Non-Intrusive Load Monitoring of HVAC Components using Signal Unmixing

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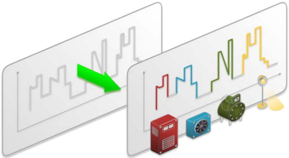
Non-Intrusive Load Monitoring (NIML)

NILM

NILM is the task of separating aggregate energy signal into the energy signal of the individual components.

- Energy conservation.
- Fault detection.
- lower costs of sensors and low intrusion installation.



HVAC load monitoring

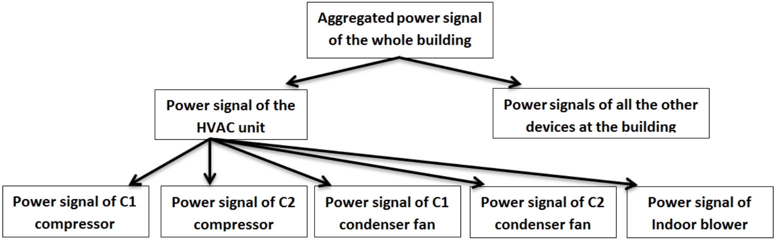
Heating, Ventilating and Air Conditioning units (HVAC) are a major electrical energy consumer in the buildings.

- Currently account for 57% of the energy used in U.S. commercial and residential buildings.
- HVAC systems commonly operate in a degraded or faulted condition:

  Continous monitoring is therefore crucial to identify the faults at the early stage and making decisions for repair.

Hierarchy disaggregation

- The first step is disaggregation of power signal of the whole building to the power signals of all the circuits and devices existing in the building.
- The second step is decomposition of the obtained HVAC power signal from the last step and estimating the power consumption profile of its components.



Disaggregation using Constrained NMF

$$\bar{X} = DA$$

$$\hat{A}_{1:k} = \underset{A_{1:k}}{\operatorname{argmin}} \left\| \bar{X} - [D_1, \ldots, D_k] \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_k \end{bmatrix} \right\|_2^2 \tag{1}$$

- $\bar{X} \in R^{m \times d}$ is the aggregated signal.
- $D_i \in R^{m \times n}$ is the energy consumption of the ith device.
- Each column of D_i and $\bar{X}$ includes one day of power signal.
- The goal is to build a model which can be used to decompose the aggregated signal to each individual device's signal.

Signal Estimation:

After calculating the activation coefficient for each device, the estimated signal for the *i*th device would be:

$$\hat{X}_i = D_i \hat{A}_i \quad (2)$$

$\bar{X} \in R^{m \times d}$, $\hat{X}_i \in R^{m \times d}$, $D_i \in R^{m \times n}$ and $\hat{A}_i \in R^{n \times d}$

Sum-to-K constraint

We propose, the sum-to-k constraint for activation coefficients A. It means for each $\hat{A}_i \in R^{n \times d}$ we should have $\sum_{j=1}^{n} A_i(j) = 1$.

$$\hat{A}_{1:k} = \underset{A_{1:k} \geq 0}{\operatorname{argmin}} \left\| \bar{X} - [D_1 \dots D_k] \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_k \end{bmatrix} \right\|_2^2 + \beta \left\| U - SA \right\|_2^2 \quad (3)$$

- $U \in R^{k \times d}$ is a matrix with all its entries equal to one.
- S is the matrix including 1 and 0 elements that we would define in some way that it forces the summation of activation coefficients for each device in matrix A to be equal to one (S has n 1's in each row).

An example:

Assume, we have $k = 4$ devices and $n = 3$ days of training data for each device and $d = 1$ day of testing for aggregated signal. Consequently, the model matrix D would be of size $m \times 12$.
By defining $S \in R^{k \times k*n}$ as the following matrix, we impose sum to K constraint for activation matrix A.

$$S = \begin{bmatrix} 111 & 000 & 000 & 000 \\ 000 & 111 & 000 & 000 \\ 000 & 000 & 111 & 000 \\ 000 & 000 & 000 & 111 \end{bmatrix}, \quad \begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{bmatrix}, A_i \in R^{3\times 1} \tag{4}$$

This sum-to-K constraint highly increases the accuracy of the disaggregation method.

Solving the optimization problem

For solving the optimization problem we use matrix augmentation which leads to solving the following optimization problem:

$$\hat{A} = \underset{A \geq 0}{\operatorname{argmin}} \left\| \begin{bmatrix} \bar{X} \\ \beta U \end{bmatrix} - \begin{bmatrix} D \\ \beta S \end{bmatrix} A \right\|_2^2 \tag{5}$$

Solving via Fast Non-Negative Least Square (FNNLS)

Dataset:ORNL

- The data was collected on the Oak Ridge National Lab (ORNL) Flexible Research Platform (FRP1).

There are 16 different devices, circuits and plugs in the building: HVAC unit, 480/208 Transformer, lighting circuits: 1, 3, 5, 7, Plug circuits: 1, 3, 5, 7, cord reel circuit, lighting control box, exhaust fan, piping heat trace, exterior lighting (lighting and emergency) and building control circuit.

Results: Building power decomposition

Table: Disaggregation Error for training and testing stages for building power disaggregation.

	Training		Testing	
	GCNMF	DDSC	GCNMF	DDSC
DISAG-ERROR	$7.5181e-16$	0.091543	0.019453	0.10463

Disaggregation Error:

$$\sum_{i=1}^{k} \frac{1}{2} \left\| X_i - \hat{X}_i \right\|_2^2 \tag{6}$$

Results: Building Energy decomposition

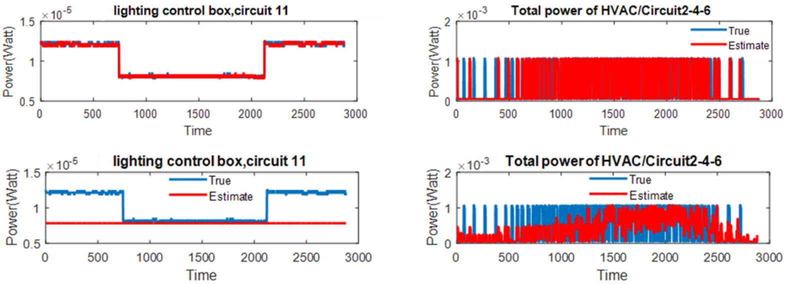


Figure: Building power disaggregation. Two top figures: Estimated power consumption profile of the HVAC and lighting control box via GCNMF method during one day. The two bottom figures: Estimated power signals using DDSC method.

Results: HVAC Energy decomposition

Table: RMSE for estimation of power consumption profile of different components of HVAC.

HVAC Components	Training-RMSE	Testing-RMSE
C1 compressor	7.9729e-19	0.0029
C1 condenser fan	0	0.00017
C2 compressor	0	0.00049
C2 condenser fan	0	0
Indoor blower	0	0

Results: HVAC decomposition: ORNL dataset

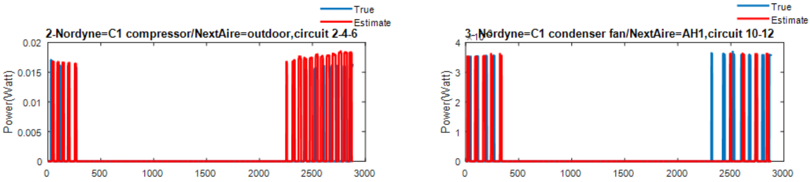


Figure: Estimated power consumption profile of compressor (left) and condenser fan (right) of HVAC unit for one day using GCNMF.

Summary:

- Proposed method based on constrained NMF outperforms the state of the art load disaggregation methods.
- Also:
- Works with low sampling rate data (1 sample per Min).
- Does not need big training data.
- Uses real aggregated signal instead of summation of the devices signals.

- Future work:
- Online and unsupervised load disaggregation
- Fault detection using NILM


Thanks for your attention!
Questions/Comments?