High-Frequency, Multiclass Nonintrusive Load Monitoring for Grid-Interactive Residential Buildings

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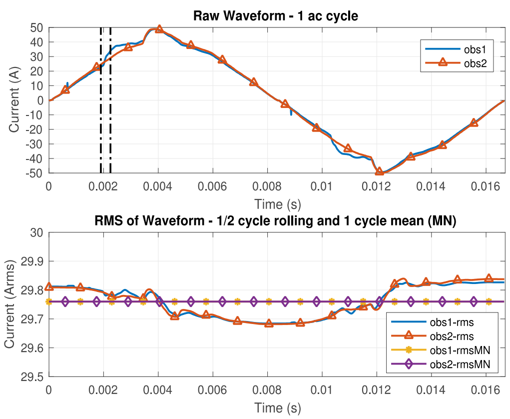
Introduction

Opportunity

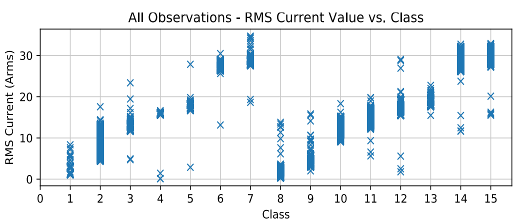
- Smart buildings can manage their net loads to provide additional flexibility to grid operators
- Crucial to enable net-load metering at non-smart residential buildings to enable greater monitoring and support grid-interactive control capabilities
- Nonintrusive load monitoring (NILM) enables effective monitoring with minimal additional equipment and cost

Background and Challenges

- Steady state measurement methods use active and reactive power or RMS current on a macro timescale
- Most existing methods using steady-state measurement methods that:
  - can result in misclassification between two different combinations of loads that have nearly identical steady-state measurements but differing instantaneous waveforms (see example)
  - require a large sample of training data and have slow response following events



Comparison of waveform (top plot) and RMS values (bottom plot) from two observations representing two different load configurations in a residential building

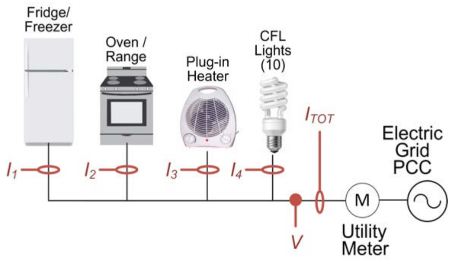


RMS current vs. class of load configurations for a residential building

NILM using transient measurements

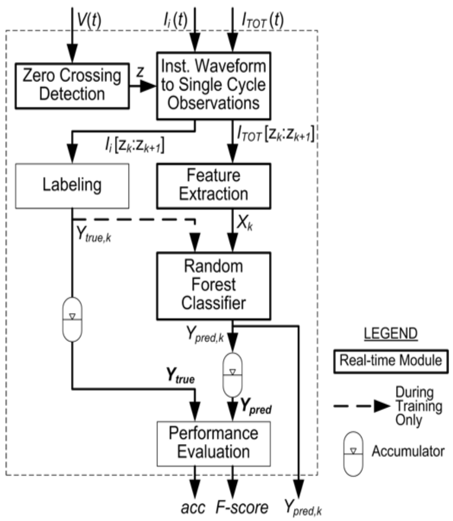
Experimental Design

- A residential-scale demonstration using four household appliances in the ESIF lab at NREL
- Four-load configuration, leads to 15 different nontrivial classes
- Five current probes and one voltage probe at the locations indicated
- Seven independent 200-second datasets for training
- Additional six independent datasets for testing



Approach

- High-speed (200 kHz) current measurement data is divided at each 60-Hz ac cycle
- Each cycle becomes an observation
- Multiclass label is formed as a single integer label with the class encoded using a binary encoding scheme
- Four key categories of features are used
  - Harmonic features
  - Steady-state RMS feature
  - Wavelet features
  - Wave shape features: derived using individual data points that represent unique characteristics of the waveform's shape
- A random forest classifier is used



Classifier Training and Tuning

- Multiple classifiers using different subsets of the features considered
- Need to have good test accuracy on not seen or rarely seen data
- Two classifiers retained with same hyperparameters but using different features
- Best hyperparameters determined using grid search
  - Classifier1 is the final classifier for which good accuracy and generalization results
  - Classifier2 has good prediction accuracy on the test data set, but does not generalize as well

Classifier	Features Included			
	Harmonic Coefficients	Normalized Harm. Coeff.	Wavelet	Wave Shape
Classifier 1	1,3,5,7,9,11, 13	5,7	All	All
Classifier 2	1,3,5,7,9,11, 13	None	None	All

Problem Formulation

N_L **loads**

- Each consuming an instantaneous current $I_i(t) = q_i(t)\overline{I_i}(t)$ where:
  - $\overline{I_i}(t)$ is the i^{th} load instantaneous current
  - $q_i = \{0,1\}$ is the on/off status
- Total current: $I_{TOT}(t) = \sum_{i=1}^{N_L} q_i(t)\overline{I_i}(t)$
- 2^{N_L} possible system load on/off states, $Y = [q_1\ q_2 \ldots q_i \ldots q_{N_L}]$

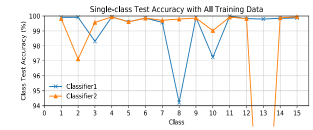
Objective:

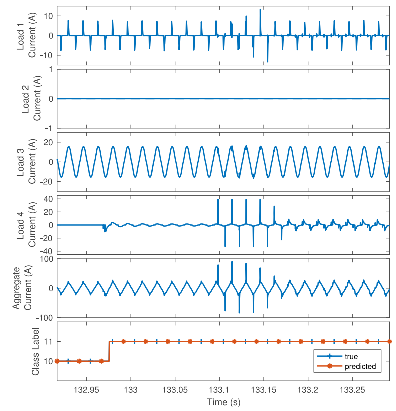
- Find a classifier that uses an input vector X of features from observation of $I_{TOT}(t)$ to predict the correct class label Y

Experimental Results

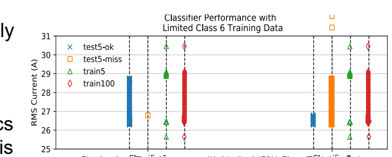
Overall Test Results with Generalization

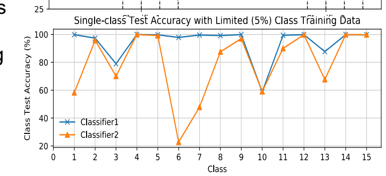
Test Data Set #	Test Accuracy [%]		F1-Score (Weighted) [%]	
	Clf. 1	Clf. 2	Clf. 1	Clf. 2
All	99.44	98.97	99.45	98.94
1	99.02	97.95	99.44	98.95
2	99.07	99.87	99.06	99.90
3	99.57	97.15	99.68	97.23
4	99.99	99.99	99.99	99.99
5	99.97	99.96	99.97	99.97
6	98.87	99.06	98.90	99.05





- Both the classifier perform reasonably well on most test data sets
- Practical NILM implementations should have good performance across a variety of load operating conditions
- To evaluate generalization performance, 95% of each class training data is discarded
- Classifier1 generalizes significantly better than Classifier2 for Class 6
  - this trend holds among most classes
  - additional normalized harmonics and wavelet features enable this
- This approach using high-speed measurements and corresponding features allows predictions to be made for each cycle, providing more granular predictions and better transient performance than state of the art methods





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