INDiC: Improved Non intrusive load monitoring using load Division and Calibration

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***Abstract*—Non-Intrusive appliance load monitoring (NIALM) is the process of disaggregating the overall electricity usage into constituent appliances. In this paper we extend the Combinatorial Optimization (CO) approach for disaggregation, which was originally proposed in the seminal work on NIALM, in following two ways: 1) Breaking the problem into subproblems and reducing the state space; 2) Applying additional constraints backed by sound domain expertise. We evaluate our approach using REDD dataset and show practical problems which need to be solved while dealing with the dataset. We also propose a metric for evaluating NILM, which we believe overcomes many shortcomings of commonly used metrics.**

I. INTRODUCTION

Buildings account for significant proportion of overall energy use in both the developing (e.g. 47% of total energy in India [1]) and the developed (e.g. 41% and 45% in US and UK respectively) countries. Modest improvements in building energy use can result in significant aggregate impact at the national scale. While several automation and management systems have been proposed for improving the operational efficiency of building systems, such systems typically lack the ability to provide detailed consumption information (e.g. appliance level consumption). Prior work [2] has shown that better feedback systems, enabling appliance level consumption, that provide insights about occupant's energy usage information further encourages energy saving behavior resulting in 5-15% savings in electricity usage.

Measuring each appliance's consumption separately, for providing such a feedback, is both prohibitively expensive and difficult to manage. Alternatively, prior research has proposed Non Intrusive Appliance Load Monitoring (NIALM) that involves separating the aggregated electricity consumption obtained at the meter level into individual appliance consumption. Several modeling and inference approaches have been proposed (e.g. Factorial Hidden Markov Model [3], Combinatorial Optimization [4]) in the past to address NIALM with varied level of accuracy. NIALM work typically assumes that all the loads are assigned to the same meter. However, many practical scenarios (e.g. use of 2-phase supply in many homes in USA and 3-phase supply for many homes in India) involve load division across different phases coming at the home level. Automated assignment of different loads in a home to each phase followed by NIALM application on each phase separately can reduce the overall modeling and inference complexity.

Further, the measurements, both at the meter level and at the appliance level, are often taken with different equipments (Current Transformers, in-line measurements, ICs[1]) each with their own accuracy levels. Calibrating these diverse measurements will be beneficial for NIALM modeling and inference. Grid conditions such as voltage fluctuations further motivate calibration. Motivated by these practical scenarios, we propose INDiC- **I**mproved **N**IALM using load **Di**vision and **C**alibration. Specific research condtributions of our work are:

- Novel approach named INDiCthat involves two simple pre-processing steps - Load Division (i.e. automated assignment of different loads in a home to each of the separate Mains) and Calibration (accounting for varied measurement accuracy across different equipments), that can be applied in a generic manner across several proposed NIALM modeling and inference approaches to further improve their accuracy.
- Extensive empirical validation, using publicly available REDD [5] dataset, establishing the effectiveness of INDiC, specifically for Combinatorial Optimization based NIALM.
- Release of open source implementation of the proposed work for comparative analysis with other NIALM approaches as an IPython notebook[2].

We believe that this is the first extensive release of a generic NIALM code base that can be used across many of the publicly available datasets and with several existing NIALM modeling and inference approaches.

II. RELATED WORK

Non-intrusive appliance load monitoring was first studied by Hart [4] in the early 1990s by examining signatures in aggregated load to indicate activities of appliances. The problem has been well studied in recent years ([6], [7], [8]) and NIALM systems can broadly be divided into two categories based on whether supervised or unsupervised disaggregation methods are used. Supervised learning techniques include optimization-based methods such as integer programming [9] and genetic algorithms [10]. These approaches are compute intensive and appliances with similar or overlapping load signatures are

[1]Example IC for power measurement is Maxim 78M6612
[2]http://www.ipython.org

difficult to discern. Other machine learning techniques (such as Artificial Neural Network (ANNs) [11] and Hidden Markov Models (HMM) [12]), have also been shown to work well for the task. Variants of HMMs such as factorial hidden Markov models (FHMMs) [3], additive FHMMs [13], conditional factorial hidden semi-Markov models [14] and difference HMMs [15] have been studied. In factorial HMMs several models evolve independently and in parallel and the observed output is some joint function of all the hidden states; additive HMMs allow emission of a single real-valued (unobserved) output from each HMM and the output is the sum of these HMMs. In difference HMMs [15] each appliance's load is modeled using a graphical model and it is disaggregated from the aggregate power – this process is repeated iteratively until all appliances for which general models are available are disaggregated. It is therefore possible to infer the probability that a change in aggregated power was generated by two consecutive states of an appliance. The applicability of these sophisticated techniques are generally hindered by the difficulty of inference from models with a large number of HMMs. Rahayu et. al. [16] propose a discriminative model for energy disaggregation that predicts the most likely appliance state configuration from aggregated load using nonparametric classification algorithms. They posit that "subset sum" type techniques are not very effective since a large portion of the home energy is not monitored directly. In this paper, we put forward a simple idea – the aggregated load can be further split up by information on mains and knowing which appliance is assigned to which main. This would make the task of disaggregation inherently easier by solving a simpler optimization problem and most of the above sophisticated machine learning based modeling approaches can still be applied to the task[3].

Several datasets have been made publicly available for benchmarking energy disaggregation algorithms including REDD[5], Blued[17], Pecan[18] and Smart*[19]. Our empirical analysis is on the REDD data primarily because this is the most popular data set for evaluating state-of-the-art NIALM approaches.

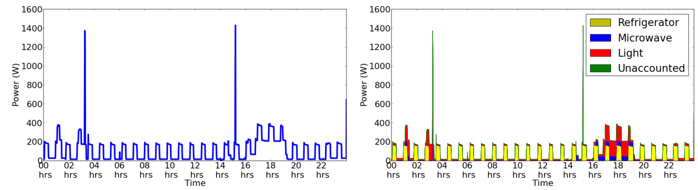
III. NIALM

A typical NIALM setup involves measuring the power mains with smart meters and individual appliances with appliance meters for ground truth. The NIALM problem in supervised setting is formulated as predicting the power sequence for n^{th} appliance, y^n, given the measured power sequence for each appliance θ^n (measured via appliance meters) and the total aggregate power sequence x (measured via smart meters). Remaining terminologies and functions are defined in Table I [5], [15], [4]. Figure 1 shows the process of disaggregation applied to a house mains, whereby the consumption patterns of 3 appliances: refrigerator, lighting and microwave can be seen. It must be highlighted that it is improbable to instrument all the appliances in a home, thus, there will be some unaccounted power, which can also be seen in the figure.

Combinatorial Optimization(CO): At a given time an appliance can only be in a single state which is given by:

$$\sum_{k=1}^{k=K} z_{t,k}^{n} = 1$$

[3]The use of combinatorial optimization is only for the purpose of illustration and there is clearly no requirement to adhere to this modeling technique alone.



(a) Aggregate Power (b) Disaggregated Power

Fig. 1: Disaggregating a home's electrical mains into 3 appliances: refrigerator, lighting and microwave. Some power is unaccounted as complete information about all appliances is not available.

TABLE I: Terminologies and Functions

Symbol	Meaning
$t \in 1,..T$	Time slice
$n \in 1,..N$	Appliance number
$\theta^n = \{\theta_1^n, ..., \theta_T^n\}$	Measured power sequence for n^{th} appliance
$\theta^{M_1} = \{\theta_1^{M_1}, ..., \theta_T^{M_1}\}$	Measured power sequence for Mains 1
$\theta^{M_2} = \{\theta_1^{M_2}, ..., \theta_T^{M_2}\}$	Measured power sequence for Mains 2
$x = \{x_1, .., x_T\} = \theta^{M_1} + \theta^{M_2}$	Measured aggregate power sequence
$e = \{e_1, ..., e_T\}$	Aggregate noise power sequence
p	Number of electrical mains in a home
N_i $where$ $i \in 1, p$	Number of loads in i^{th} mains
$y^n = \{y_1^n, ..y_T^n\}$	Predicted power sequence for n^{th} appliance
$k \in 1, ..K$	Appliance power state
$z^n = \{z_1^n, ..z_T^n\}$	Appliance state sequence for n^{th} appliance,$z_i^n \in [1, ..K]$
$z_{t,k}^n \in 0, 1$	Whether n^{th} appliance is in k^{th} state at time t
$\mu^n = \{\mu_1^n, ..\mu_K^n\}$	Power draw by n^{th} appliance in k^{th} state
θ_{k^1,k^2}^n	Measured power sequence when n^{th} appliance transitions from k^1 to k^2 state
$Mapping[n] \in M_i$ where $i \in 1, 2$	Mapping of n^{th} appliance to i^{th} Mains
$Downsample(s, filter, resolution)$	Function to downsample a timeseries s to a $resolution$ according to specified $filter$
$Preprocess([s^1, ..s^n], method)$	Function to ensure that n timeseries start and end at same times and handling missing data using specified $method$
$Sort([s^1, ..s^n], parameter, order)$	Function to sort n timeseries according to $parameter$ in specified $order$
$Event\_Detection(s, threshold)$	Function returning magnitude and times of step events in time series whose absolute s value is greater than $threshold$

The power consumption by n^{th} appliance in k^{th} state at time t is given by:

$$\hat{\theta}^n_{t,k} = \sum_{k=1}^{K} z^n_{t,k} \mu^n_k$$

The overall power consumption of all appliances at a given time t is given by:

$$\hat{x}_t = \sum_{n=1}^{N} \sum_{k=1}^{K} z^n_{t,k} \mu^n_k$$

The error in power signal (unaccounted power) after the load assignment explained above is given by:

$$e_t = |x_t - \sum_{n=1}^{N} \sum_{k=1}^{K} z^n_{t,k} \mu^n_k|$$

Combinatorial optimization tries to find the optimal combination of appliances in different states which will minimize this error term, by the following state assignment scheme:

$$z_t = argmin_{z_t} |x_t - \sum_{n=1}^{N} \sum_{k=1}^{K} z^n_{t,k} \mu^n_k|$$

The corresponding predicted power draw by n^{th} appliance is given by:

$$y^n = \{\mu^n_{z^n_1}, ..\mu^n_{z^n_T}\}$$

This optimization problem resembles subset sum problem [20] and is NP-complete. The state space size of this optimization function is K^N, which means it is exponential in the number of appliances.

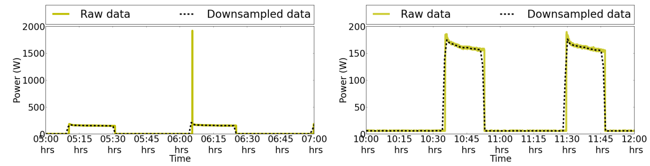
Load division: In the US, homes have 2 electrical mains corresponding to different phases. Many Asian countries have multiple meters per home. Different loads are electrically connected to different mains/meters. Since an NIALM deployment requires monitoring different electrical mains/meters, we leverage the load division to perform disaggregation on these mains separately to improve load disaggregation. Assuming that a home has p mains/meters, out of a total of N loads in the home we assign N_i loads to i^{th} mains where $Mapping[n]$ indicates the mapping of an appliance to a mains. After load assignment to different mains, the state space size for i^{th} mains is given by K^{N_i}. This leads to an exponential reduction in state space. As a practical example, if a home has two mains and 20 loads equally distributed across the two mains, state space size before load division is given by 2^{20} and after load division is 2^{10}. CO formulation for i^{th} mains after load division is given by the following optimization function:

$$z_t = argmin_{z_t} |\theta^{M_i} - \sum_{n=1}^{N_i} \sum_{k=1}^{K} z^n_{t,k} \mu^n_k| \; where\; i \in 1, p$$

The corresponding predicted appliance power sequence for appliances belonging to i^{th} mains is given by: $y^n = \{\mu^n_{z^n_1}, ..\mu^n_{z^n_T}\}$

The optimization is subject to the following constraints. Firstly, sum of loads assigned to different mains must be equal to the total number of loads. This is given by: $\sum_{1}^{p} N_i = N$

Secondly, at a given time, an appliance can only be in a single state which is given by: $\sum_{k=1}^{k=K} z^n_{t,k} = 1$



(a) Filtering startup transients

(b) Filtering voltage fluctuations and oscillations

Fig. 2: Effect of downsampling appliance data

Thirdly, an appliance can belong to one and only one mains. Thus, Mapping[n] is a one to one function.

Fourthly, the sum of power of appliance assigned to i^{th} mains is always lesser than or equal to the power of the corresponding mains, which is given by e_t term for i^{th} mains to be non negative.

IV. INDiC NIALM

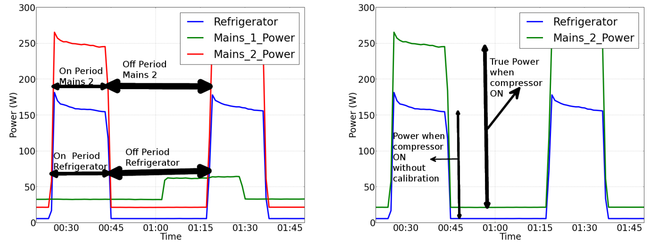
In this section we explain our algorithm- Improved Non intrusive load monitoring using load Division and Calibration (INDiC). While INDiC can be used with any modeling technique described in Section II we present INDiC-CO (INDiC using Combinatorial optimization as modeling approach). The various steps of INDiC-CO NIALM shown in Algorithm 1 are described below.

Preprocessing: Since multiple data streams (appliances and mains power time series) from varied hardware are measured, it is highly likely that some hardware malfunctions during the data collection process. In the preprocessing step we ensure that all the time series start and end at the same time and handle missing data using techniques such as forward filling (padding).

Downsampling: While performing CO it is desired that transients and fluctuations in the power signal are filtered[4]. The transients occur due to the high starting current of the appliance, whereas the fluctuations are a consequence of minor voltage fluctuations and oscillatory nature of appliances. Figure 2a and Figure 2b show how starting current and voltage fluctuations can be filtered by down sampling. Filters such as mean/median can be used to down sample a time series to a time window, where the value assigned to a time window is the mean/median of values occurring during that time window in the original series.

Assigning Loads to Mains[4]: This step aims to identify the mapping between appliances and mains. Patterns corresponding to appliances having higher peak power are generally easier to extract from main signal, thus we sort the appliance in decreasing order of peak power. Starting from the appliance having highest peak load we compare its power at all times with both mains. If at any time the power of the appliance is greater than either mains, we can assign the appliance to the other mains. However, if we are not able to assign an appliance to mains this way, we find the times when events (absolute change in power is greater than a threshold of 15

[4]While our approach is fine tuned for 2 Mains it can be easily extended to support further load division



(a) Assigning refrigerator to Mains 2 since refrigerator power > Mains 1 power and events in Mains 2 and refrigerator occur at same time

(b) Calibrating refrigerator power consumption

Fig. 3: Calibrating and assigning refrigerator to Mains 2

Watts) occur in the appliance power series. This should be a subset of times of events occurring in one of the mains to which this appliance is assigned. The threshold of 15 Watts is to ensure that minor voltage fluctuations are not counted as events. After an appliance has been assigned to a mains, its power sequence is subtracted from the corresponding mains to simplify mains assignment for remaining appliances. Figure 3a shows how refrigerator is assigned to mains 2 since during this time interval its power is more than that of mains 1. Also, one may verify it by observing that the events in mains 2 and refrigerator power series occur at same time.

Clustering: We use prior knowledge about number of states (K) of an appliance to cluster its power draw into different states. We chose kmeans++[21] as our clustering approach owing to its scalability and the improvements it offers over kmeans in terms of speed and accuracy.

Appliance Power Calibration: Power measured by appliance level meters may need calibration due to the following reasons:

- Difference in measurement of different measurement instrument (diagram showing CC, ZWave, etc) [22]
- Fluctuation in voltage causes power to fluctuate as well
- Missing meta data, whether real or apparent power is being measured at appliance level

In comparison to appliance data, mains data is usually measured using better precision hardware. Thus, we keep mains data as a reference and calibrate appliance data against it. Since in OFF states (state 1) appliance power consumption is almost zero, it does not require any calibration. We find out times when appliance transitions from a lower state to a higher state. During these times, we find the ratio of the magnitude of power change occurring in the assigned mains and the appliance. This ratio serves as a corrective multiplicative factor for a particular state of an appliance. Cluster centroids obtained in the previous step are multiplied by this factor to obtain calibrated cluster centroids.

Combinatorial optimization: Combinatorial optimization is now performed separately for both mains as per the description in Section III.

Algorithm 1: INDiC-CO

Input: $x, \theta^n, \theta^{M_1}, \theta^{M_2}$
Output: y^n, μ_k^n

Preprocessing

$\theta^1, ..\theta^n, \theta^{M_1}, \theta^{M_2} \leftarrow Preprocess([\theta^1, ..\theta^n, \theta^{M_1}, \theta^{M_2}], forward\ fill)$

Downsampling

for $n \in 1, N$ **do**
  $\theta^n \leftarrow Downsample(\theta^n, mean, resolution)$
$\theta^{M_1} \leftarrow Downsample(\theta^{M_1}, mean, resolution)$
$\theta^{M_2} \leftarrow Downsample(\theta^{M_2}, mean, resolution)$
$s \leftarrow Sort([\theta^1, ..\theta^n], peak\ power)$

Appliance to Mains mapping

for $Appliance\ n \in s$ **do**
  if $\theta_t^n > \theta_t^{M_1}\ for\ any\ t \in 1, T$ **then**
    $Mapping[n] = M_2$
  else if $\theta_t^n > \theta_t^{M_2}\ for\ any\ t \in 1, T$ **then**
    $Mapping[n] = M_1$
  else
    if $Event\_Detection(\theta^n, threshold).Times \subset Event\_Detection(\theta^{M_1}, threshold).Times$ **then**
      $Mapping[n] = M_1$
    else
      $Mapping[n] = M_2$
  $\theta^{Mapping[n]} \leftarrow \theta^{Mapping[n]} - \theta^n$

Divide data into train and test set

Clustering on train set

for $n \in 1, N$ **do**
  $\mu_k^n \leftarrow Cluster(\theta^n, K, clustering\_algorithm)\ for\ k \in 1, K$

Calibration on train set

for $n \in 1, N$ **do**
  for $k \in 2, K$ **do**
    $\mu_k^n \leftarrow \frac{\mu_k^n * Step\_Changes(\theta_{k-1,k}^n, threshold).Magnitude}{Step\_Changes(\theta_{k-1,k}^{Mapping[n]}, threshold).Magnitude}$

Combinatorial optimization on test set

Solve combinatorial optimization as described in Section III
return y^n, μ_k^n

V. Evaluation

We use Reference Energy Disaggregation Data Set (REDD) [5] for validating our algorithms. This dataset contains power data for mains (2 phases) as well as appliances from 6 homes in Boston area collected in the summer of 2011. The data is made available as raw, high frequency (sampled at 15 KHz) and low frequency (Mains at 1 Hz, appliances at 0.3 Hz). Considering the practical implications of residential smart meter installation, we believe that low frequency data represents the most realistic scenario and thus we use this data for analysis.

A. Evaluation Metric

Commonly used metrics such as accuracy, sensitivity and specificity can be misleading when applied to NIALM. We illustrate this with the help of a confusion matrix whose [m,n] entry in indicates the number of times appliance in state m is predicted to be in state n. It can be seen from the confusion matrix in Figure 4 that since stove is mostly in state 1 (Off), accuracy will be largely decided by accuracy for this state. This will overshadow the accuracy for state 2 (On) which is unintended. Thus, we use the following metrics which have been used in the past work [15], [5]:

Mean Normalized Error (MNE%): Normalized error in the energy assigned to an appliance n over time period T, given by:

$$MNE(n) = \frac{|\sum_{t=1}^{T}\theta_t^n - \sum_{t=1}^{T} y_t^n|}{\sum_{t=1}^{T}\theta_t^n} \tag{1}$$

above metric will give a 0 MNE for cases such as follows: $y^n = [0, 10, 0, 10]$ and $\theta^n = [10, 0, 10, 0]$, which can be misleading. Thus, we propose a modified Mean Normalized Error metric further referred as MNE which is sensitive to such cases.

$$MNE(n) = \frac{\sum_{t=1}^{T}|\theta_t^n - y_t^n|}{\sum_{t=1}^{T}\theta_t^n} \tag{2}$$

Since it is a known fact that $|\sum a - \sum b| \leq \sum |a-b|$ where a and b are vectors containing floating point numbers, our results might look worse than if the original definition of MNE were used.

RMS Error (RE Watts): RMS error in power assignment to an appliance n per time slice t given by:

$$RE(n) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\theta_t^n - y_t^n)^2} \tag{3}$$

Both these quantities represent error, the lesser they are the better is the prediction.

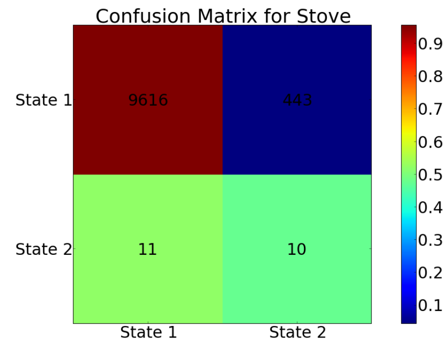


Fig. 4: Confusion Matrix showing predicted state accuracy for Stove

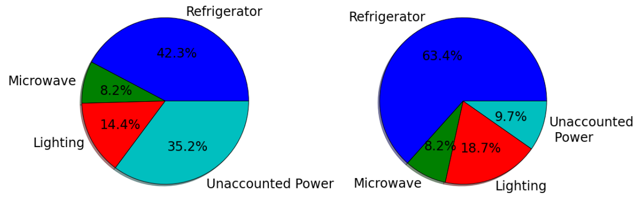
B. Empirical Analysis

We performed empirical analysis on REDD dataset Home 2, which consists of 11 channels (including 2 mains and 9 appliances). We believe that the same analysis can be easily repeated across multiple homes. We preprocessed the data and downsampled it to one minute using mean filter. Since we had two weeks of clean data, we used the first week as the train set and the second week as the test set. We used INDiC-CO algorithm described earlier to assign loads to different mains and calibrate appliance data. Table II shows the assignment of loads to different mains. Further this table also shows the learnt power states of these appliance via k-means++ clustering. Refrigerator and lighting showed significant difference in power states post calibration. Based on prior experience and appliance circuity, we believe that since only these two appliances needed calibration, it may be a case that the appliance level monitor measured real power instead of apparent power. These loads constitute a major chunk of Mains 2 power. Figure 5 shows the reduction in unassigned power due to calibrating these two appliances. Two appliances - washer dryer and disposal are ignored from the analysis since washer dryer had a peak power consumption of 8 W (which means it was Off throughout) and the contribution of disposal to overall power was less than 0.1 %.

To show the significance of load division and calibration, we considered 4 possible cases: i) no calibration, no load division; ii) no calibration, load division; iii) calibration, no load division; iv) calibration, load division (INDiC-CO). These results are presented in Table III. For the overall dataset, it can be seen that MNE reduces from 187% to 39%, RE reduces from 478 W to 168 W, after applying INDiC-CO. All appliances show reduction in MNE and RE after applying INDiC-CO. However, there is significant improvement in correctly predicting refrigerator and lighting. Figure 6 shows the confusion matrix for refrigerator prediction pre and post applying INDiC-CO. It can be seen that after applying INDiC-CO there is a vast improvement in predicting refrigerator's state 1 and 2.

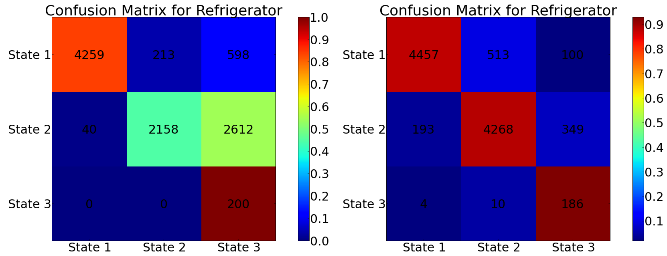
VI. Conclusion and Future Work

The conclusion goes here. We also provide mains load assignment of all 6 homes from REDD to further the research in this direction.



(a) Without applying calibration (b) After applying calibration

Fig. 5: Mains 2 Break down by load



(a) Without applying DiCaCo (b) After applying DiCaCo

Fig. 6: Confusion Matrix for refrigerator disaggregation

- Applying model on noisy datasets
- 2 D CO (when Real and Reactive Power are known)
- Factoring in Time of Day etc.
- Factoring in Appliance Correlation
- Factor in switch continuity, essentially leads to Factorial HMM
- Distributed NILM

TABLE II: Mains assignment and appliance states power

Appliance	Mains	States Power (W)					
		Pre calibration			Post calibration		
Refrigerator	2	7	162	423	9	210	423[5]
Microwave	2	10	832	1730	10	832	1730
Lighting	2	9	96	156	10	110	178
Dishwasher	1	0	256	1195	0	256	1195
Stove	1	0	374	-	0	374	-
Kitchen	1	5	727	-	5	727	-
Kitchen 2	1	1	204	1032	1	204	1032

TABLE III: MNE and RE with and without INDiC-CO

	Without calibration				With calibration			
	Without load division		With load division		Without load division		With load division	
Appliance	R.E. Watts	M.N.E. %	R.E. Watts	M.N.E. %	R.E. Watts	M.N.E. %	R.E. Watts	M.N.E. %
Refrigerator	136	109	71	32	130	95	59	21
Microwave	102	98	97	110	104	97	96	109
Lighting	51	164	48	195	44	83	38	60
Dishwasher	406	2947	63	100	377	2517	63	100
Stove	77	1191	36	281	75	1118	36	281
Kitchen	64	182	58	168	69	196	58	168
Kitchen 2	95	267	91	117	92	230	91	117
Overall	478	187	161	58	450	157	168	39

- Adaptive Learning

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