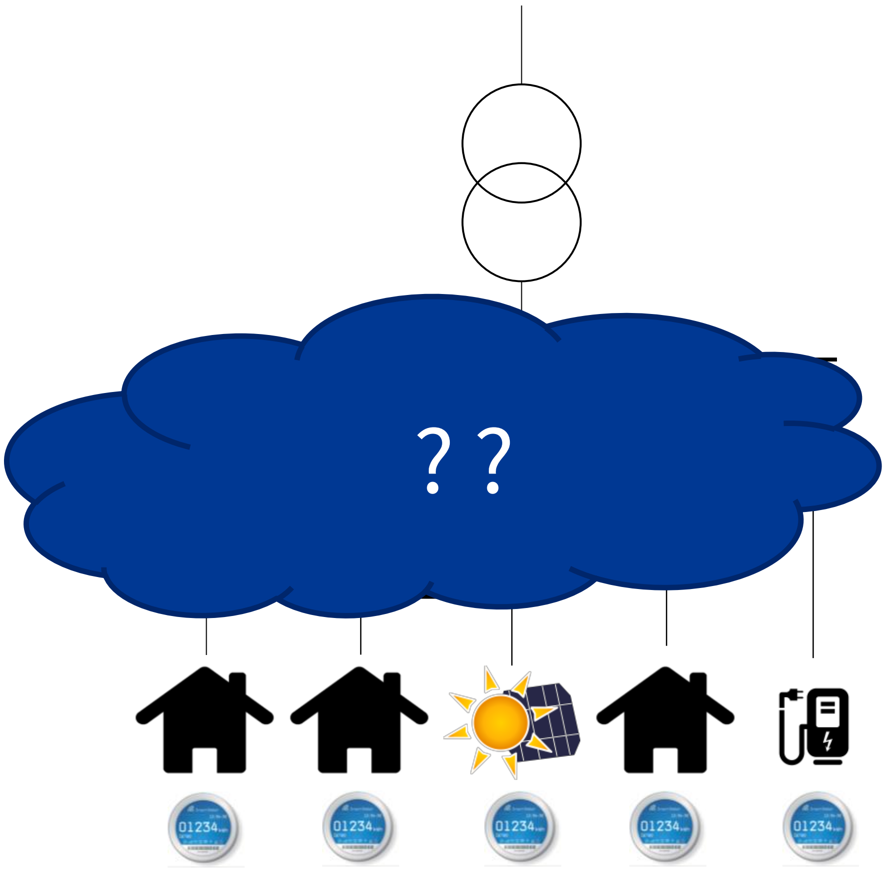
  - Grid configuration often not known 100% and sometimes not stored in a digital processable way



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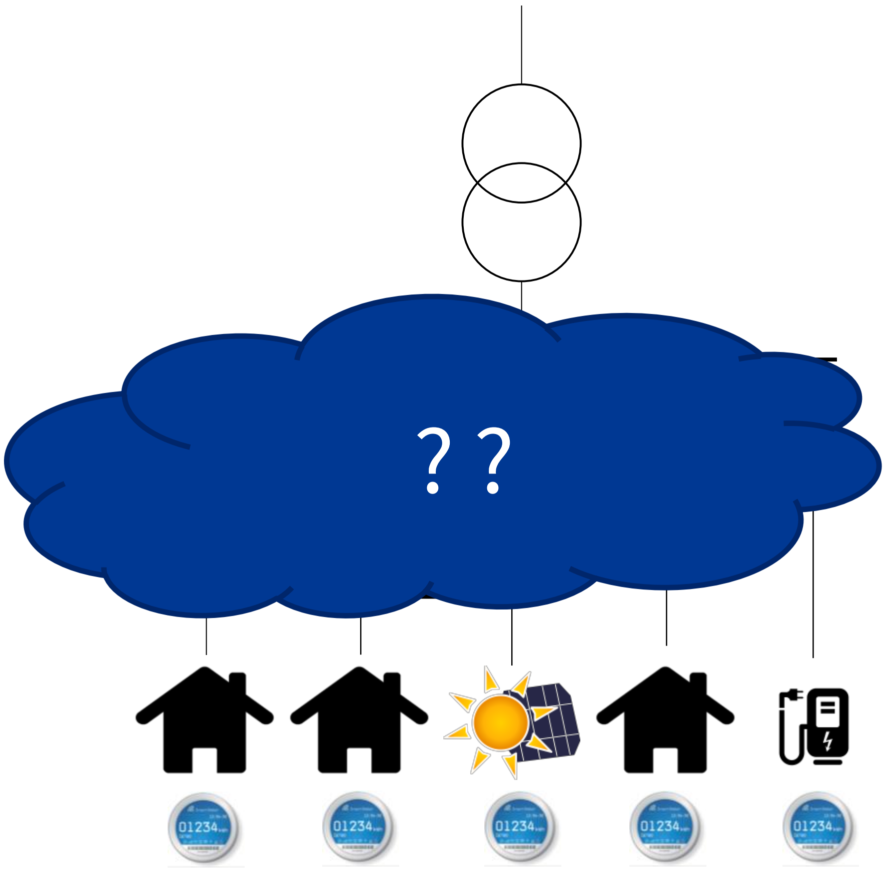

→ Data-driven State Estimation (SE)

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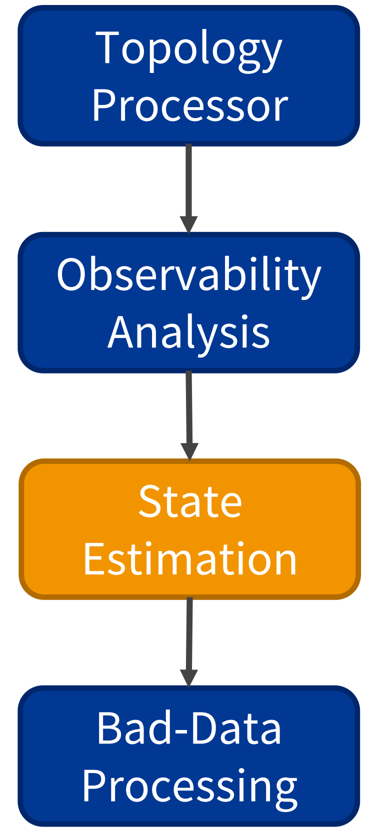
2. State Estimation (1/2) [1, 2, 3]

Goal of State Estimation?

- Infer system state from a subset of measurements



2. State Estimation (1/2) [1, 2, 3]

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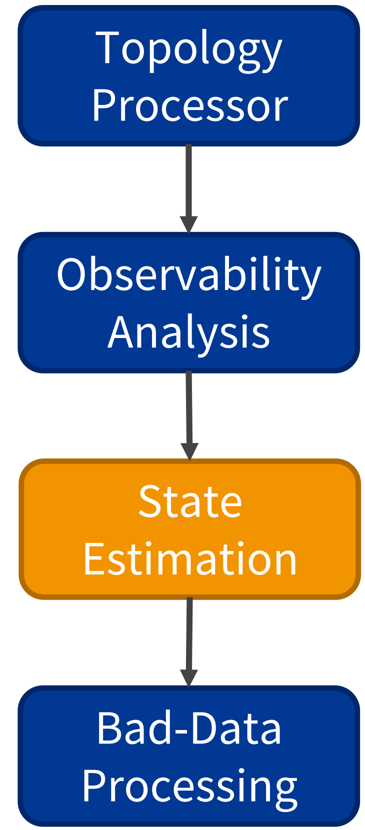
State Estimation

- <u>Static State Estimation</u>
- Multiarea State Estimation
- Forecasting State Estimation



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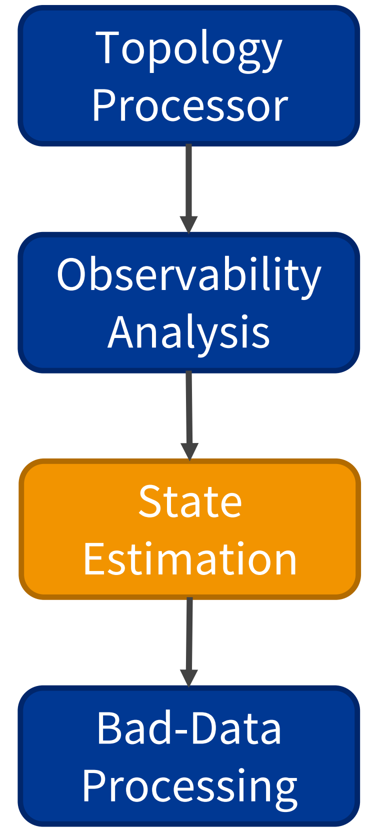
Distribution System State Estimation

- Optimization Problem [4]
- Bayesian Network [5]
- Consensus Algorithms [6, 7]
- Machine Learning [8, 9]



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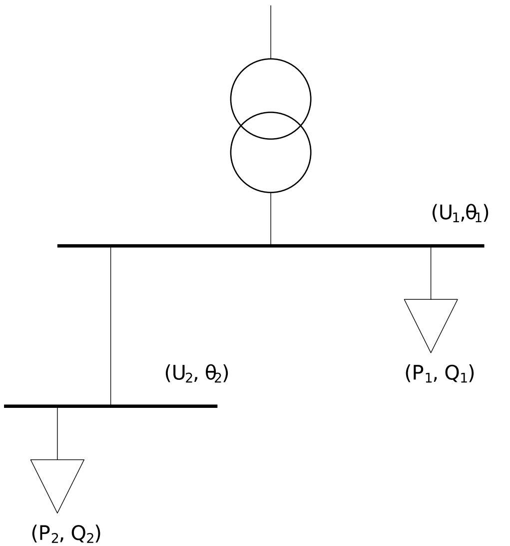
What is the state of a system?

- $x = [U_1, \dots, U_N, \theta_1, \dots, \theta_N] \in \mathbb{R}^{2N}$
- $z \in \mathbb{R}^L, L > 2N$, $(P, Q, U$ at busses)



Exemplary low voltage grid

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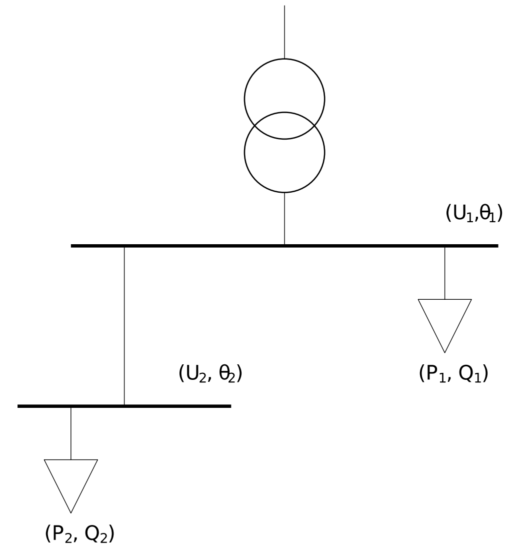
Relation

- $z = h(x) + n$
- $h(\cdot)$ is a set of nonlinear functions defined by Kirchhoff's laws and the power network admittance matrix, n estimation error



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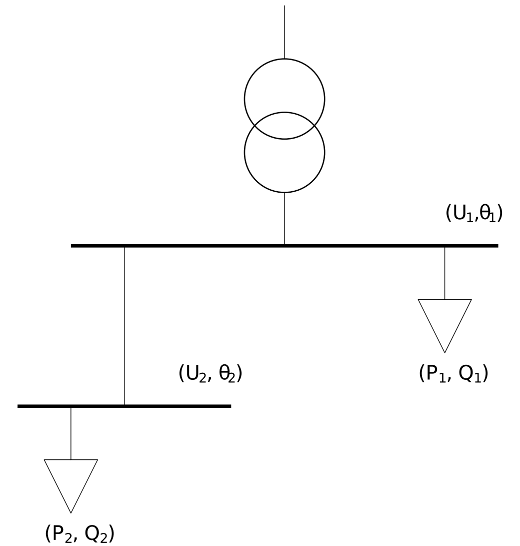

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Traditional State Estimation Solver

- $\hat{x} = \arg\min_x [z - h(x)]^T W^{-1} [z - h(x)]$
- Using Weighted Least Squares method

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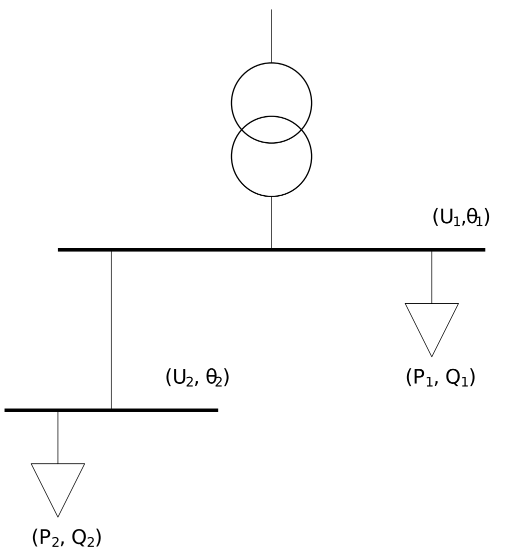
➔ function $\boldsymbol{h}(\boldsymbol{x})$ requires grid topology information



Exemplary low voltage grid

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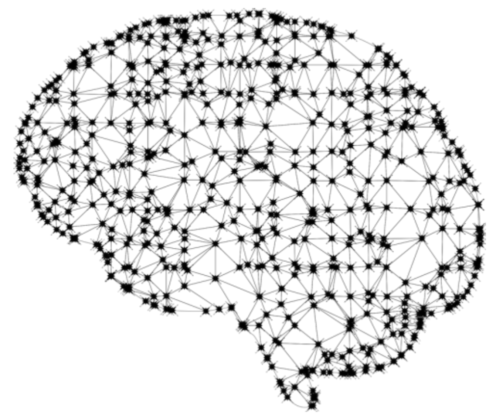
Data-Driven State Estimation

- $X = [U_1, \dots, U_N, \theta_1, \dots, \theta_N, P_1, \dots, P_M, Q_1, \dots, Q_N] \in \mathbb{R}^{2(N+M)}$
- $Y_t = X_t,\ t \leq 2(N+M)$
- $\bar{X}_t = X \setminus X_t$



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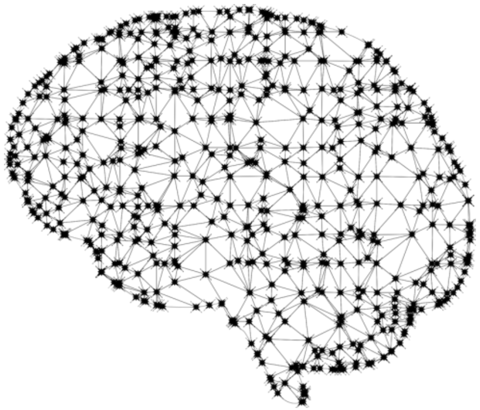


Machine Learning Model

- $\hat{Y}_t = f(\bar{X}_t)$
- Model fitting on training data
- Model evaluation on test/validation data

➔ Estimation of one single output parameter requires all input parameters

3.1. Dependency Graph Modelling

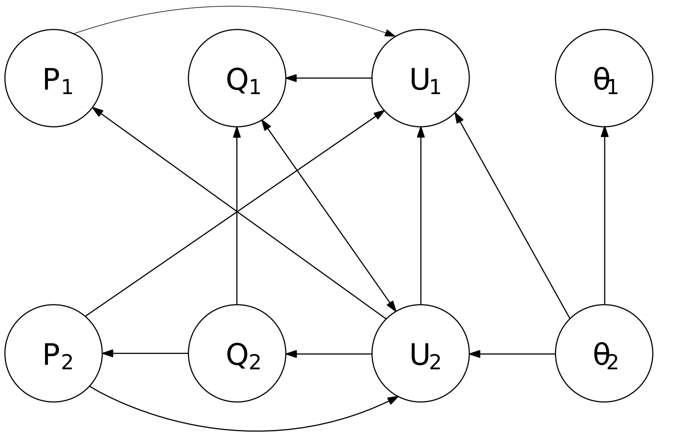
Input: $X \in \mathbb{R}^{2(N+M)}$

Output: Adjacency matrix A

Dependency Graph (DG)

- Correlation analysis
- (Absolute Difference analysis)
- (Logical Post processing, e.g., remove dependencies between two p values)
- Selection of n most influencing parameters

➔ directed graph as adjacency matrix

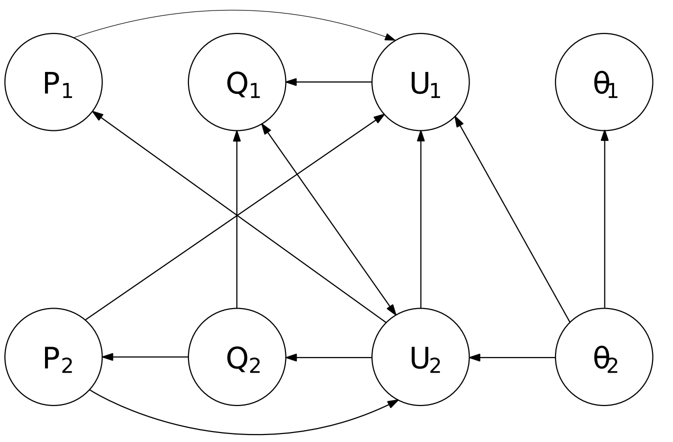


Exemplary dependency graph

3.2. Machine Learning

Input: $X \in \mathbb{R}^{2(N+M)}, A$

Output: $\hat{Y}$ for each single parameter



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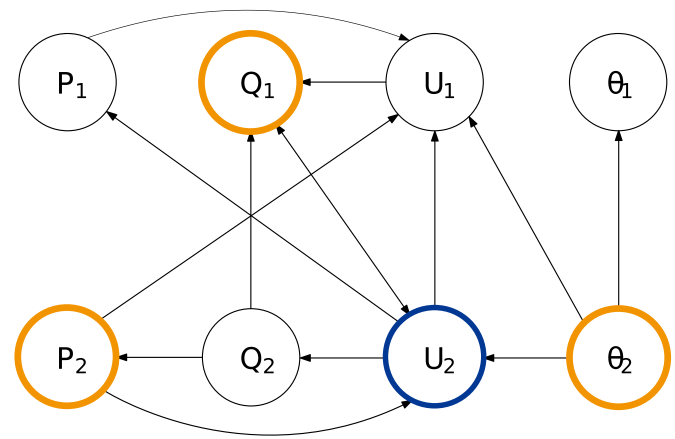
Machine Learning

- One ML model for each node in the DG
- Input parameter taken from neighboring nodes



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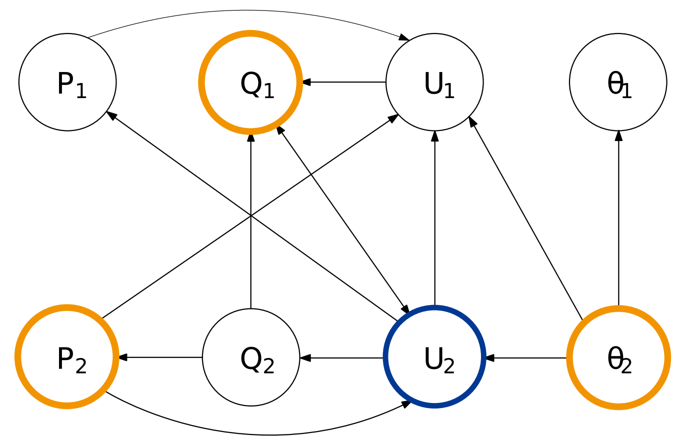

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Prediction of multiple parameters

- Estimate parameter where all incoming nodes are available
- Iterate through the DG

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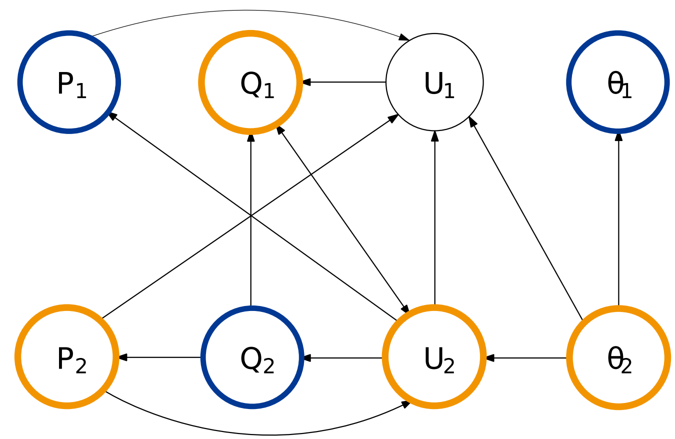

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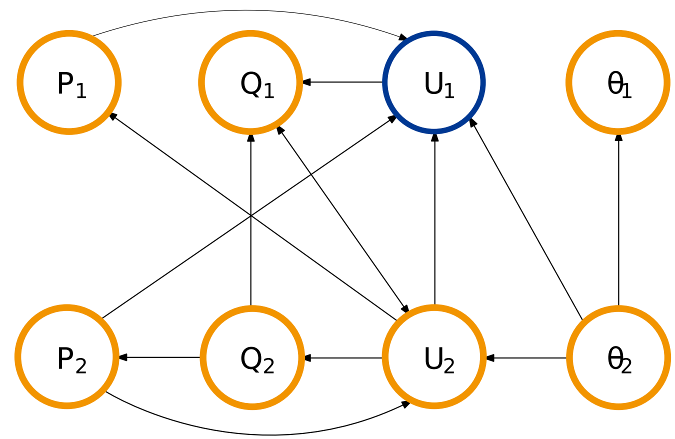

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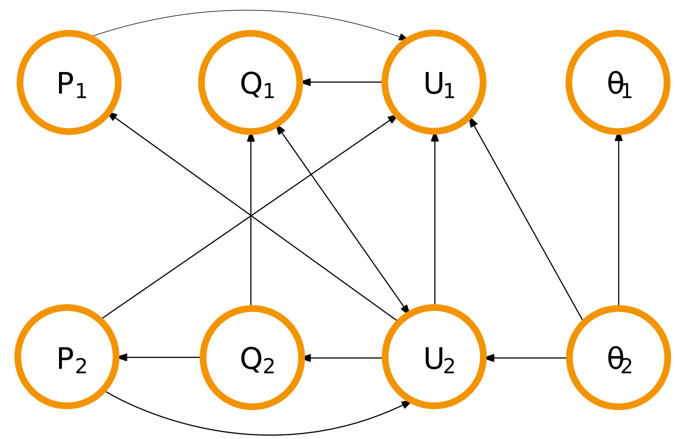

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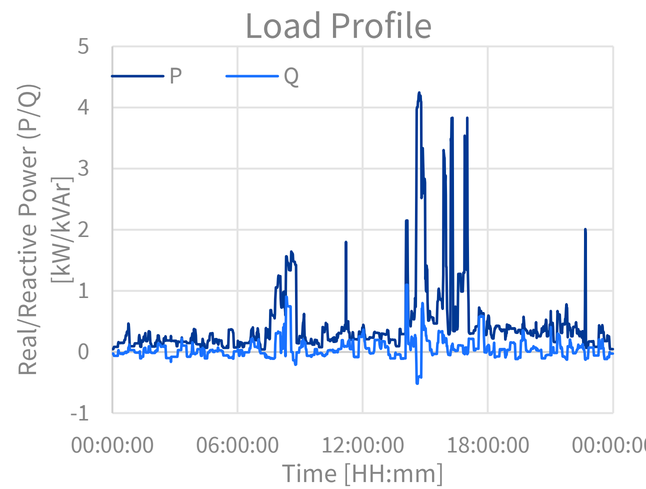
Data Sampling Strategies

- Realistic load profiles and a power flow solver
    - Load profiles [10] + DIgSILENT PowerFactory



Household load profile

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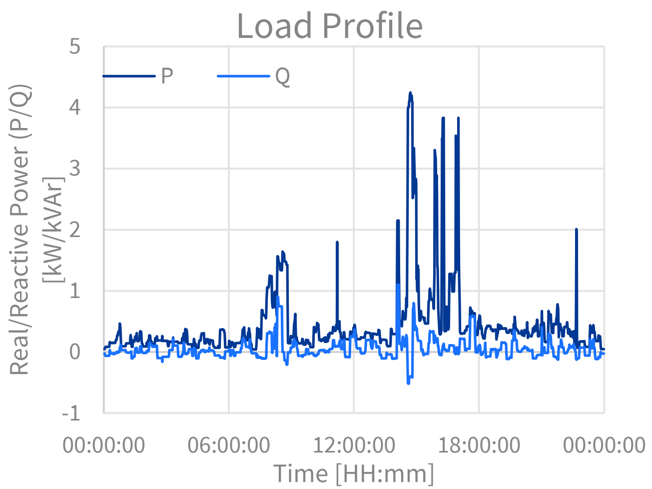
- Monte-Carlo simulation for P, Q at each load
  - Omit (P,Q) with power factor less than 0.7



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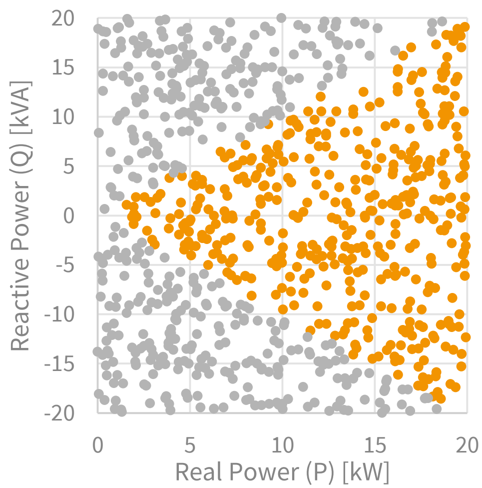

MC simulated load data

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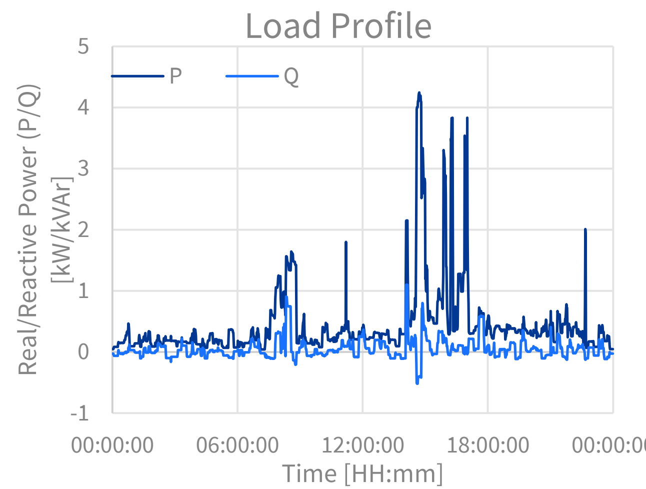
- One-at-a-time sensitivity analysis of the power grid on P, Q of each load
  - Result of pulse measurements



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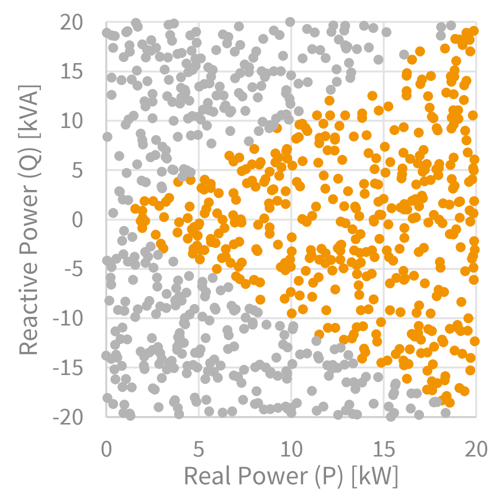

MC simulated load data

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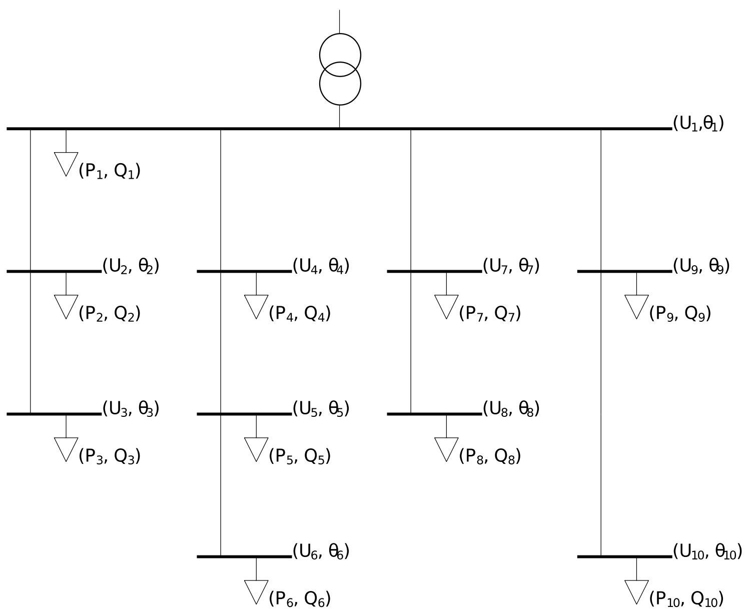
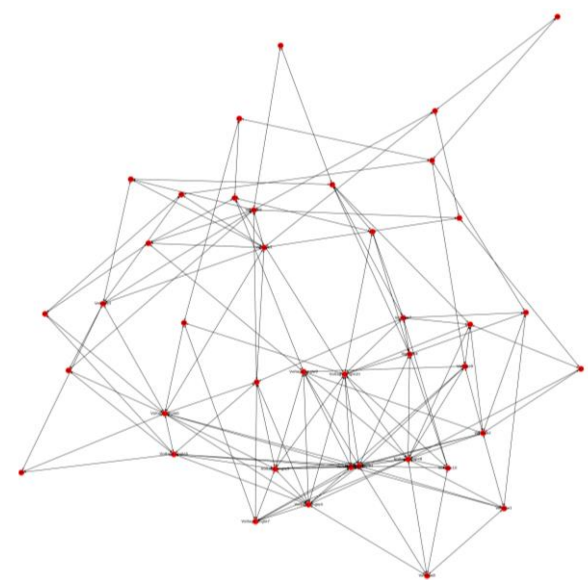
Setup

- Low voltage grid with 10 household loads ➔ 40 parameter
- Monte-Carlo samples ($P \in [0\ kW, 20\ kW], Q \in [-20\ kVAr, 20\ kVAr]$)
- Voltage magnitude and angle calculation by PowerFactory[1] using the sampled (P, Q) values



Evaluation low voltage grid

Dependency graph creation



Resulting dependency graph

[1] https://www.digsilent.de/de/powerfactory.html

ML Evaluation

- Three different models
- 20 input parameter for each of the 40 models
- 5-fold-cross validation

P	$[0\ kW, 20\ kW]$
Q	$[-20\ kVAr, 20\ kVAr]$
U	$[204\ V, 232\ V]$
θ	$[-4.27°, 0.86°]$

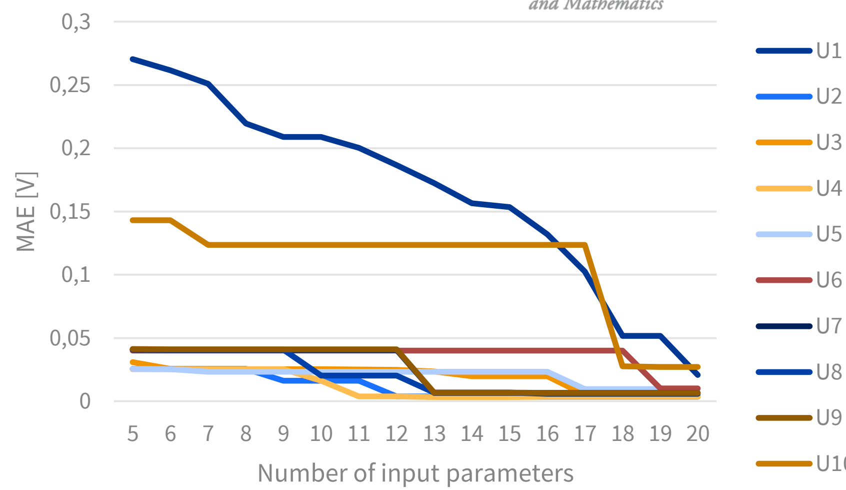
Parameter Ranges

Parameter	Linear Regression	KNN	Random Forest
U_1	**0.021 V**	0.13 V	0.358 V
θ_2	**0.001 °**	0.019 °	0.123 °
…	…	…	…
P_1	**0.057 kW**	2.725 kW	4.5 kW
Q_7	**0.075 kVA**	0.823 kVA	2.421 kVA
…	…	…	…

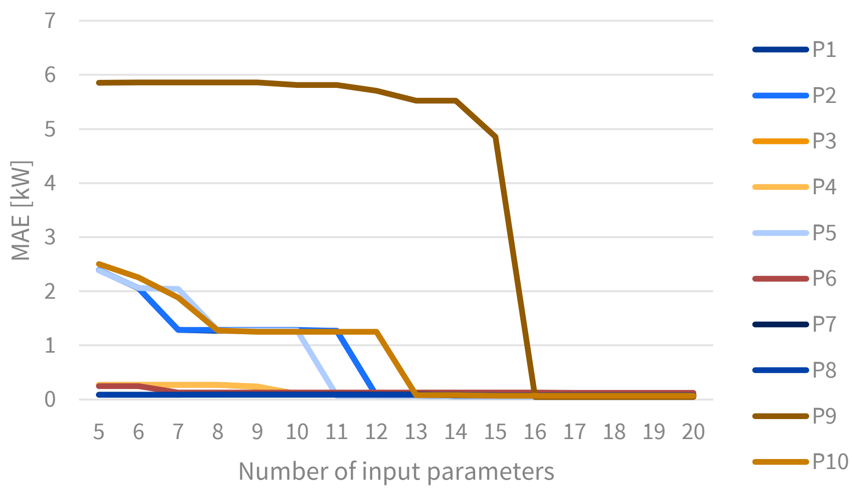
Excerpt of Mean Absolute Error using 20 input parameter in the dependency graph

Sensitivity of the DG creation

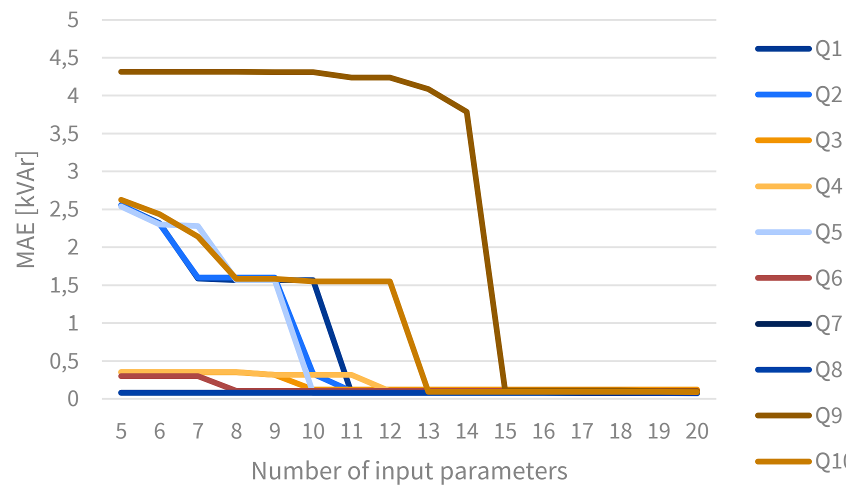
- 13+ from 40 parameter yield reasonable results
- Predictability depends on parameter selection strategy and grid location



Mean Absolute Error estimating voltage

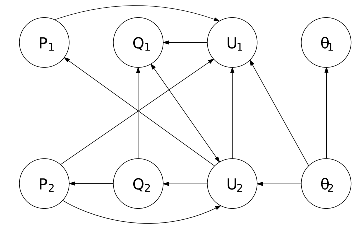


Mean Absolute Error estimating real power

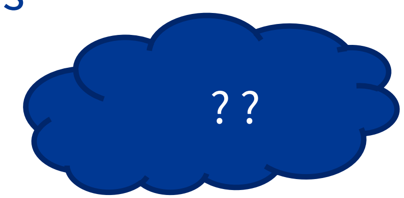


Mean Absolute Error estimating reactive power

5. Conclusion



- Conclusion
  - Data-driven static state estimation seems promising when using a dependency graph to reduce the input parameter set
  - Applicable to distribution systems where the topology is not known



- Open Points
  - Include plausibility checks and data pre/post processing
  - Increase accuracy by rechecking all available single parameter models
  - Comparison to calculated state estimation with inaccurate topology information
  - Performance evaluation

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Thank you for your attention!

Time for Discussions!