Residential Customer Load Pattern Recognition Techniques

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1 Problem Definition

Accurate and reliable electric load pattern recognition of residential loads provides critical information that can enable households to effectively manage the electric loads and provides awareness about the actual energy performance of houses. It can also help to estimate the energy consumption of end uses, or to detect equipment degradation based on load monitoring system. For example, some electric loads, such as fans, monitors and TVs, could be turned off automatically when not in use. But, the majority of loads connected to a building remain unidentified due to the lack of intelligent load identification and monitoring capability. Smart meter data can help in applications such as demand response programs for households. Traditional load monitoring techniques are intrusive techniques which involve physical placement of sensors on individual appliances to gather end-use load data but it poses as a long-term intrusion onto the private life and property. So, recently non-intrusive techniques of load monitoring are used as an alternative to intrusive metering which is based on the analysis of appliance energy signatures. The main advantage being that only a single monitoring point in the house is required to gather end-use load data. But, the multi-dimensional data is a challenge for the data mining of load patterns. Apart from that, the variability of residential consumption patterns is another major problem for deciding on the characteristic consumption patterns. In this report we analyze different techniques that have been proposed for load monitoring and present a thorough literature survey of these techniques and assess their effectiveness for this task. We also discuss the cons of some of the selected base paper which we will attempt to implement in the next part of the project.

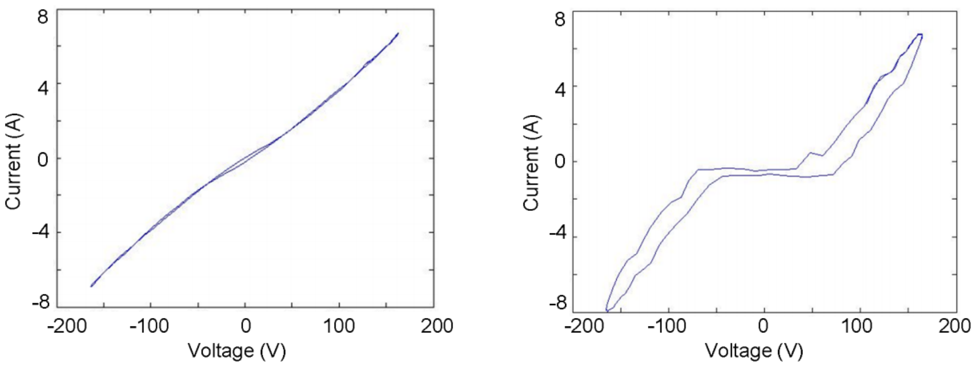
2 Literature Survey

2.1 V-I Trajectory

The instantaneous voltage-current plot gives a 2-D form of load signature which helps in characterizing the loads [Har92]. The features of shape of this curve like asymmetry, looping direction, area, curvature of mean line, self-intersection, and slope of middle segment, area of segments and peak of middle segment can be used for the pattern recognition to identify different loads. Further **hierarchical clustering** can be used to classify the appliances [LFL07]. For e.g. the V-I trajectories of a space heater and an LCD TV are plotted in figure 1 [Du+10].Since the heater is roughly a constant resistor; the trajectory is linear. While the LCD TV has an internal power supply,because of which the current is discontinuous when voltage is low.

Cons

- This method is that it is computationally expensive.



(a) Space Heater (b) LCD TV

Figure 1: V-I trajectories of a space heater and a LCD TV [Du+10]

2.2 Real and Reactive Power

The variations in real and reactive power can be used to identify the types of load [Sul91]. First, the real power (P) and reactive power (Q) are recorded by a measurement device. Then, the values are compared with a predefined database of load power. Based on the relative positions of different loads in the complex P-Q plane, the type of the load is identified. Loads which are far from each other in the plot can be identified only using real and reactive power. The success rate for load identification of large residential loads has been shown to be greater than 80 %. This method fails in case of many MELs in residential buildings which consume approximately same real and reactive power, so points corresponding to them are very near to each other in the P-Q plane. So, rule-based algorithms are applied to dis-aggregate loads based on real and reactive power measurements of electric energy consumption data, along with assumptions about the customer behavior. If two or more loads have similar demand levels decision tree analysis technique is used to distinguish between them, based on the assumptions such as the time of day or the length of usage. Plot of the real and reactive power of typical loads of residential buildings in the P-Q plane [Har92] Figure 2.

Cons:

- This method is based on steady-state power consumption. Therefore, it requires waiting until the transient behavior settles down so that steady-state values can be measured.
- Some loads in commercial and residential buildings do not yield reliable steady-state measurements.

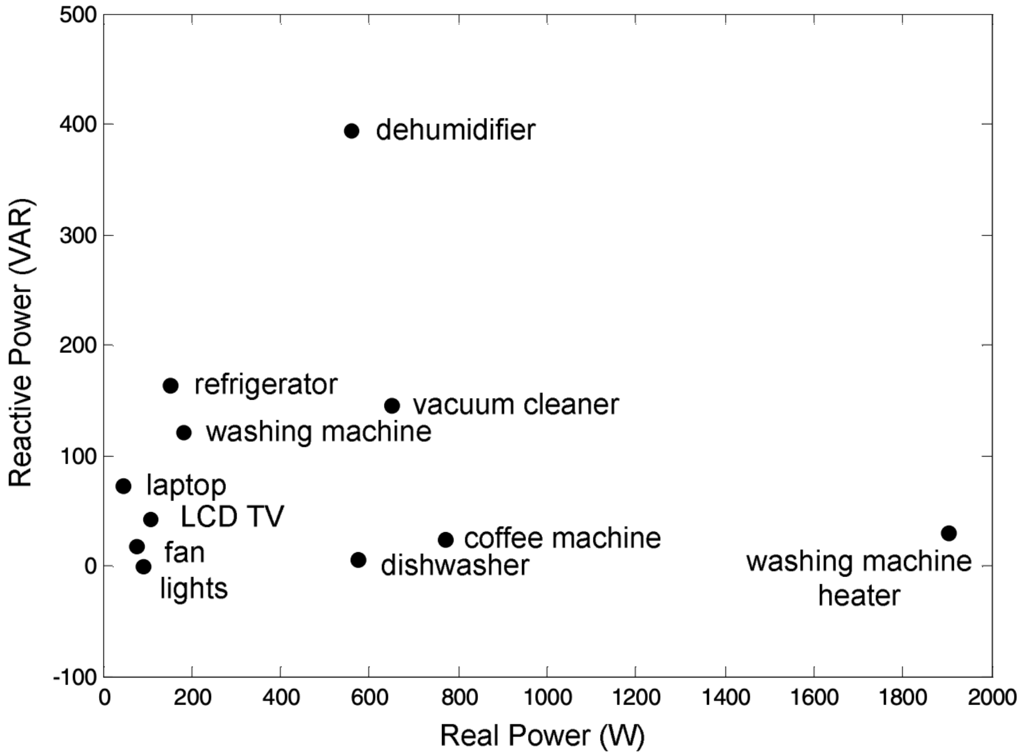


Figure 2: Real and reactive power of electric loads in residential buildings in the P-Q plane.[Har92]

2.3 Eigenvalue Analysis and SVD

In this method, time series of the current waveform are rearranged into a matrix form [Lam+05]. Then SVD is applied to calculate its eigenvalues. Now different loads have different wave forms shape and hence different eigenvalues. For instance, larger loads have a higher first eigenvalue. Thus, this method can also correlate to the power consumed by the load.

Cons:

- Since eigenvalues are defined only for square matrix, its necessary to have n cycles of data if each contains n sampled data points. So, requirement of data is higher.
- If sampling frequency of waveform is changed, a new matrix is obtained thus giving different eigenvalues for same load. Thus, this method is not consistent with the change of sampling rate

2.4 Current Waveform Characteristic and Harmonics

The **current waveform** and the **phase difference between the current and voltage** are good enough to describe a load[Sai+08]. Peak current, average current and RMS current, displacement power factor and the total harmonic distortion in current are used as features for identification. Then **nearest neighbour technique** is applied for recognition. Other important key "steady-state signature" is the power factor. It can clearly distinguish purely resistive loads, motor-drive loads, and power electronic loads. Non-linear loads like MELs result in harmonics. Thus, current harmonics can be used to identify these loads. To improve the identification accuracy, it can be combined together with P-Q plane methods and transient power methods for load identification.

Cons:

- It is not feasible to compare the waveforms directly in application because of computational limitations and sensitivity issues.

2.5 Transient Power

Transient behavior of a load is closely reflects the physical task that the load performs [Sha+08]. Hence most loads have repeating transient profiles which can help in identification of variable loads. Also, power of transient harmonics provides extra information for variable loads, which is helpful in identifying variable drive connected loads as drive startup is generally repeatable, controlled by a microprocessor.

Cons:

- High sampling rate and continuous monitoring are required to analyze transient power.

COMPARISON OF IDENTIFICATION ACCURACY FOR DIFFERENT LOADS IN BUILDINGS

Methods	Loads in Buildings			
	Linear	Nonlinear Loads		
	Heaters …	LCD TVs, Chargers …	Fluorescent Lights …	Washers …
Real and Reactive Power	✓	✓	✓	✓
Current Harmonics		✓	✓	
Power Factor	✓	✓		
V-I Trajectory	✓	✓		
Current Eigenvalues			—	—
Transient Power			✓	✓
Wavelet Transform			✓	✓

Figure 3: Comparison of Identification Accuracy for Different Loads in Buildings[Har92]

2.6 Optimization of Identification metrics

Here, the objective function is defined as the minimum residue while comparing the unknown loads with a set of candidates extracted from the known database, as given below [Sul91].

$$min\ Obj_j = \sum_{k=1}^{N} w_k(\hat{y}_{(kj)} - y_{(k)})^2$$

$\hat{y}_{(kj)}$ = feature k extracted from the known feature-database of load j

$y_{(k)}$ = feature k extracted from the unknown load

w_k = weight of feature k

N = total number of features

A one-to-one comparison with the known database is performed when the load features are extracted from a single load. The residue is computed between the unknown and the known individual load signatures. The target load is the known load with the minimum residue. The weight of a feature, w helps to adjust the significance of features.
When the unknown is a composite load containing more than one load's signature, the optimization method becomes more complex. Methods such as genetic algorithms [CKL06], integer programming, dynamic programming approaches, particle swarm optimization, fuzzy logic or multi-algorithm framework have been proposed to solve this problem.

Cons:

- This method assumes that all features of loads are already known and it is largely based on this database whereas many loads have several operating states and they consume different level of power in different states.

- For example, a TV set could be in operating, standby, and off modes. It generally consumes less power in standby mode than the operating mode, but the features are almost the same except in magnitudes. Thus, methods based on optimization method could be totally wrong in some cases.

2.7 Artificial Neural Networks

Artificial neural networks (ANN), can be used to identify the appliance loads by training it to learn the specific features of different appliances. It is suggested in [Roo+94] to train a number of neural networks in cascade, which are then used as pattern classifiers to identify the various loads. Steady-state appliance signatures, such as fundamental frequency quantities, current, power and impedance contours and harmonic frequency current information and distortion power serve as the inputs of neural networks. Multi-layer-perceptron (MLP), radial-basis-function (RBF), and support vector machines (SVM) are applied in [CSL00], [SNL06]. Data from Fourier analysis of the input current waveform of multiple devices are used to train the models. A comparison of performance showed that multi-layer-perceptron and SVM-based models are good to determine the presence of particular loads based on their harmonic signatures.
Cons:

- These methods cannot visualize the high dimensional data before and after the pattern recognition process. SVM can give good accuracy using non-linear kernel, but it does not show the reason of the failure and which load is most likely to be recognized.

3 Base Papers

One of our base papers is [BMY18]. Post segmentation of the constituent appliances from the acquired raw data, our task will be to identify these said appliances.

3.1 WHAT is the method and WHY utilize it

Neural Networks have been a largely un-utilized technique in this application. Ensemble methods are used because they have been shown to give much more accurate results in applications where we expect diverse input vectors. Ensemble methods rely on the observation that the results of multiple weakly trained networks when combined appropriately, outputs a comparatively better result. There are different ensemble techniques that can be used to combine the results. These techniques differ majorly on the basis of the composition of constituent networks (homogeneous, heterogeneous).

3.2 Detailed Explanation

The sampling frequency of the data-set (PLAID plug load appliance identification data-set) is 30KHz with a grid frequency of 60Hz. One of the advantages of Neural Network based techniques is one of not being reliant on extraction of features that are hard-coded.

1. Using the provided sampling and grid frequencies, we extract one complete cycle from the raw I and V data. Each period will have a total of $d = f_s/f_g$ samples per period.

2. Normalization of data on the range of $[-1, 1]$. This is a standard procedure which is known to aid the learning of Neural Networks.

3. We then construct the input vector for the Network by stacking the normalised I and V values to create a $2d \times 1$ dimensional vector.

4. We augment/expand the data by introducing phase shift of ϵ samples d/ϵ times. The advantage of this step is that it removes the need to phase align the data and makes the Network much more robust to phase variations in the input data. Neural Networks are also very data hungry algorithms and thus benefit from more data.

3.2.1 Ensembling

Ensembling is a techniques which is very well known for increasing the accuracy and robustness of the Network to input data especially in the case where the learning algorithms is sensitive to changes in training set. It combines multiple small scale neural networks trained for completing small subsets of a problem to determine the solution to the bigger problem as a whole. Specifically we use the **Bootstrap Aggregation** ensembling technique.

Going by the notation of the basis paper, Given a set $\Omega = \{w_m\}_{m=1}^{M}$ of M classes, for each class combination $(w_i, w_j)_{i<j}$, a binary classification neural network $\hat{\theta}_{w_i,w_j}$ is trained on the appropriately selected subset of training data(i.e. where the true class of the example is w_i or w_j). Hence in total, we train $\binom{M}{2}$ base models.

Finally, our base neural networks output:

$$\hat{\theta}_{w_i,w_j}(x) = \left[\hat{p}_{w_i,w_j}(x), \hat{p}_{w_j,w_i}(x)\right]$$

where, $\hat{p}_{w_i,w_j}(x)$ is the probability that the input data x belongs to class w_i over class w_j in which case, the target vector for our network $\hat{\theta}_{w_i,w_j}$ becomes $[1, 0]$.

Our final ensemble prediction can take two forms:

Confidence Weighted Voting

$$\hat{w}(x) = \arg\max_{w_i \in \Omega} \sum_{j \neq i} \hat{p}_{w_i,w_j}(x)$$

Un-weighted Majority Voting

$$\hat{w}(x) = \arg\max_{w_i \in \Omega} \sum_{j \neq i} \mathbb{1}\big(\hat{p}_{w_i,w_j}(x) > \hat{p}_{w_j,w_i}(x)\big)$$

here $\mathbb{1}$ is the indicator function to return binary output based on the parenthesized condition.

Finally, the author uses validation based early stopping to prevent over-fitting utilizing 30 % of the train set as validation.

3.3 Evaluation

The author uses the PLAID publicly available data-set with $M = 11$. Hence a total of $\binom{M}{2}$ base networks are trained. The dimensions of the networks are as follows:

2 layer fully-connected Neural Network

$2d$ input neurons

30 hidden neurons

2 output neurons

Due to existence of transients, the last two cycles of each measurement are taken. $\epsilon = 10$ samples expands the data-set by a factor of $d/\epsilon = 50$. The $\tanh$ activation function is chosen for the neurons expect for the output layer which utilizes the $softmax$ function. Further, the utilize MATLAB's implementation of conjugate gradient descend. Samples from one building are separated out as the test set.

4 Results

F!S = F-1 Score

TPR = recall

PPV = precision

TNR = specificity

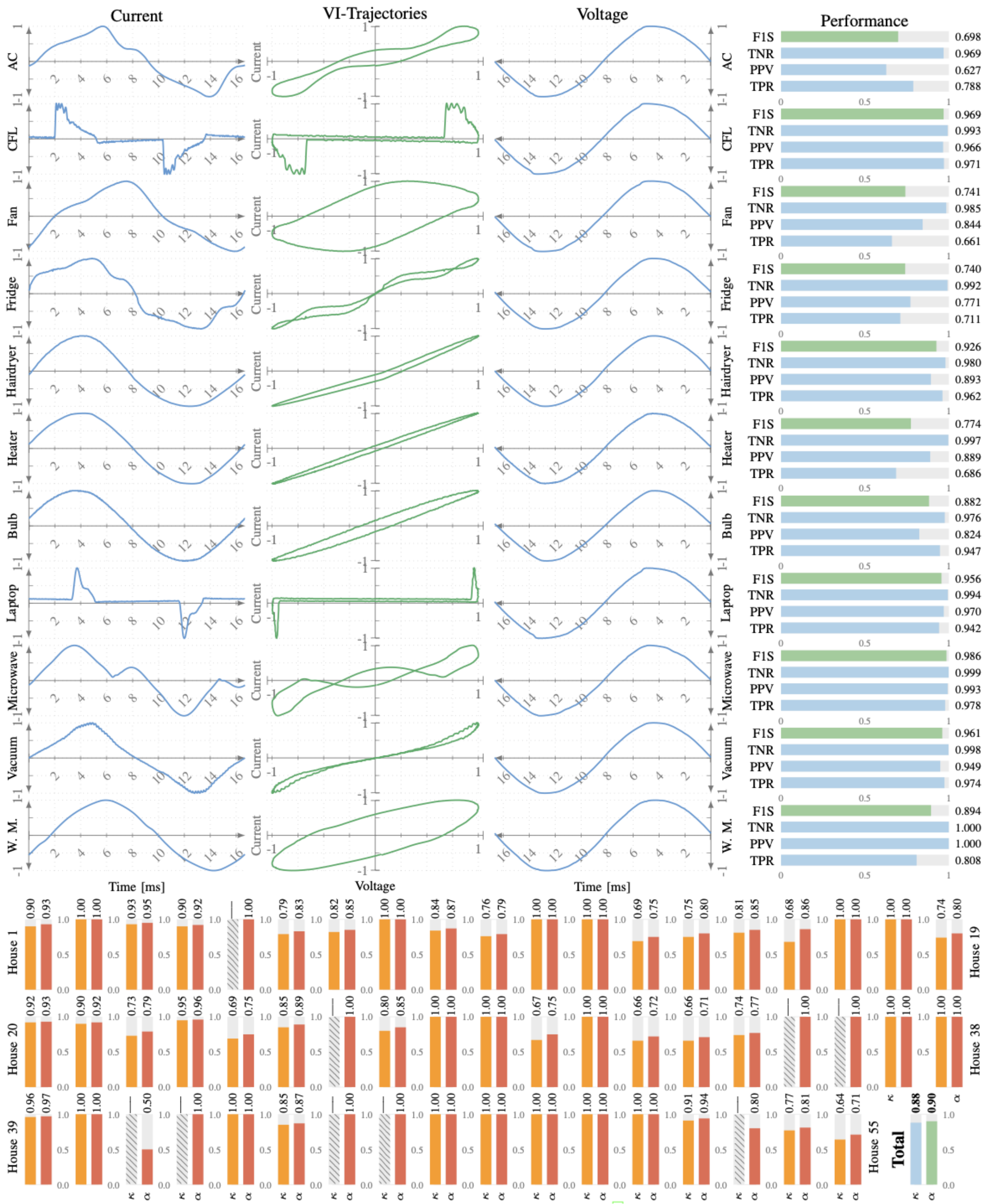


Figure 4: Current, voltage, and VI-trajectories of selected samples from PLAID dataset [Gao+14] are shown to the left. The appliance categories and IDs, from top to bottom, are (1) air conditioner, 1010, (2) CFL, 20, (3) fan, 766, (4) fridge, 6, (5) hairdryer, 444, (6) heater, 716, (7) bulb, 57, (8) laptop 28, (9) microwave, 10, (10) vacuum cleaner, 730, and (11) washing machine, 488. The per-category evaluation metrics are shown to the right while the per-house metrics are in the bottom. The best evaluation results are = 0.882 and = 0.897.[BMY18]

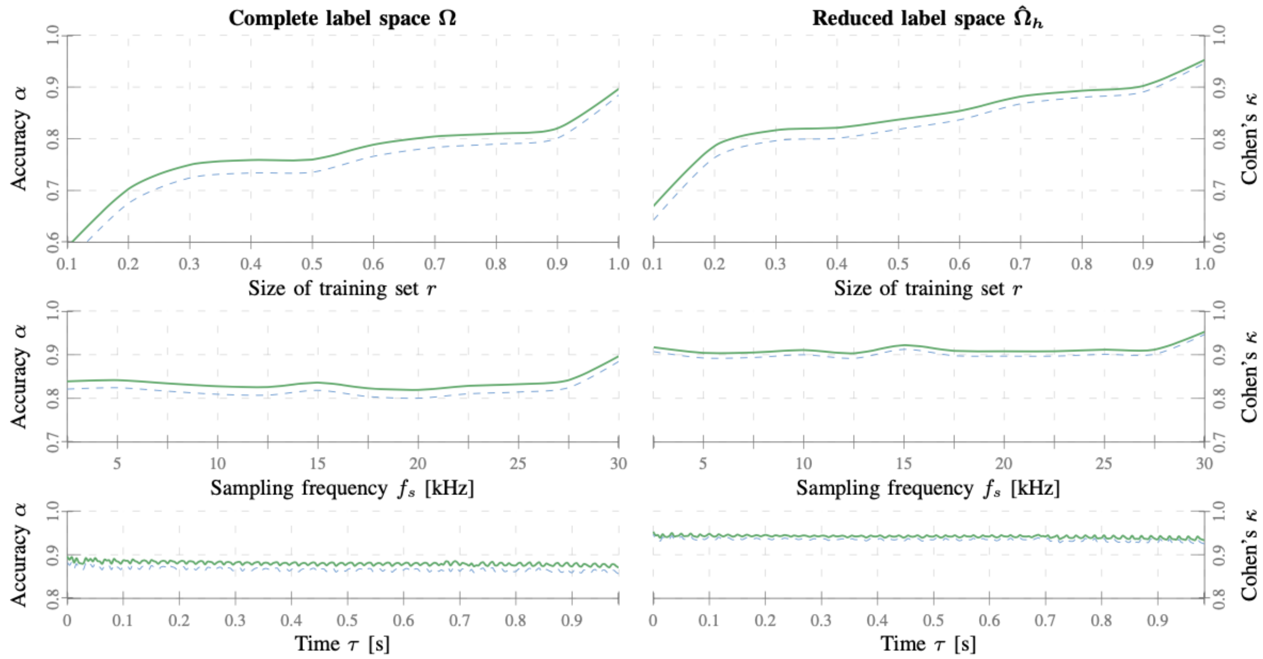


Figure 5: Aggregate evaluation results as a function of (a) training set size, (b) sampling frequency, (c) time shift. On the right are the same experiments with reduced label spaces based on prior knowledge of the label space for each target household[BMY18]

- As we can clearly see in the experimental results shown in figure 5, Reduction in training set size to a factor r has a very noticeable and drastic effect on the accuracy of the network.
- Although the reduction in sampling frequency has a visible effect, the model is able to maintain the accuracy above 80% even at sampling rates lower than 5KHz. This shows that most of the extracted features are [present in the lower frequencies.
- We can see in the third study that introducing phase displacement has negligible effect on the accuracy of the network.
- Knowledge about the list of appliances of each house hold can noticeably improve the performance. However, it must be kept in mind that the availability of this information is not easy.]

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