Phase Identification in Real Distribution Networks with High PV Penetration Using Advanced Metering Infrastructure Data

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A Sempra Energy utility

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Background

Many distribution network monitoring and control applications rely on accurate network models; however, the network models maintained by utilities can become outdated. With the widespread deployment of advanced metering infrastructure (AMI), abundant measurement data from low-voltage secondary networks are available. This data can be used for phase identification to improve the network models. The existing phase identification techniques work well in passive distribution feeders that do not have photovoltaic (PV) generation. This paper proposes a robust phase identification algorithm based on supervised machine learning that accurately identifies the AMI meter phase connectivity in the presence of significant PV generation. The proposed algorithm does not require network topology information or feeder-head measurement data. The algorithm is validated using the AMI measurement data collected in the field and the field-validated phase connectivity database on two real distribution feeders from San Diego Gas & Electric Company that have significant PV generation.

Feeder Characteristics

- 12-kV feeder with a peak load of 10.3 MW
- One substation load tap changer, three capacitor banks for voltage regulation
- More than 4,200 single-phase nodes
- Distributed PV generation of ~70% relative to the peak load.

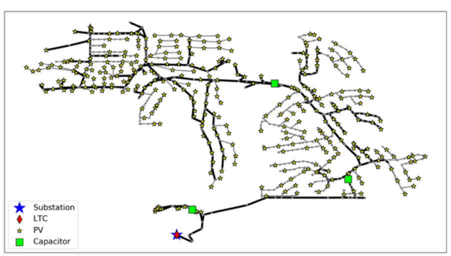

Figure 1. Topology of the distribution feeder 1

- 12-kV feeder with a peak load of 13.3 MW
- One substation load tap changer, two capacitor banks for voltage regulation
- Distributed PV generation of ~24% relative to the peak load.

Figure 2. Topology of the distribution feeder 2

Phase Identification using Random Forest Classification

Algorithm Phase identification using random forest classifier

1: Load AMI data set.

2: Perform data preprocessing: data cleaning and standardization.

3: Load training data, including field-validated phase labels for the AMI meters in the training data.

4: Construct a random forest classifier using the training data.

5: Input the voltage time-series testing data to the random forest classifier and obtain the corresponding phase connectivity.

6: Save the phase identification results for post-processing.

Assumptions and Limitations

- The number of phase connections in the feeder is known
- The training data including the accurate phase labels for the meters in the training dataset are available
- The proposed phase identification algorithm uses voltage time series data from the AMI meters. The power consumption data from the conventional meters is not used
- The training data parameters such as data duration, granularity, number of meters etc. influence the phase identification accuracy

Phase Identification Results

Feeder 1

- The Feeder 1 has a mix of phase-to-neutral and phase-to-phase meter connectivity
- It is composed of primarily overhead distribution lines
- A phase identification accuracy of ~90% is achieved on the full dataset from Feeder 1

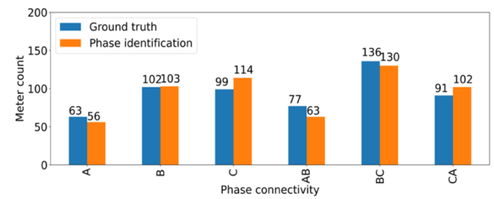

Figure 3. Phase identification results of Feeder 1

Table 1. Phase identification results of Feeder 1

Data set	Phase label	Phase connectivity						Total
		A	B	C	AB	BC	CA	
Full	Ground truth	63	102	99	77	136	91	568
	Correct phase ID	55	98	98	56	126	81	514
Testing	Ground truth	45	72	70	54	96	64	401
	Correct phase ID	37	68	69	33	86	54	347
Training	Ground truth	18	30	29	23	40	27	167
	Correct phase ID	18	30	29	23	40	27	167

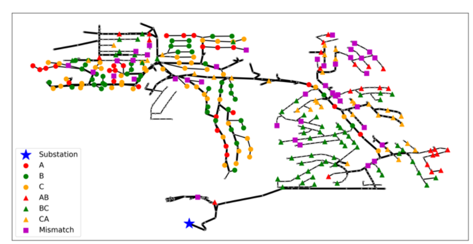

Figure 4. Geographic distribution of phase identification match/mismatches in Feeder 1.

Feeder 2

- The Feeder 1 has predominantly phase-to-neutral meter connectivity
- This is primarily an underground distribution system
- A phase identification accuracy of ~94% is achieved on the full dataset from Feeder 2

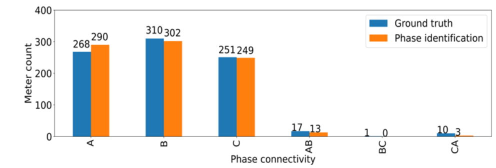

Figure 5. Phase identification results of Feeder 2

Table 2. Phase identification results of Feeder 2

Data set	Phase label	Phase connectivity						Total
		A	B	C	AB	BC	CA	
Full	Ground truth	268	310	251	17	1	10	857
	Correct phase ID	260	293	241	12	0	3	809
Testing	Ground truth	188	217	176	12	1	7	601
	Correct phase ID	180	200	166	7	0	0	553
Training	Ground truth	80	93	75	5	0	3	256
	Correct phase ID	80	93	75	5	0	3	256

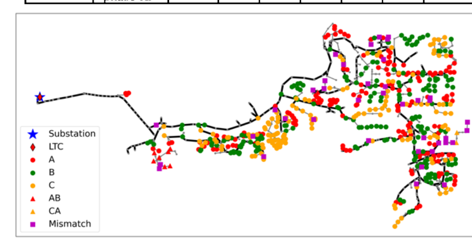

Figure 6. Geographic distribution of phase identification match/mismatches in Feeder 2.

Conclusion

A robust phase identification algorithm based on supervised machine learning is proposed. The algorithm can be applied to distribution feeders having significant PV generation and a mix of phase-to-neutral and phase-to-phase meter connectivity. The performance is demonstrated using the AMI data collected in the field from two real distribution feeders of SDG&E having significant PV generation and varied characteristics.

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