Extending Combinatorial Optimization for Non-Intrusive Appliance Load Monitoring

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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

NILM definition [1]

Motivation

- Feedback 15 energy savings % [2]
- Potential use cases from Hart paper, benefit to
  - Utility
  - End Users
  - Appliance Makers

Typical setup

- How is NILM done- H/W requirements, Put a picture

Previous work

Several classification [3], [4], [5]:

- High vs Low frequency
- Time vs Frequency domain analysis
- Supervised vs Unsupervised

Trends and work

- Additive Factorial HMM
- Difference HMM [6]

Datasets

Recent datasets have spurred this field

- REDD [7]
- Blued [8]
- Smart* [9]

II. About Dataset

- 6 home data, summer of 2011, Boston
- 14 days per home
- Submetered information made available
- High Freq., Low frequency data, we chose low freq data for our analysis
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III. Terminologies/ Notations

Borrow the notation used by Parson and Hart.

- Input: Aggregate power sequence: $x = \{x_1, .., x_T\}$
- Infer: Power draw by constituent appliance: $y_n = \{y_{1,n}, ..y_{T,n}\}$
- Time slice: $t \in 1, ..T$
- Appliance: $n \in 1, ..N$
- Appliance state: $z_n = \{z_1, ..z_T\}$

IV. Problem Formulation

This approach resembles subset sum problem and tries to minimize the difference of total observed power from the sum of various possible subsets coming from various combinations of appliances in different states. For each appliance we assume **K** states and at a given time, an appliance can only be in a single state. This is given as: $z_{t,n,k} \in \{0, 1\}$ and,

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

The power drawn by each appliance is given by:

$$\mu_n = \{\mu_{n,1}, ..\mu_{n.K}\}$$

Thus, CO can be formulated as:

$$z_t = argmin_{z_t} |x_t - \sum_{n=1}^{N} \sum_{k=1}^{K} z_{t,n,k} \mu_{n,k}|$$

- Statespace is K^N

- We assign different loads to different mains, N_i loads to $Mains_i$, $\sum_{1}^{p} N_i = N$. Now different state spaces are K^{N_1}.... We can define the overall state space as $\max K^{N_i}$
As a practical example, two mains, 20 appliance, state space before = 2^{20}. After = 2^{10}. Exponential reduction in state space.

V. Algorithm

Flowchart- TO go as image/flow diagram

1) Data Preprocessing
    a) Aligning Mains and Appliance Level data
    b) Down sampling to 1 minute resolution
2) Load Assignment based on
    a) Appliance usage times
    b) Appliance Periodicity
    c) Appliance Power threshold
    d) Correlation amongst different appliance usage
3) Data Recalibration using the following
    a) Step changes occurring in Mains vs Appliances
    b) Isolating single appliance usage
4) Appliance states identification using clustering (Possibly talk about unbalanced data, but leave it for future work)
5) State space creation
6) Applying CO for different mains
7) Find energy distribution by appliance and assign weights (To be used in results)

Explanation of above steps

A. Data Pre processing

- Aligned data
- Downsampling and why it is needed
    - Sub metered data collected sometimes at 3s sometimes at 4 s
    - Getting rid of transients, also suggested by Hart
    - Reducing power fluctuations occuring due to voltage fluctuations. Put figure showing reduction in transients and signal smoothing

B. Load assignment

Draws inspiration from work by Parson et. al [6]

VI. Metrics

- Show confusion matrix and argue that accuracy can be misleading, state 0 domi nates in all appliances and will most probably always be predicted correctly
- Hart pointed towards residual power as an evaluation metric, REDD paper talks about % of energy recovered
- METRIC 1: Given an appliance having m states, we propose power weighted appliance accuracy, as follows
$$ApplianceAccuracy = \frac{\sum_{i=1}^{m} Accuracy(i) * Power(i)}{Power(i)}$$
- METRIC 2: In this we also take into consideration the amount of time an appliance is in a particular state
- Overall Accuracy : Based on energy weights of different appliance, for instance .4* Fridge +.2*Light+... This is important since it shows the relative importance of larger loads
- Switch continuity

VII. Results

VIII. Conclusion

The conclusion goes here.

IX. Future Work

- 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

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