



## Low-Complexity Non-Intrusive Load Monitoring Using Unsupervised Learning and Generalized Appliance Models

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# Low-Complexity Non-Intrusive Load Monitoring Using Unsupervised Learning and Generalized Appliance Models

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**Abstract**— Awareness of electric energy usage has both societal and economic benefits, which include reduced energy bills and stress on non-renewable energy sources. In recent years, there has been a surge in interest in the field of Load Monitoring, also referred to as Energy Disaggregation, which involves methods and techniques for monitoring electric energy usage and providing appropriate feedback on usage patterns to homeowners. Unsupervised Non-Intrusive Load Monitoring is a key area of study, and practical solutions have wide implications for energy monitoring. In this paper, a low-complexity unsupervised NILM algorithm is presented, which is designed toward practical implementation. The algorithm is inspired by a fuzzy clustering algorithm called Entropy Index Constraints Competitive Agglomeration (EICCA), but facilitated and improved in a practical load monitoring environment to produce a set of generalized appliance models which are used to detect appliance usage within a household. Experimental evaluation conducted using energy data from Reference Energy Data Disaggregation Dataset (REDD) indicates that the algorithm has out-performance for event detection compared with recent state of the art work for unsupervised NILM when considering common NILM metrics such as Accuracy, Precision, Recall, F1-Measure, and Total Energy Correctly Assigned (TECA).

**Index Terms**—Home Energy Management, Non-Intrusive Load Monitoring, Unsupervised Learning, Appliance Modeling

## I. INTRODUCTION

Understanding the way people consume electric energy has a number of widespread benefits. From the viewpoint of consumers, they can tell exactly how their daily activities are contributing to their energy bill, and furthermore what they can do to improve their energy usage. On the side of the energy suppliers, the provision of such electric energy consumption information can enable them to better align their electric energy generation and transmission with the requirements of

consumers. Given the increasing need for electric energy with the continued growth of IoT technologies and the growing inclusion of individuals who previously had no access to electricity to the national electricity grid, it is important to ensure the optimal usage of this resource. While a number of nations, mainly developed nations, have begun to widely adopt renewable sources of energy, quite a number still rely on coal-powered electricity generation which has a significant effect on the environment, both on local and global scales. In summary, understanding how people utilize electric energy can be beneficial to both financial standing and also well-being.

Modern approaches to energy management utilize Smart Home technologies to enable energy efficiency and conservation [1] [2] [3]. While these approaches are extremely beneficial, the required infrastructure presents a barrier for adoption. The work presented in this paper takes into consideration home environments that are resource constrained but require a means to monitoring energy usage nonetheless.

Achieving the goals of energy efficiency and energy conservation first requires the ability to monitor electric energy usage. This is done via smart meter technology which has seen a surge in deployments in recent years. Smart meters are able to capture the electric energy signal and transmit it to networked devices in order to offer further analysis and data mining. Such a process is referred to as Load Monitoring or alternatively Energy Disaggregation. Load Monitoring is categorized as either Intrusive, Semi-Intrusive, or Non-Intrusive. Intrusive Load Monitoring (ILM) monitors energy usage via smart meters that are attached to each appliance or device that needs monitoring. Semi-Intrusive Load Monitoring (SILM) utilizes a subset of smart meters to capture a subset of electric energy usage and infers the rest. Lastly, Non-Intrusive Load Monitoring (NILM) makes use of a single smart meter which captures the aggregated electric energy signal. The goal is then

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to discover the appliances that are contributing to the aggregated signal. NILM is the preferred approach for real-world solutions due to the fact that it has a reduced financial cost and lessens the burden of involvement for the energy monitoring process on the user or homeowner. Equation (1) presents a summary of the NILM problem.

$$P(t) = \sum_{i=1}^n P_i + e(t) \quad (1)$$

where  $P(t)$  is the total power load as seen at time  $t$ ,  $P_i$  is the individual power contribution of appliance  $i$ , and  $e(t)$  is a small noise or error term.

Unsupervised learning has recently gained popularity in NILM work. The main benefit of unsupervised learning is the removal of the dependence on a set of training data. This results in solutions that can be deployed and learn according to the environment where they operate, and therefore greatly simplifies the entire process. One of the major challenges with the application of unsupervised learning in NILM is minimizing the computational complexity as solutions will be deployed in resource constrained environments such as homes. In this work, a fuzzy clustering algorithm is proposed for NILM to address this challenge. An unsupervised approach is therefore presented to provide a low-complexity NILM solution, and a practical approach to offering informative feedback to homeowners.

The rest of the paper is structured as follows: Section II provides a review of recent research work on NILM. Section III introduces the proposed algorithm and provides a walkthrough of its sub-components. The evaluation of the algorithm is presented in Section IV with additional discussion on the outcomes of experimental evaluation processes. Lastly, Section V presents a summary of the research work and a discussion on possible future extensions.

## II. RELATED WORK

NILM was first proposed by Hart in the 1990s [4]. Since then numerous research work has been published with improvements to the initial design and different approaches all with the goal of achieving the same objectives. The typical NILM workflow consists of the following steps: 1) Power Signal Acquisition, 2) Event Detection, 3) Feature Extraction, and, 4) Learning & Inference. The first step involves acquiring aggregated energy measurement at an adequate rate so that distinctive load patterns can be identified. Low sampling rates of 1Hz are typically used for NILM as they can be captured by smart meters without modification. High-frequency sampling rates require sophisticated hardware which can introduce additional costs to the energy monitoring process. With the aggregated energy having been acquired, the next step is then to detect the operating states of appliances. The current NILM approaches can be classified as *event-based* or *state-based*, depending on the event detection strategies that are utilized. Event-based approaches focus on state transition edges generated by appliances and use change detection algorithm to identify the start and end of an event [5] [6]. All appliance types have a unique energy consumption pattern often termed as appliance signatures. This unique energy consumption pattern is often used to uniquely identify and recognize appliance

operations from the aggregated load measurements [7]. There are two main classes of appliance signatures used by NILM researchers for appliance identification, namely, *transient* features and *steady-state* features. Transient features are short-term fluctuations in power or current before settling into a steady-state value. These features uniquely define appliance state transitions by extracting features such as shape, size, duration, and harmonics of the transient [7]. Steady state features are related to more sustained changes in power characteristics when an appliance changes its running state, as shown in Fig. 1. These features include commonly cited *active power*, *reactive power*, *current*, and *current and voltage waveforms*. The final step of the NILM process is then to analyze the extracted appliance signatures and learn a set of appliances models that can be used to infer the electric energy consumption.

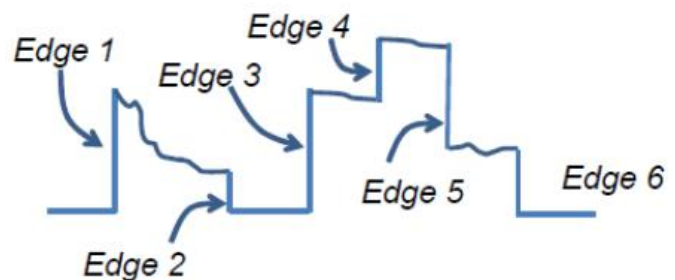


Fig. 1. Rising and falling edges possibly indicating changes in state of appliances and therefore significant events of energy usage.

Several state of the art unsupervised NILM algorithms have been proposed using different approaches including variants of Hidden Markov Models (HMMs), and most recently Graph Signal Processing (GSP), and Deep Learning.

Several HMM-based NILM algorithms for energy disaggregation at low sampling rate have been proposed in the literature. In [8] an unsupervised technique for energy disaggregation using a combination of four FHMM variants is proposed. The authors use low-frequency real power feature and assume a binary state of appliances (ON and OFF state only). To learn model parameters, Kim's approach uses Expectation Maximization (EM) algorithm and employ Maximum Likelihood Estimation (MLE) algorithm to infer load states. The performance of Kim's technique is limited to few number of appliances, requires appliances to be manually labelled after disaggregation, and suffers from high computational complexity which makes it unsuitable for real-time applications [9].

The work presented in [10] proposes a new inference algorithm for unsupervised energy disaggregation called Additive Factorial Approximate MAP (AFMAP) that is computationally efficient and does not suffer from local optima. The AFMAP algorithm is used to perform approximate inference over the additive FHMM. However, the model requires appliances to be manually labelled after off-line disaggregation and have a low performance for electronics and kitchen appliances.

Parson et al. [11], introduce an approach that uses a different HMM from [10] as Bayesian network for disaggregation of active power with 60s sampling rate. To perform inference, the

1 authors use an extension of the Viterbi algorithm and propose  
 2 an EM training process to build a generic appliance model for  
 3 learning the model parameters. This generic model is then tuned  
 4 to specific appliance instances using only aggregate data from  
 5 home in which NILM is being applied.

6 A fully unsupervised NILM framework based on non-  
 7 parametric FHMM using low-frequency real power feature is  
 8 presented in [12]. They use the combination of slice sampling  
 9 and Gibbs sampling to do inference that simultaneously detect  
 10 number of appliances and disaggregate the power signal from  
 11 the composite signal. However, for larger disaggregation  
 12 problems this inference algorithm becomes a limitation as it  
 13 may get stuck in local optima [13].

14 Makonin et al. [14] present an NILM algorithm for low-  
 15 frequency sampling rate that uses a super-state HMM in which  
 16 a combination of modeled appliances states is represented as  
 17 one super state. The authors propose a new variant of Viterbi  
 18 algorithm called sparse Viterbi algorithm. This algorithm  
 19 performs computationally efficient exact inference instead of  
 20 relying on approximate inference method like in FHMM based  
 21 approach.

22 Despite the fact that HMM-based NILM approaches have  
 23 been widely used in energy disaggregation they require an  
 24 expert knowledge to set a-priori values for each appliance state.  
 25 Their performance is therefore limited by how well the  
 26 generated models approximate appliance true usage [15].

27 Graph Signal Processing (GSP) or signal processing on graph  
 28 is an emerging field that extends classical signal processing  
 29 theory to data indexed by general graphs [16]. GSP represents  
 30 a dataset using a graph signal defined by a set of nodes and a  
 31 weighted adjacency matrix [17].

32 The first GSP-NILM approach that is neither state-based nor  
 33 event-based was presented in [18]. The authors, leverage on the  
 34 work by [19] to perform low-complexity multi-class  
 35 classification of the acquired active power readings without the  
 36 need for event detection to detect appliance changing states.  
 37 However, this approach is supervised and employs GSP only  
 38 for data classification [17].

39 Zhao et al. [15, 17] propose a blind, low-rate and steady state  
 40 event-based GSP approach that does not require any training.  
 41 The proposed GSP-NILM disaggregates any aggregate active  
 42 power dataset without any prior knowledge and relies upon the  
 43 GSP to perform adaptive threshold, signal clustering and  
 44 pattern matching.

45 Different Deep Learning architectures such as Recurrent  
 46 Neural Network (RNN) [20], Convolutional Neural Network  
 47 (CNN) [20] [21] [22], Auto Encoder [20] and a combination of  
 48 Deep Learning and HMM [22] [23] [24] have been employed  
 49 to the energy disaggregation problem. While Deep Learning  
 50 approaches have achieved success in NILM with regards to  
 51 accuracy, the dependence on large amounts of data in order to  
 52 be well generalized are a hindrance for real-world applications.

53 Additional approaches for NILM include fuzzy sets [25]  
 54 [26], decision trees [27] [28], support vector machines [29]  
 55 [30], sparse coding [31] [32], metaheuristics [33], integer  
 56 programming (IP) [34] [35], and cepstrum-smoothing [36].  
 57 Further review of approaches in NILM are presented in [37]

[38] [39].

The work presented here is an extension of our previous work  
 [40] [41] which introduced an unsupervised NILM algorithm  
 based on Competitive Agglomeration (CA) [42] and  
 subsequently Entropy Index Constraints Competitive  
 Agglomeration (EICCA) [43]. In this paper we present our  
 modified unsupervised NILM algorithm which provides an  
 approach to learning appliance models without any reliance on  
 prior information or data, with the goal of providing  
 informative feedback to homeowners.

### III. PROPOSED WORK

The proposed algorithm is subdivided into a set of modules,  
 each focusing on a single aspect of the NILM process. Due to  
 the ease of installation and minimal cost we only consider the  
 use of a single smart meter which captures the data at a low-  
 sampling rate of 1Hz. We further consider the use of the active  
 power (P) appliance signature due to the fact that it can be  
 extracted from the energy signal using a simple process.

#### A. Architecture

The proposed algorithm is envisioned to function as part of a  
 wider framework encompassing the NILM process in a  
 household. This framework requires a minimal architecture  
 which includes a smart meter and a low-power energy device  
 for processing the data and disseminating information to  
 homeowners. This architecture can be seen in Fig. 2.

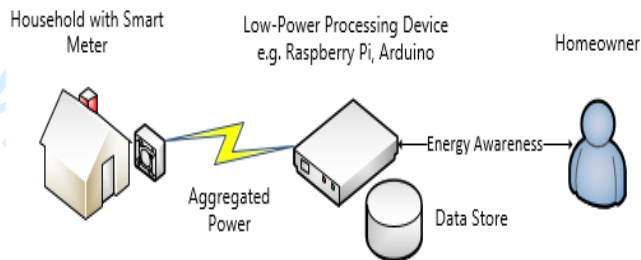


Fig. 2. Overview of energy disaggregation framework. Energy data is acquired at rate of 1Hz using a smart meter, and then sent to a low-power device for further processing. The low-power devices processes the data and provides feedback to the homeowner enabling them to be better informed about their electric energy usage.

#### B. Algorithm Overview

##### 1) Data Acquisition

The initial step is to get the necessary data required by the algorithm. This process begins by acquiring the aggregated energy data via a smart meter attached to the mains of the household. This data is then transmitted to a low-power energy device that handles the processing of the data and further communication to the homeowner.

##### 2) Event Detection and Feature Extraction

The initial step in the processing pipeline is detecting the usage of appliances given the aggregated energy data and extracting features that can be used to model appliances. This is done by recognizing events which denote significant changes in power which could be attributed to an appliance changing from one state to another. The assumption made in this step is that only a single appliance will change its state during the time

interval. To extract the features we first need to establish a *significance threshold* which will be used to filter out those events that do not provide useful information. In this work we utilize a significance threshold of  $5W$  which accounts for low power devices such as phone chargers. The feature extraction process is summarized in (2).

$$\Delta P_{t_i} = P_{t_{i+1}} - P_{t_i} \quad (2)$$

where  $\Delta P_{t_i}$  is the difference in active power between two 1 second intervals  $P_{t_{i+1}}$  and  $P_{t_i}$ . If  $\Delta P_{t_i} \geq 5W$  then the event is denoted as being significant and the difference is stored as a feature for further use.

The extracted features consist of both negative and positive transitions. Given that a negative transition will likely have a corresponding positive transition of similar magnitude and vice-versa we simplify the features by transforming them into an invariant form which is done by converting them to their absolute form. This similarity between positive and negative transitions can be seen in Fig. 3 which displays the distribution of a set of features extracted from single day energy usage in a household.

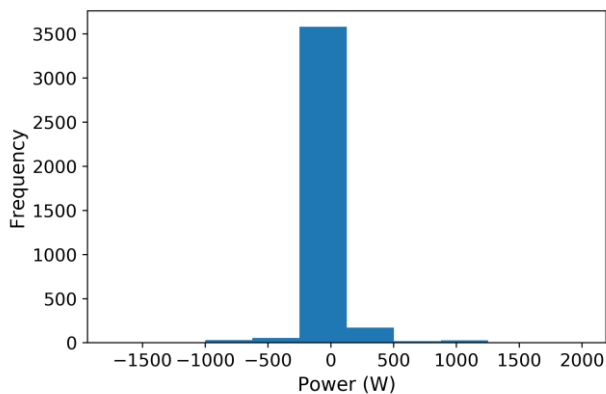


Fig. 3. Feature distribution from a single day of energy usage.

Once the features have been extracted they are then reduced to a generalized form via clustering. In order for this process to be unsupervised the number of feature clusters need not be fixed. We therefore make use of an adaptation of the EICCA which is a clustering technique that begins with an over-specified number of clusters, and gradually reduces this number by making cluster members compete for membership among the clusters. Clusters with low cardinality are eliminated upon every iteration until the clusters stabilize. This trait makes an adapted EICCA suitable to discover potential appliance types in the aggregated energy data. Such an approach also avoids additional steps required to specify the number of appliance types upfront.

### 3) Model Learning and Inference

The output of the Event Detection and Feature Detection step is a set of generalized features. These features can be used to attribute the energy usage to a group of commonly recognized power states. In order to better inform homeowners of their energy usage, these features need to be transformed into appliance models which are a composite of features. The appliance models can then better describe the energy usage to

the homeowner.

Appliance models can be broadly categorized as those with two states (ON/OFF), and those with multiple states. Appliances with ON/OFF states are referred to as Type I in NILM. Multiple state appliances covers finite states, constantly ON, and continuously variable states, which are referred to as Type II, Type III, and Type IV respectively. To define the appliance models we consider two scenarios:

#### a) Two State Appliance Models

Given that the features represent both positive and negative transitions with the same magnitude they are each expanded into two-state appliance models with the positive transition representing the ON state and the negative transition representing the OFF state.

#### b) Multi-State Appliances Models

To define multi-state appliance models we further examine the aggregated energy signal and try to match a pattern of usage where two significant events occur subsequently. This is done in two phases where we consider significant events that occur immediately after one another, and those that are separated by a single time window of steady-state. The defined appliance models are then stored for further use in inferring their usage.

The final step is to recognize the usage of appliance models in the aggregated energy signal. As the features are generalized, exact matches to significant events are not possible, we therefore considered a significant event as being recognized if the feature matched it within a 5% error margin and within  $5W$  of the magnitude of the significant event. The latter condition is introduced to cater for small variations that exceed the 5% error margin but are actually within  $5W$  of the actual event. The process for the model inference is two-fold, and is as follows:

#### a) Evaluation of Feature and Appliance Model

The first task is to evaluate the features and appliance models to verify whether they are suitable for further use in appliance usage recognition. This considers common NILM metrics such as Accuracy, Precision, Recall, F1-Measure, and Total Energy Correctly Assigned (TECA), which will be further discussed in Section IV-A.

#### b) Recognition of Appliance Model Usage

The second task is to detect significant events and attribute the energy consumption to the defined appliance models. This is done by monitoring the aggregated energy signal and comparing each significant event to the existing appliance models. Each matched significant event is tied to the operation of an appliance model, which can be used to denote patterns of energy usage in a household, and to identify periods of high energy consumption during the day.

## IV. EXPERIMENTAL EVALUATION

To validate and evaluate the proposed work, a set of experiments have been conducted making use of energy data provided by the six houses in the Reference Energy Data

Disaggregation Dataset (REDD) [44].

The experiments were setup to validate the performance of the algorithm in accordance to commonly cited NILM metrics, and most importantly the feasibility of the algorithm for practical implementation. In *Context 1* we considered the disaggregation of energy data from the six REDD houses for both a single day period and over a three day period. In *Context 2* we focused on the feasibility of the algorithm using single day energy data from REDD House 2. We further evaluated our approach to model learning and inference in this context. *Context 3* verifies the performance of the algorithm when run on a low-power energy device. The main focus of the experimentation was data from House 2 of REDD due to its common use for additional experimental evaluation outside of the NILM performance metrics in literature, and sufficient level of appliance complexity for evaluating energy disaggregation.

The parameters of the adapted EICCA were set as follows:  $C_{max} = 100$ ;  $\eta = 5$ ;  $\tau = 10$ ,  $\varepsilon = 10^{-3}$ ; and  $\varepsilon_I = 0.05$ .

The algorithm and experiments were implemented using Python 3.6 and made use of the NumPy and Pandas libraries. The experiments were conducted on a Dell Inspiron 14z-N411 computer running a Core i5-2450M processor with 8GB RAM, and 1TB storage. Context 3 was performed on a Raspberry Pi 3 Model B running a 64-bit Broadcom BCM2837 ARM v8 processor with 1GB RAM and 2GB storage.

#### A. NILM Metrics

NILM has a number of metrics that are used to evaluate different approaches used by researchers. For our experiments we considered a subset of the commonly cited metrics namely, Precision (3), Recall (4), F-Measure (5), Total Energy Correctly Assigned (TECA) (6), and Accuracy (7), in order to evaluate the performance of the algorithm.

$$\text{Precision } (P) = \frac{TP}{TP+FP} \quad (3)$$

$$\text{Recall } (R) = \frac{TP}{TP+FN} \quad (4)$$

$$f\text{-Measure } (f_1) = \frac{2 \cdot P \cdot R}{P+R} \quad (5)$$

$$\text{TECA} = 1 - \frac{\sum_{t=1}^T \sum_{i=1}^K |\hat{y}_t^{(i)} - y_t^i|}{2 \sum_{y=1}^T \bar{y}_t} \quad (6)$$

$$\text{Accuracy } (Acc.) = \frac{TP+FN}{TP+FP+TN+FN} \quad (7)$$

Where *Precision* is the positive predictive values, *Recall* is the true positive rate or sensitivity, *TP* is true-positives (correctly predicted that the appliance was ON), *FP* is false-positives (predicted appliance was ON but was OFF), and *FN* is false-negatives (appliance was ON but was predicted OFF). *F-Measure* is the harmonic mean of Precision and Recall, and *TECA* measures the amount of energy that was correctly classified.

#### B. Experiments

##### 1) Context 1: Algorithm Performance

The evaluation process of the algorithm considered single day and three energy data gathered from REDD houses 1 to 6. The first step was to validate the chosen method for event

detection and feature extraction. Fig. 4 presents the distribution of the features given their original form and after transformation by the feature extraction process from both single day and three day energy usage. The transformed features can be seen to retain their magnitude while taking on a positive only form. This indicates that our chosen approach is valid and ensures that the feature space is reduced which further simplifies future processing given a resource constrained environment.

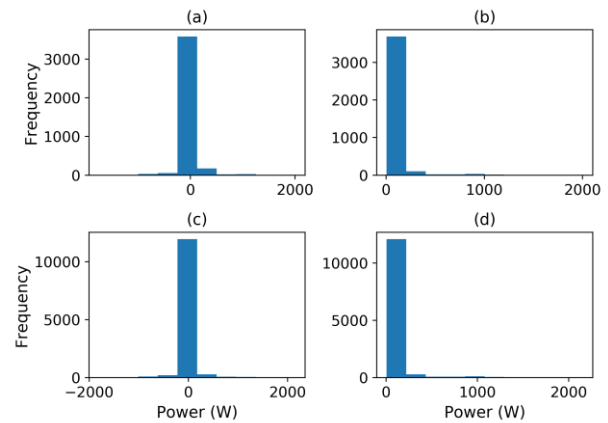


Fig.4. (a) Single day actual feature distribution (b) Single day transformed feature distribution (c) Three day actual feature distribution (d) Three day transformed feature distribution, from REDD House 2.

With the features having been extracted and transformed, the next step was to generalize them using the clustering algorithm. The results of this process for features from REDD House 2 can be seen in Fig. 5.

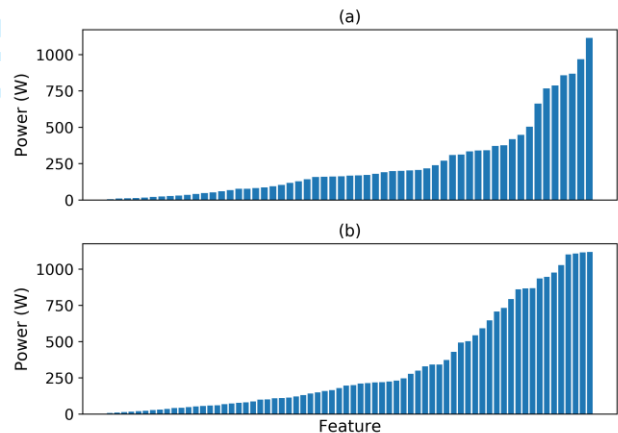


Fig.5. Generalized features from (a) single day energy usage (b) three day energy usage, from REDD House 2.

The results indicate that the proposed algorithm enables us to generalize the features and produce a set that can be considered for model learning. Given that this process has discovered the “optimal” set of features from the initial set, it can then be justified that the work presented utilizes an unsupervised learning approach to energy disaggregation.

The final step of this section is to evaluate the performance of the algorithm using the generalized features and the subset of NILM metrics mentioned in Section IV-A. The results of the evaluation process for single day and three day energy usage can be seen in Table I and Table II respectively.

TABLE I  
NILM METRICS FOR SINGLE DAY ENERGY USAGE

REDD House	Acc. (%)	P (%)	R (%)	$f_1$ (%)	TECA (%)
1	94.71	93.71	95.58	94.63	81.40
2	98.36	98.58	97.80	98.18	91.73
3	97.90	97.74	97.92	97.83	91.95
4	98.98	99.02	98.86	98.94	93.65
5	99.20	99.36	98.73	99.04	98.84
6	97.93	97.69	98.14	97.91	83.25

TABLE II  
NILM METRICS FOR THREE DAY ENERGY USAGE

REDD House	Acc. (%)	P (%)	R (%)	$f_1$ (%)	TECA (%)
1	95.96	95.67	96.17	95.92	63.61
2	98.90	98.97	98.60	98.79	93.89
3	88.99	85.39	90.44	87.84	77.16
4	97.80	97.32	98.22	97.77	90.82
5	95.04	94.46	94.59	94.52	75.13
6	97.37	97.01	97.61	97.31	83.10

The evaluation metrics provide an indication that the algorithm has good performance in terms of recognizing events that occurred in aggregated energy for each of the six REDD houses. The results for Accuracy, Precision, Recall, and F1-Measure were generally good for both single day and three day energy usage. However a dip in performance can be seen in these metrics for House 3 for three day energy usage, which could possibly indicate a period of increased complexity in terms of appliance composition. The TECA metrics varied across houses with lowest performance in houses 1, 3, and 6. These houses are known to have a larger number of appliances in use which could be contributing factor to these results. However the performance for this metric is also generally good across houses and periods of energy usage.

In summary, the algorithm performed generally well given energy with varying complexity. It can also be seen that the generalized features are able to detect quite a high number of the energy usage events occurring in the energy usage for the

six REDD households. This is further indicated in Fig. 6 which provides a comparison between the actual significant events (Fig. 6a and Fig. 6b) and the detected significant events (Fig. 6c and Fig. 6d).

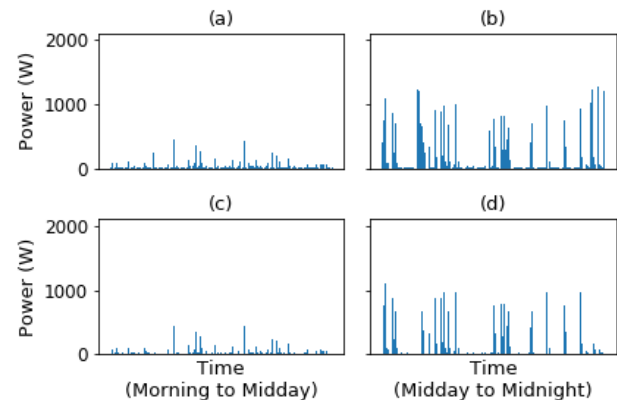


Fig. 6. Comparison between Actual significant events shown in (a) and (b) and Detected significant events shown in (c) and (d), from single day energy usage in REDD House 2.

A comparison was made between this work and recent state of the art approaches which utilize similar metrics and energy data for evaluation. Given the wide variety of techniques used in NILM research work, direct comparisons between experimental results are not possible, as taken into consideration for this evaluation. The comparison between single day energy disaggregation and the state of the art work is presented in Table III. The comparison indicates that the proposed approach generally has better performance across metrics when compared to some of the similar recent state of the art NILM algorithms.

TABLE III  
COMPARISON WITH STATE OF THE ART

Approach	Acc. (%)	P (%)	R (%)	$f_1$ (%)	TECA (%)
FHMM [10]	-	82.70	60.30	71.29	-
HDP-HSMM [45]	-	-	-	-	81.50
DTW [46]	-	91.24	81.77	86.16	-
House 1	94.71	93.71	95.58	94.63	81.40
House 2	98.36	98.58	97.80	98.18	91.73
House 3	97.90	97.74	97.92	97.83	91.95
House 4	98.98	99.02	98.86	98.94	93.65
House 5	99.20	99.36	98.73	99.04	98.84
House 6	97.93	97.69	98.14	97.91	83.25

## 2) Context 2: Modeling Learning and Inference

Single day energy data from REDD House 2 was used in

order to evaluate the chosen approach to model learning and inference. The energy usage for the single day can be seen in Fig. 7.

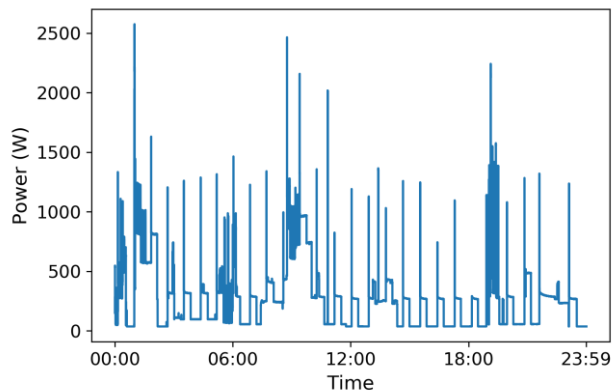


Fig.7. Single day energy usage from REDD House 2.

The first step was to verify the multi-state appliance modeling process. As mentioned in Section III-A, the algorithm aims to define multi-state appliance models. The detected events were examined by the algorithm, and subsequently detected events were combined into multi-state models. A further step was taken to merge models based on commonalities in feature usage. Fig. 8 displays all the discovered appliance models and the interactions of their internal states for the given period of energy usage, and a subset of these appliance models is provided in Fig. 9. Fig. 8 and Fig. 9 indicate that there are some common patterns in the energy usage based on the internal state interactions of the appliance models. The patterns are more pronounced in Fig. 9 which shows that these interactions could possibly represent the usage of certain types of appliances. Given the large number of generated appliance models as seen in Fig. 8, the goal for future work will be to reduce them to a manageable set that represents operations that are similar to real world devices.

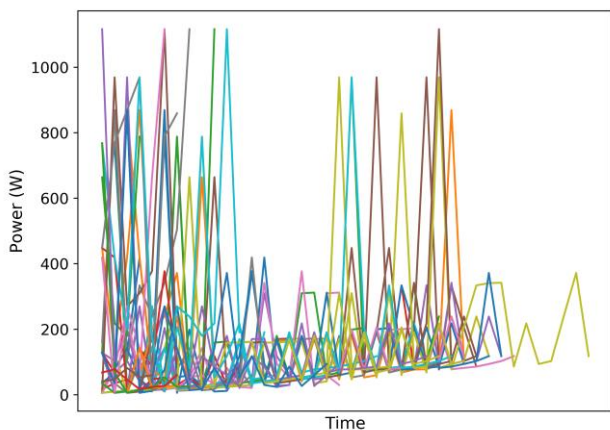


Fig.8. Internal state interactivity for all discovered appliance models during single day energy usage from REDD house 2.

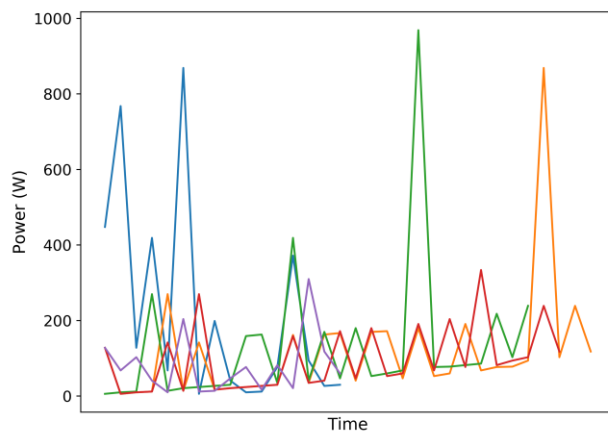


Fig.9. Internal state interactivity for subset of discovered appliance models during single day energy usage from REDD house 2.

The final step was to use the discovered appliance models to provide insights on future energy usage. To achieve this the appliance models learnt from a single day of usage were used to track energy usage in the following day (Fig. 10).

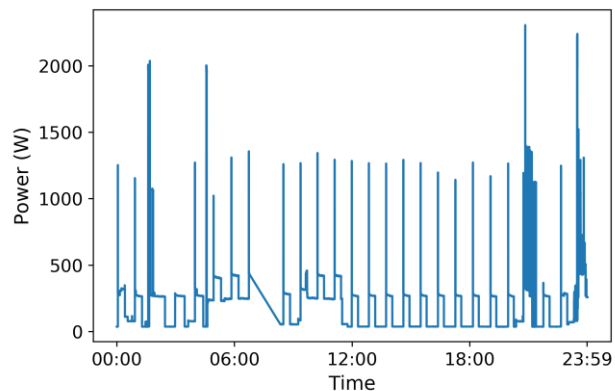


Fig.10. Energy usage in subsequent day of REDD house 2.

To limit complexity, the experiment was conducted using the two-state appliance models. To provide valuable feedback to the homeowner, the outcome of this step was to highlight events of high energy usage during the day. High energy usage was defined as any power usage over 350W, and the results are displayed in Fig. 11, which shows that sporadic occurrences of high energy usage throughout the day with a majority of the occurrences happening late in the night.

Additionally NILM metrics were used to evaluate the energy disaggregation for the new period, and these are shown in Table IV. The metrics indicate that the appliance models discovered in the previous day can be applied to subsequent periods of energy usage. The results of the energy disaggregation, in particular the TECA metric, however indicates that new features may need to be incorporated to insure that previously unseen patterns of energy usage can be better detected.

TABLE IV  
NILM METRICS FOR SUBSEQUENT DAY ENERGY USAGE

REDD House	Acc. (%)	P (%)	R (%)	$f_1$ (%)	TECA (%)
2	96.20	96.79	94.71	95.74	87.95





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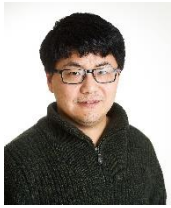


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Review Only