UNIVERSITY OF DENVER

Data-Driven Scalable Phase Identification in Modern Distribution Grids

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Outline

- Introduction to Phase Identification
- Phase Identification Solutions
- Proposed Model
- Analysis Results
- Conclusion

Phase Identification

Photo: Anish Regmi

Why is this necessary?

- Power Grid Operation and Maintenance Procedures
- Distribution Network Load Balancing
- Component connectivity is often altered and not documented, especially after outages
- Grid topology reconstruction begins with identifying the phase connectivity of loads

Phase Identification

Hardware-Driven Solutions:

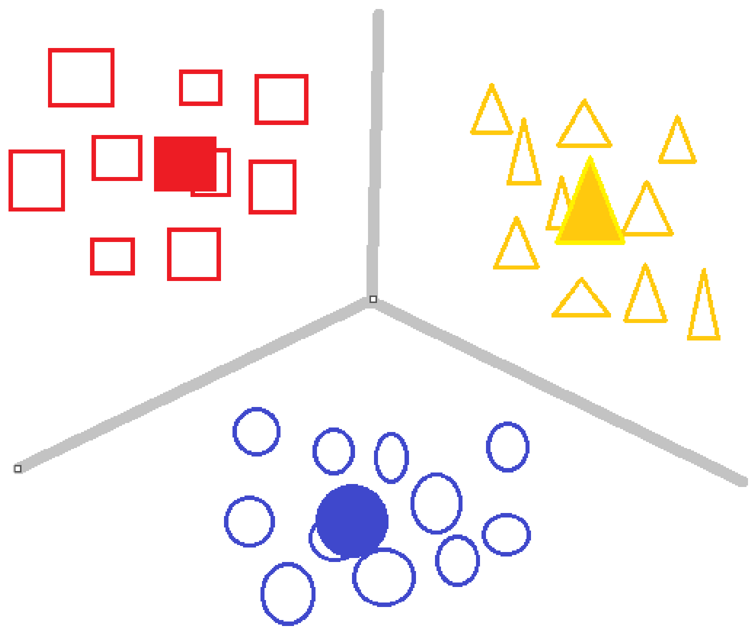
- Micro PMUs
- Voltage Signal Injection

A phasor measurement units

Phase Identification

Data-Driven Solutions:

- Voltage Clustering
- Voltage Correlation
- Consumptions Correlation
- Consumption Aggregation

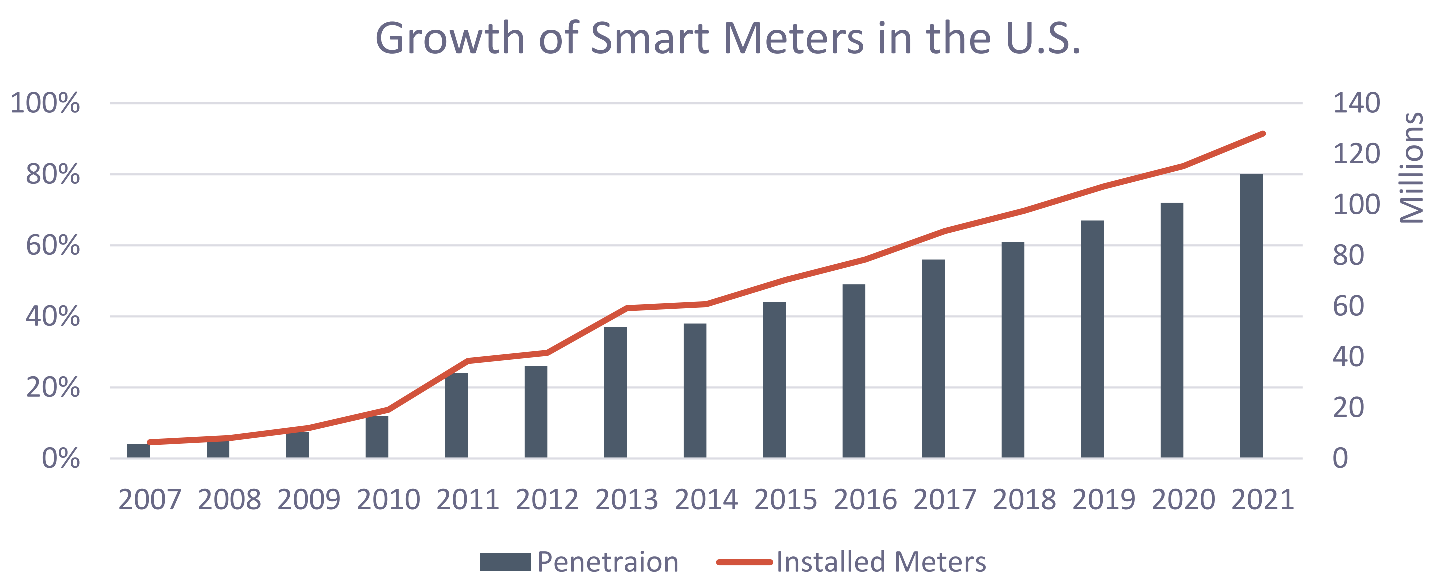


Basics of Clustering by Justin Osborne

Modern Distribution Grid

Using Smart Meters Data:

- Smart meters’ growth rate increases the observability of the network
- The data obtained from smart meters can be used for phase identification



Smart Meters growth in the United States (Source: The Federal Energy Regulatory Commission)

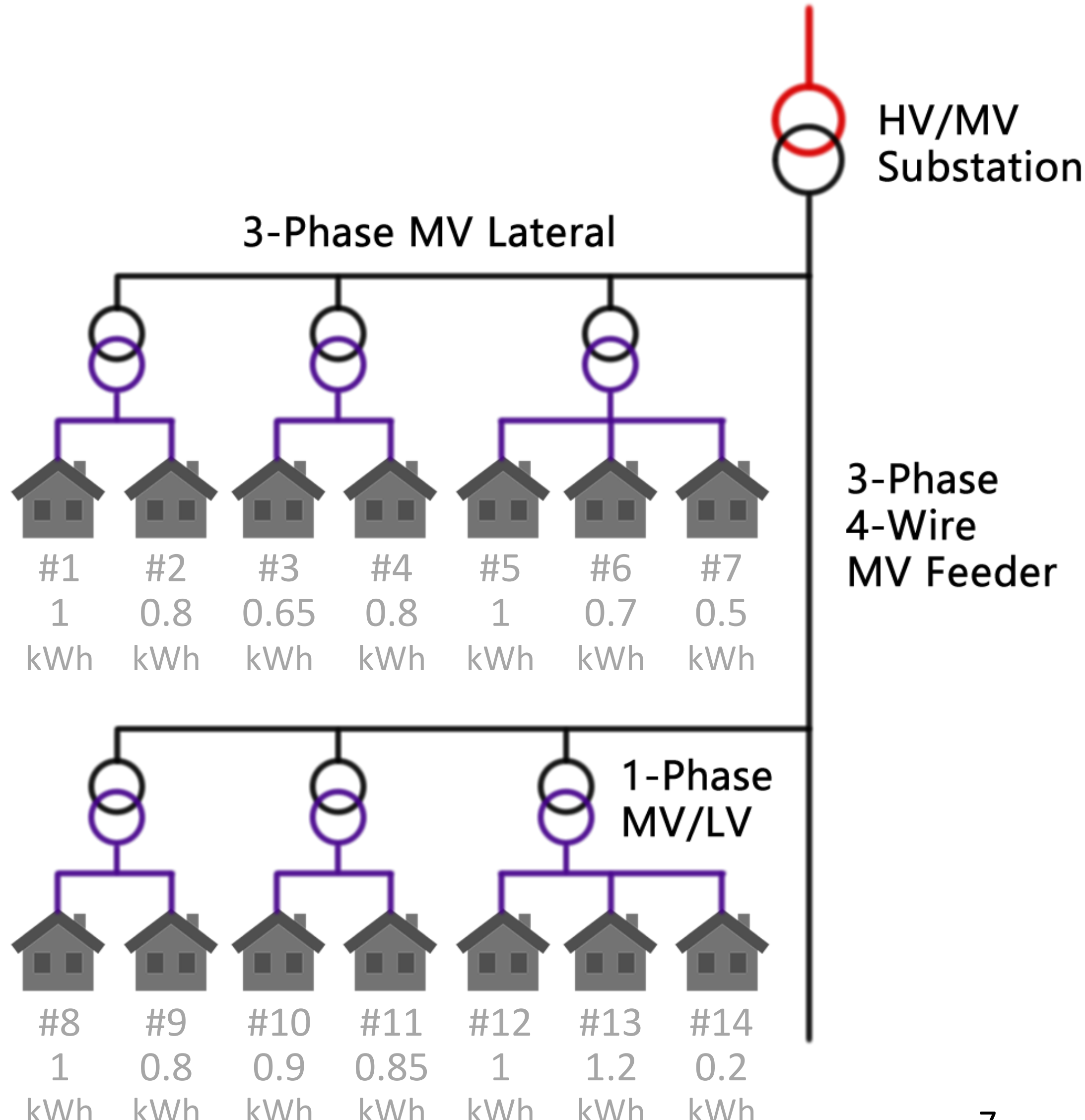
Solution

A simplified scenario:

Having consumed power measurements from smart meters and the distributed load from the substation for a given time interval:

Substation Measurement:

- Phase A = 3.5 kWh
- Phase B = 4.0 kWh
- Phase C = 4.5 kWh



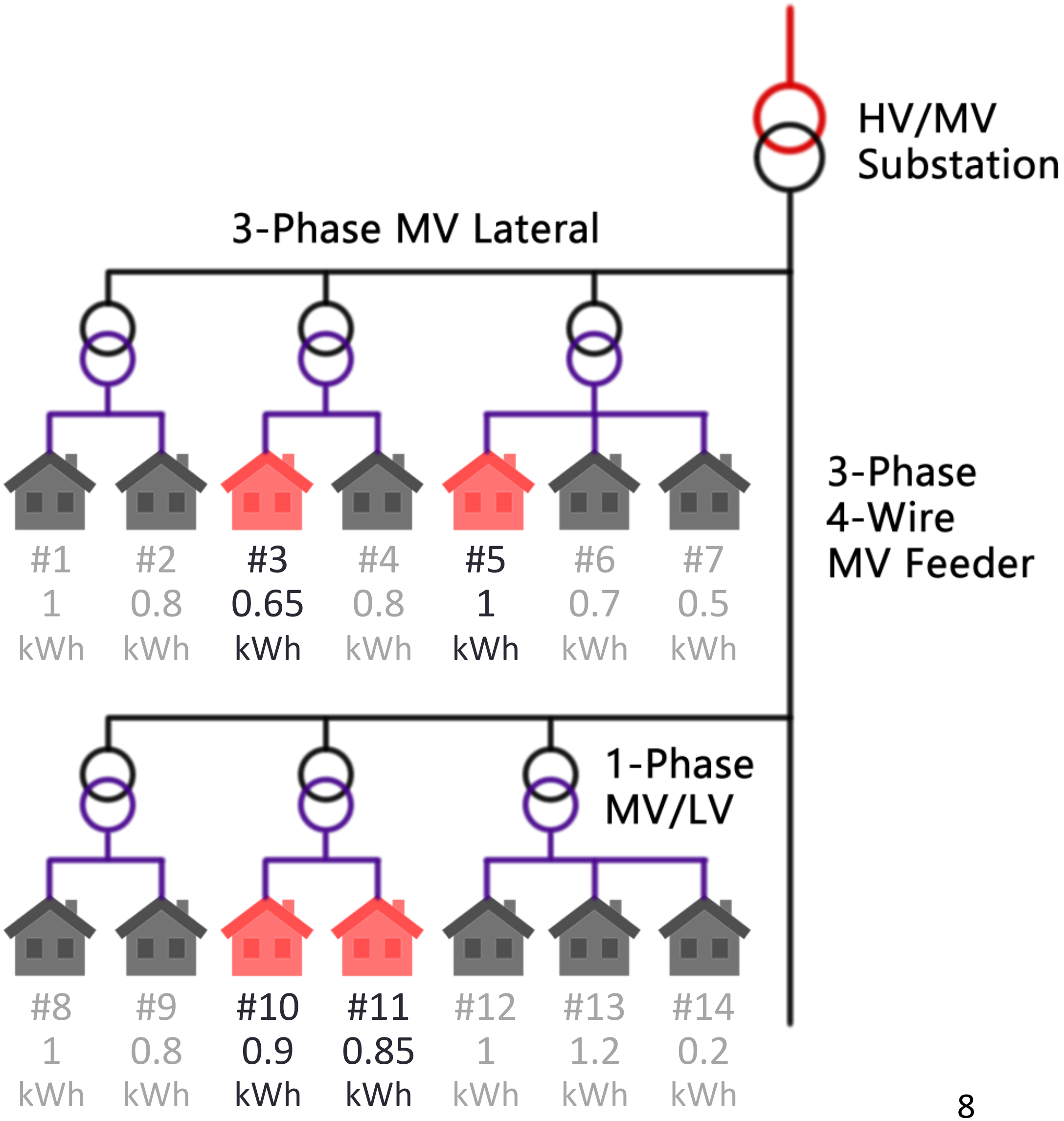
Solution

For Phase A:

Substation Measurement:
- 3.5 kWh

Aggregated Consumptions of #3, #5, #10, #11:
- 3.4 kWh

Distribution Loss:
- 0.1 kWh



Solution

For Phase B:

Substation Measurement:

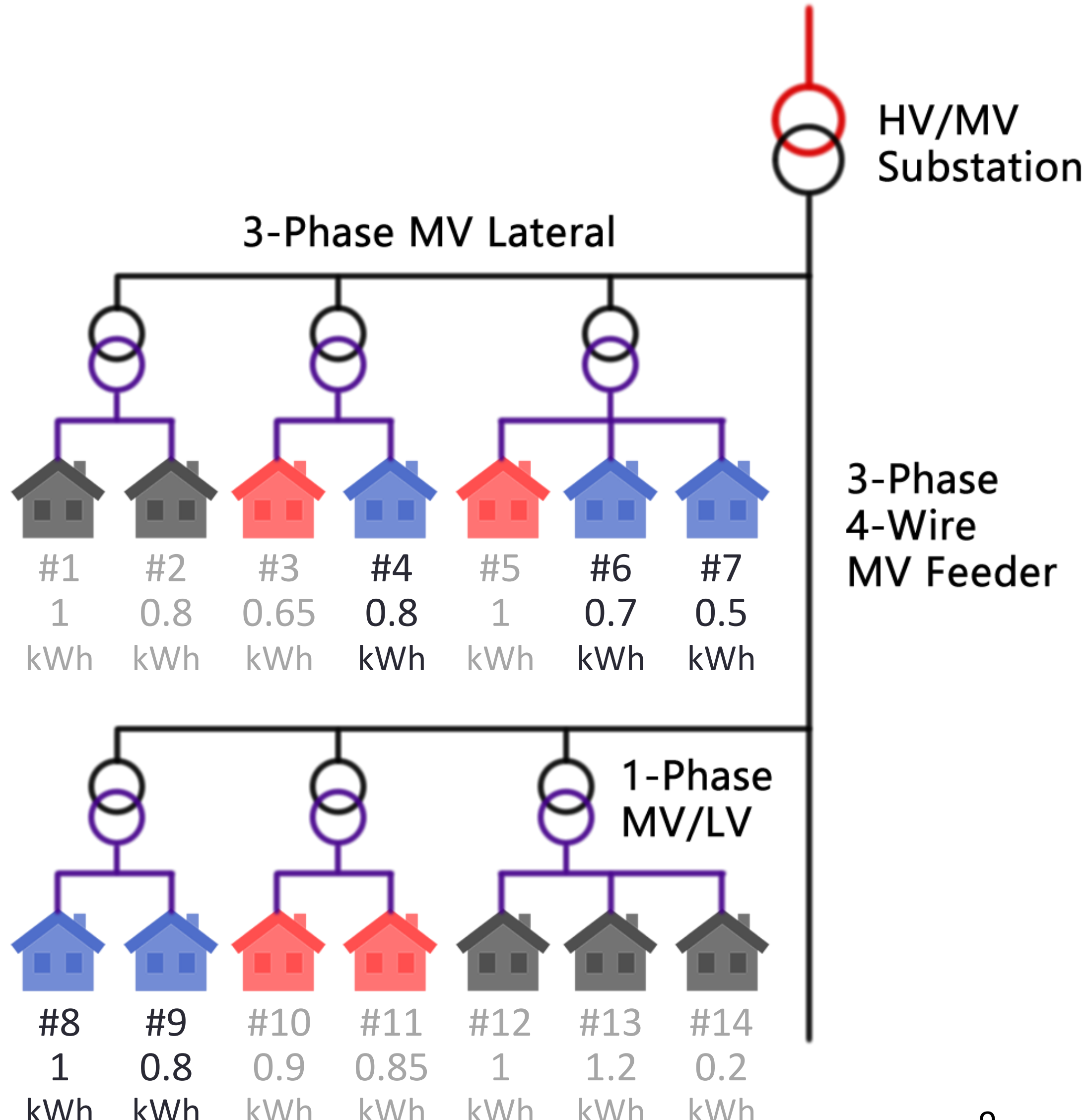
- 4 kWh

Aggregated Consumptions of #4, #6, #7, #8, #9:

- 3.8 kWh

Distribution Loss:

- 0.2 kWh



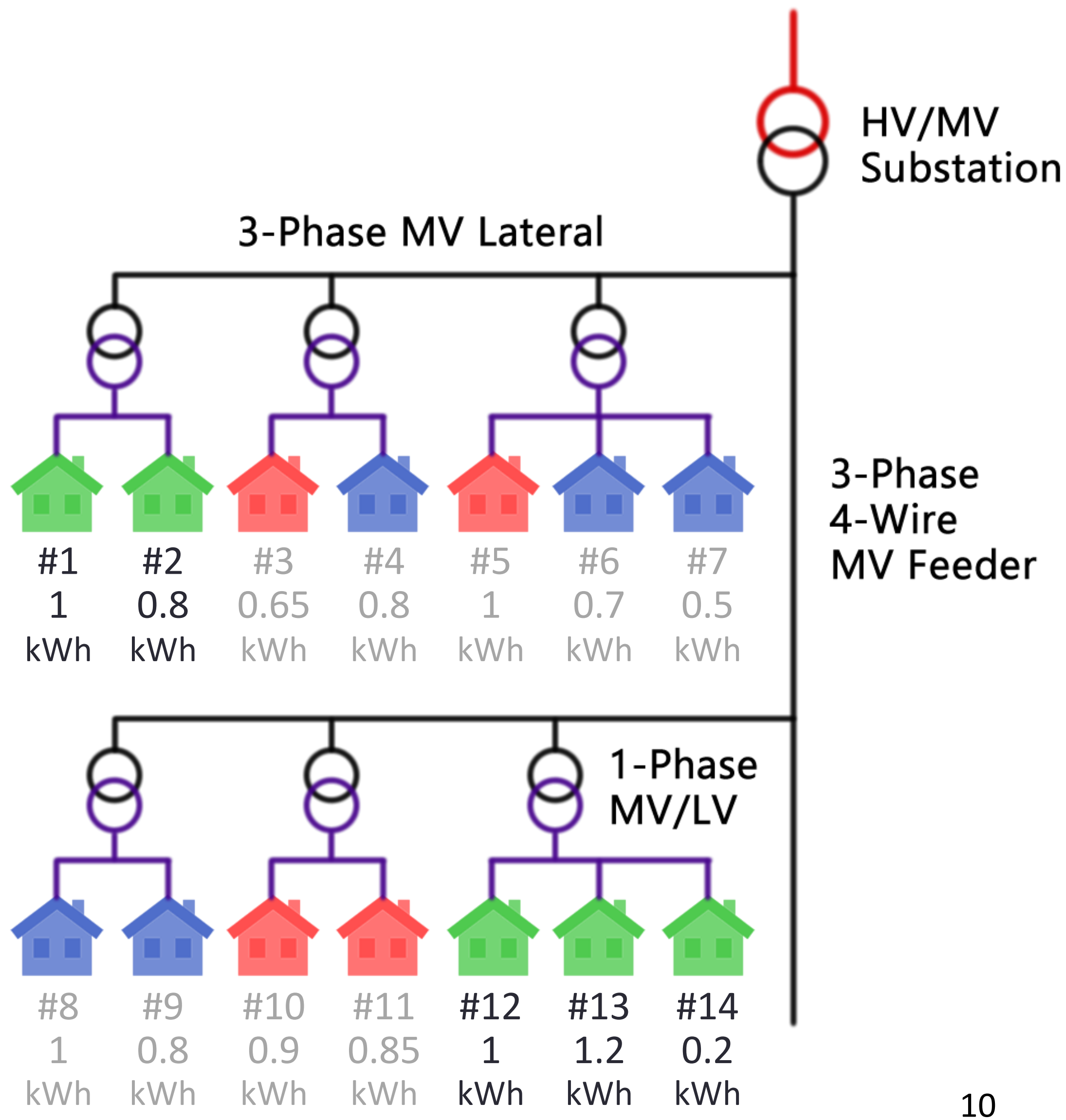
Solution

For Phase C:

Substation Measurement:
- 4.5 kWh

Aggregated Consumptions of #3, #5, #10, #11:
- 4.2 kWh

Distribution Loss:
- 0.3 kWh



Proposed Model

Mixed-Integer Quadratic Programming Model:

Find connectivity of the loads by minimizing the squared difference between consumed and lost load with distributed load, for each phase, at each measurement.

$$\min_{x} \sum_{q=1}^{Q} \sum_{t=1}^{T} \left(\sum_{n=1}^{N} a_{tn} x_{qn} + p_{qt}^{L} - p_{qt}^{S} \right)^{2}$$

s.t. $\quad x_{qn} \in \{0, 1\} \qquad \forall n \in N, q \in \{a, b, c\}$

$$\sum_{q=1}^{Q} x_{qn} = I_n \qquad \forall n \in N$$

Proposed Model

Expectations:

- A Data-driven method that employs smart meter and substation measurements
- Accounting for measurement loss and noise
- Accounting for distribution loss
- Accounting for load profiles homogeneity
- Applicable to large-scale networks
- Applicable to networks with lower than 100% AMI penetration rate
- Independent of the number of consumers in each phase
- Assuming that all consumers' phases are unknown

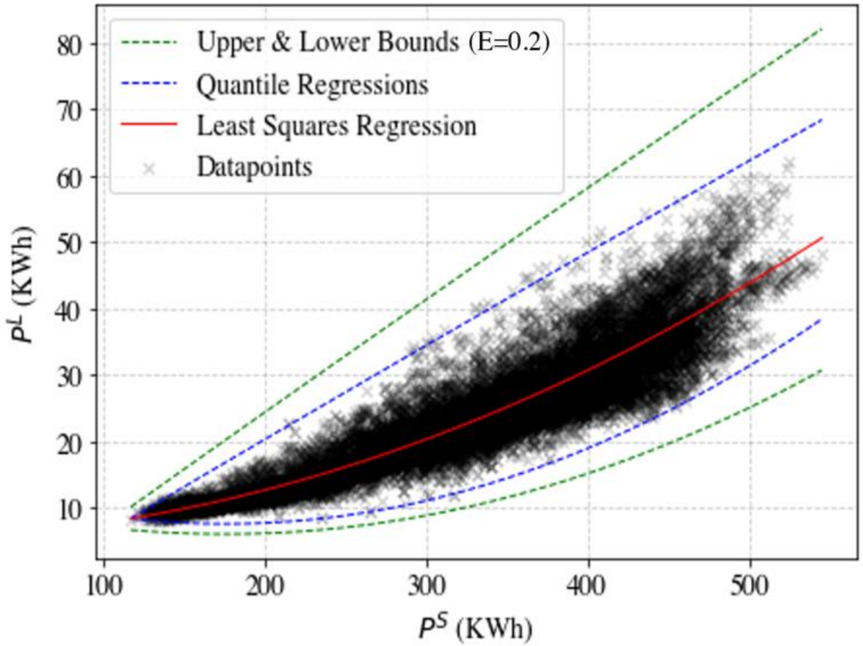
Distribution Loss

Analyzing distribution loss of the network:

- Least squares regression algorithm to estimate distribution Loss
- Quantile regression to find the lower and upper bounds of the estimation
- The Boundaries can be fed to the model as constraints
- A coefficient (E) to relax the constraints to account for outliers

Distribution loss estimation for 21K demand and loss datapoints

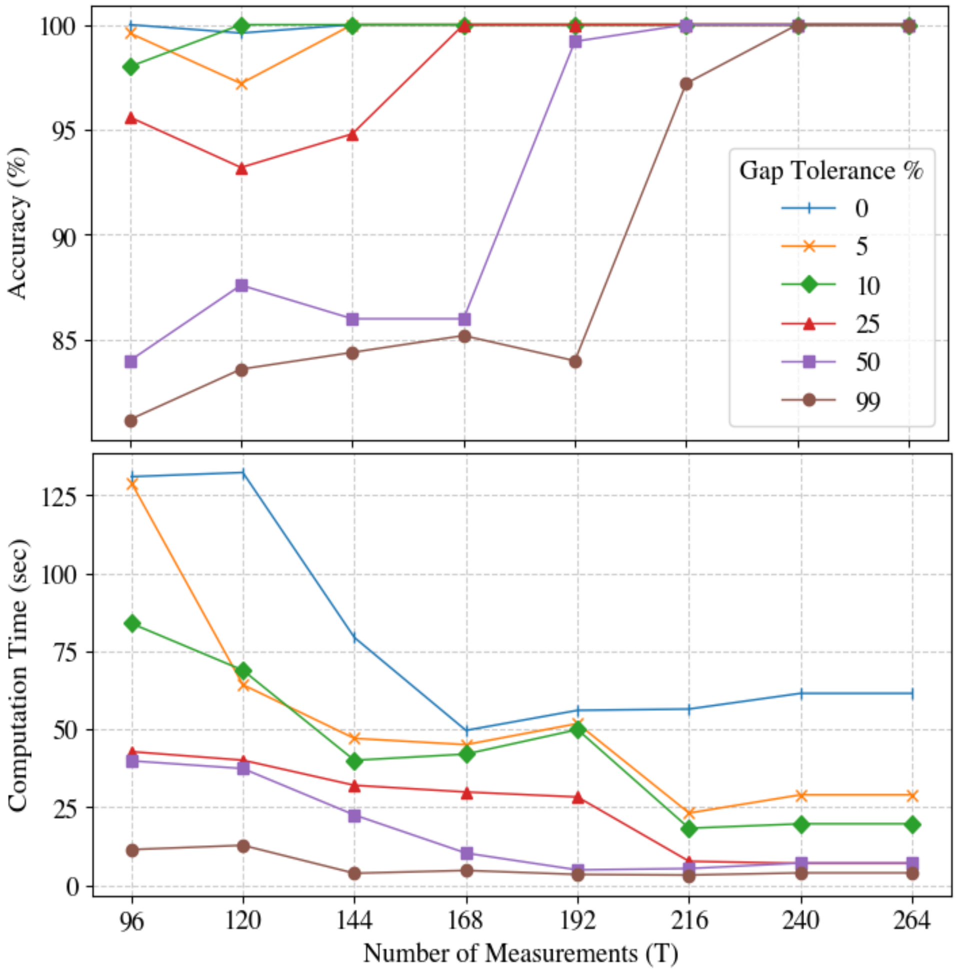
Distribution loss



Distributed Load

Measurements Window

Analyzing a system with 250 loads



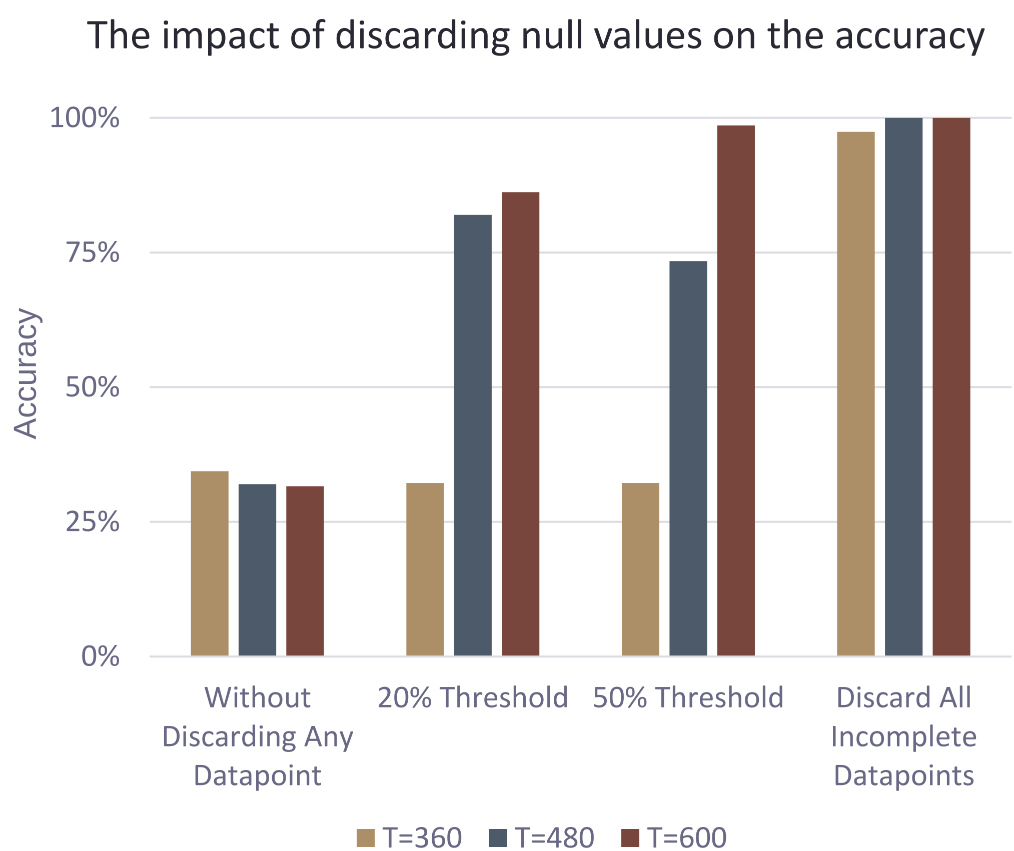
- A wider measurement range increases the accuracy.
- A higher optimality gap requires more measurements.
- The number of consumers strongly affects both parameters.

Measurement Loss

Analyzing a system with 500 loads

(30% null values - 360, 480, and 600 available measurements)

- Unrecorded values in the consumption measurement that produce outliers
- This will result in a disparity between the amount of distributed load and the consumed load
- The impact of null values decreases as the window of measurements increases
- The best approach is to discard all uncomplete datapoints



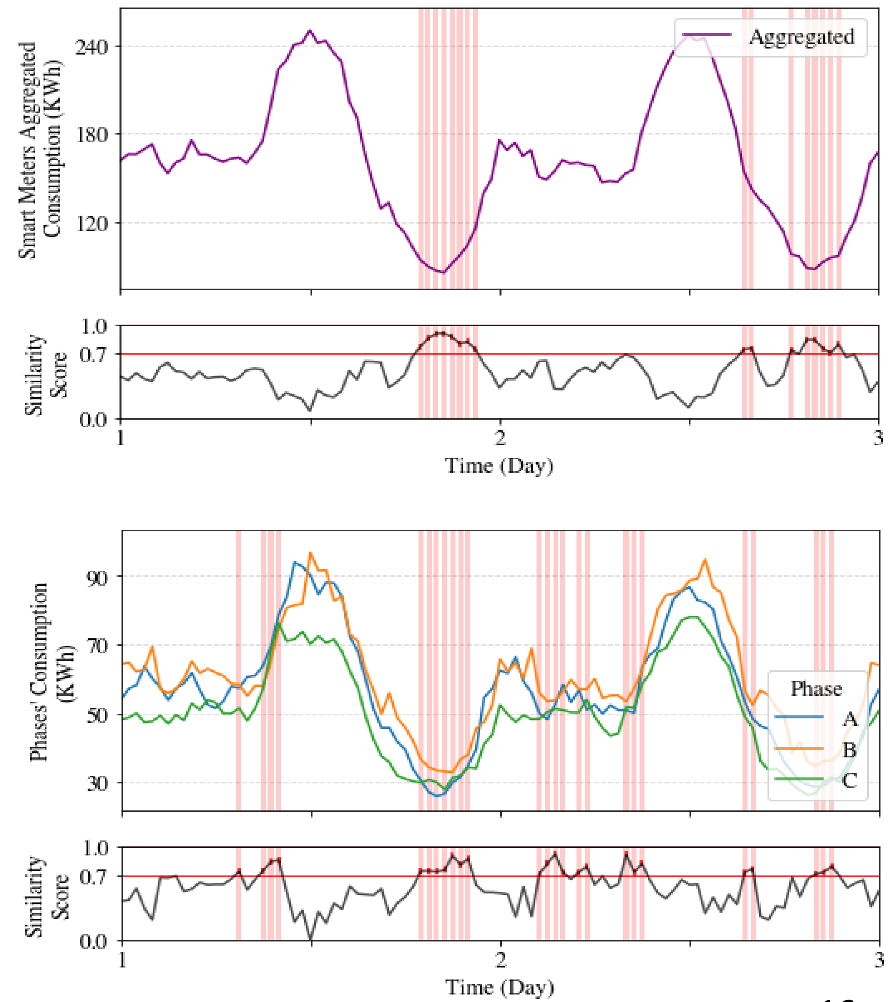
Load Profile Similarity

- Load profiles usually have similar patterns
- Datapoints with close values of measurements will cause the solver to reach the wrong solution
- Each data point is labeled with a similarity score

$$S_t = 1 - \frac{\sigma_t - \min(\sigma)}{max(\sigma) - \min(\sigma)} \quad \forall t \in T$$

- Data points with a high similarity score should be discarded

The similarity score of load profiles in a system with 500 loads over 96 measurements

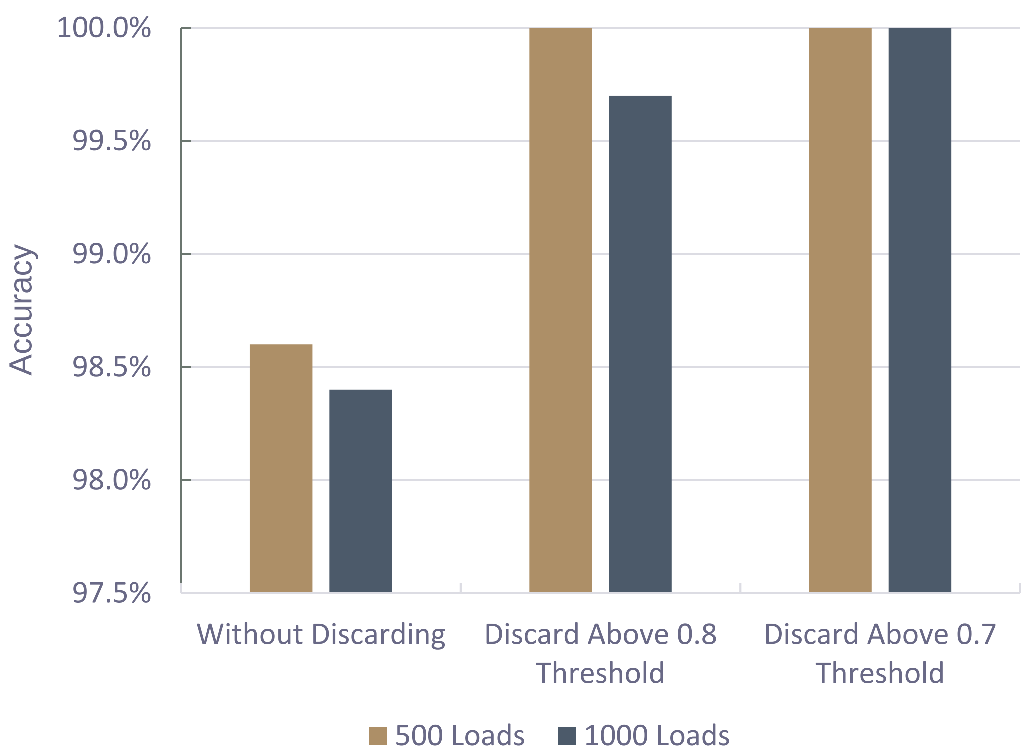


Load Profile Similarity

Analyzing two systems with 500 and 1000 loads

(960 available measurements)

The impact of discarding datapoints on the accuracy



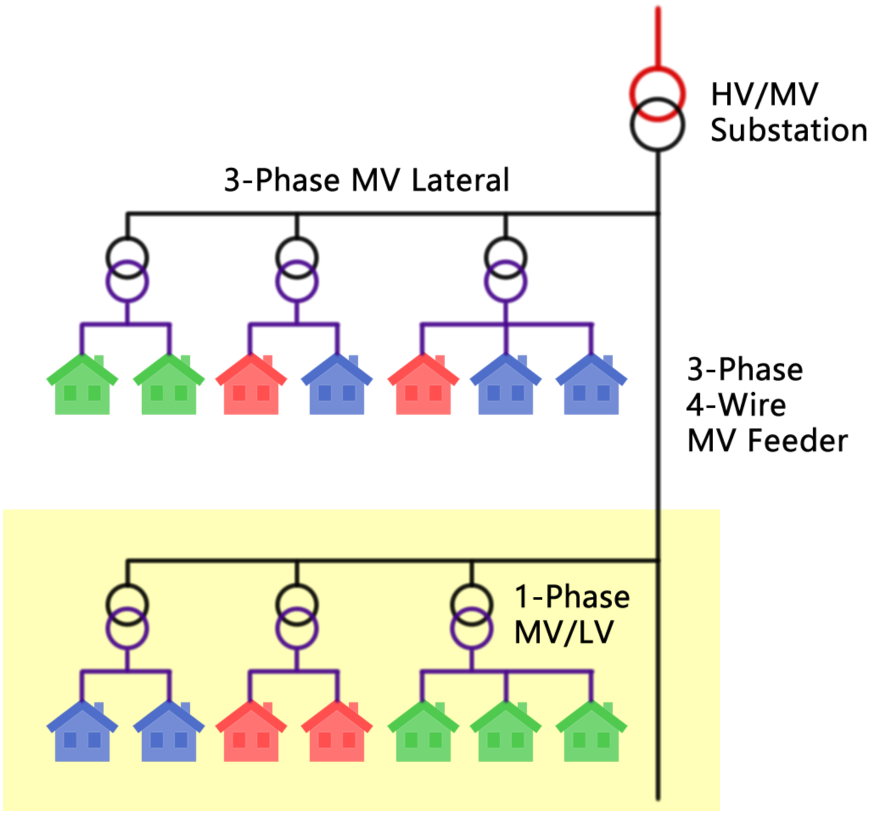
- The impact of profile similarity increases with the size of the network.
- Choosing the data points with the lowest similarity score is the most effective approach.

Clustering Single-Phase Loads

To reduce the complexity of the problem single phase loads on the same phase can be considered as one load.

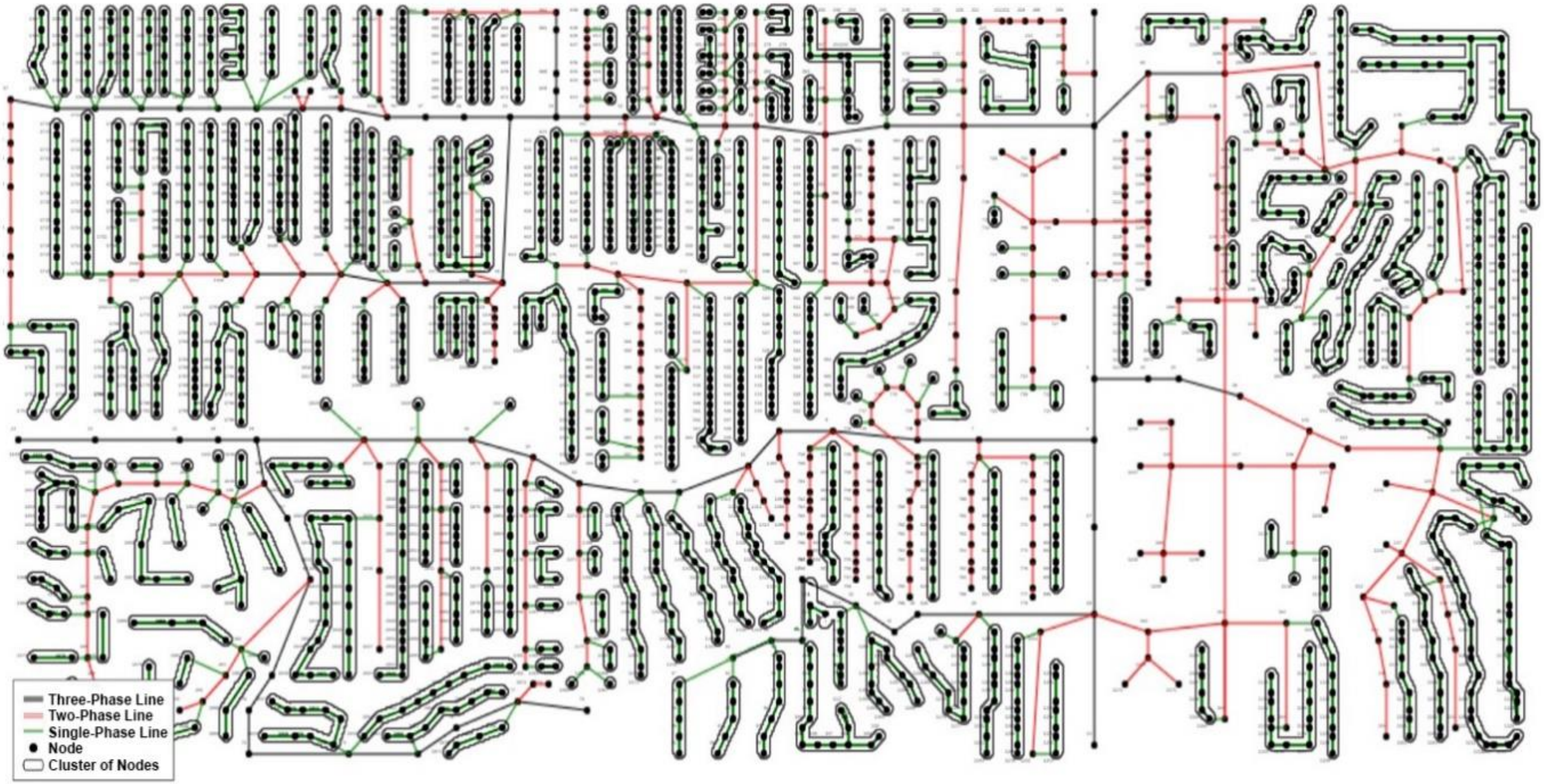
- Using minimal topology data:
  - Geographical Coordinates
  - Type of the line
  - Nearby Loads

- DBSCAN Clustering algorithm



Clustering Single-Phase Loads

Allocation of single-phase nodes in a 2500-load-bus system



Clustering Single-Phase Loads

Analyzing a system with 2500 loads

# Of Clusters	N After Clustering	T Measurements	Computation Time (s)	Accuracy
Without Clustering		1920	~5 hours	99.56%

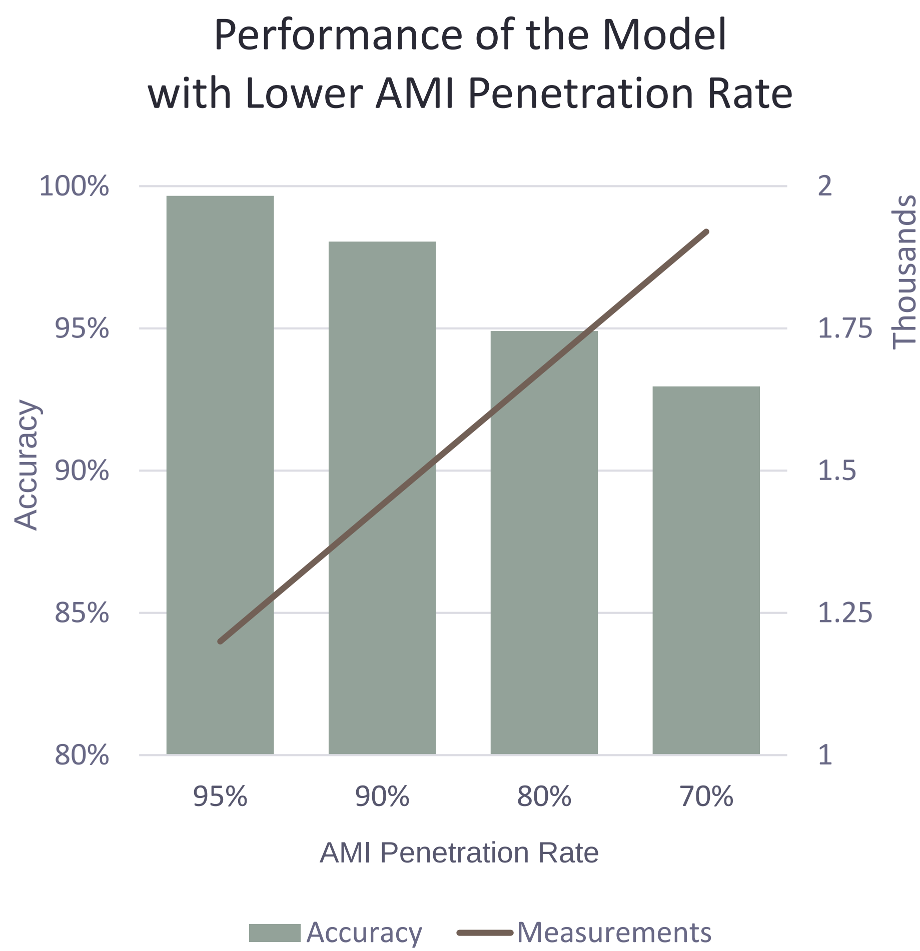
- The complexity of the model reduces
- Clustering can be done with only minimal information from topology data.
- The proposed model is independent of the topology data

Clustering Single-Phase Loads

2500-load-bus system with AMI penetration rate < 100%

(1205 Loads After Clustering)

- Performance is improved by the distribution loss lower and upper bounds
- This method is still effective for older networks that are not fully equipped with smart meters
- It is possible to identify the phase of the unmetered loads



Conclusion

- A scalable data-driven method for phase identification in distribution grids
- The model was challenged by the appearance of noise and outliers with increasing network size
- To increase performance, a regression algorithm was utilized to estimate the distribution loss
- The optimality gap and measurement interval should be selected appropriately
- To choose optimal data points, two criteria were evaluated. Similarity Score and null value ratio
- Using 40 days of measurements and only consumption data, the phase of 2500 loads was identified with high accuracy
- Single-phase loads were clustered using the DBSCAN algorithm, which enhanced the performance in networks with a low AMI penetration rate.

Thank You

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