A new approach for supervised power disaggregation by using a deep recurrent LSTM network

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Content

Motivation

Limitations of current NILM approaches

Unsupervised event based

event detection	event matching	clustering	reconstruction

- difficult for multi-state loads
- not suitable for variable loads
- not scalable to a large number of loads and events

- no load specific disaggregation
- hand crafted feature extraction
- sampling frequency higher than the line freqency needed

missing robustness

Supervised eventless

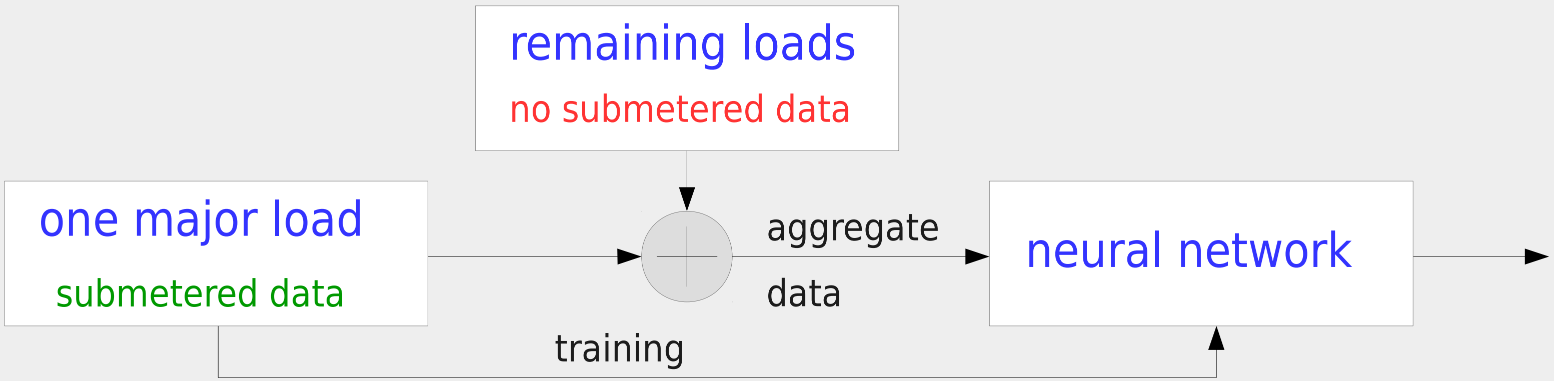
Factorial Hidden Markov Model (FHMM) for single channel source separation

- not scalable due to exponential complexity
- exact training and inference intractable
- HMM of each load has to be known

missing scalability

Our approach

Supervised Neural Network based approach for single channel source extraction



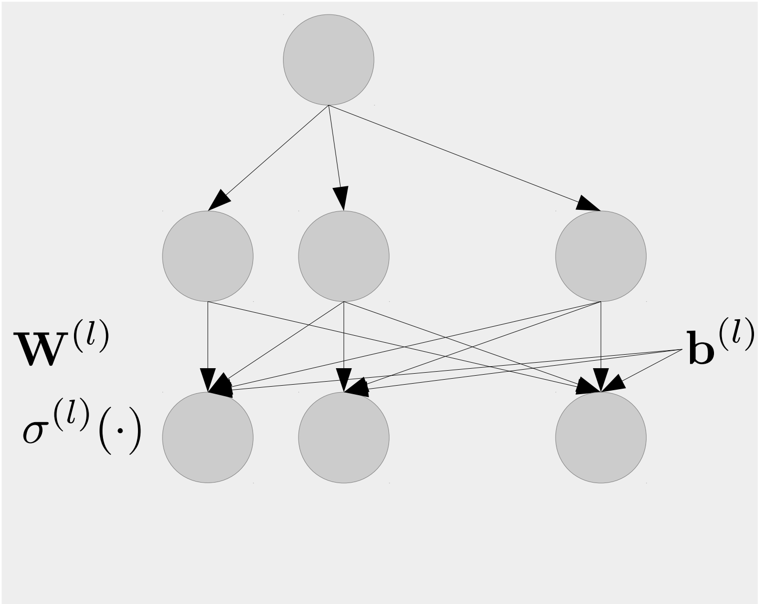
- remaining loads treated as time varying noise

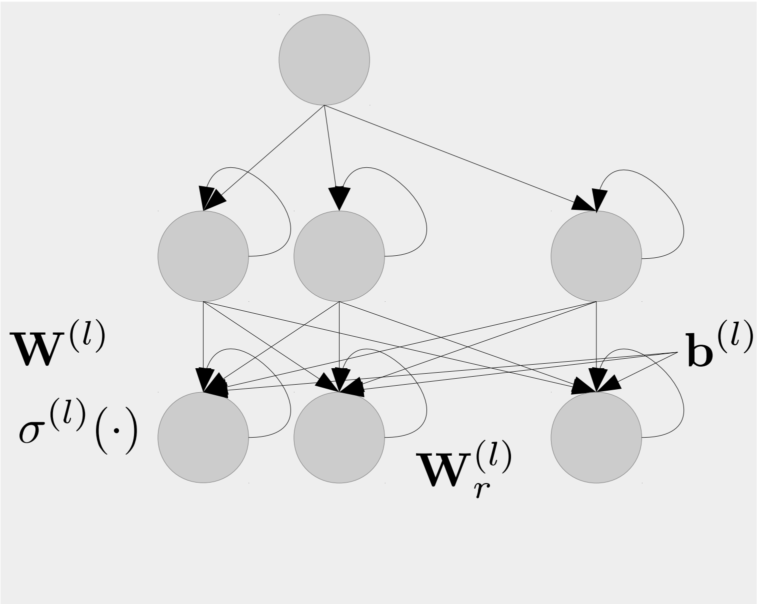
- scalable to many loads
- no hand crafted feature extraction
- assignment of power traces to specific loads possible
- suitable for multi-state and variable load devices
- suitable for low frequency (<1Hz) real power data only

- submetered training data needed

Recurrent Neural Network (RNN)

Feedforward Neural Network	Recurrent Neural Network





Feedforward Neural Network

- multiple layers of units
- feedforward connections

- universal static mapper
- used for classification and regression

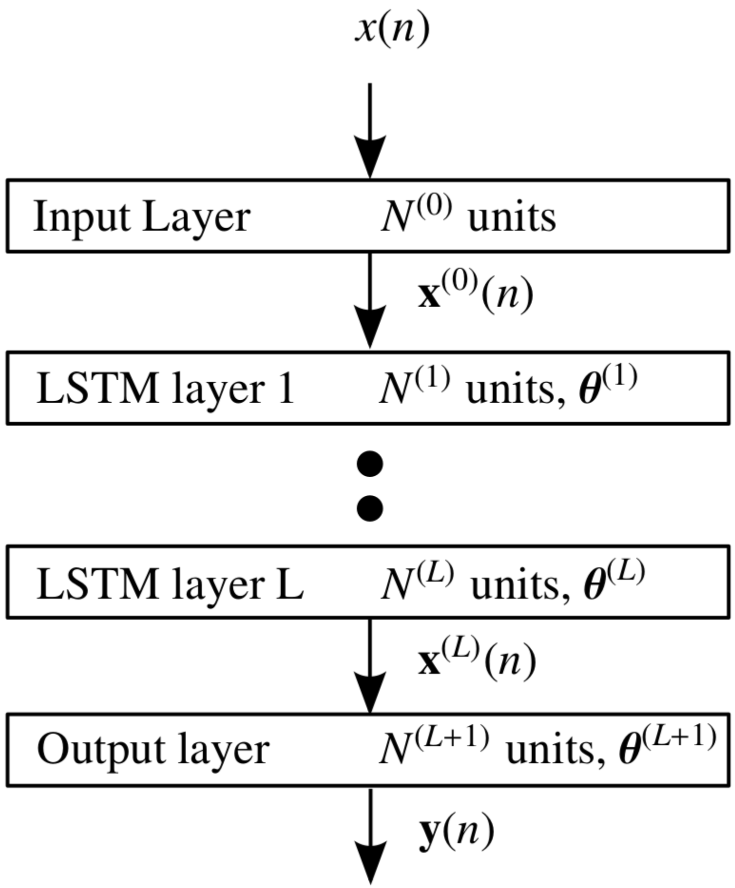
Recurrent Neural Network

- feedback connections allowed in each layer

- can learn any causal time-varying mapping
- used for sequence labeling and prediction

Model layout

Layout



- Use forward-backward processing to allow noncausal mapping

Mapping

$$\mathbf{x}^{(0)}(n) = [x(n), x(n-1), \ldots, x(n - N^{(0)} + 1)]^T \in \mathbb{R}^{N^{(0)}}$$

Gates $\mathbf{i}^{(l)}(n) = g(\mathbf{x}^{(l-1)}(n), \mathbf{x}^{(l)}(n-1), \mathbf{s}^{(l)}(n-1))$

$$\mathbf{o}^{(l)}(n) = \ldots$$

$$\mathbf{f}^{(l)}(n) = \ldots$$

$$g(\mathbf{x}, \mathbf{y}, \ldots, \mathbf{z}) = \mathbf{W}_x\mathbf{x} + \mathbf{W}_y\mathbf{y} + \ldots + \mathbf{W}_z\mathbf{z} + \mathbf{b}$$

States

$$\mathbf{s}^{(l)}(n) = \mathbf{i}^{(l)}(n) \circ \tanh\left(g(\mathbf{x}^{(l-1)}(n), \mathbf{x}^{(l)}(n-1))\right) + \mathbf{f}^{(l)}(n) \circ \mathbf{s}^{(l)}(n-1)$$

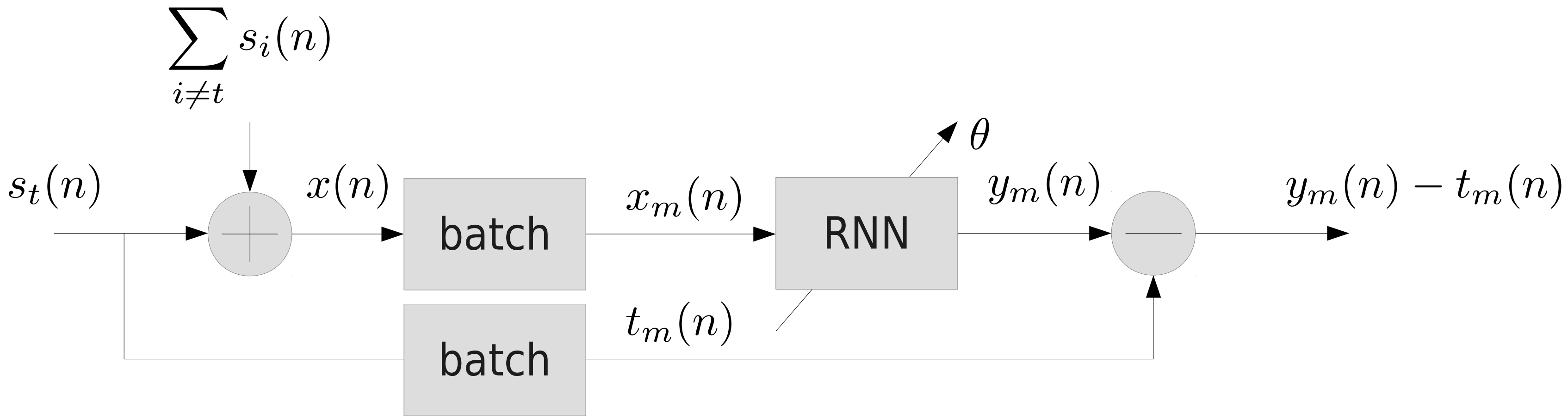
Output

$$\mathbf{x}^{(l)}(n) = \mathbf{o}^{(l)}(n) \circ \tanh(\mathbf{s}^{(l)}(n))$$

$$\mathbf{y}(n) = \sigma^{(L+1)}(\mathbf{W}^{(L+1)}\mathbf{x}^{(L)}(n) + \mathbf{b}^{(L+1)}) \in \mathbb{R}^{N^{(L+1)}}$$

Application to NILM

Extraction of target signal $s_t(n)$ with bidirectional RNN



Training pairs

$x_m(1), \dots x_m(B)$

$t_m(1), \dots, t_m(B)$

...signals divided into M blocks of length B

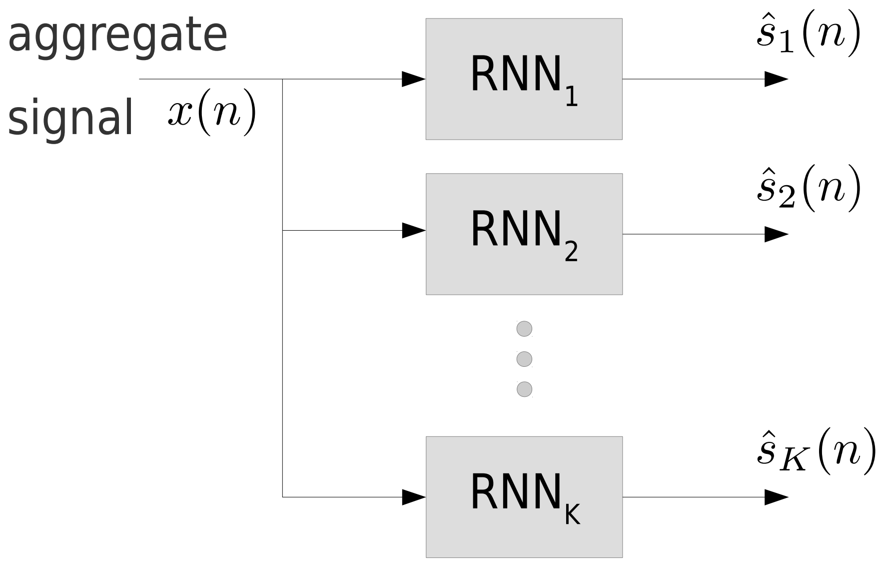
Cost

$$J(\boldsymbol{\theta}) = \sum_{m=1}^{M} \sum_{n=1}^{B} (y_m(n) - t_m(n))^2 + \lambda_1 ||\boldsymbol{\theta}||_1 + \lambda_2 ||\boldsymbol{\theta}||_2^2$$

Optimization

stochastic gradient descent | momentum | learning reate decay

Extraction of multiple loads

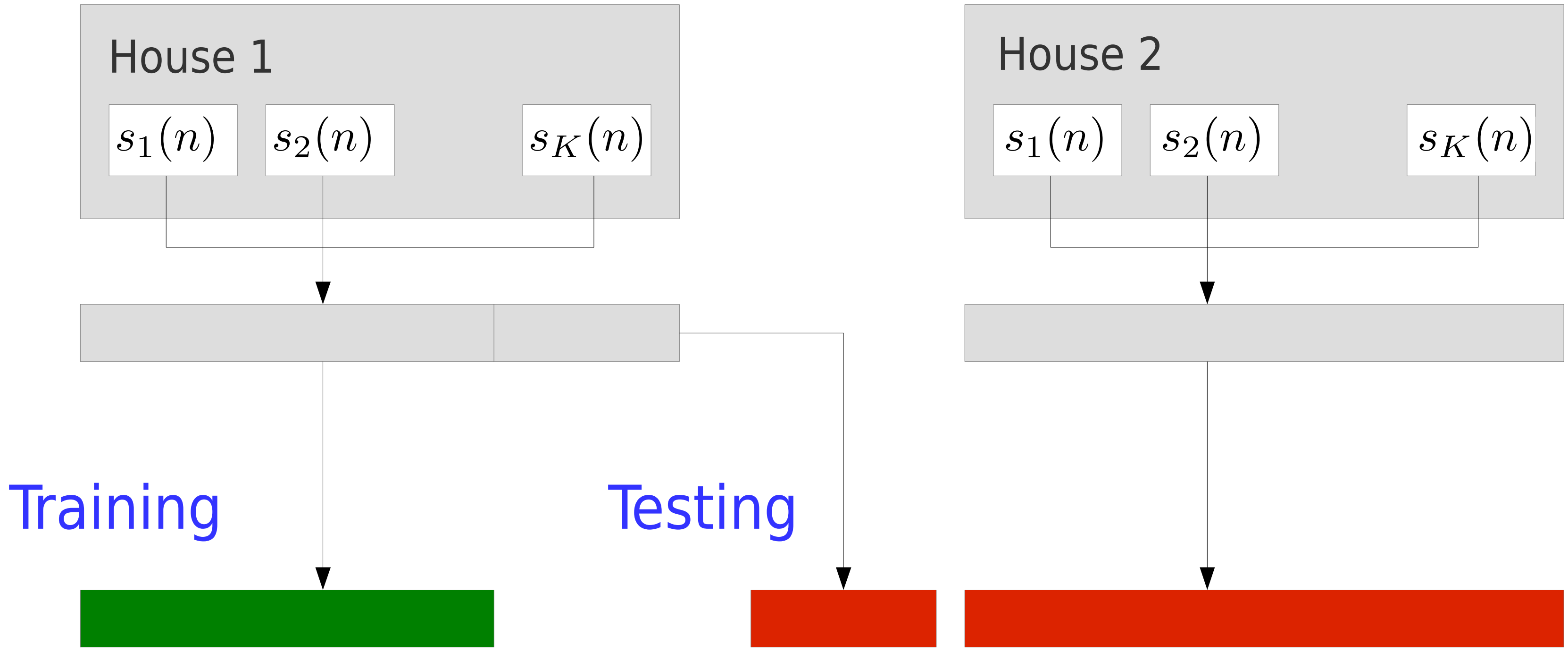


- Train multiple models by using mltiple submeter measurements
- Use one model to extract one major load separately out of the aggregate signal
  → easily extendable to new loads

Using Reference Energy Disaggregation Dataset (REDD)

- #loads: K=16
- #hours: 620h

- #loads: K=9
- #hours: 258h



Experiments

Network setup

- Input layer
  - $N^{(0)} = 10$
- Two recurrent layers
  - $N^{(1)} = N^{(2)} = 140$
- Output layer
  - $N^{(L+1)} = 1$
- #Parameters 485801

Target appliances

- Refrigerator
  - on/off device
  - periodic power consumption
  - small amplitude
- Dishwasher
  - multi-state device
  - nonperiodic
  - fixed pattern
- Microwave
  - multi-state device
  - nonperiodic
  - random pattern

Metrics

- Estimated energy

$$\hat{E}_t = \frac{1}{F_s} \sum_{n=1}^{N} \hat{s}_t(n)$$

- Consumed energy

$$E_t = \frac{1}{F_s} \sum_{n=1}^{N} s_t(n)$$

- NRMS

$$\text{NRMS} = \sqrt{\frac{\sum_{n=1}^{N} (\hat{s}_t(n) - s_t(n))^2}{\sum_{n=1}^{N} s_t^2(n)}}$$

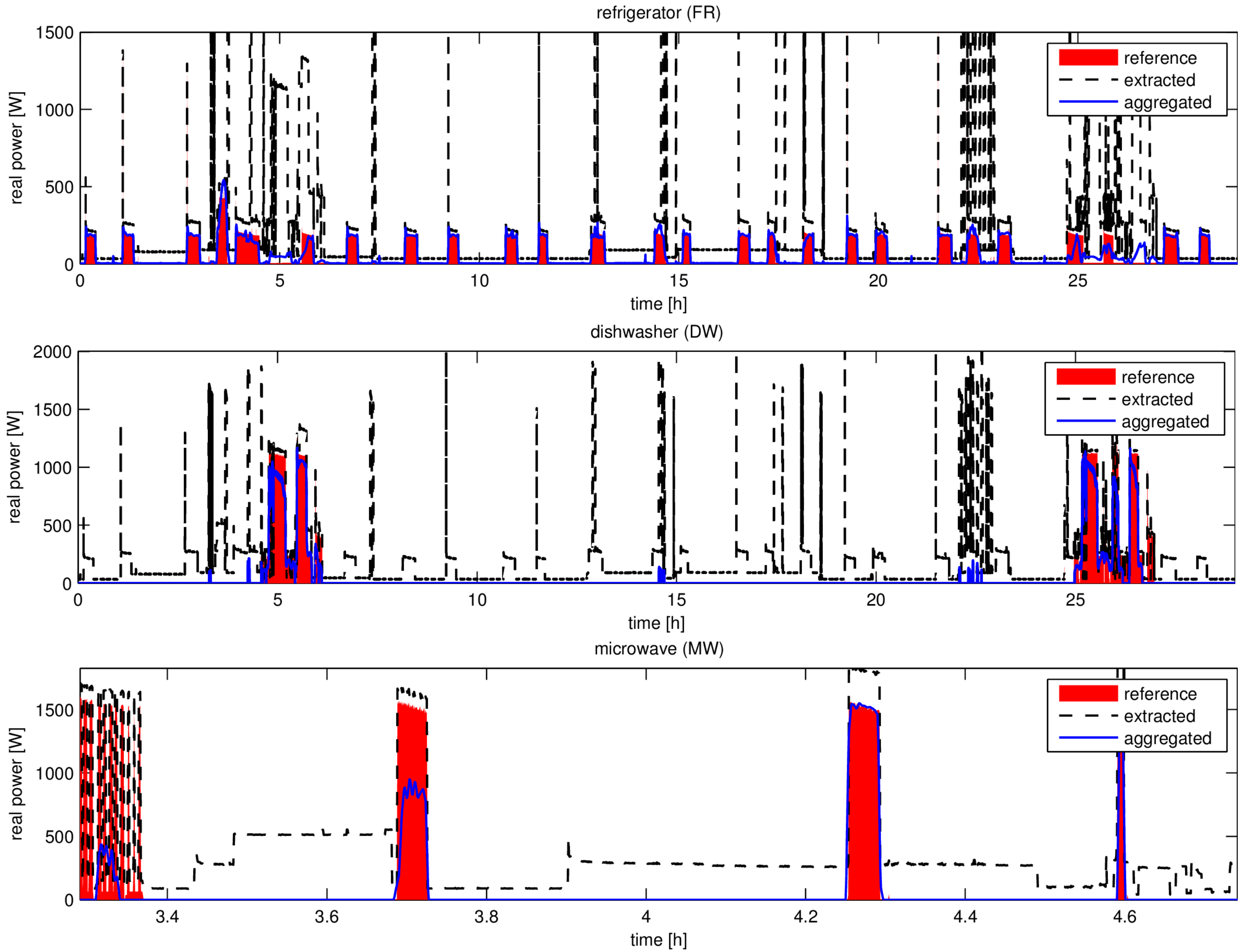
For active periods

$$s_t(n) \geq \gamma, \ \hat{s}_t(n) \geq \gamma$$

- Precision
- Recall
- F1 score

Experiments

Results for house 1



- details in following MATLAB demonstration

Experiments

Metrics for validation on house 1

Appl.	E_t	$\hat{E}_t$	NRMS	F1	R	P
FR	23.9	23.0	0.33	0.91	0.98	0.85
DW	11.1	10.50	0.35	0.79	0.87	0.73
MW	7.8	7.9	0.74	0.66	0.83	0.54

Table 1. Validation on test set of house 1 with $E = 63.37kWh$

Metrics for validation on house 2

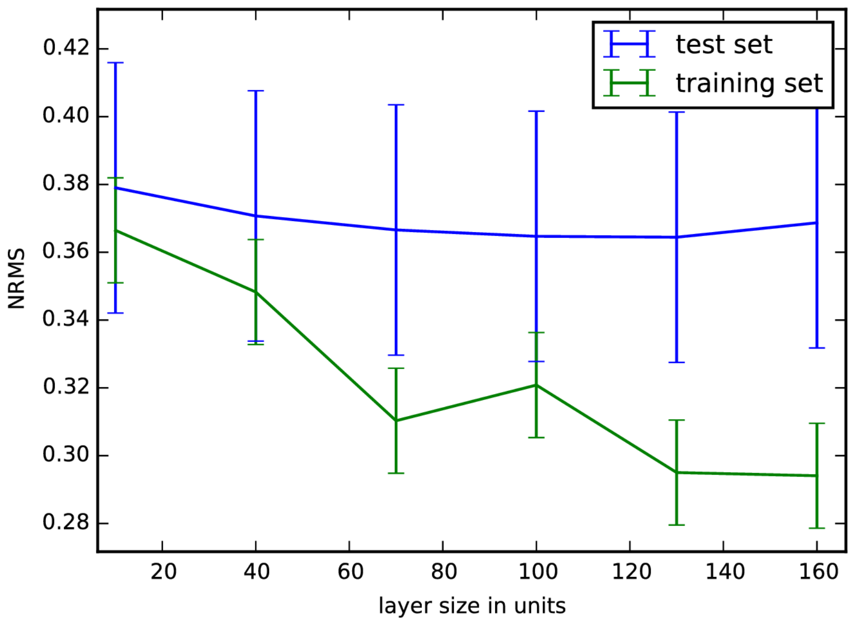
Appl.	E_t	$\hat{E}_t$	NRMS	F1	R	P
FR	20.7	20.6	0.35	0.93	0.96	0.91
DW	2.36	3.26	0.31	0.68	1.0	0.52
MW	4.0	2.11	0.58	0.09	0.05	0.5

Table 2. Validation on house 2 with $E = 36.6kWh$

- Models trained from house 1 work well for house 2 → high robustness

Experiments

Overfitting to training set



- result heavily dependent on initialization
- larger layer allows for more complex mappings
- network tends to overfit to training data
- increase of validation error between 120 and 160 units layer size chosen to 140 units

Conclusion

Advantages of the approach

- Bidirectional RNN can be used for supervised load disaggregation
- Good performance for appliances with recurring patterns
- Eventless for all types of loads
- Allow low-frequency (<1Hz) power meter
- No feature engineering

Drawbacks

- Need submeter data
- Networks tend to overfit for little training data

Future work

- Combination of DNN and HMM for disaggregation
- Domain adaption for different loads of same kind