Poster: Energy Disaggregation for Identifying Anomalous Appliance

Haroon Rashid
IIIT Delhi, New Delhi
haroonr@iiitd.ac.in

Pushpendra Singh
IIIT Delhi, New Delhi
psingh@iiitd.ac.in

ABSTRACT

Energy disaggregation research claims that it can be used to identify anomalous appliances. Our study proposes a technique which checks how accurate is disaggregated data in identifying such appliances. The evaluation of proposed technique on four different homes shows that disaggregation enables to find anomalies in air conditioner and refrigerator with an average F-score of 0.35, which is low on a scale of 0 to 1.

CCS CONCEPTS

•Computing methodologies →Anomaly detection; •Hardware →*Energy metering; Smart grid;*

KEYWORDS

Anomalous appliance identification, Energy disaggregation

ACM Reference format:
Haroon Rashid and Pushpendra Singh. 2017. Poster: Energy Disaggregation for Identifying
Anomalous Appliance. In *Proceedings of BuildSys '17, Delft, Netherlands, November 8–9, 2017,* 2 pages.
DOI: 10.1145/3137133.3141438

1 INTRODUCTION

Buildings waste up to 20% of energy due to faulty appliances and abnormal user behavior. Detecting such wastage early and identifying the anomalous appliance from various home appliances on time may result in energy savings. Studies show that giving such type of feedback to consumers results in more than 12% energy savings [2].

Several existing works detect anomalies by using single smart meter data [1, 7]. Such works detect anomalies, but they cannot identify an appliance resulting into energy wastage, which is a hard problem given the range of appliances used in buildings. This makes it impossible for a building owner to track the anomalous appliance. However, energy disaggregation claims that it can be used to identify an anomalous appliance from smart meter data.

This paper studies how effective is disaggregation in identifying an anomalous appliance. We propose a technique namely **UNUM** - which takes appliance's power consumption data to detect anomalies. Further, we evaluate **UNUM** on both disaggregated and sub-metered data to find the potential of disaggregation in anomaly detection. The evaluation shows that disaggregated data reduces anomaly detection F-score by 28% and 81% as compared to sub-metered data of Air Conditioner (AC) and Refrigerator respectively.

BuildSys '17, Delft, Netherlands

DOI: 10.1145/3137133.3141438

2 METHODOLOGY

In residential buildings, AC is most energy-hungry appliance and refrigerator runs throughout the day. Therefore we restrict our study on these two appliances only. Proposed technique, **UNUM** takes appliance's power consumption data as input and outputs anomaly status.

UNUM works in two phases: train and a test phase. In train phase, it takes power consumption trace of an appliance of historical T days and builds a model. In the test phase, it takes same appliance's power trace of a test day and compares whether the consumption on a test day follows the built model. A deviation observed is flagged as an anomaly. Steps used in train phase are:

(1) Input historical T days power consumption trace of an appliance during which it worked normally.
(2) Use k-means clustering algorithm to identify ON and OFF compressor states of an appliance. This results into two clusters corresponding to ON and OFF states.
(3) For each state, identify timestamps of first and last power consumption reading as *head* and *tail*. Compute the duration D_s of each state as $D_s = tail - head$. Also, compute the magnitude M_s of each state as an average of all power consumption readings within that state.
(4) Use trapezoidal rule to compute area A_s of each state. It uses all power readings of a state between *head* and *tail* to compute A_s.
(5) For all ON states, compute mean over D_s, M_s, A_s as $\overline{D}$, $\overline{M}$, $\overline{A}$ respectively and compute standard deviation over A_s as $\sigma_a = standard\_deviation(A_s)$. Similarly, repeat all these statistics for OFF state.

Therefore, **UNUM** creates a model for each state of appliance and a model is represented by a quadruple ($\overline{D}$, $\overline{M}$, $\overline{A}$, σ_a).

In the test phase, **UNUM** takes power consumption trace of an appliance of a test day and calculates all defined statistical features. Next, it uses following set of rules to decide whether the test day consumption is anomalous, and if yes then which type, i.e., elongated duty-cycle or frequent cycling. In elongated case, appliance remains in ON state for the significantly longer duration while as in frequent cycling case appliance switches between ON and OFF states frequently.

Rule # 1: If an appliance switches between ON and OFF states frequently, then it is a frequent anomaly type.

$$A^i_{testday} < \overline{A}^i - n * \sigma^i_a, \forall_{i \in \{ON,OFF\}} \quad (1)$$

	Power ratings (W)		# of insertions		Duration (hours)	
Home	AC	Refrig.	AC	Refrig.	AC	Refrig.
1	2500	150	6	4	6 - 12	6 - 12
2	1800	140	7	4	6 - 12	6 - 08
3	4000	090	6	4	6 - 12	6 - 10
4	1200	110	6	5	7 - 09	4 - 12

Table 1: Details of inserted anomalies in AC and refrigerator.

where $n_{>0} = \{n \in \mathbb{R} | n > 0\}$ represents the number of standard deviations (σ).

Rule # 2: If an appliance remains in ON state for an extended period, then it is an elongated duty-cycle anomaly type.

$$A_{testday}^{ON} > \overline{A}^{ON} + n * \sigma_a^{ON} \tag{2}$$

3 EVALUATION

Dataset: We use publicly available dataset, Dataport, for the evaluation of **UNUM**. Dataport contains both aggregate and sub-metered appliance data at a one-minute sampling rate. We selected three months (June - August 2014) of data from four out of 300 homes of Dataport due to their high disaggregation accuracy. Since there is no publicly available anomaly annotated dataset, so we inserted anomalies in the dataset manually. Table 1 shows the statistics of inserted anomalies. Appliances used in these homes were: AC, refrigerator, furnace, oven, and dryer.

Disaggregation Techniques: We use existing disaggregation techniques such as Factorial-Hidden Markov Model (FHMM) [5] and classical Combinatorial Optimization (CO) [4] to obtain disaggregated appliance data.

Experimental Settings: For both **UNUM** and disaggregation techniques, we use one month of data for training and remaining two months of data for testing. We use open source implementations of FHMM and CO provided in NILMTK toolkit[1] for disaggregating the aggregate meter data [3]. Both of these techniques were used with their default settings. **UNUM** is implemented in `Python` and the value for n was empirically found as 1.5.

3.1 Results

Disaggregation Performance: We use the same accuracy metric as defined by Kolter et al. to show disaggregation performance of FHMM and CO [6].

$$\text{Accuracy} = 1 - \frac{\sum_{t=1}^{T} \sum_{i=1}^{n} |y_t^i - \hat{y}_t^i|}{2 \sum_{t=1}^{T} \bar{y}_t} \tag{3}$$

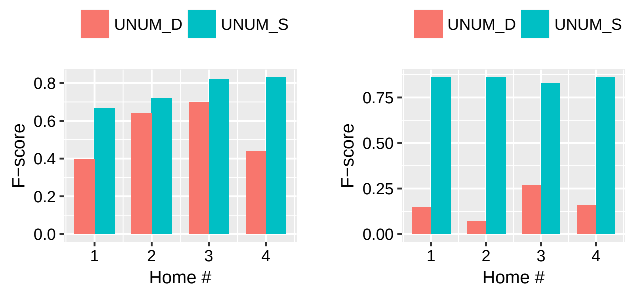
where y_t^i and $\hat{y}_t^i$ represents sub metered and disaggregated power consumption of appliance i at time t respectively. $\bar{y}_t$ represents aggregate power consumption at time t, n represents number of appliances and T represents the timestamp of last observation.

Table 2 shows the disaggregation accuracy of FHMM and CO in these four homes. FHMM performs better than CO, so all subsequent results are obtained using FHMM.

UNUM's Performance: During the test phase, first, we use FHMM technique to get disaggregated appliance level data. Next, we use **UNUM** on each appliance's power trace separately to identify an anomaly, if any. To evaluate the efficacy of **UNUM**, we also run

Technique	Home 1	Home 2	Home 3	Home 4
FHMM	0.71	0.55	0.53	0.50
CO	0.62	0.51	0.47	0.44

Table 2: Disaggregation Accuracy



(a) AC (b) Refrigerator

Figure 1: F score of UNUM_S and UNUM_D on AC and refrigerator.

UNUM on sub-metered appliances data available in the Dataport dataset. We refer the process of running **UNUM** on sub-metered and disaggregated data as **UNUM_S** and **UNUM_D** respectively. Therefore, comparing the **UNUM_S** and the **UNUM_D** should show how effective is energy disaggregation in identifying anomalies.

Figures 1(a) and (b) shows F-score for both **UNUM_D** and **UNUM_S** in AC and refrigerator. On average, in AC, **UNUM_S** and **UNUM_D** result in F-score of 0.76 and 0.54 respectively. In case of a refrigerator, **UNUM_S** and **UNUM_D** result in F-score of 0.85 and 0.16 respectively. Lower **UNUM_D**'s F-score in all homes indicates that it is difficult for existing disaggregation techniques to find anomalous refrigerator instances correctly.

4 CONCLUSION

Energy disaggregation claims that it can be used to identify anomalous appliance. Our study on two appliances shows that it has not reached the level yet to identify anomalous appliance with an acceptable accuracy.

5 ACKNOWLEDGEMENTS

We thank TCS for supporting PhD of H. Rashid and Infosys Center for Artificial Intelligence for partially supporting P. Singh.

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