Secondary Network Parameter Estimation for Distribution Transformers

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***Abstract*—Time series active power and voltage data recorded by electricity smart meters in the US have shown to provide immense value to utilities beyond customer billing when coupled with advanced analytics. Distribution system secondary circuit topology and parameter estimation (DSPE) is one such use-case that has been developed extensively. DSPE utilizes smart meter voltage and active and reactive power information to determine the topology and cable impedances of the low-voltage network. However, most smart meters do not record reactive power information. While the impact of unknown power factors is minimal on estimating low-voltage cable impedances, the information becomes critical to estimate transformer impedances. This paper explores how the DSPE algorithm can be extended for single-phase distribution transformers without power factor measurements at the customers.**

***Index Terms* - AMI, linear regression, parameter estimation, power factor, transformer impedance.**

I. Introduction

Smart meter installments in the US have seen a substantial growth in the last decade. As of 2016, nearly half of the 152 million electricity customers in the US have smart meters. The primary objective driving AMI investments has been automated, timely, and accurate billing, and utilities have reported an average of $6 million savings per project per year from remote billing and metering services [1]. Additionally, smart meter data have shown to provide immense value to utilities and consumers when coupled with data analytics. Beyond billing, AMI has been used to forecast and model residential load demand [2], identify meters connected to service transformers [3], discover non-technical losses [4] etc. Table I summarizes a literature review of smart meter analytics.

A widely utilized application of smart meter data is distribution system secondary circuit topology and parameter estimation (DSPE). Utilities can estimate the topology as well as cable impedances of the secondary network using time series voltage (V) and active (P) and reactive (Q) power information [3]. Theoretically, this algorithm can also be extended to estimate transformer impedances. However, while state-of-the-art meters can provide information on harmonics, load power factor, etc., several utilities choose to record only voltage and active power to reduce communication bandwidth requirements and data storage requirements. Section IV shows that not having reactive power measurements does not impact the estimation accuracy for DSPE of the low-voltage cables. However, due to relatively higher inductance and X/R ratios of transformers, Q becomes critical to estimate the impedance of service transformers connecting the low-voltage network to the medium-voltage system. The contributions of this paper include:

1. Developing a method to estimate load power factors using smart meter voltage and active power data. This will provide utilities with more visibility into power factor (PF) trends on their feeder and help determine those customers with poor PF.
2. Simultaneously estimating service transformer impedances, which will allow utilities to extend the DSPE algorithm beyond low-voltage cables. This is done by building the network ground up and using V and P measurements from smart meters and estimated Q.

Section II explains the simulation setup to generate synthetic AMI data. Section III describes the DSPE algorithm and its results on the AMI data-set with and without power factor information. Section IV describes the approach to retrieve load reactive power and improve impedance estimation using estimated Q. Recommendations, future work, and conclusions are included in Section V.

II. Approach and Simulation Setup

In order to generate synthetic AMI data, a distribution feeder was simulated in OpenDSS. The OpenDSS simulation is based on EPRI's Test circuit 5 [14]; a 12.47 kV residential feeder with 1379 residential loads and 591 transformers. 12 months of active power data at 1-minute intervals were extracted from Pecan Street [15] and imported into the simulation to generate high-resolution voltage data at each consumer node. This consumption data was collected from homes located in Austin, Texas between 2013-2017. A pictorial representation of the simulated feeder is shown in Fig. 1. More details of the platfrom can be found in [17]

Reactive power data was not available. Hence, various power factor profiles were assigned to different meters. The diverse profiles are described in Table II.

The standard assumption is that load power factors, especially for residential feeders are quite high and do not vary significantly. This might not always be true in an environment of changing and complex loads. Reference [18] has shown that the drop across the service transformer is much more

TABLE I
SUMMARY OF SMART METER ANALYTICS

Category	Application	Data Requirements	References
Topology Correction/ Modeling	Phase Identification	Voltage magnitude	[20]
	Meter-Transformer Mapping	Voltage magnitude	[6]
	Secondary Network Parameter Estimation	Voltage magnitude, active & reactive power	[7]
Load Analysis	Load Modeling & Consumer Segmentation	Active Power, Weather data,	[9]
	Load Forecasting	Price Information	[2]
	Load Disaggregation - Electric Vehicle Detection	Active Power	[8]
	Rooftop Solar Identification	Active Power, Voltage mag, Solar Irradiance	[10]
Power Loss	Detection of Non- technical losses	Load data, Voltage mag	[4]
	Outage Management	GIS, Voltage mag, Time of outage	[11]
	Fault Detection	Voltage magnitude, active & reactive power	[12]
Feeder Analysis	Detection of Low/High Voltage Areas	Voltage magnitude	[13]

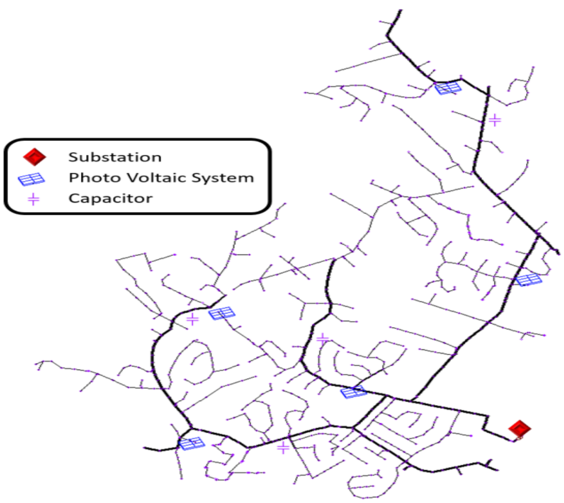

Fig. 1. Circuit plot of EPRI Circuit 5

TABLE II
POWER FACTOR RANGE FOR DIFFERENT METERS

House Number	Uniform PF Distribution Between
1-197	0.79 - 0.81
198-394	0.79 - 0.85
395-591	0.79 - 0.89
592-788	0.89 - 0.91
789-985	0.85 - 0.95
986-1182	0.79 - 0.99
1183-1379	0.97 - 0.99

than the traditionally assumed 1V with lower power factors. A wide range of power factors was purposefully selected in this simulation to test the robustness of the algorithm to a wide range of power factors.

III. SECONDARY NETWORK PARAMETER ESTIMATION

The first step in developing the topology of low voltage networks is to determine the connectivity between meters and their respective service transformers. Several papers have shown that time-series voltage between closely connected buses correlate much higher than with buses that are electrically further away [5]. Researchers have achieved more than 99% accuracy by utilizing methods such as correlation, clustering, mutual information etc. on voltage [19] and geographic information system (GIS) data. Fig. 2 illustrates this concept and shows voltage profiles of neighboring and non-neighboring buses.

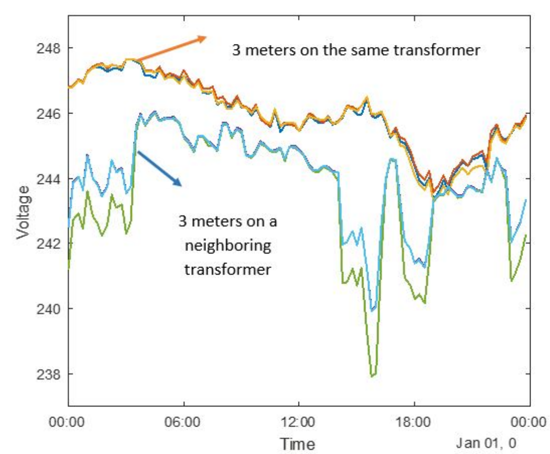

Fig. 2. Voltage profiles of neighboring and non-neighboring meters

Once the meters are paired, cable parameters can be determined using linear regression as introduced in [20] and [3]. These algorithms are based on the voltage drop approximation equation as explained below:

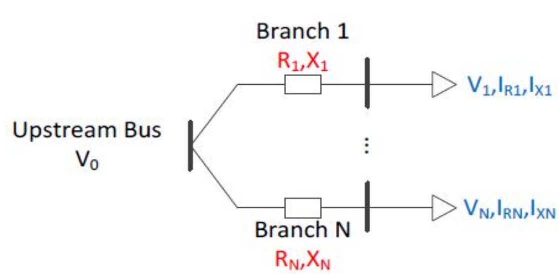

Fig. 3. Radial distribution system secondary system parameter estimation. The measured values (blue) are used to estimate the circuit topology and impedance (red) [3]

For Fig. 3, the equations for each parallel branch are:

$$V_o = V_1 + I_{R_1}R_1 + I_{X_1}X_1 + \epsilon_1 \quad (1)$$

$$V_o = V_2 + I_{R_2}R_2 + I_{X_2}X_2 + \epsilon_2 \tag{2}$$
$$\dots$$
$$V_o = V_n + I_{R_n}R_n + I_{X_n}X_n + \epsilon_n \tag{3}$$
$$\text{where } I_R = P/V,\ I_X = Q/V;$$

P and Q are load active and reactive power and V_o is the voltage at the upstream bus, which is often the secondary of the service transformer for the low-voltage network. This can be rewritten in the form of a linear regression problem to determine R and X:

$$V_1 - V_2 = V = I_{R_2}R_2 + I_{X_2}X_2 - I_{R_1}R_1 - I_{X_1}X_1 \tag{4}$$

Inputs to the algorithm are time series voltage and power (active and reactive) data, and the outputs are the estimated cable resistance and reactance. This algorithm can be extended for service transformer assuming the primary voltage for neighboring transformers are equal (V_o).

Furthermore, an analysis on the primary network revealed challenges in extending this method beyond distribution transformers, that is, to estimate medium voltage cable impedances. The average voltage drop between neighboring transformers on the medium voltage side in the simulation over 1 year was less than 2V. This results in approximately 0.066V when referred to the secondary; ($^{2\times240V}/_{7.2kV}$). With meter accuracy classes 0.2 and 0.5 introduced by ANSI standards C12.20-2010, voltage errors up to 1.2V can occur. Moreover, many utilities do not choose to store more than 100mV resolution (1 decimal value) in their databases. This would make it difficult to capture voltage drops on the medium-voltage network that is required to formulate the linear regression problem. Hence the service transformer is the most upstream asset that can be analyzed via smart meter data.

The results of DSPE applied on the entire circuit consisting of 1379 residential customers, are summarized in Table III.

TABLE III
SUMMARY OF ALGORITHM ERRORS FOR CIRCUIT 5 TEST SYSTEM

Parameter Estimation		
Mean Absolute Error	**Error in R**	**Error in X**
Cable	1.206 %	2.62%
Transformer	1.43 %	4.60%

IV. ESTIMATING IMPEDANCES WITHOUT LOAD POWER FACTOR

Often, smart meters do not record Q or power factor information. One approach is too assume some reasonable power factor for impedance estimation. Reference [17] has shown that knowledge of possible cable types installed and their corresponding X/R ratios is extremely powerful. Similarly, utility operators might be aware of a range of possible transformer X/R ratios on their grid. This information can be leveraged to restrain the slope of the linear regression problem. Table IV shows the accuracy for transformer and cable impedance estimation without power factor information and restrained X/R ratio on the test system discussed in section II using 1 year of data at 15 minute intervals.

TABLE IV
ACCURACY OF DSPE ALGORITHM WITHOUT POWER FACTOR DATA

Asset	X/R range	Assumed PF range	Mean Abs. Error
Cable	0.25 - 0.4	0.85-0.95	3.4%
Transformer	1.0 - 1.4		66%

It can be seen that power factor information is not necessary to determine secondary cable impedances. This is because for low cable X/R ratios, the voltage drop due to reactive power ($I_X X$) is much less than the drop contributed by active power. A work around was possible by speculating Qs and likely X/R ratios. However, due to higher X/R ratios, this does not work for transformers. Inaccurate Q estimates can lead to grossly inaccurate transformer impedances.

Hence, to look beyond the transformer, we need a smart way to determine load power factor profiles. The next section develops such an analysis and establishes the minimum information required to substitute unknown PF. Additionally, this allows utilities to monitor daily power factor profiles at a granular level and low cost.

V. PROPOSED ALGORITHM

The underlying principle behind the algorithm is to estimate parameters of the secondary network such as cable impedances that do not change with time and have a low sensitivity to incorrect data. Leveraging this, time varying values such as reactive power consumption can then be calculated by building on top of DSPE algorithms. This information can in turn be utilized to calculate transformer impedances.

We begin with the assumption that every meter on the feeder reads only voltage and active power at 60 minute intervals or less. Additionally, a few meters also read reactive power (Q). The pseudo-code below explains how this reactive power information can be used to determine Q for neighboring meters. The final goal is to determine the required percentage of meters with Q readings to estimate PF for the rest of the feeder.

An example of this algorithm is illustrated for transformer cluster #103, #209, #266. The connectivity model is shown in Fig. 4. The algorithm has been implemented on four months of simulated data at 15 minute intervals.

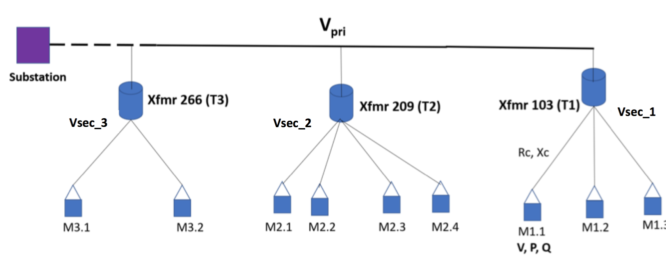

Fig. 4. Network connectivity between Transformers (Xfmrs) 103, 209, 266

Algorithm 1 Power factor and transformer impedance estimation

Input: Time stamped V, P, GIS $\forall$ meters, sparse Q

Output: network connectivity, asset impedances, load PF

1: Use V and GIS to pair all meters with their transformer.Cluster all transformers s.t. min(number of meters $\in$ cluster with accurate Q readings) = 1

2: Estimate R_c, X_c of cables from meter to transformer using V, P, assumed PF and constraining X/R ratio

3: Calculate Secondary voltage $Vsec$ for each transformer

Repeat $\forall$ **clusters** :

4: $\forall$ meters with Q readings, estimate accurate $Vsec$ and Q for neighboring meters on same transformer

5: Employ DSPE algorithm on $Vsec$, Q (assumed and actual) and P for neighboring transformer pairs to estimate transformer impedances R_t, X_t

6: Update estimates by finding nearest possible transformer impedance value

7: Calculate primary voltage $Vpri$ using R_t, X_t for transformer with calculated or measured Q

8: Estimate the next neighboring transformer's Q by assuming same primary voltages

9: Continue estimating Q $\forall$ transformers in cluster.

The following information is either measured or known:

- Time stamped voltage V, active power P for all meters at 15 minute intervals
- Reactive power measurements Q for M1.1
- Medium voltage connectivity, i.e. transformer neighbors

We assume that all meters have been correctly paired with their respective service transformers. This corresponds to step 1 in algorithm 1.

Steps 2 & 3: Estimate Cable Impedances and Transformer Secondary Voltage. Generating random power factors for all meters except M1.1 and constraining the X/R ratio of the low voltage cables, the following result were achieved:

TABLE V
CABLE IMPEDANCE AND SECONDARY VOLTAGE ESTIMATE ACCURACY

Transformer ID	Mean Accuracy of Cable Impedances	Accuracy in Secondary Voltage Estimate
103	97.23%	99.99%
209	97.57%	99.96%
266	97.82%	99.99%

Step 4: Estimate reactive power consumption on neighboring meters. Using the secondary voltage estimated at transformer 103 from M1.1, the reactive power consumption at M1.2 and M1.3 can be estimated by reorganizing equation 1. These estimates can be summed up to determine the total reactive power through transformer 103. Results are illustrated in Table VI and Fig. 5. MAE here is the mean absolute error over all time steps of 15 minute intervals.

$$V_{sec1} = V_{M1.1} + \frac{P_{M1.1} \times R_{c1}}{V_{M1.1}} + \frac{Q_{M1.1} \times X_{c1}}{V_{M1.1}} \quad (5)$$

$$Q_{M1.2} = (V_{sec1} - V_{M1.2} - \frac{P_{M1.2} \times R_{c2}}{V_{M1.1}}) \times \frac{V_{M1.2}}{X_{c2}} \quad (6)$$

TABLE VI
MEAN ABSOLUTE ERROR IN Q ESTIMATES FOR M1.2, M1.3 AND T1

Asset ID	M1.2	M1.3	T1
MAE in Q Estimate	6.68 %	5.43%	3.7%

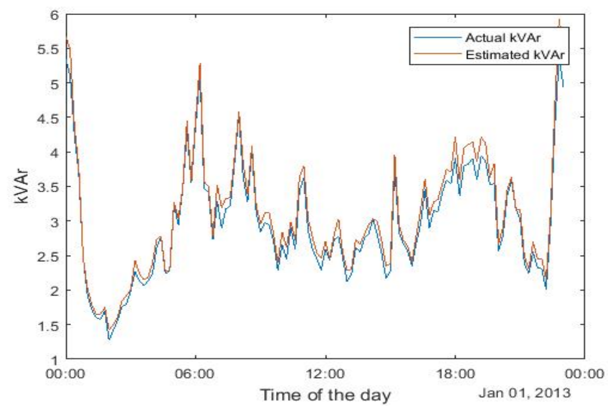

Fig. 5. Estimated vs Actual reactive power profile for transformer 103

Steps 5 & 6: Estimate neighboring transformer impedance The results of steps 5 and 6 from algorithm 1 for transformer neighbors 103 and 209 are shown in Table VIII.

These impedance values can be corrected to match the actual values if the different types of transformers installed on the feeder are known. A range of possible impedance values can be extracted from manufacturing data sheets. In this simulation the unique impedances and corresponding number of transformers are shown in Table VII:

TABLE VII
NUMBER OF TRANSFORMERS IN OPENDSS SIMULATION WITH CORRESPONDING RESISTANCE AND REACTANCE

Number of Transformers	32	18	120	304	59	47
Resistance (Ω)	0.0092	0.0150	0.0215	0.0346	0.0634	0.0979
Reactance (Ω)	0.0154	0.0230	0.0307	0.0461	0.0768	0.1152

Steps 7 & 8: Calculate primary voltage from previous transformer and Impedances of next transformer. Calculating impedances for transformer 266 is even easier as the primary voltage can be calculated from transformer 209, assuming the medium voltage is the same for neighboring transformers. Estimating its impedances can be turned into a linear regression problem follows:

$$V_{pri} - V_{sec103} = P_{103} \times R_t / V_{sec103} + Q_{103} \times X_t / V_{sec103} + \epsilon_1 \quad (7)$$

The results from all the transformer impedance estimates are shown in Table VIII.

TABLE VIII
TRANSFORMER IMPEDANCE ESTIMATION

Transformer ID	Resistance (Ω)		Reactance (Ω)	
	Actual	Estimate	Actual	Estimate
103	0.0346	0.0370	0.0461	0.0492
209	0.0215	0.0219	0.0307	0.0292
266	0.0346	0.0338	0.0461	0.4394

VI. FINAL RESULTS

The above algorithm was carried out for various other clusters. The results for a similar cluster are shown in Table IX. Furthermore, it was determined that for at least 75% accuracy in Q estimation, 1 transformer in every cluster of 5 neighboring transformers needs to report accurate reactive power from one of its meters. In the OpenDSS feeder simulation used in this paper, there are 591 pole-top transformers and 1379 meters. According to the analysis above, 8.57% of meters, evenly spaced across the feeder, need to measure Q along with V and P to extract PF profile for every service transformer on the feeder. This is because errors accumulate as we traverse further from the meter that records Q.

TABLE IX
MEAN ABSOLUTE ERROR IN ESTIMATING REACTIVE POWER CONSUMPTION FOR ANOTHER GROUP OF TRANSFORMERS

Transformer Number	102	183	139	330	477
MAE in Q Estimate	6.45%	15.44%	6.86%	19.67%	26.62%

VII. CONCLUSIONS

This paper explores the feasibility of extracting load power factors when only active power and voltage data are available from smart meters. The power factor estimates are further employed to improve secondary network parameter estimates, especially transformer impedances. By fixing parameters of the secondary network that do not change and have a low sensitivity to incorrect data, i.e. cable impedances, it is possible to estimate time varying values such as reactive power consumption. The authors have built on top of existing meter-transformer mapping and secondary network parameter estimation algorithms to sequentially extract critical and missing information.

Future analysis includes testing the algorithm in the presence of noisy data and inaccurate measurements. Since load power factors are generally very high for residential feeders, marginal discrepancies in voltage data can cause large errors in reactive power estimates. Furthermore, the algorithm should also be validated on real utility data that reads Q in addition to voltage and active power.

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