Distribution System Model Calibration Algorithm Documentation

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I. Introduction

The code in this library was developed by Sandia National Laboratories under funding provided by the U.S. Department of Energy Solar Energy Technologies Office as part of the project titled “Physics-Based Data-Driven grid Modelling to Accelerate Accurate PV Integration” Agreement Number 34226. More information about the project and resulting publications can be found at https://www.researchgate.net/project/Intelligent-Model-Fidelity-IMoFi.

Three distribution system model calibration algorithms are included in this release. There are two algorithms for performing phase identification: one based on an ensemble spectral clustering approach and one based on leveraging additional sensors placed on the medium voltage. Start with the CA_Ensemble_SampleScripts.py file and the SensorMethod_SampleScript.py file, respectively. The third algorithm identifies the connection between service transformers and low-voltage customers (meter to transformer pairing algorithm). Start with the MeterToTransPairingScripts.py file.

There is also a sample dataset included to facilitate the use of the code. The dataset will load automatically when using one of the sample scripts provided. For more details, please see Section IV.

This code and data are released without any guarantee of robustness under conditions different from the ones tested during development.

Questions or inquiries can be directed to Logan Blakely (Sandia National Laboratories) at lblakel@sandia.gov.

II. Phase Identification

1. Spectral Clustering Ensemble Method

The code for the spectral clustering ensemble method is broken into three files: CA_Ensemble_SampleScripts.py, CA_Ensemble_Funcs.py, and PhaseIdent_Utils.py. Start with the CA_Ensemble_SampleScripts.py file; it will automatically load the required sample data and run the spectral clustering ensemble algorithm. CA_Ensemble_Funcs.py contains the primary functions that make up the method, and PhaseIdent_Utils.py contains helper functions.

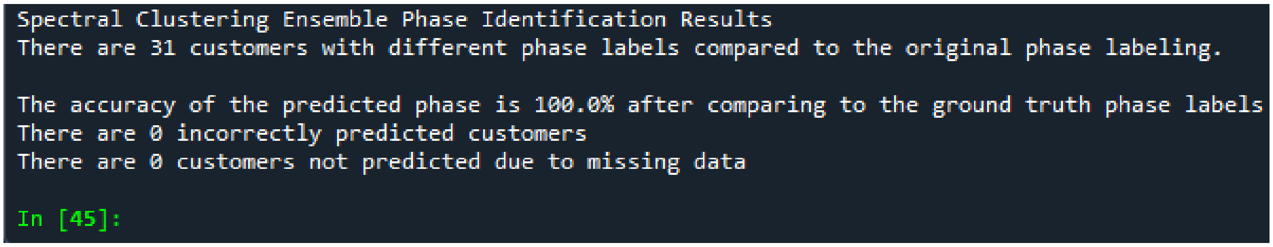
For more details on this method, please see [1].

a. Overview

This algorithm performs phase identification of customers by using their voltage timeseries measurements to cluster similarly related customers, without any other data requirements of topology information, customer power measurements, or measurements from the substation or transformers. It takes as input the voltage timeseries from advanced metering infrastructure (AMI) meters which have been converted into per-unit representation and transformed into a change in voltage timeseries by taking the difference in adjacent measurements. We recommend using at least 11520 datapoints of AMI data. The algorithm is an ensemble, thus more data provides a larger ensemble and generally better results. If more data is available we recommend using the full dataset. The algorithm may still perform well with smaller datasets, depending on the data quality and feeder topologies, but we do expect some degradation in results if the dataset is smaller than 11520 datapoints. We do not recommend using the algorithm on datasets with fewer than 2880 datapoints. The algorithm has been tested on AMI data using measurement intervals from 1-min to 60-min and performs well in each case as long as there are a sufficient number of datapoints available. The algorithm loops through the available data in interval sizes specified by the windowSize parameter. A windowSize of 384 is recommended; our testing shows that value works consistently and should be used in most cases. At each iteration, customers with missing data during that window are excluded, and the remaining customers are clustered using the sklearn implementation of spectral clustering. If a customer is excluded from all windows, they are not included in the final results. The clustering results from each window are used to build a co-association matrix where the entries for customers that were clustered together are incremented. After all windows have been processed, the co-association matrix is normalized by dividing each entry by the number of windows where that pair of customers were both included in the window (i.e. neither customer was excluded due to missing data). The normalized co-association matrix is then used as a pre-computed affinity matrix to the spectral clustering algorithm for the final clustering determination. The number of final clusters can be set based on the feeder topology. 4 or 7 final clusters might be a good place to start, however this parameter may change from feeder to feeder. For example, if the feeder has voltage regulation devices a larger number of clusters may be required. The resulting clusters will be groupings by phase, but the final mapping from the cluster to a particular phase is left to a subsequent step. If the original utility labels are available and you believe they are at least 50% accurate, then the final mapping can be done using a majority vote with the original labels. This is what is done in the sample script provided. The algorithm also outputs the final cluster labels field which represents groupings by phase without necessarily knowing which phase specifically. Manual inspection of a subset of customers from each cluster could assign the final phase predictions for each cluster if the original labels are suspect.

b. Output Description

The two primary outputs from the spectral clustering ensemble phase identification method are finalClusterLabels from the CAEnsemble function and predictedPhases from the CalcPredictedPhaseNoLabels function. The finalClusterLabels field contains the results from the final cluster assignment; these cluster labels correspond to phase groupings but are not mapped to a particular phase. If the original phase labels are available, and you believe they are at least 50% accurate, then they can be used to do the mapping between the clusters in finalClusterLabels and particular phases. This is the predictedPhases field where each customer has been assigned a predicted phase based on the final cluster and a majority vote using the original utility labels.



```
Spectral Clustering Ensemble Phase Identification Results
There are 31 customers with different phase labels compared to the original phase labeling.

The accuracy of the predicted phase is 100.0% after comparing to the ground truth phase labels
There are 0 incorrectly predicted customers
There are 0 customers not predicted due to missing data

In [45]:
```

Figure 1 - Output screenshot for the spectral clustering ensemble phase identification algorithm using the sample data

The final results are written to a csv file containing the customer ID, original phase labels (with errors), true phase labels, predicted phase labels, the confidence score discussed in the next section, and the final cluster label. Any customers which were omitted from the analysis due to missing data are moved to the end of the csv and given a predicted phase label and confidence score value of -99 to indicate that they were not included in the phase identification results.

c. Confidence Score – Modified Silhouette Coefficients

Also included in the outputs is a confidence score for each customer in the form of a modified version of silhouette coefficients. The Silhouette Coefficient is a well-established clustering metric, and more details on the original formulations can be found in [2]. The general form of the silhouette coefficient is shown below.

$$s = \frac{(b - a)}{\max{(a, b)}}$$

Where a is the mean distance between a sample and all other points in its same cluster, and b is the mean distance between a sample and all other points in the next nearest cluster. We have modified the Silhouette Coefficient in our case to be phase aware. The next nearest cluster for the b value calculation is required to be the next nearest cluster *predicted to be a different phase* than the current sample's cluster. This provides a more appropriate metric for a confidence score in our case. Values near 1 indicate high confidence in the phase prediction and lower values indicate less confidence in the results. Resuls do vary by dataset, however a suggested heuristic is that values < 0.2 should be considered low confidence predictions. A histogram of all silhouette coefficients is plotted to provide an overview of the confidence score for the entire dataset.

d. Function Descriptions

This section contains function descriptions for each function in the CA_EnsembleFuncs.py file.

i. CAEnsemble

This function implements the ensemble of Spectral Clustering for the task of phase identification task. The ensemble size is determined by the number of sliding windows available given the windowSize parameter. In each window, the cluster labels are returned by the spectral clustering algorithm and that clustering is then used to update a co-association matrix based on pairwise paired/unpaired information in the cluster labels. That weight matrix is then used for a final clustering into the final clusters which represent phase groupings. The original utility phase labels are not used in this function. The mapping of the final clusters to particular phases is left to a subsequent step. For more details, please see this paper: L. Blakely and M. J. Reno, "Phase Identification Using Co-Association Matrix Ensemble Clustering," IET Smart Grid, no. Machine Learning Special Issue, Jun. 2020.

```
Parameters
---------
  voltage:  ndarray of float (measurements, customers) -
    voltage timeseries for each customer.  The timeseries
    should be pre-processed into per-unit, difference (delta)
    representation.  This pre-processing is an essential step.
  kVector: ndarray of int - a vector of the possible values of
    k for the windows
  kFinal:  int - Number of clusters for the final clustering
  custID: list of str - list of customer ids
  windowSize:  int - The size (in number of measurements) of the
    sliding window
  lowWindowsThresh: int - the minimum number of windows before
    printing a warning that some customers had few windows
    due to missing data.  The default value is set to 4 if
    this parameter is not specified.
  printLowWinWarningFlag: boolean - allows supression of the printout
```

```
          if customer has only a few windows in the ensemble.  The
          default value is True.  If a customer is only present in
          a small number of windows the co-association matrix will not
          be built adequately for that customer (although it will not
          affect other customers).  Thus, results for customers with
          few windows should be considered low confidence predictions
          and likely discarded

    Returns
    -------
        finalClusterLabels:  ndarray of int (1, customers)
          array of the final cluster labels representing the
          phases, but they will not match in number to the actual phases
          Determining which cluster number goes with which real phase
          is left for a future step.  This parameter is one that
          depends on the topology of the feeder.  For more discussion
          see the paper by B.D. Pena listed above.  Starting values
          to try for this parameter might be 4 or 7, topologies with
          voltage regulators in the feeder may require a larger
          number of final clusters.
        noVotesIndex:  list of int - list of customer indices that
          did not receive any votes (i.e. were removed from all
          windows).  This occurs due to missing data for a customer.
          If all windows for that customer contain missing data, then
          that customer will be eliminated from the analysis.
        noVotesIDs:  list of str - list of customer ids that did not
          recieve any votes (i.e. were removed from all windows due
          to missing data)
        clusteredIDs:  list of str (customers) - list of customers IDs
          that were clustered during the ensemble.  The length of
          clusteredIDs plus the length of noVotesIDs should equal
          the total number of customers
        custWindowCounts: ndarray of int (customers) - the count,
          for each customer, of the number of windows that were
          included in the analysis, i.e. the number of windows that
          were not excluded due to missing data.  This count is
          significantly affected by the value chosen for the
          windowSize parameter.  Customers with a low number of
          windows in the ensemble should be considered low confidence
          in the final prediction as they will not populate the
          co-association matrix properly.
```

ii. SPClustering

This function takes a window of timeseries data for the total number of customers and the number of desired clusters and performs the spectral clustering algorithm on that data, returning the cluster labels for each customer. This is the internal spectral clustering function which is called for each window (and each value in kVector). These results are used to build the co-association matrix. The kernel function has been hardcoded here to be the Radial Basis Function ('rbf') based on the results of this research.

```
Parameters
---------
  features: ndarray of float (customers, measurments) - a
    'window' of time series measurements where customers with
    missing data are removed.  Any NaN values in this matrix
    will cause the Spectral Clustering function to fail.
  k:  int - Number of clusters

Returns
-------
  clusterLabels:  list of int - The resulting cluster label of
    each customer (1-k)
```

iii. SPClustering_Precomp

This function takes a precomputed affinity matrix, in the form of a co-association matrix generated by CAEnsemble and will use that to construct the final clusters representing the three phases.

```
Parameters
---------
  aggWM: ndarray of float, shape (customers, customers) affinity
    matrix of paired/unpaired weights aggregated over all
    available windows.
  kFinal: int - the number of final clusters. This parameter
    should be set based on the feeder topology.  Setting this
    parameter to 4 of 7 is a good place to start.  If the feeder
    in question has voltage regulating devices a larger number
    of final clusters may be required.

Returns
-------
  clusterLabels:  list of int - The resulting cluster label of
    each customer (1-k)
```

2. Sensor-based Method

The code for the sensor-based phase identification method is broken into three files: SensorMethod_Funcs.py, SensorMethod_SampleScript.py, and PhaseIdent_Utils.py. Sensor_Method_Funcs.py contains the primary functions for the sensor-based method. PhaseIdent_Utils.py contains helper functions. SensorMethod_SampleScript.py is the place to start; the sample data will load automatically and run the algorithm.

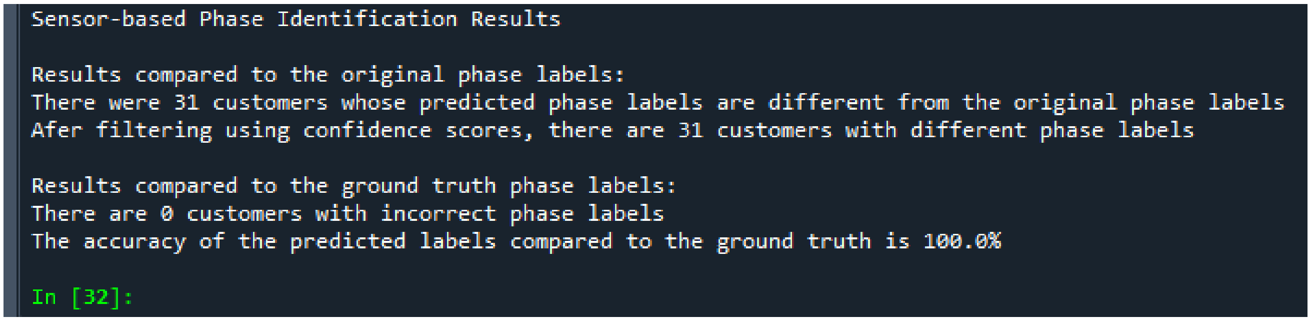
For more details on this method, please see [3].

a. Overview

The sensor-based phase identification method takes voltage timeseries from AMI meters and sensors located on the medium-voltage distribution system (this research used IntelliRupters©). Based on the known phases of the medium-voltage sensors located around the feeder, the phase of each AMI meter is determined based on the correlations to the phase voltage measurements from the other sensors. The voltage timeseries should be pre-processed into a per-unit representation and then converted to a change in voltage timeseries by taking the difference of adjacent measurements. A window ensemble approach is employed where intervals of data, specified by the windowSize parameter, are taken independently. Correlation coefficients are calculated between each customer and each sensor data stream (3 data streams per sensor, one for each phase). Any customers with missing data during a window are excluded from consideration during that window. The other parameter to set is the CC Separation Filter threshold (CCSepThresh); this parameter filters the correlation coefficients produced by individual windows using the Correlation Coefficient Separation Score. Using a window size of 96 and a CC Separation filter value of 0.06 might be a reasonable place to start. Ranges of 96-384 for the window size and 0.02 – 0.06 for the CC Separation filter appear to be reasonable choices for the data we've tested. Once all available data has been used, the mean of the correlation coefficients is taken. The highest correlated sensors with each customer then vote on the predicted phase for each customer. The number of votes should be determined by the number of available sensors on the feeder and other considerations such as the number of voltage regulation devices in the system. Our work uses 5 votes. Finally, confidence metrics are calculated for each customer to give an indication of confidence in the phase prediction.

b. Output Description

The primary output of the sensor-based phase identification method is the predictedPhaseLabels field. This will contain the phase labels for each customer (excluding those omitted due to missing data) which were assigned by the sensor-based method. Figure 2 shows the output produced by running the SensorMethod_SampleScript.py using the included sample data. The predictions are compared both to the original utility labeling and the ground-truth phase labeling.



```
Sensor-based Phase Identification Results

Results compared to the original phase labels:
There were 31 customers whose predicted phase labels are different from the original phase labels
Afer filtering using confidence scores, there are 31 customers with different phase labels

Results compared to the ground truth phase labels:
There are 0 customers with incorrect phase labels
The accuracy of the predicted labels compared to the ground truth is 100.0%

In [32]:
```

Figure 2 - Output screenshot for the sensor-based phase identification method using the sample data

c. Function Descriptions

i. AssignPhasesUsingSensors

This function takes customer voltage timeseries and voltage timeseries from other sensors and assigns a phase label to the customer based on votes from the highest correlated sensors. For more details, see the paper listed above.

```
Parameters
---------
  voltageCust:  ndarray of float (measurements, customers)
    AMI voltage timeseries for each customer.  Each column
    corresponds to a single customers timeseries.  This data
```

```
            should be in per-unit, difference (delta) representation.
            That preprocessing is a critical step.
        voltageSens:  ndarray of float (measurements, sensors*phases*datastreams)
            voltage timeseries for the sensor datastream.  Each column
            corresponds to a sensor datastream timeseries.  This data
            should be in per-unit, difference (delta) representation.
            The measurements dimension should match in length and
            measurement interval with voltageCust
        custIDInput: list of str - the list of customer IDs.  The
            length and indexing should match with the customer dimension
            (axis 1) of voltageCust
        sensIDInput: list of str - the list of sensor IDs.  Each sensor will
            likely have measurements for all three phases, so this list
            will have repeating groups in that case.  The length and
            indexing should match axis 1 of voltageSens
        phaseLabelsSens: ndarray of int (1, sensors*3) - the phase
            labels for each sensor.  This assumes that each sensor will
            have measurements for all three phases.
        windowSize: int - the number of samples to use in each window
        numVotes: int - the number of sensors to use in making the
            phase prediction for each customer.  The default for this
            parameter is 5.  Make sure this number is less than or
            equal to the total number of sensors available.
        dropLowCCSepFlag: boolean - If true this flag calls the
            function to drop CC values where the CC Separation is below the
        ccSepThresh value.  The default value is False, mean all
            CC values are considered.
        ccSepThresh: float - if dropLowCCSepFlag is set to True, then
            this parameter must also be passed.  CC values in each
            window, where the CC Separation is below this value are dropped.
        minWindowThreshold: int - the minimum number of windows that
            must be available for each customer.  If a customer has
            fewer windows then they are omitted from the analysis.
    Returns
    -------
        newPhaseLabels: ndarray of int (1, customers) - the
            predicted phase labels for each customer
        ccMatrix: ndarray of float (customers, customers) - the final,
            median, correlation coefficients for all customers over
            all windows
        custIDFound: list of str - the customer IDs for customers
            which were predicted, i.e. not eliminated due to missing
            data.  This list will match the dimensions of all other
            outputs of this function
        noVotesIndex: list of int - the indices of customers who were
            removed from all windows
        noVotesIDs: list of str - the customer IDs of customers who
            were removed from all windows
        omittedCust: dict - two keys minWindows and missDataOrFiltered
            minWindows is a list of customer IDs which were omitted
            from the analysis because they did not meet the minimum
            number of windows, and missDataOrFiltered is a list of
            customer IDs which were omitted due, either to missing data
            or being filtered due to the CC Separation filter
        sensVotesConfScore: list of float - each entry is the percentage of sensors
            which agree on the phase prediction for that customer
        winVotesConfScore: list of float - each entry is the percentage of windows
            which have the same phase vote for each customer.  This is
            calculated by considering the phase of the sensor datastream with
            the highest CC in each window as a vote
        ccSeparation: list of float - each entry is the difference between the
            highest CC and the next highest CC, considering the mean CC across
            windows.
        confScoreCombined: list of float - the combination of the sensVotes and
            the ccSeparation.  Obtained by multiplying those scores together
        custWindowCounts: ndarray of int (customers) - the count,
            for each customer, of the number of windows that were
            included in the analysis, i.e. the number of windows that
            were not excluded due to missing data.  This count is
            significantly affected by the value chosen for the
            windowSize parameter
```

ii. CCSensVoting

This function takes a row of correlation coefficients for one customer and uses the highest correlated datastreams to vote on the predicted phase based on this row of CC. If all the votes come from different sensors (as they should) then the function takes the mode of votes. If a sensor has repeated votes, this indicates more than one phase of the sensor is highly correlated with this customer. This sometimes occurs with sensors near the substation but is undesirable. In this case, those sensors are eliminated from voting, and only the remaining sensors, in the numVotes highest correlated sensors, are used for the prediction.

```
Parameters
---------
    ccRow: ndarray of float (numSensors) - the correlation
        coefficients between one customer and the set of sensors
    numVotes: int - the number of votes to use in the prediction
    phaseLabelsSens: ndarray of int (1, numSensors) - the phase
        labels for each sensor.  The dimensions should match the
        length of ccRow
    sensID: list of str - the list of sensors IDs. The length of
        this should match the dimensions of ccRow and phaseLabelsSens
Returns
-------
    phasePrediction: int - the phase predictions for this customer
    votes: list of int - the votes that led to this prediction
    voteIndices: list of int - the indices of the sensors used
        in the phase prediction
        voteIDs: list of str - the sensor IDs contributing to the votes
```

iii. *CalcConfidenceScores4Sensors*

This function calculates 4 per-customer confidence scores for the Sensor/IntelliRupter phase identification method. 1. sensVotes is the percentage of sensors that agree on the predicted phase for the customers. Only the sensors included in the votes are considered. 2. winVotes is the percentage of windows that agree on the predicted phase. 3. ccSeparation is the difference between the CC on the predicted phase versus the next highest CC. 4. CombConfScore is the winVotes and the sensVotes multiplied together. Note that these scores measure the consistency of the method across windows and do not necessarily imply accuracy. Note that if any customers were not predicted due to missing data (entries in noVotesIDs) all of the confidence metrics will be recorded as 0 for those customers. If sensPhasesInput only has three entries, the function will omit the sensor agreement and combined score metrics, assuming that the substation was used instead of the sensors.

```
Parameters
---------
    ccMatrixAllWindows: ndarray of float (num customers, number of sensors, number of windows) -
        the correlation coefficient values between a particular customer and a set of
        sensors. The indexing of axis 0 must match the indexing for
        custIDList.  The indexing of axis 1 must match the indexing for sensIDInput
    meanCCMatrix: ndarray of float (num customers, number of sensors) -
        The mean correlation coefficients over all windows.  If any
        customers were eliminated due to missing data, then the whole
        column will be NaN
    custIDList: list of str - the list of customer IDs.  This list must
        match the indexing for ccMatrixInput axis 0
    sensIDInput: list of str - the list of sensors IDs.  This list must
        match the indexing for ccMatrixInput axis 1
    sensPhasesInput: ndarray of int (1, sensor datastreams) - the
        phase labels for each sensor datastream
    noVotesIDs: list of str - the list of customers which were excluded
        from the phase prediction due to missing data
    numVotes: int - the number of sensor votes included in the phase
        prediction
    allWindowVotes: ndarray of int (customers,windows) - the phase vote
        for each customer in each window.  Windows where the customer was
        omitted contain -999
    allSensVotes: list of ndarrays of int - the sensor votes for each customer
        The length of the main list is the number of customers.  Each list
        item is the sensor votes from the highest correlated sensors, up
        to numVotes sensors.  The length of these arrays may vary if some
        sensors were excluded from voting.
        analysis
    newPhasLabels: ndarray of int (1, customers) - the predicted phase
        labels for each customer

Returns
-------
```

```
sensVotesConfScore: list of float - each entry is the percentage of sensors
   which agree on the phase prediction for that customer.  This may
   be 0 if sensPhasesInput had 3 entries, i.e. in the substation
   case
winVotesConfScore: list of float - each entry is the percentage of windows
   which have the same phase vote for each customer.  This is
   calculated by considering the phase of the sensor datastream with
   the highest CC in each window as a vote
ccSeparation: list of float - each entry is the difference between the
   highest CC and the next highest CC, considering the mean CC across
   windows.
confScoreCombined: list of float - the combination of the sensVotes and
   the ccSeparation.  Obtained by multiplying those scores together.
   This may be 0 if sensPhaseInput had 3 entries, i.e. in the substation
   case.
numWindows: list of int - the number of windows included in each
   customers window voting score
```

iv. AssignPhasesUsingSubstation

Note this function is not included in the sample script. It is simply included as a comparison algorithm if desired.

This function takes customer voltage timeseries and voltage timeseries from the substation and assigns a phase label to the customer based on the highest correlation with one of the substation phases. This is a comparison method to the sensor-based method

```
Parameters
---------
   voltageCust:  ndarray of float (measurements, customers)
      full-length voltage timeseries for each customer.  This
      should be in per-unit and delta voltage form
   voltageSub:  ndarray of float (measurements, phases)
      full-length voltage profiles for each substation phase.
      This should be in per-unit and in delta voltage form.
   custIDInput: list of str - the list of customer IDs
   subIDInput: list of str - the list of substation IDs.  This
      will likely be the substation name repeated three times.
      This is necessary for the confidence score function
   phaseLabelsSub: ndarray of int (1, num phases) - the phase
      labels for each of the substation datastreams
   windowSize: int - the number of samples to use in each window
Returns
-------
   ccMatrixSub: ndarray of float (customers, numPhases) - the final,
      median, correlation coefficients for all customers over
      all windows
   custIDUsed: list of str - the list of customer IDs which were
      predicted.  If no customers were lost due to missing data
```

```
            this will match custIDInput.
        noVotesIndex: list of int - the indices of customers who were
            removed from all windows
        noVotesIDs: list of str - the customer IDs of customers who
            were removed from all windows
        predictedPhases: ndarray of int (1, customers) - the predicted
            phase labels based on correlation with the substation
        winVotesConfScore: list of float - each entry is the percentage of windows
            which have the same phase vote for each customer.  This is
            calculated by considering the phase of the sensor datastream with
            the highest CC in each window as a vote
        ccSeparation: list of float - each entry is the difference between the
            highest CC and the next highest CC, considering the mean CC across
            windows.
    """
```

III. Meter to Transformer Pairing

The code that implements the meter to transformer pairing task is broken into three files: M2TFuncs.py, M2TUtils.py, and MeterToTransPairingScripts.py. M2TFuncs.py implements the primary functions for the methodology. M2TUtils.py implements helper functions. MeterToTransPairingScripts.py is the place to start; this file will load the sample data and run the algorithm.

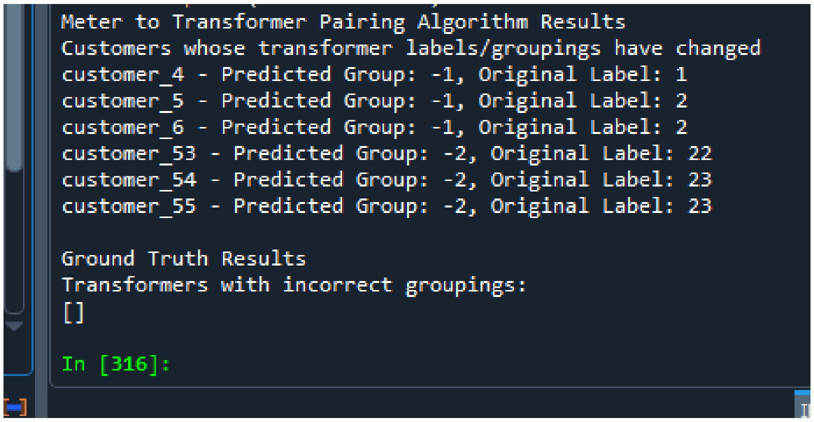
For more details on this method, please see [4].

1. Overview

This method uses correlation coefficients analysis of the customer voltages to flag transformer groupings which likely contain errors, and then a linear regression methodology using voltage, real power, and reactive power data is used to correctly group the customers by service transformer. The input to the meter to transformer pairing algorithm is voltage magnitude, real power, and reactive power timeseries AMI data. The algorithm is divided into two stages. In the first stage, pairwise correlation coefficients are calculated between all pairs of customers. Then, the original transformer labels are used to inspect the correlation coefficients for each transformer grouping. If any of the pairwise correlation coefficients are below a specified threshold then the transformer is flagged for inspection in the second stage of the algorithm. Stage 1 is done using a ranked approach with multiple thresholds such that stage 1 results in a ranked list of flagged transformers, so that the earlier in the list the transformer appears, the worse the correlation coefficients were in that transformer grouping. In stage 2, a pairwise linear regression is done between all customers. This produces a mean-squared-error (MSE) value that functions as a type of goodness-of-fit metric for the regression, a resistance coefficient, and a reactance coefficient. The resistance and reactance values function as a type of distance matrix between customers. The MSE values and are used as a filter for the reactance matrix, where pairs with high MSE are discarded. The algorithm currently sets the MSE threshold by finding the minimum MSE value and adding a small amount to that value. This parameter could also be set manually if desired. The resulting, filtered, reactance matrix is used to assign new transformer groups to the flagged transformers/customers from Stage 1. Customer pairs serviced by the same transformer will have reactance ‘distances’ lower than the reactance due to the influence of two transformers.

2. Output Description

The primary output of the meter to transformer pairing algorithm is the predictedTransLabels field returned by the CorrectFlaggedTransErrors function. This field contains a list of transformer labels, unchanged labels remaining the same, and new transformer groupings labeled with negative integers. There is not a straightforward way to map the new groupings (designated with negative integers) to physical transformers; that is left as a subsequent task. The sample data produces output as shown in Figure 3. The two customers whose labels were changed (customer_4 and customer_53) are in new transformer groups with the other customers serviced by their respective transformers. You can see this by comparing the results in predictedTransLabels to the ground-truth transformer labels in transLabelsTrue variable. The 'Transformers with incorrect groupings' list is empty because the algorithm was 100% successful in finding the correct transformer groupings. Any transformers whose groupings are incorrect when compared to the ground-truth labels would be listed here.



```
Meter to Transformer Pairing Algorithm Results
Customers whose transformer labels/groupings have changed
customer_4 - Predicted Group: -1, Original Label: 1
customer_5 - Predicted Group: -1, Original Label: 2
customer_6 - Predicted Group: -1, Original Label: 2
customer_53 - Predicted Group: -2, Original Label: 22
customer_54 - Predicted Group: -2, Original Label: 23
customer_55 - Predicted Group: -2, Original Label: 23

Ground Truth Results
Transformers with incorrect groupings:
[]

In [316]:
```

Figure 3 - Output screenshot for the meter to transformer pairing algorithm

3. Function Descriptions

a. RankFlaggingBySweepingThreshold

This function takes a vector of possible threshold values (probably correlation coefficients) and creates a ranked list of flagged transformers based on which had relatively lower cc values when they were flagged.

```
Parameters
---------
  transLabelsInput: ndarray of float (1, customers) - the transformer
    label for each customer
  notMemberThresholdVector: list of float - the list of possible
    thresholds below which customers are considered not on
    the same transformer
  ccMatrix: ndarray of float (customers, customers) - the array
    of pairwise correlation coefficients.
Returns
-------
  allflaggedTrans: list of list of int - each entry in the list
    contains the list of flagged transformers for that
    threshold value.  This allows identification of the
    threshold value responsible for flagging each
```

```
        transformer
    allNumFlagged: list of int - the number of flagged transformers
        for each threshold value.  The length of this list will
        match the length of notMemberThresholdVector
    rankedFlaggedTrans: list of int - a ranked list containing all
        flagged transformers over all threshold values. Values at
        the beginning of the list had relatively lower cc threshold
        values when they were flagged.
    rankedTransThresholds: list of float - a list of thresholds that
        correspond in index to rankedFlaggedTrans denoting which
        CC threshold flagged that transformer
```

b. CCTransErrIdent

This function uses the correlation coefficients to detect errors in transformer groupings. This is simply used to flag customers as potential errors.

```
Parameters
---------
    transLabelsInput: ndarray of float (1, customers) - the transformer
        label for each customer
    notMemberThreshold: float - the threshold below which customers
        are considered not on the same transformer
    ccMatrix: ndarray of float (customers, customers) - the array
        of pairwise correlation coefficients.

Returns
-------
    flaggedCust: list of int - the list of indices of the flagged
        customers
```

c. AdjustDistFromThreshold

Uses the specified threshold of the comparison matrix to replace values in a second matrix. Values less than 0 in the matrix2Adjust are replaced. For example, the way this is usually used is if the comparison matrix is the MSE matrix and the threshold is 0.2, then for any cell in the MSE matrix with a higher MSE than 0.2, the corresponding cell in the second matrix, for example, the reactance distance matrix, is set to the replacement value which is usually a very high value. Effectively this function filters a matrix, like the reactance distance matrix, by high values in the MSE matrix. Values less than 0 in the reactance distance matrix are known to be bad values.

```
Parameters
---------
    compMatrix: ndarray of float (1, customers) - the matrix
        containing the values used as a threshold to remove values
        from matrix2Adjust.  This matrix must be a 'distance'-type
        matrix.  Often this is the pairwise MSE matrix containing
        the mean-squared error results from a pairwise regression
        formulation
    matrix2Adjust: ndarray of float (1, customers) - the second matrix
                that will have values replaced.
    threshold: float - value used to flag values in the comparison matrix above
                  the threshold for which the corresponding cells in
                  matrix2Adjust will be replaced by a given replacement value.
    replacementValue: float - value used to replace flagged cells in matrix2Adjust
      In the meter to transformer pairing task this is often set to the
      max value in the matrix2Adjust field, so that the value is
      discarded, but remains within the range of the variable

  Returns
  -------
    adjustedMatrix: ndarray of float (1, customers) - the final matrix adjusted
                by replacing the cells in matrix2Adjust corresponding with the
                thresholded cells from compMatrix with a given replacement value.
```

d. CorrectFlaggedTransErrors

This function takes a list of flagged transformers and produces a list of predicted customer labeling errors and a prediction for the correct labeling

```
  Parameters
  ---------
    flaggedTrans: list of flagged transformers
    transLabelsInput: ndarray of float (1, customers) - the transformer
      label for each customer
    custIDInput: list of str - the customer ID's
    ccMatrix: ndarray of float (customers, customers) - the
      matrix of pairwise correlation coefficients
    notMemberThreshold: float - the threshold for flagging customers as not
      being connected to the same transformer as another customer
    mseMatrix: ndarray of float (customers, customers) - the
      mse values from a pairwise linear regression
    xDistAdjusted: ndarray of float (customers, customers) - the
      reactance distance, adjusted by the r-squared values
    reactanceThreshold: float - the threshold for considering a
      customer to be the only customer on a transformer. The
      default value of 0.046 which was determined as an average
      value for reactance across two transformers.
  Returns
  -------
    predictedTransLabels: ndarray of int (1, customers) - the
      predicted transformer labels for each customer. 'New' labels
      are given by negative labels.  Those should reflect correct
      transformer groupings but not the original labels themselves.
    allChangedIndices: list of lists of int - each entry in the
      list is the list of indices which changed under each
```

```
   successive flagged transformer
allChangedOrgTrans: list of lists of int - each entry in the
   list is the list of the original transformer label for
   customers which changed their label
allChangedpredTrans: list of lists of int - each entry in the
   list is the list of the predicted transformer label
   for each customer which changed their label.  'New'
   transformer labels will be negative.  Thus, the customer
   groupings should match physical transformers but the
   utility label is to be determined.
```

IV. Sample Data

1. Overview

The sample data included in this release consists of timeseries data for 200 single-phase customers, 10 sensors, and the substation at 15-minute intervals with a total of 11,520 measurement points, or approximately four months. The customer advanced metering infrastructure (AMI) data, as well as the sensor and substation, consist of voltage magnitude, real power, and reactive power timeseries. The voltage magnitude data is in Volts and the real power and reactive power are in Watts and Var, respectively. There are also phase labels, transformer labels, and ID's for each AMI and sensor. The data is included as .npy files which is the numpy data format. More information on the file format can be found here, https://numpy.org/devdocs/reference/generated/numpy.lib.format.html

The data was synthetically generated using real load profiles from customers in the southern U.S. which was then placed on EPRI Ckt. 5. A quasi-static time series (QSTS) simulation was run using Open DSS was to produce voltage magnitudes and reactive power profiles for the AMI meters, sensors, and substation.

2. Injected Data Issues

The sample data includes several data issues that have been injected into the original data files. These are measurement noise, missing data, incorrect phase labels, and incorrect transformer labels.

a. Measurement Noise

For the voltage data, normally distributed noise was injected with a specified standard deviation. For the AMI data, the standard deviation was set to 0.07% of the mean (240V in this case). This value was determined using a meter testing report provided by one of our utility partners. 0.07% was the demonstrated standard deviation of noise in the 0.5 meter class they were testing. Using 0.07% standard deviation also ensures that 99% of the noise is within 0.2% which is the maximum deviation allowed by the 0.2 meter class. For the sensors, a standard deviation of 0.04% was used. This value was determined via analysis of the sensor data provided by our utility partners. For the real and reactive power, small amounts of uniformly distributed noise were added to the measurements, up to a maximum of +/- 100W and 100VAr respectively.

b. Missing Data

Approximately 0.2% missing data was injected into the voltage, real power, and reactive power AMI timeseries. No missing data was injected into the sensor data. We assumed that all measurements would be missing simultaneously from the AMI meter, thus the missing data is in the same locations between all three data streams on a given meter. A minimum missing interval (1 datapoint) and a maximum missing interval (48 datapoints) was specified, and missing data was injected into each customer independently.

c. Incorrect Phase Labels

Two phase label files are included for the AMI data, one contains the ground-truth phase labels and the other contains a set of phase labels where 18 customers have been given an incorrect phase label. The set of phase labels with errors included is intended to represent a set of labels for the utility model that contains some unknown amount of errors. The phase labels for the sensor and substation data streams are the ground-truth phase labels; no error injection was done to those labels.

d. Incorrect Transformer Labels

There are two transformer label files included for the AMI data, one contains the ground-truth transformer labels and the other contains a set of phase labels where two selected customers have been given an incorrect transformer label. These are as follows: customer_3 transformer was changed from 1 to 2 and customer_53 transformer was changed from 23 to 22. Thus, there are two customers with incorrect transformer labels, but there are 4 transformers whose customer groups are now incorrect. Transformers 1, 2, 23, and 22 have incorrect groups. Transformers 1 and 23 are missing one customer each and Transformers 2 and 22 have one additional customer each.

3. Included Data Files

CustomerIDs_AMI.npy

custIDInput: list of str - This is a list of customer IDs as strings. The
length of this list should match the customer dimension of voltageInput

PhaseLabels_Sensor.npy

sensPhases: ndarray of int (1, sensor datastreams) - the phase labels of
the sensors in integer form. 1 - Phase A, 2 - Phase B, 3 - Phase C. The
number of sensor datastreams should match the dimensions and indexing of
axis 1 in voltageInputSens

PhaseLabelsTrue_AMI.npy

phaseLabelsTrue: ndarray of int (1, customers) - This contains the
ground-truth phase labels for each customer, if available. Note that,
in practice this may not be available, but for testing purposes this
is provided along with functions to evaluate the phase identification
accuracy against the ground-truth labels.

PhaseLabelsErrors_AMI.npy

phaseLabelsErrors: ndarray of int (1, customers) - This contains the phase labels for
each customer in integer form (i.e. 1 - Phase A, 2 - Phase B,
3 - Phase C). Any integer notation may be used for this field; it is
only used to assign the final phase predictions. In practice, this
field could even be omitted, the phase identification results from
CAEnsemble will still be grouped by phase, and the assignment of final
phase labels could be left for a post-processing step by the utility.
The dimensions of this matrix should be (1, customers).

These are assumed to be the original, utility labels, which may contain some number of errors. The sample data included with these scripts has ~9% of phase labels injected with errors. This can be seen by comparing this field with the entries in phaseLabelsTrue which contains the ground-truth phase labels

ReactivePowerData_AMI.npy

qDataInput: ndarray of float (measurements, customers) - the reactive power measurements for each customer in VAr

RealPowerData_AMI.npy

pDataInput: ndarray of float (measurements, customers) - the real power measurements for each customer in Watts

SensorsIDs.npy

sensIDs: list of str - the IDs for the sensors in string form. The length of this list should match the length and indexing of the sensor datastreams dimension of voltageInputSens and sensPhases. (The IDs will be repeated for the different phase datastreams of the same sensor)

TransformerLabelsErrors_AMI.npy

transLabelsErrors: ndarray of int (1, customers) - the transformer labels for each customer which may contain errors. In the sample data, customer_4 transformer was changed from 1 to 2 and customer_53 transformer was changed from 23 to 22

TransformerLabelsTrue_AMI.npy

transLabelsTrue: ndarray of int (1, customers) - the transformer labels for each customer as integers. This is the ground truth transformer labels

VoltageData_AMI.npy

voltageInput: ndarray of float - This matrix contains the voltage measurements (in volts) for all customers under consideration. The matrix should be in the form (measurements, customers) where each column represents one customer AMI timeseries. It is recommended that the timeseries interval be at least 15-minute sampling, although the algorithm will still function using 30-minute or 60-minute interval sampling

VoltageData_Sensors.npy

voltageInputSens: ndarray of float (measurements, sensor datastreams) – the sensor voltage timeseries. Each column should be a sensor datastream with measurements in volts. The length of the measurement’s dimension should match in length and timestamp with the voltageInputCust field. Each data stream will correspond to one measurement field and phase for a particular sensor. Currently, our work is using the average voltage field from the sensors. For example, if there are 10 sensors in the system, and the average voltage field is used, each sensor will have measurements from each of the three phases A, B, C. Thus the length of the sensor datastreams dimension will be 30. Our work utilized IntelliRupters which take measurements on either side of the device, thus it might be expedient to downselect to one of the two datastreams, as the two datastreams will either be repeated (closed devices) or measuring two different sections of the grid (open devices).

V. Code Notes

The included code was developed in Python 3.7.3. Standard libraries are noted below with the version used in the development of this code.

- numpy (1.20.2)
- pathlib (2.3.5)
- scikit-learn (0.24.2)
- matplotlib (3.3.4)
- seaborn (0.11.1)
- scipy (1.6.2)
- pickle
- datetime
- warnings
- copy
- sys

VI. Related Publications from the Project

This section contains references for other publications related to this work and produced during the course of this project.

For a discussion of parameter tuning for the spectral clustering ensemble phase identification method, please see [5].

For a direct comparison of phase identification methods, including between voltage-based methods and power-based methods, please see [6].

For an analysis of common types of errors found in distribution systems, please see [7].

For discussion on AMI data quality issues and requirements, please see [8], [9].

For work on estimating distribution system parameters such as wire type and length, please see [10].

For work on locating and estimating parameters for behind-the-meter PV installations, please see [11]–[13].

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[8] L. Blakely, M. J. Reno, and K. Ashok, "AMI Data Quality And Collection Method Consideration for Improving the Accuracy of Distribution System Models," presented at the IEEE Photovoltaic Specialists Conference (PVSC), Chicago, IL, USA, 2019.

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