# Energy disaggregation on hourly whole-building electricity data

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# Outline

- Background and motivation
- Disaggregation Model
- Data
- Disaggregation Results
- Summary

# Background

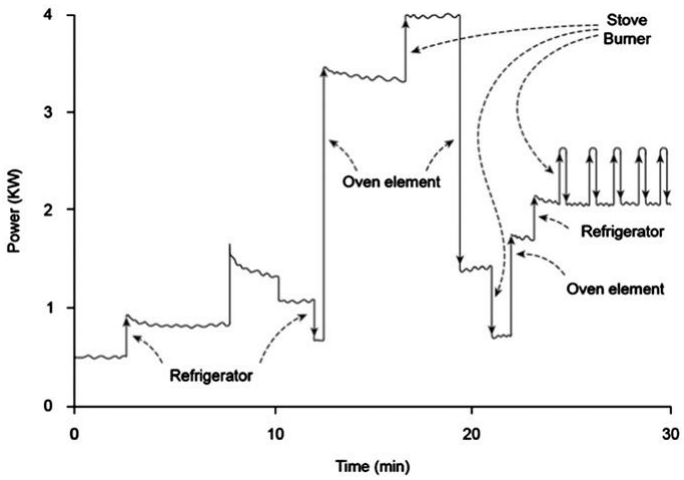
- Why disaggregation
  - Efficient energy arrangement, redesign better appliance
  - Improve building operational efficiency
  - Energy saving, reducing cost of energy supply
- Research status[1]

| Data freq | 1h-15min | 1min - 1s (Hz) | 1-60Hz | 60Hz-2kHz | 10-40kHz | >1MHz |
|---|---|---|---|---|---|---|
| Data features | Duration and time of appliance use | Steady state steps/ power transitions | | Current, voltage, low order harmonics | Current, voltage, medium order | Current, voltage, high order |
| Algorithm | Machine learning, sparse coding | Steps signatures database matching | | Event identification | Machine learning, FHMM | Machine learning, neural network |
| Appliances identified | loads related with temp, continuous, time | Top<10 types: refrigerator, ACs, heaters, dryers, etc. | 10-20 types | Not known | 20-40 types: toasters, computers, etc. | 40-100 specific appliances: light 1, light 2 |

[1] K. Carrie Armel, et. al., Energy policy 52 (2013) 213-234.

# Background

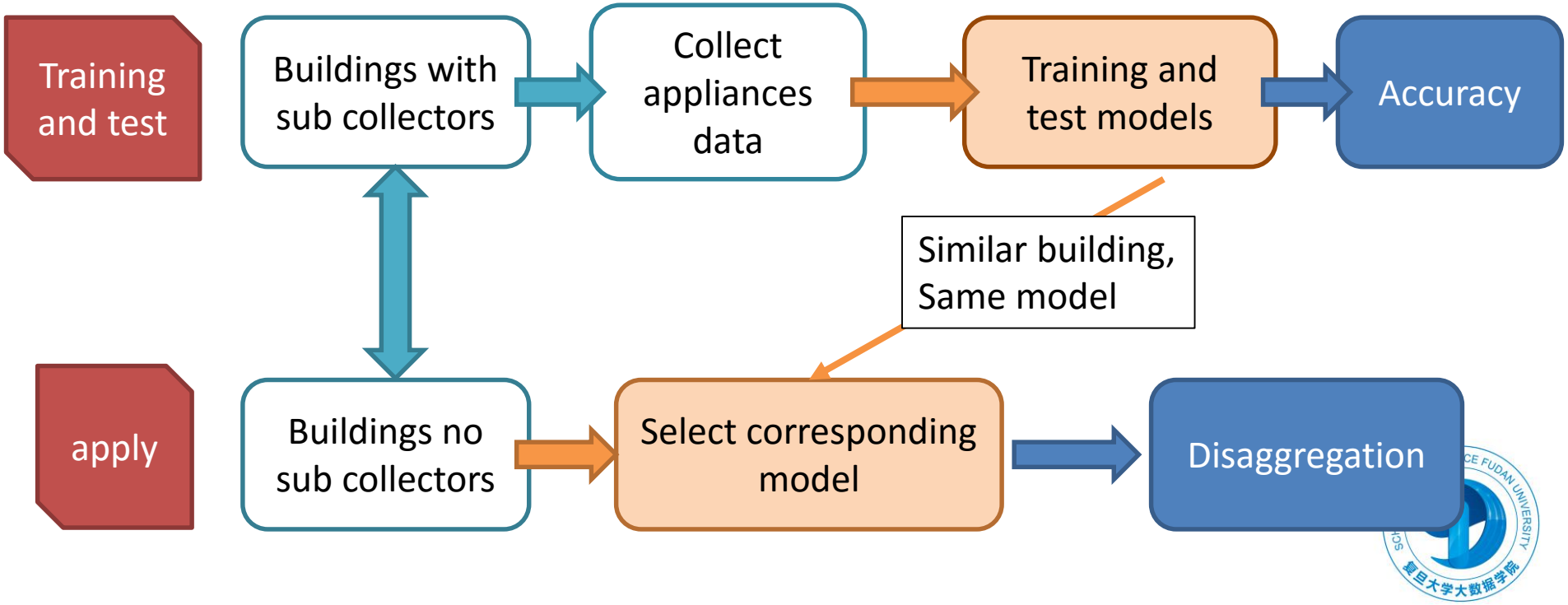
- Traditional methods
  - Event based disaggregation, electricity data alone
    - ✓ Unsupervised models
  - High frequency electricity data
    - ✓ Appliance power curves
    - ✓ lab experiments
- For low frequency data
  - supervised
  - Sparse coding
  - FHMM model
    - ✓ more information input (adopted)




Disaggregation to appliances.
(Hart, 1992, IEEE 80 (12), 1870–1891. )

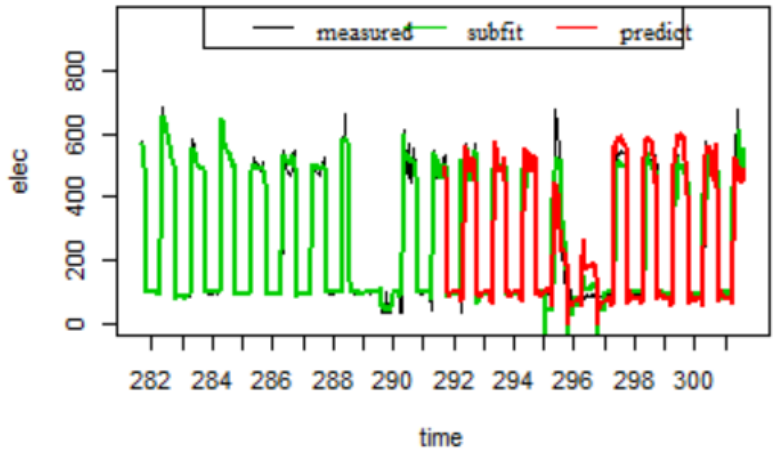
# Motivation

- Supervised disaggregation for commercial buildings
  - Calibrate the meters for appliances
  - Training model, improve accuracy
  - Disaggregation for buildings without sub meters



# Disaggregation

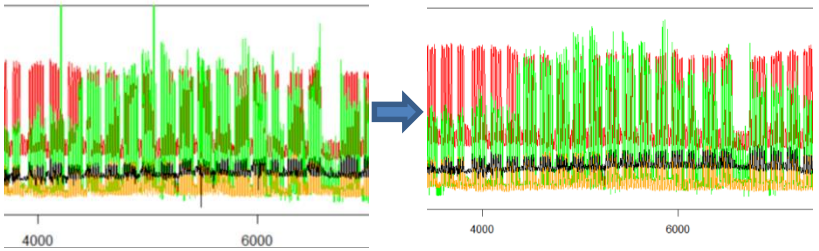
- Model set
  - Training + test sets
    - ✓ First part, training model with all observation
    - ✓ Second part, test the model with only total data
- Steps
  1. Data loading and cleaning
  2. Model training for appliances
  3. Predict for each appliance
  4. Repair by total data
  5. Calculate the accuracy

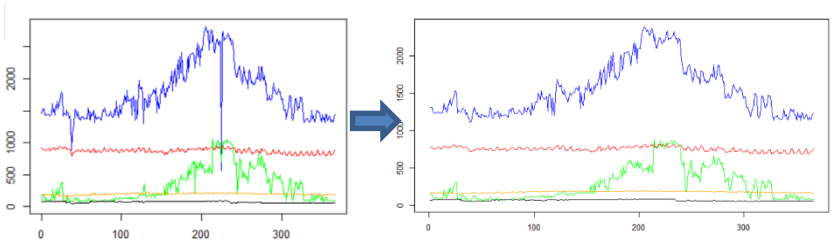



Model training and disaggregation

# Disaggregation: data cleaning

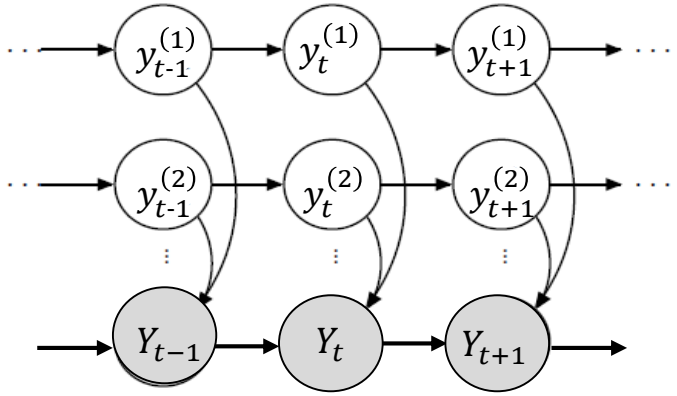
- Clean methods
  - Outliers: 3 standard deviation, 4 weeks for reference
  - Missing: Linear interpolation
- For real data
  - clean respectively, appliances, weekday, weekend, hours
  - Aggregation data, compare to the sum of separated appliances
    - ✓ Larger parts,  smaller parts



# Disaggregation: FHMM model training

- FHMM Model




$$p\left(Y_t\left(S_t^{(1:N)}\right)\right) \sim N\left(\sum_{i=1}^{N} \bar{y}_t^{(i)}\left(S_t^{(i)}\right), \Sigma^2\left(S_t^{(1:N)}\right)\right), \qquad 1 \le S_t^{(i)} \le m^{(i)}$$

where $i$ for separated appliance, $m^{(i)}$ is the number of states for $i$-th appliance, and

$$\bar{y}_t^{(i)}\left(S_t^{(i)}\right) = c_i\left(S_t^{(i)}\right) + \vec{\beta}_i\left(S_t^{(i)}\right) \times \overrightarrow{\mathrm{Out}_t} = f^{(i)}\left(S_t^{(i)}\right)$$

$$p\left(y_t^{(i)}\left(S_t^{(i)}\right)\right) \sim N\left(\bar{y}_t^{(i)}\left(S_t^{(i)}\right), \sigma_i^2\left(S_t^{(i)}\right)\right)$$

- State probability, transition matrix are combination of appliances
- Number of states $\prod_{i=1}^{N} m^{(i)}$



[1] Kolter, et.al.(2012) International Conference on Artificial Intelligence and Statistics Pp. 1472–1482.

# Disaggregation: FHMM model training

- HMM model for each appliance
  - Initial state probability

$$\sum_{j=1}^{m^{(i)}} \delta_j^{(i)} = 1, \qquad 1 \le j,k \le m^{(i)}$$

  - Transition matrix

$$\Gamma^{(i)} = \left(\gamma_{jk}^{(i)}\right), \qquad \gamma_{jk}^{(i)} = p\left(S_t^{(i)} = j \middle| S_{t+1}^{(i)} = k\right)$$

$$\sum_{k=1}^{m^{(i)}} \gamma_{jk}^{(i)} = 1, \qquad 1 \le j,k \le m^{(i)}$$

  - Number of degree of freedom

$$\mathrm{NDF} = \left(m^{(i)} - 1\right) + \left(m^{(i)^2} - m^{(i)}\right) + m^{(i)} \times (n_{out} + 1) + m^{(i)}$$

Initial state | Transition matrix | Outer effects | Normal dis

# Disaggregation: FHMM model training

- Estimation with EM algorithm by definite $m^{(i)}$

$$\log \mathbf{L_T}^{(i)} = \log \boldsymbol{\delta}^{(i)} + \sum_{t=2}^{T} \log \boldsymbol{\gamma}^{(i)}_{S_{t-1},S_t} + \sum_{t=1}^{T} \log \boldsymbol{p}\left(y_t^{(i)}\left(S_t^{(i)}\right)\right)$$

Initial state | Transition matrix | Conditional probability density

$$= \sum_{j=1}^{m^{(i)}} u_j^{(i)}(t) \log \delta_j^{(i)} + \sum_{j,k=1}^{m^{(i)}} \left(\sum_{t=2}^{T} v_{jk}^{(i)}(t)\right) \log \gamma_{jk}^{(i)} + \sum_{j=1}^{m^{(i)}} \sum_{t=1}^{T} u_j^{(i)}(t) \log p\left(y_t^{(i)}\left(S_t^{(i)}\right)\right)$$

- The third part

$$u_j(t)\left(y_t - \hat{y}_t(j)\right) \sim N(0, \sigma_j^2)$$

$$\sigma_i^2 = \frac{\sum_{t=1}^{T} u_i(t)\left(y_t - \hat{y}_t(i)\right)^2}{T}$$

the parameters equals to that from linear regression

$$u_j(t)y_t = c_j u_j(t) + u_j(t)\vec{\beta}_i\left(S_t^{(i)}\right) \times \overrightarrow{\mathrm{Out}_t} + \varepsilon_t(j)$$

# Disaggregation: FHMM model training

- Decide the number of states $m^{(i)}$
  - Loop from 2 to 25

$$\text{residual} = y_t^{(i)} - \sum_{j=1}^{m^{(i)}} \hat{y}_t(S = j) \times p(S_t^{(i)} = j)$$ weak stable

$$\text{BIC} = \log \frac{\text{SSR}_\text{p}}{T} + \log(T) \frac{ndf}{T}$$ least

$$\frac{\left(y_t^{(i)} - mean(y^{(i)})\right)}{sd(y^{(i)})} < 5$$ no outliers

  - Repeat fitting, take best fit result



# Disaggregation: predict

- Appliance, multi stages (h), get the expected value

1. State prob now $\vec{u}(t) = \vec{\boldsymbol{p}}_{\boldsymbol{t}}(\boldsymbol{S}|\boldsymbol{y}_{\boldsymbol{t}}) = \frac{\vec{\boldsymbol{p}}_{\boldsymbol{t}}(\boldsymbol{S})^{\boldsymbol{T}}\vec{\boldsymbol{p}}_{\boldsymbol{S}}(\boldsymbol{y}_{\boldsymbol{t}})}{\sum \vec{\boldsymbol{p}}_{\boldsymbol{S}}(\boldsymbol{y}_{\boldsymbol{t}})}$
2. State prob future $\vec{\boldsymbol{p}}_{\boldsymbol{t+h}}(\boldsymbol{S}) = \vec{u}(t)^T \boldsymbol{\Gamma}^{\boldsymbol{h}}$
3. State value future $\vec{\boldsymbol{y}}_{\boldsymbol{t+1}}(\boldsymbol{S}) = c_j + \sum_{k=1}^{n} \beta_{jk} \times \mathrm{Out}_{k,t+\boldsymbol{h}} \left(S_t^{(i)} = j\right)$
4. Expect value $\hat{y}_{t+1} = \vec{\boldsymbol{p}}_{\boldsymbol{t+h}}(\boldsymbol{S})^{\boldsymbol{T}}\vec{\boldsymbol{y}}_{\boldsymbol{t+h}}(\boldsymbol{S})$

- Aggregation data, determine state probability

1. State probs $U_s(t) = \prod_{i=1}^{N} u_{j_i}^{(i)}(t)\,, s = \sum_{i=1}^{N} j_i \times \prod_{k=1}^{i-1} m^{(k)}$
2. State prob next $\vec{\boldsymbol{p}}_{\boldsymbol{t+1}}^{\boldsymbol{tot}}(\boldsymbol{S}) = \vec{U}_s(t)^T \boldsymbol{\Gamma}^{\boldsymbol{tot}}$
3. Measured value next $Y_{t+1}$
4. Conditional prob $\vec{U}_S(t+1) = \vec{\boldsymbol{p}}_{\boldsymbol{t+1}}^{\boldsymbol{tot}}(\boldsymbol{S}|\boldsymbol{Y}_{\boldsymbol{t}}) = \frac{\vec{\boldsymbol{p}}_{\boldsymbol{t+1}}^{\boldsymbol{tot}}(\boldsymbol{S})^{\boldsymbol{T}}\vec{\boldsymbol{p}}\left(Y_{t+1}\left(S_{t+1}^{(1:N)}\right)\right)}{\sum \vec{\boldsymbol{p}}\left(Y_{t+1}\left(S_{t+1}^{(1:N)}\right)\right)}$

# Disaggregation: result

- Repair appliances prediction by deviation

$$y_{t+1day}^{(i)} = \hat{y}_{t+1day}^{(i)} + per_1 \times per_2 \times \left( Y_{t+1day} - \sum_{i=1}^{N} \hat{y}_{t+1day}^{(i)} \right)$$

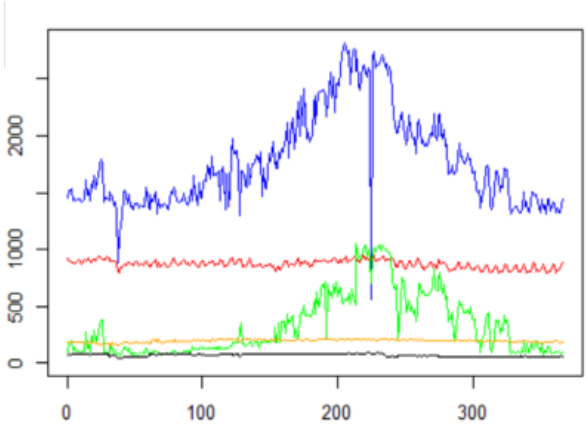
where $\mathrm{per}_1(\Delta) = \frac{\hat{y}_{t+1day}^{(i)} - y_t^{(i)}}{\sum_{i=1}^{N} \hat{y}_{t+1day}^{(i)} - y_t^{(i)}}$, $\mathrm{per}_2(\Delta) = \frac{\sum_{j=1}^{m^{(i)}} prob_j^{(i)} \times \sigma^{(i)^2}}{\sum_{i=1,j=1}^{n,m^{(i)}} prob_j^{(i)} \times \sigma^{(i)^2}}$

- Accuracy (relative uncertainty)

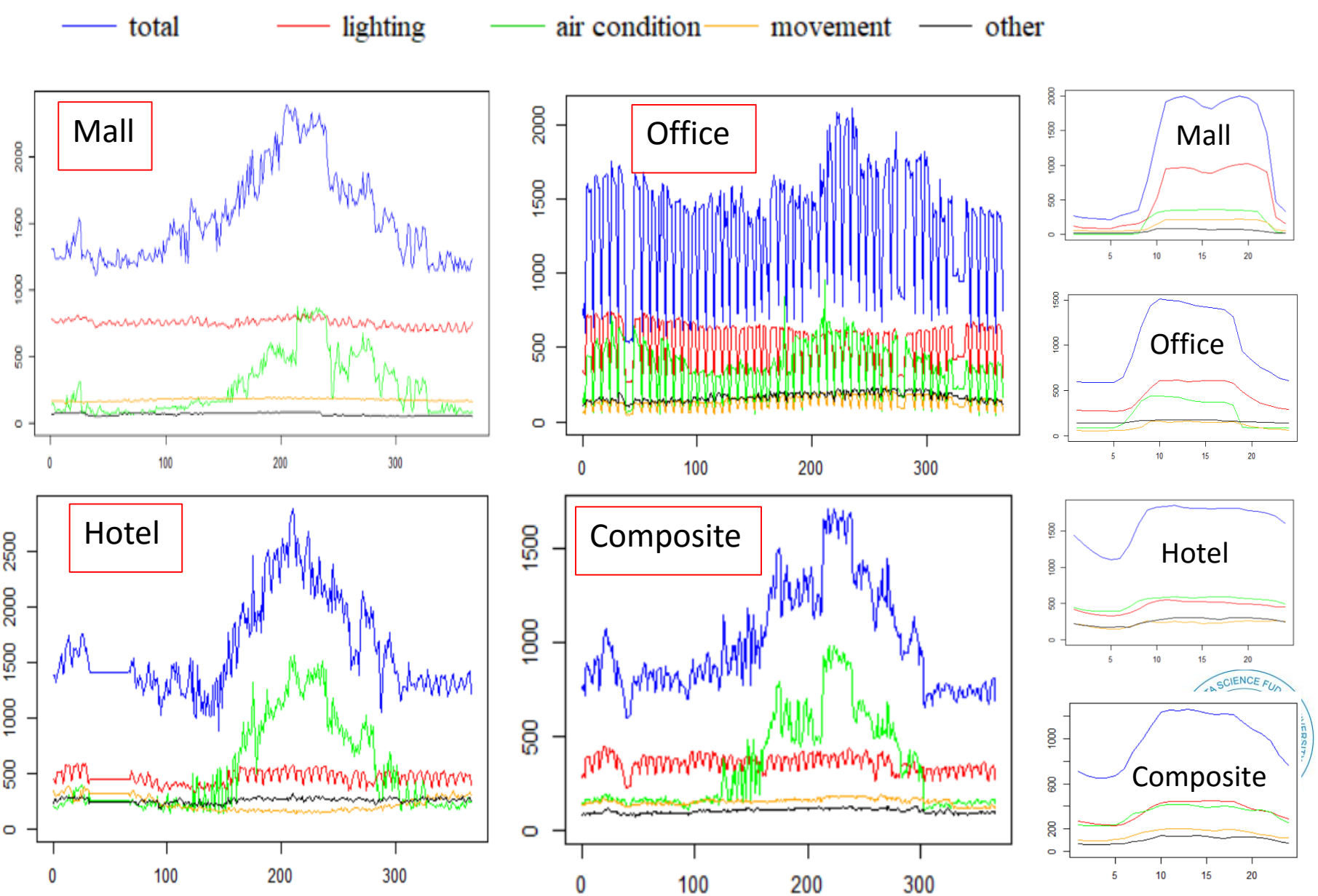
$$\mathrm{rela} = \sqrt{\frac{\sum_t (\mu_t - y_t)^2}{\sum_t y_t^2}}$$

# Data

- Electricity
  - Mall, office, hotel, composite
  - Time: 2016-1-1 0:00 to 2016-12-31 23:00, hourly
  - Measured items: total, lighting, air condition, movement, others
- More
  - Temperature(2), raining, wind velocity, pressure, humidity
  - Holiday: 10 legal holiday, 11 weekend, 00 workday;
  - Day-night: dummy variable; hour, 0~23
- Cleaning
  - Outliers
  - Missing values
  - Unknown = total-sum



# Data status


total
lighting
air condition
movement
other
Mall
Office
Hotel
Composite
Mall
Office
Hotel
Composite

# Data status

- Electricity (day night obvious, air condition season sensitive)

| mall | hour | Total (kWh) | Light (kWh) | AC (kWh) | Mv (kWh) | Other (kWh) |
|---|---|---|---|---|---|---|
| Day | 9-22 | 1200~2300 (season) | 800 | 0-800 (season) | 200 | 100 |
| night | 23-8 | ~200 | 100 | 0 | 20 | 0 |

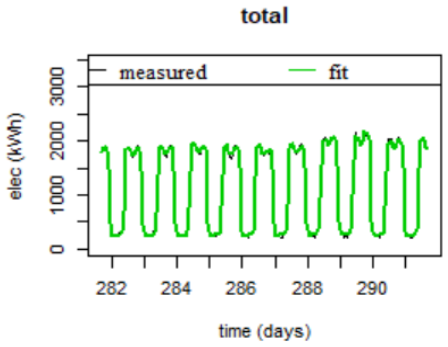
- Comparison all

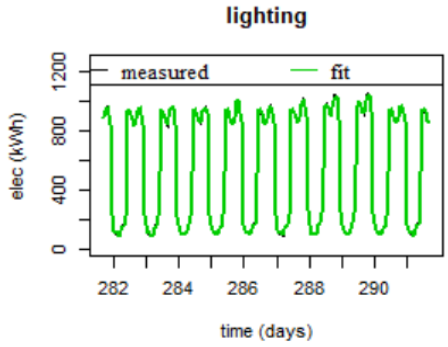
| | Mall | Office | Hotel | Composite |
|---|---|---|---|---|
| Max (kWh) | 2500 | 2000 | 3500 | 2500 |
| Day | 9-22 | 6-18 | 8-23 | 8-22 |
| Dominant | Lighting | lighting | Acs summer, lighting other | Acs summer, lighting other |
| Week cycle | No | Lighting, Acs, movement | Lighting | Lighting |
| Common | Air conditions sensitive to season, large fluctuation; spring festival effect obvious, difference between appliances small | | | |

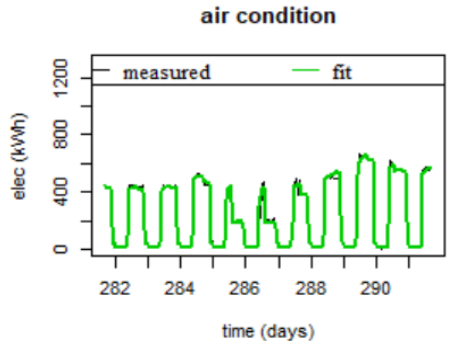
# Disaggregate result: mall

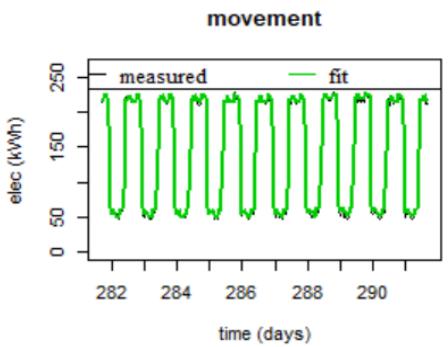
- Training

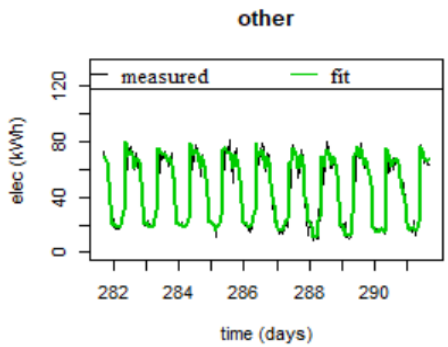
| Item | Lighting | Air condition | Movement | Others | Unknown | Tot |
|---|---|---|---|---|---|---|
| N states | 16 | 13 | 12 | 16 | 11 | 12 |
| Sigma | 15.02 | 20.9 | 4.98 | 3.41 | 31.38 | 67.04 |
| Rela err (%) | 1.98 | 5.33 | 2.91 | 15.25 | 8.61 | 3.90 |

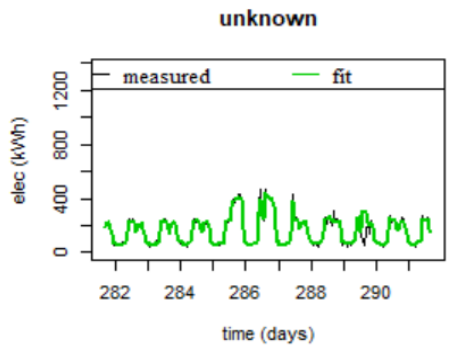


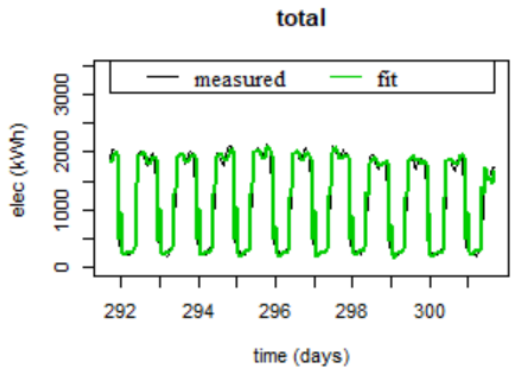



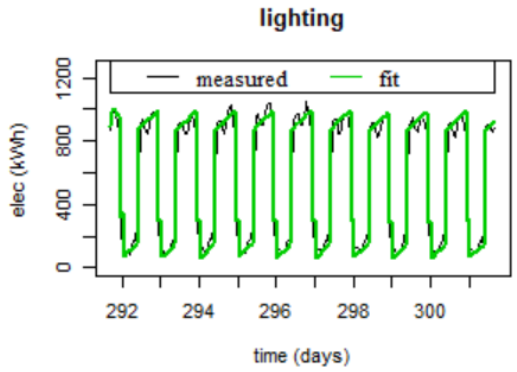



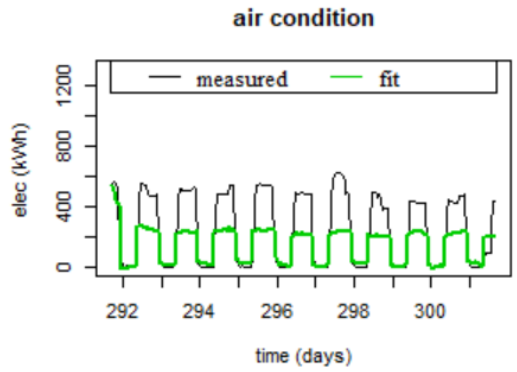
# Disaggregate result: mall

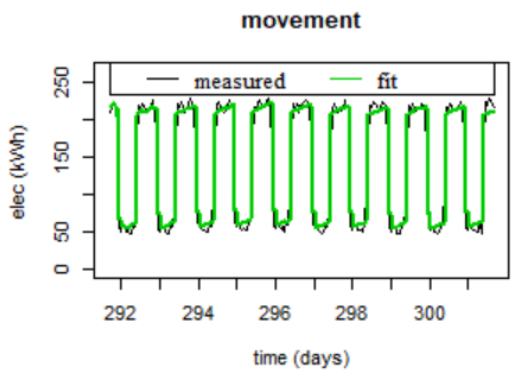
- Predicting in testing set

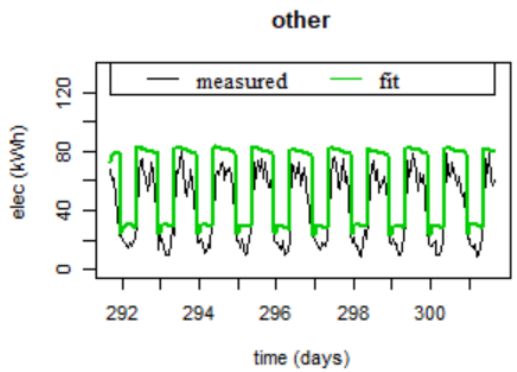
| Item | Lighting | Air condition | Movement | Others | Unknown | Tot |
|---|---|---|---|---|---|---|
| Stages | Multi | Multi | Multi | Multi | Multi | One |
| Rela err (%) | 13.99 | 55.39 | 12.52 | 38.32 | 34.10 | 16.33 |

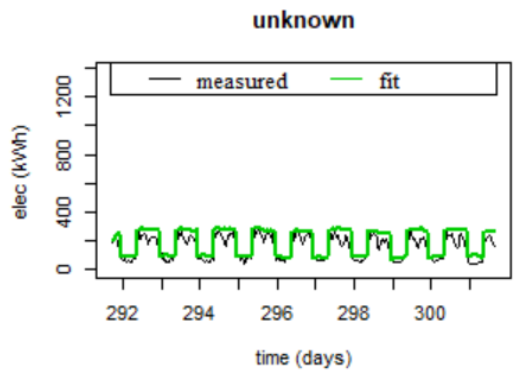


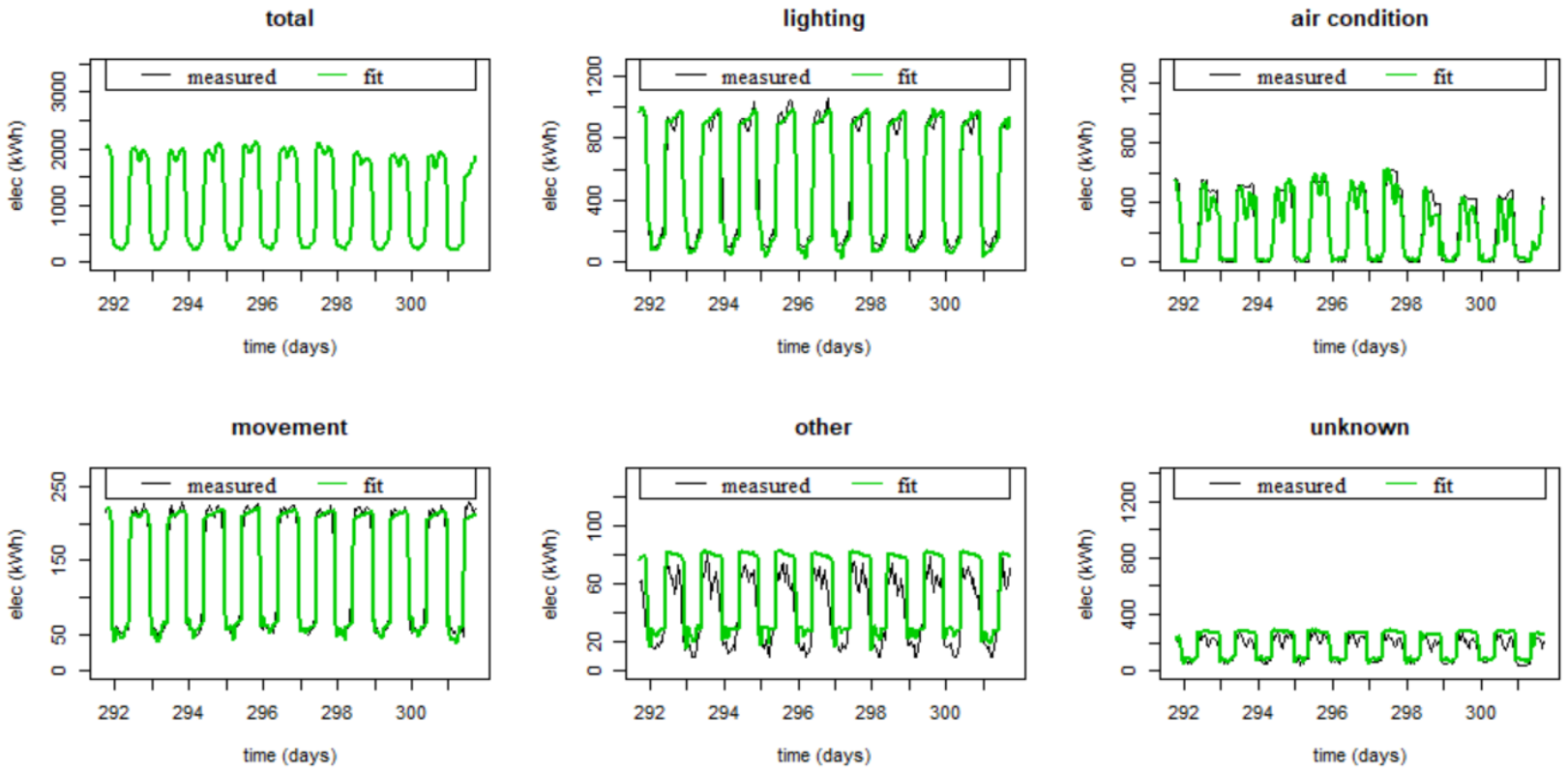



# Disaggregate result: mall

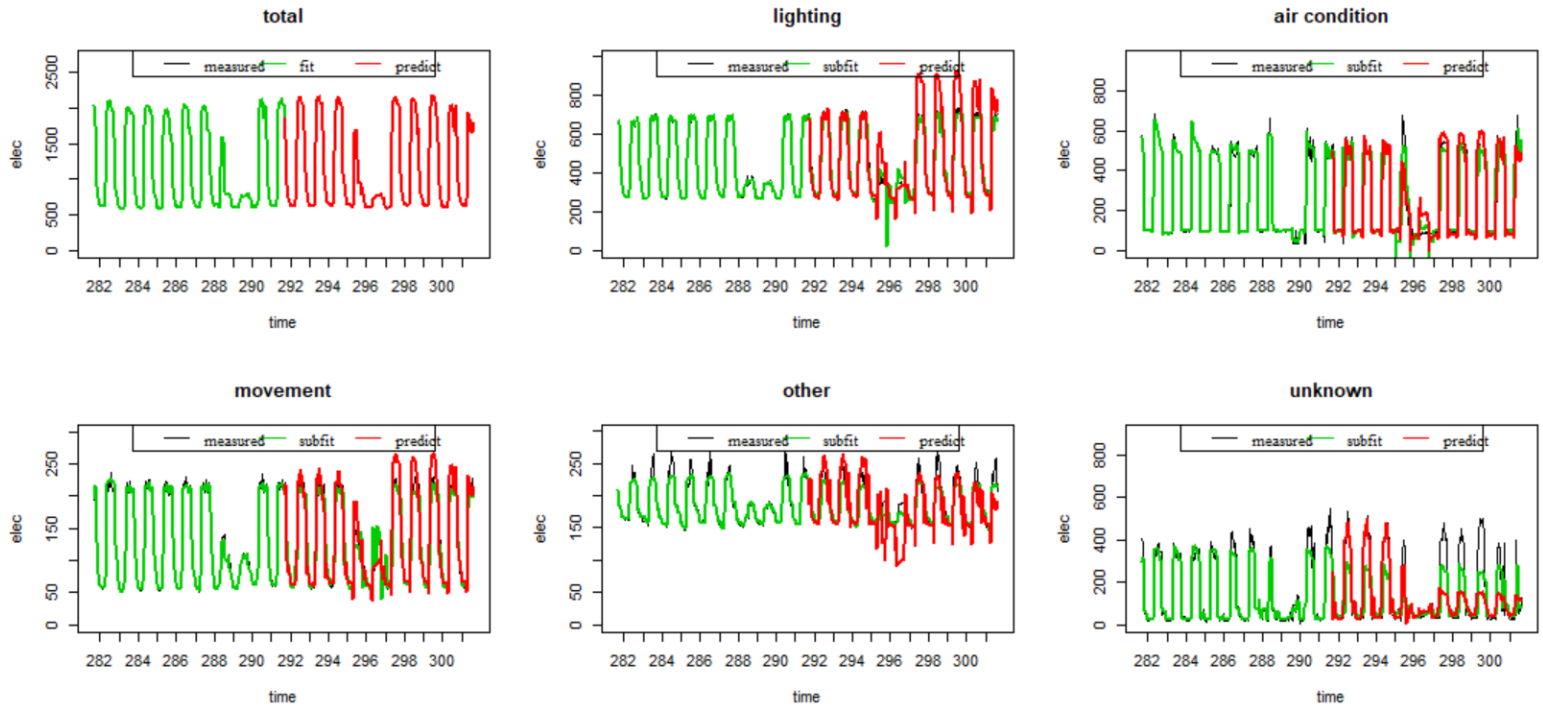
- Repair by aggregation data

| Item | Lighting | Air condition | Movement | Others | Unknown |
|---|---|---|---|---|---|
| relative err(%) | 12.46 | 37.53 | 10.52 | 32.02 | 32.25 |



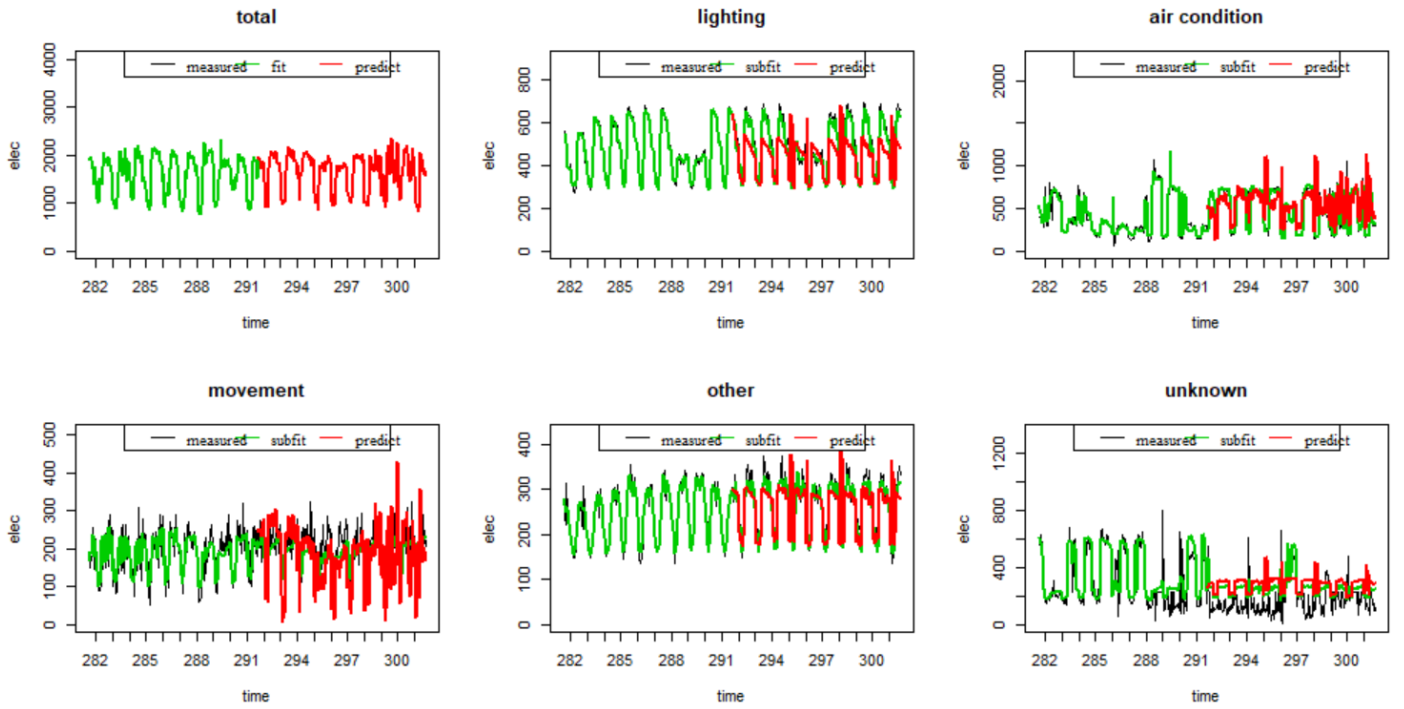
# Disaggregate result: office

| Item | Lighting | Air condition | Movement | Others | Unknown | Tot |
|---|---|---|---|---|---|---|
| N states | 13 | 12 | 13 | 10 | 4 | 18 |
| Training rela err (%) | 2.13 | 6.32 | 4.29 | 3.76 | 27.13 | 2.87 |
| sigma | 11.61 | 23.19 | 6.31 | 7.12 | 43.81 | 40.4 |
| Predict rela err (%) | 19.59 | 43.47 | 25.70 | 15.93 | 72.43 | 19.11 |
| Last rela err (%) | 14.01 | 29.50 | 20.63 | 19.35 | 61.26 | — |



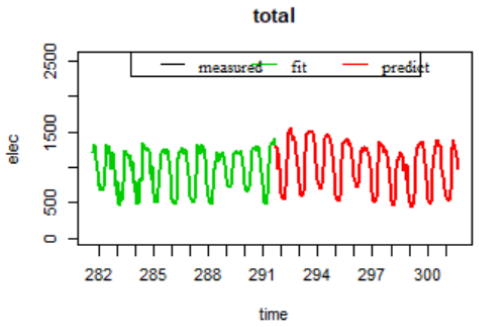
# Disaggregate result: hotel

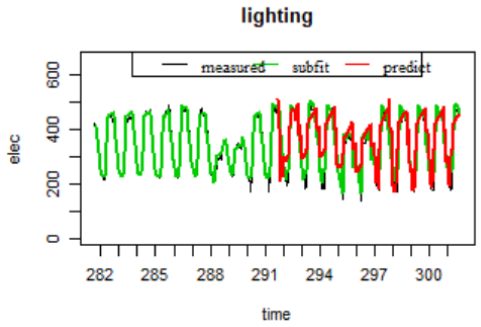
| Item | Lighting | Air condition | Movement | Others | Unknown | Tot |
|---|---|---|---|---|---|---|
| N states | 10 | 7 | 3 | 8 | 3 | 7 |
| Training rela err (%) | 3.06 | 6.67 | 14.16 | 5.64 | 25.17 | 4.04 |
| sigma | 17.09 | 62.44 | 30.03 | 16.98 | 92.08 | 98.82 |
| Predict rela err (%) | 16.14 | 50.67 | 22.85 | 13.79 | 95.20 | 11.21 |
| Last rela err (%) | 16.92 | 36.21 | 33.91 | 14.93 | 96.57 | — |

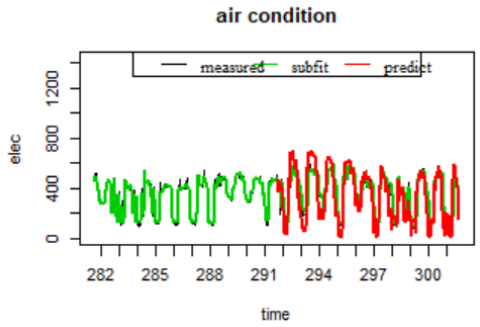


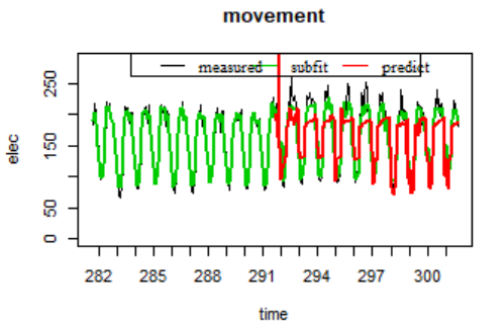
# Disaggregate result: composite

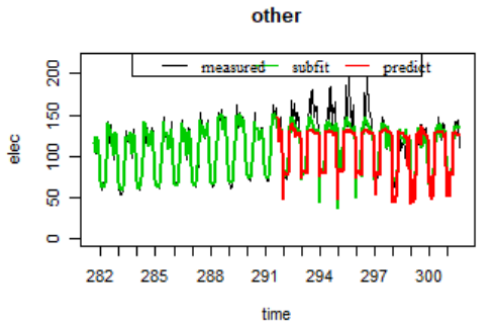
| Item | Lighting | Air condition | Movement | Others | Unknown | Tot |
|---|---|---|---|---|---|---|
| N states | 18 | 9 | 10 | 9 | 3 | 10 |
| Training rela err (%) | 2.45 | 5.38 | 4.04 | 4.63 | 35.93 | 3.15 |
| sigma | 10.93 | 29.48 | 8.05 | 6.13 | 25.94 | 44.56 |
| Predict rela err (%) | 22.14 | 46.68 | 23.92 | 18.13 | 64.91 | 9.09 |
| Last rela err (%) | 13.97 | 35.47 | 18.72 | 15.82 | 62.97 | — |

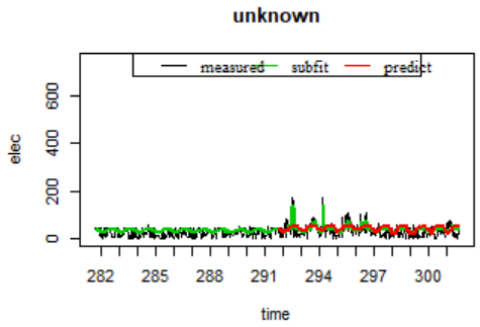


# Disaggregation comparison

| Item | | Lighting | Air condition | Movement | Others | Unknown | Tot |
|---|---|---|---|---|---|---|---|
| Training relative error (%) | Mall | 1.98 | 5.33 | 2.91 | 15.25 | 8.61 | 3.90 |
| | Office | 2.13 | 6.32 | 4.29 | 3.76 | 27.13 | 2.87 |
| | Hotel | 3.06 | 6.67 | 14.16 | 5.64 | 25.17 | 4.04 |
| | Composite | 2.45 | 5.38 | 4.04 | 4.63 | 35.93 | 3.15 |
| Result relative error (%) | Mall | 12.46 | 37.53 | 10.52 | 32.02 | 32.25 | — |
| | Office | 14.01 | 29.50 | 20.63 | 19.35 | 61.26 | — |
| | Hotel | 16.92 | 36.21 | 33.91 | 14.93 | 96.57 | — |
| | Composite | 13.97 | 35.47 | 18.72 | 15.82 | 62.97 | — |

- Testing relative uncertainty larger than training
- The larger of relative uncertainty for training, the larger disaggregation
- Performance similar for buildings
- Air condition, unknown largest both training and disaggregation, for large fluctuation

# Summary

- Extend FHMM model with bonus data to disaggregate hourly whole-building electricity consumption into appliances
- Apply the method to several commercial buildings
  - Successfully disaggregate and get rules of appliances
  - Performance for different buildings are similar
  - Model training perfect, relative uncertainty lower than 7%
  - Model testing, air condition not good for large fluctuation
- Extend to similar buildings without collectors
  - Input the characters of buildings into the model
  - Training different models for different type buildings
  - Important for energy monitoring, need response, accurate prediction

Thank you!