A Fully Unsupervised Appliance Modelling Framework for NILM

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3rd International Workshop on Non-Intrusive Load Monitoring

May 15 2016 in Burnaby , BC, Canada

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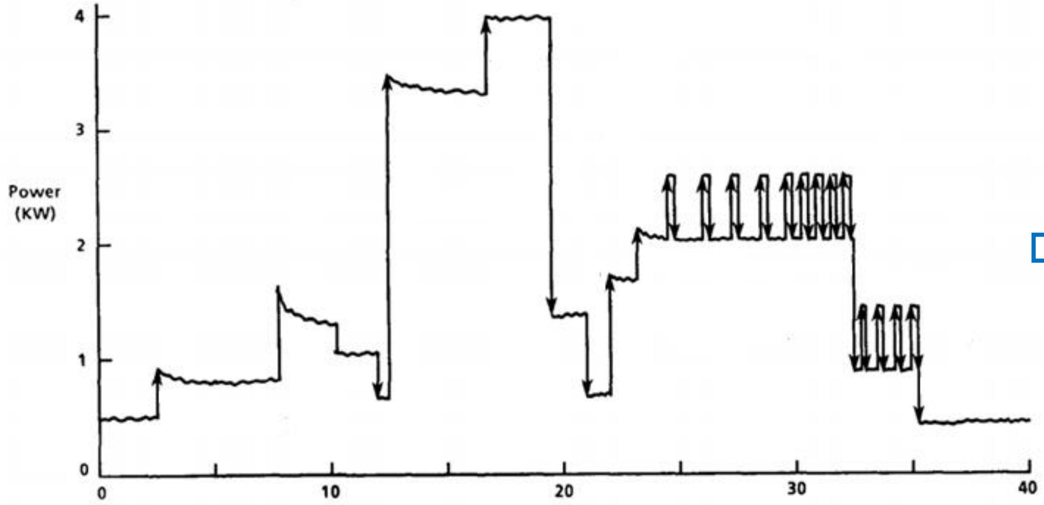
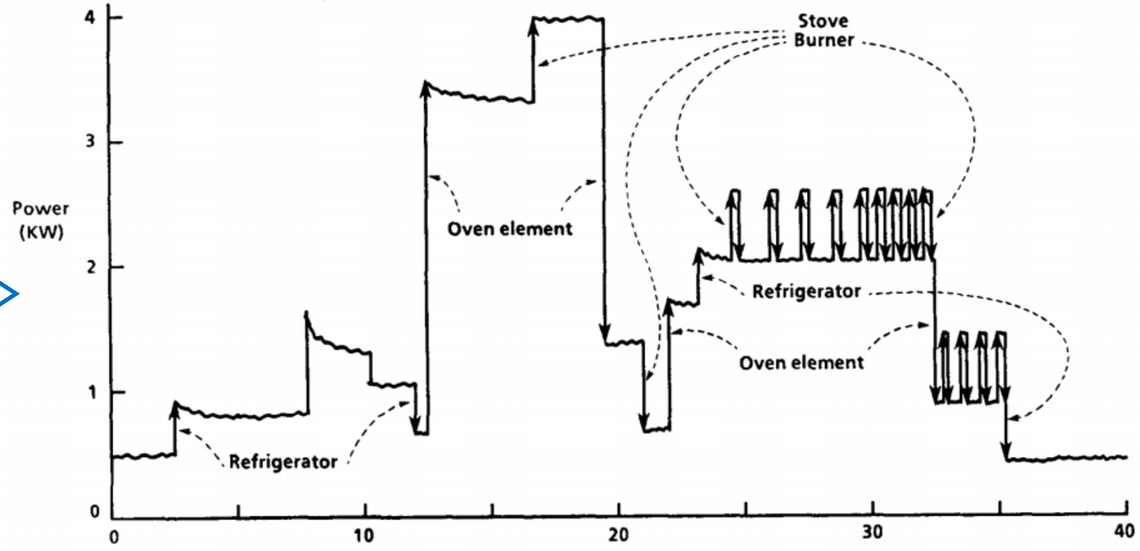
NILM

- NILM analyses the aggregate electricity usage data measured at the power supply entrance of the electric load to acquire the appliance-level specific consumption information via pattern recognition techniques and machine learning methods.

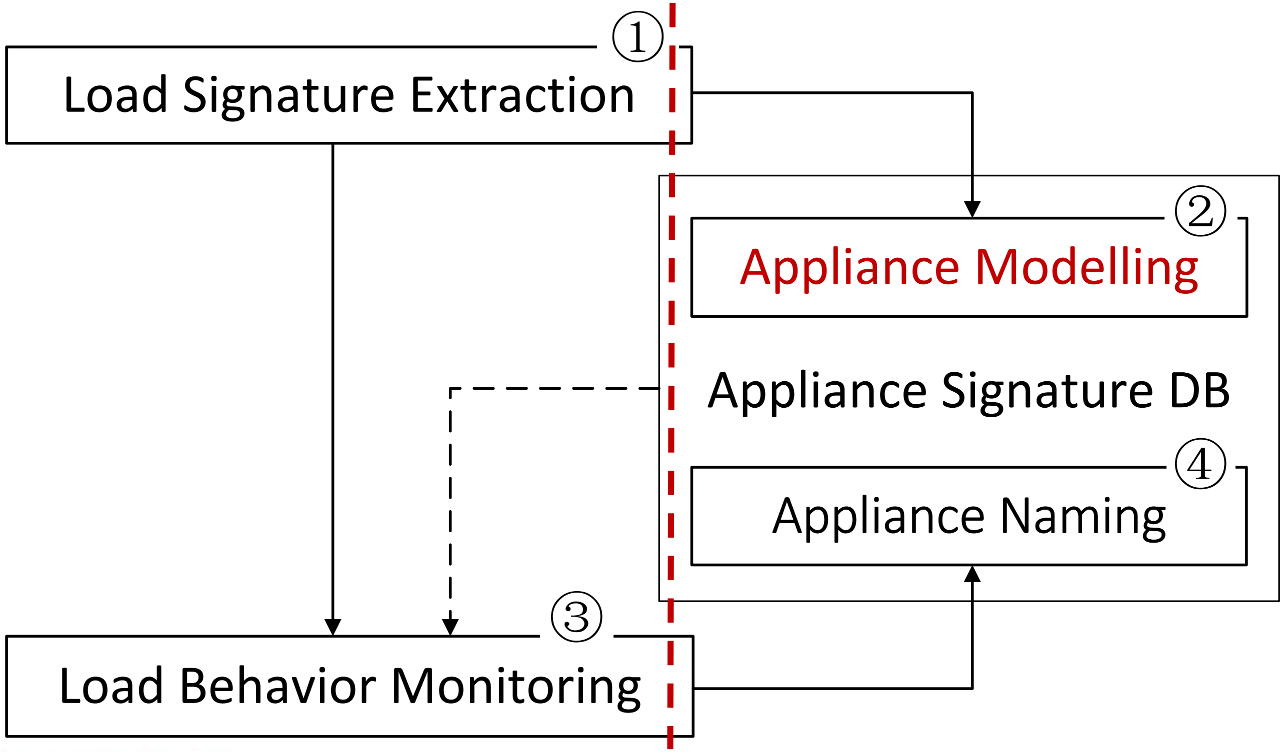


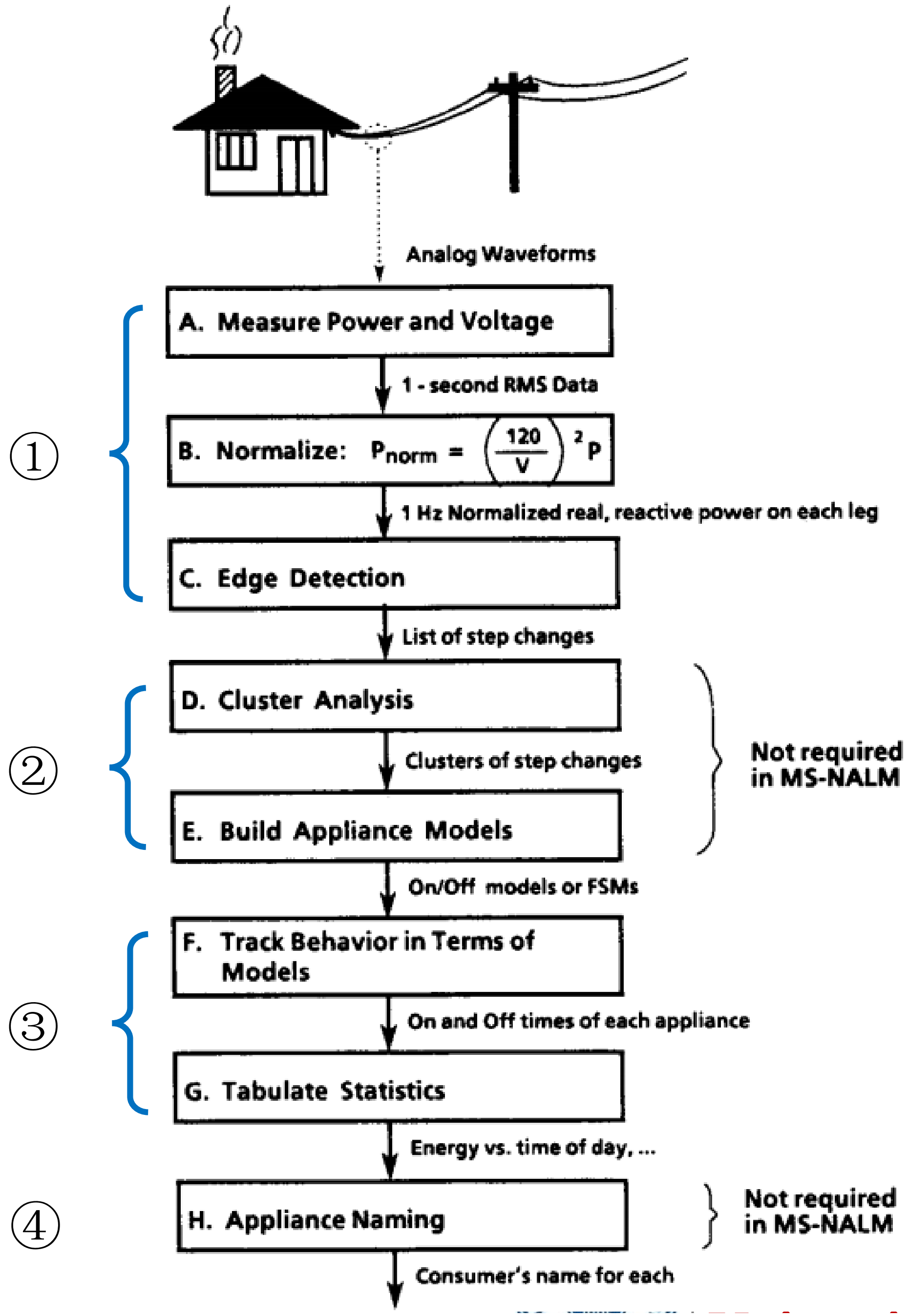


Source: G.W. Hart “Nonintrusive appliance load monitoring” (1992)

NILM

- Principles





Origins from G.W. Hart "Nonintrusive appliance load monitoring" (1992)

Introduction

- Load Modelling is the prerequisite for implementing NILM

- Finite state machine(FSM) is the most common adopted method

  ✓ Supervised Modelling
  (supervised parameter learning from a complete set of labeled signature samples)

  ✓ Semi-supervised Modelling
  (unsupervised parameter learning with the knowledge of the state set and topology of the model)

  ✓ Fully unsupervised Modelling

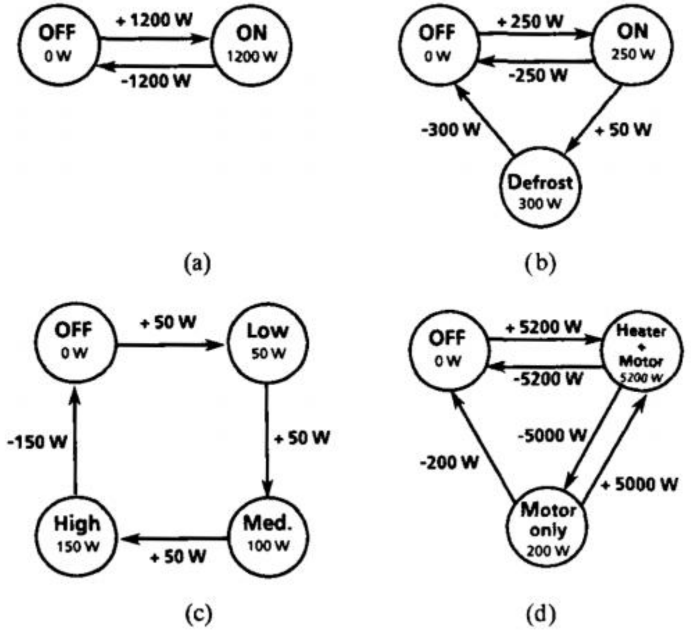


Fig. 4. Finite-state appliance models: (a) generic 1200 W two-state appliance, e.g., toaster; (b) refrigerator with defrost state; (c) "three-Way" lamp; (d) clothes dryer.

Source: G.W. Hart "Nonintrusive appliance load monitoring" (1992)

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Introduction

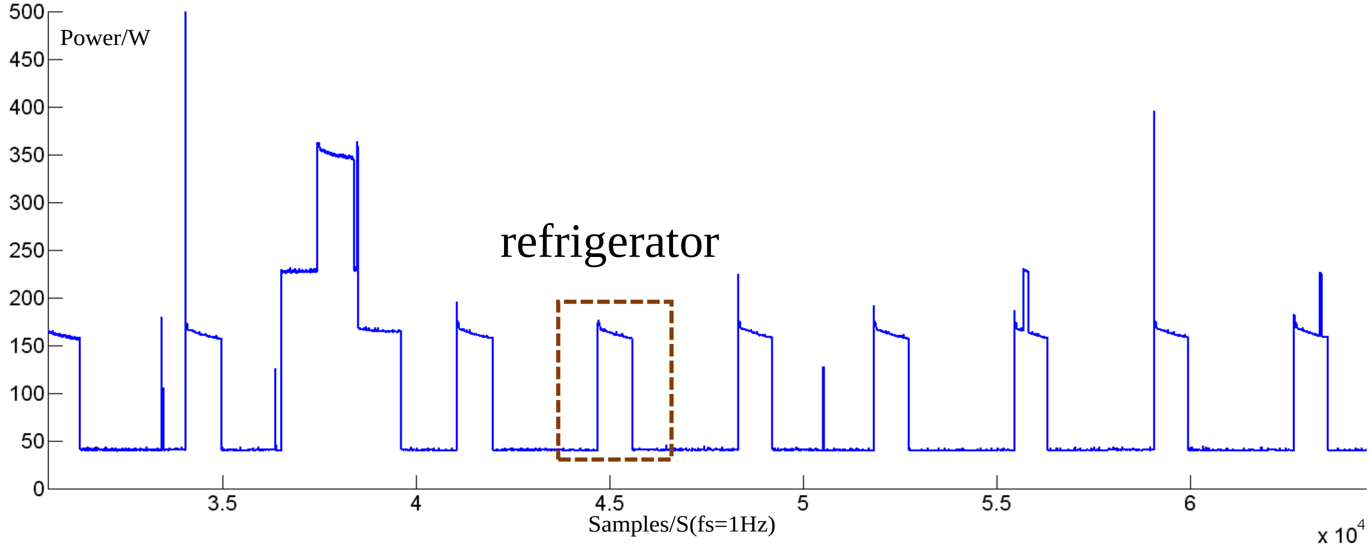
✓ **Fully unsupervised appliance modelling**

- Get complete state set, topological structure and model parameters of FSM
- from the aggregate load data
- without any priori knowledge

Framework Overview

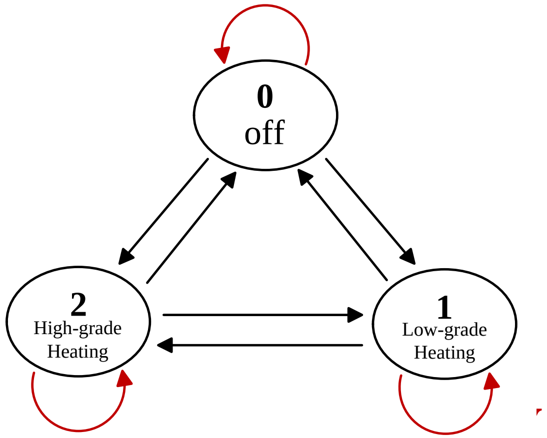
Fact and Assumption: repeated appliance behavior patterns

Figure drew by the power data from the public dataset “Blued”



Ideas:

- Simple Cycle Event Sequence(SCES) pattern constructing FSM
- Use the frequent pattern mining techniques to extract appliance SCES-patterns and combine them



FSM Model Topology of a three-state hair drier

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Framework Overview

- Five Steps：

Detection of IsoES

↓ the set of $\mathbf{\Omega}_{\text{IsoES}}$

Clustering and Labelling of load events

↓ logical name of event

Mining the SCES patterns

↓ the set of $\mathbf{\Omega}_{\text{SCES}}$

Grouping of the SCES patterns

↓ groups of SCES patterns

FSM model topology generation and parameter estimation

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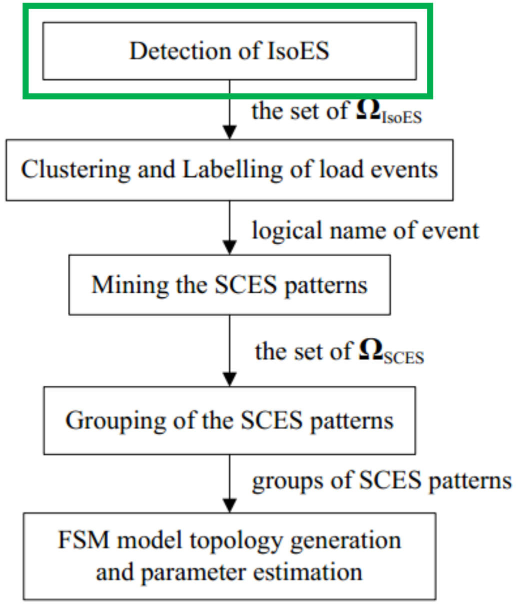
Proposed Methods

Step1: *Detection of IsoES*:

- Isolated load Event Sequence (IsoES)
- Taking IsoES as event sequence record in **ESDB**
  - ✓ IsoES detection method



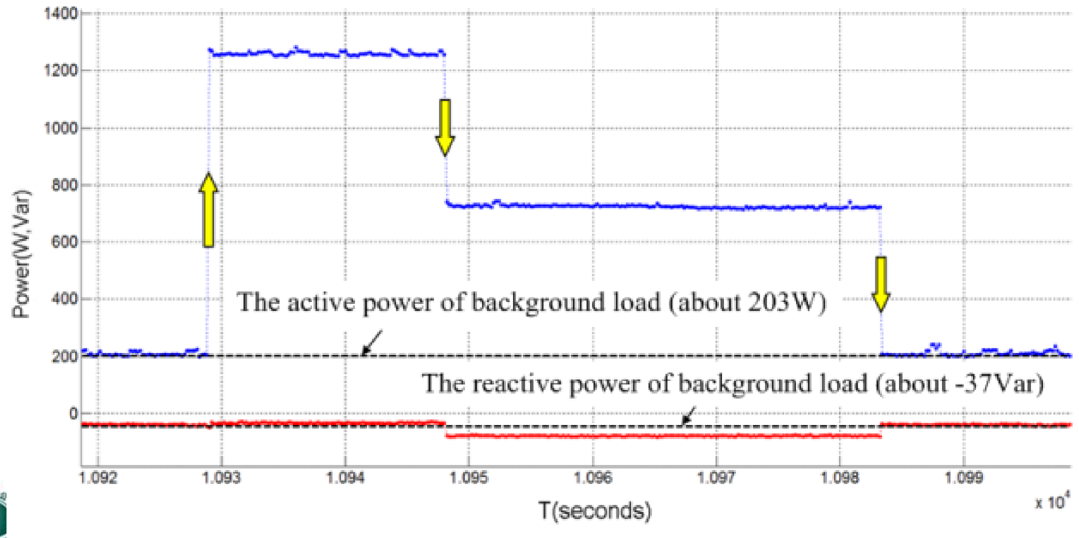


Fig.3. The power curve of a three-state hair drier

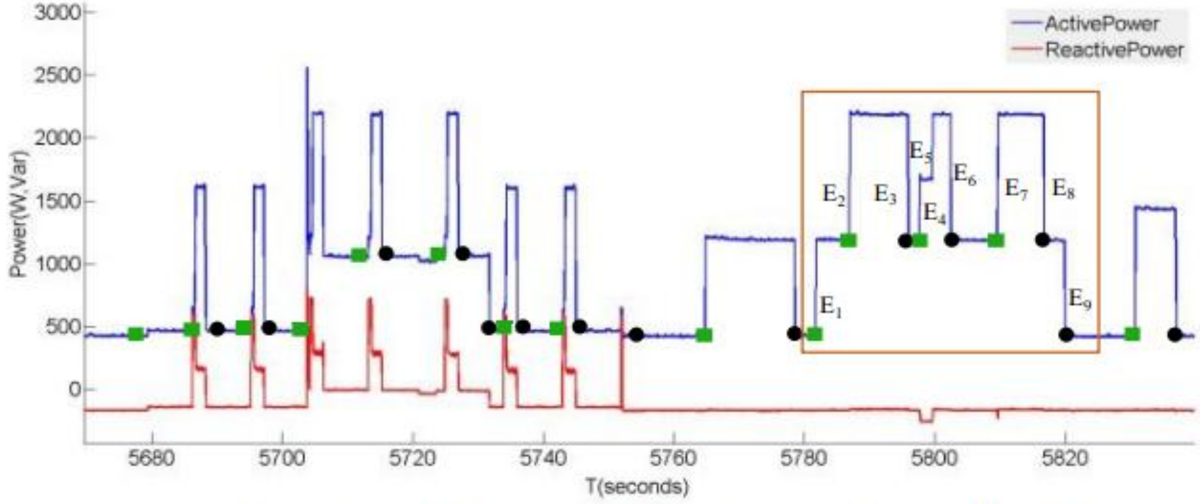
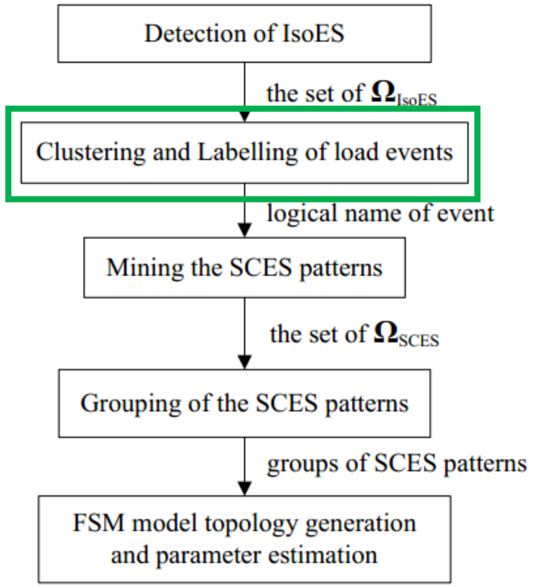


Fig.4. Results of the IsoES detection in the total load

Proposed Methods

Step2: *Clustering and Labelling of load events*(in **ESDB**)



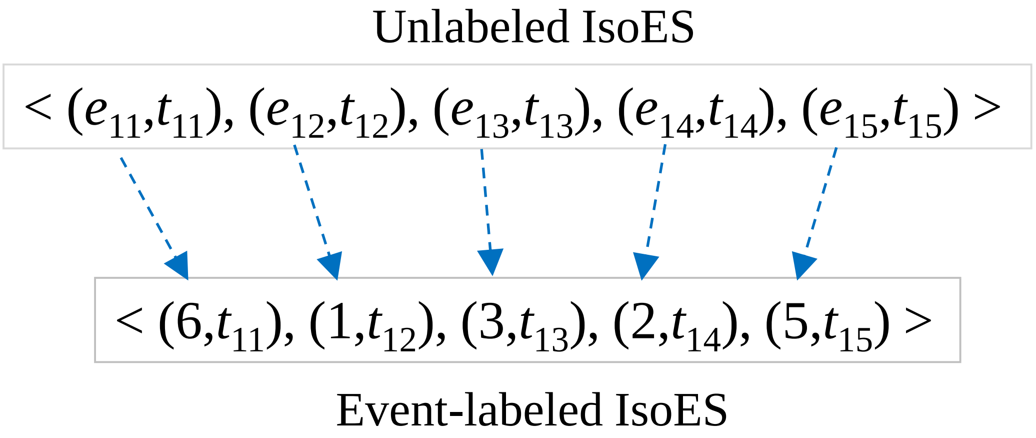
◆ Get a unique logical name for each event

◆ any clustering analysis method not requiring cluster number

✓ *mean-shifting clustering* method

✓ signature vectors representing event $\boldsymbol{e}$

$$\boldsymbol{\beta} = [P_1, Q_1, P_3, Q_3, P_5, Q_5, P_7, Q_7, \ldots\ldots]$$



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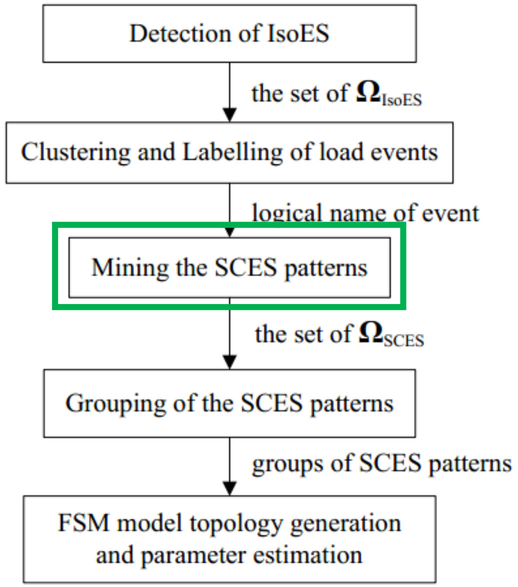
Proposed Methods



Step3: *Mining the SCES patterns*

- ◆ Frequent Event Sequence (FES) patterns mining
  - ✓ Class *GSP* (*Generalized Sequential Pattern*) algorithm

Table1: Example of ESDB used in the proposed framework

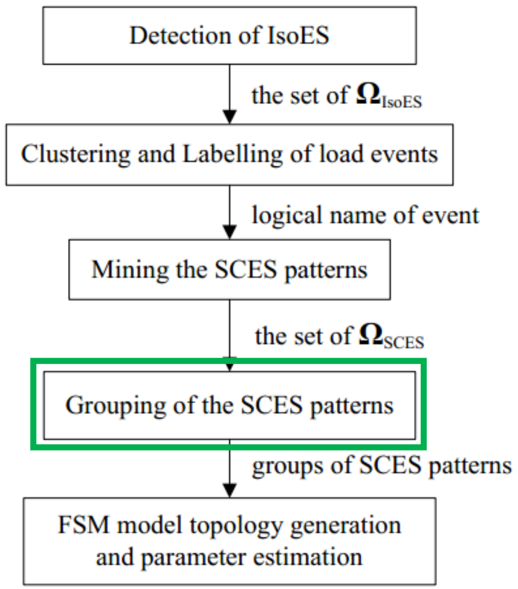
ID of Event sequence	Event Sequence
1	< (**6**,t_{11}), (**1**,t_{12}), (3,t_{13}), (**2**,t_{14}), (5,t_{15}) >
2	< (3,t_{21}), (4,t_{22}), (7,t_{23}), (5,t_{24}) >
3	< (**6**,t_{31}), (8,t_{32}), (**1**,t_{33}), (10,t_{34}), (**2**,t_{35}) >
…	…
k	< (**6**,t_{k1}), (**1**,t_{k2}), (9,t_{k3}), (15,t_{k4}), (**2**,t_{k5}) >
…	…

- ◆ Filtering out the SCES patterns with the β-ZLSC constraint

Proposed Methods

Step4: *Grouping of the mined SCES patterns*

- Divide the acquired SCES patterns into different groups associated with different appliances



Fact and Assumption:

the load events produced by different appliances are different

⇩

Event Correlation Rule

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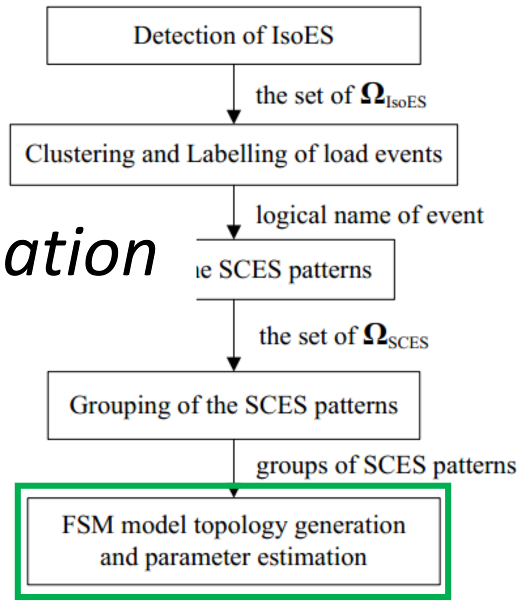
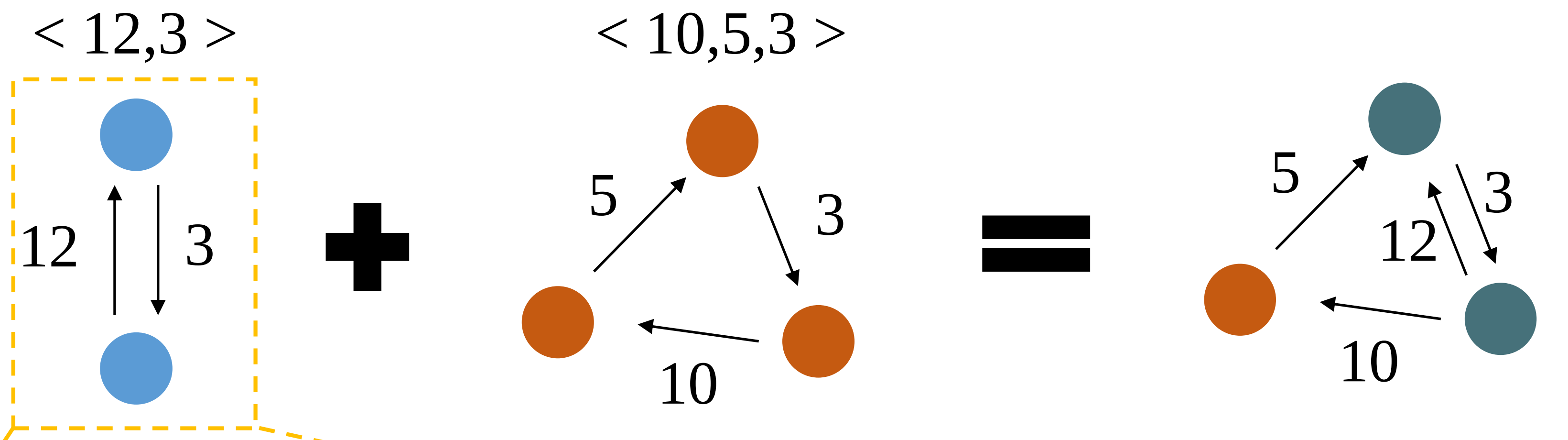
Proposed Methods



Step5: *FSM model topology generation and parameter estimation*

Incremental <u>Topology Generation</u> and <u>Parameter Estimation</u> **(ITGPE)**

TG

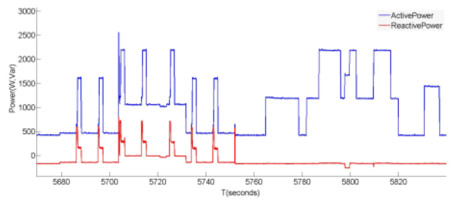


PE

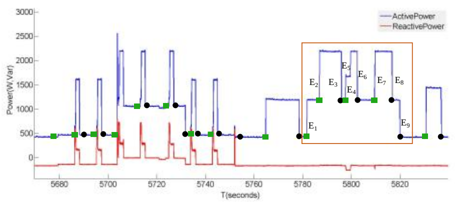
$12\text{:}\ \{\Delta P_{12}, \sigma_{12}\}\quad \Delta\hat{P}_{12}=\Delta P_{12}\text{-}(\Delta P_{12}+\Delta P_3)/2\quad \hat{\sigma}_{12}=\sqrt[2]{{\sigma_{12}}^2+{\sigma_3}^2}/2$

$3\text{:}\ \{\Delta P_3\ , \sigma_3\ \}\quad \Delta\hat{P}_3\ =\Delta P_3\ \text{-}(\Delta P_3+\Delta P_{12})/2\quad \hat{\sigma}_3\ =\sqrt[2]{{\sigma_3}^2+{\sigma_{12}}^2}/2$

Experiments



Aggregate load data
(24h, 1Hz)



76 IsoESs

Table 2: The results of load event clustering

Cluster label	△P(W)	No. of elements	Cluster label	△P(W)	No. of elements
1	-3101	5	***9***	-585	18
2	1145	25	***10***	496	4
3	-1009	15	***12***	1011	13
4	781	4	***14***	-762	4
5	513	4	***15***	609	18
8	-1130	24	***17***	3142	5

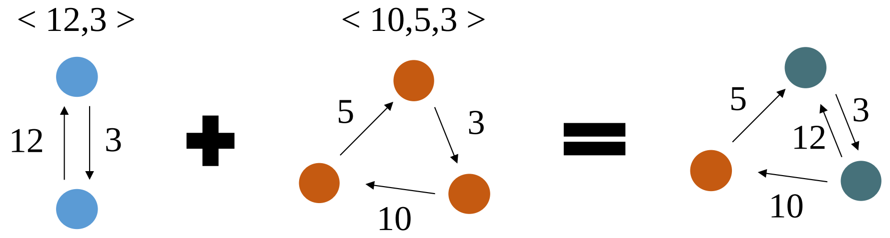


Table 3: The results of SCES pattern mining

ID of SCES pattern	SCES (cluster label, see Table 2)			Frequency of SCES pattern
1	***2***	***8***	—	23
2	***4***	***14***	—	4
3	***12***	***3***	—	12
4	***15***	***9***	—	16
5	***17***	***1***	—	5
6	***10***	***5***	***3***	4

Table 4: The results of FSM model parameters

ID of appliance	μ(W)	σ(W)	Appliance name
1	{**0**,1138/298}	{**0**,22/23}	Microwave oven
2	{**0**,772/1}	{**0**,11/2}	Electric oven
3	{**0**,496/-56,1009/-4}	{**0**,9/19,19/3}	Hair drier
4	{**0**,597/147}	{**0**,21/8}	Vacuum cleaner
5	{**0**,3122/-8}	{**0**,13/11}	Electric Heater

Conclusions

- A fully unsupervised appliance FSM modelling framework is proposed and validated on real measured data

- The applicability of the existing NILM technologies is improved

- Moving towards the realization of the auto-setup NILM

Future work

- Comprehensive testing and analysis on more measured data
- Improvement on the methods and algorithms used by different modules of the framework
- Appliance Naming for the acquired FSM model

Q&A

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