A NOVEL DNN-HMM-BASED APPROACH FOR EXTRACTING SINGLE LOADS FROM AGGREGATE POWER SIGNALS

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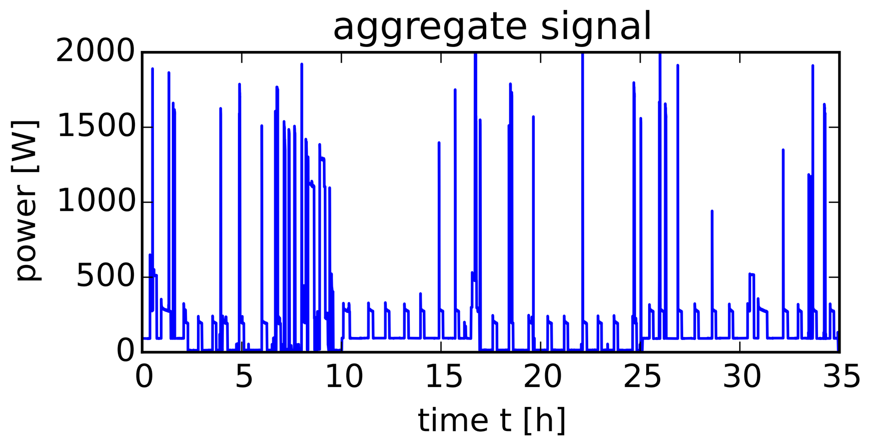
1. Introduction

1.1 Non-intrusive load monitoring

- Estimate power consumed by individual loads from aggregate power signal
- Aggregate signal $x(n) = \sum_{k=1}^{M} x_k(n),\ x_k(n) \in \mathbb{R}^+$ consists of real power measurements of up to hundreds of loads



- Single loads are non-stationary with strong temporal relations from seconds to many hours
- Established techniques for single channel source separation fail

1.2 Contribution

- Combination of Deep Neural Network (DNN) and Hidden Markov Model (HMM) for signal extraction from single channel measurements

2. DNN-HMM Network

2.1 Idea

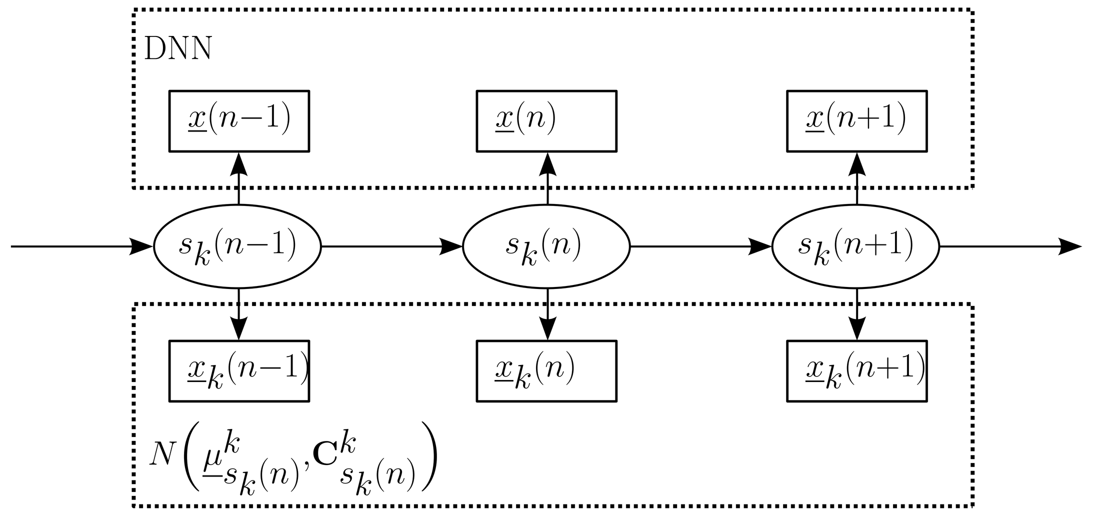


Abbildung 1: *The DNN-HMM network for signal extraction*

- Use DNN-HMM as generative model for
  - Observation sequence of aggregate signal $\{\underline{x}\} = \{\underline{x}(1), \ldots, \underline{x}(N)\}$
  - Observation sequence of single load $\{\underline{x}_k\} = \{\underline{x}_k(1), \ldots, \underline{x}_k(N)\}$
  - Hidden state sequence $\{s_k\} = \{s_k(1), \ldots, s_k(N)\}$
- Train one DNN-HMM for each target load contained in aggregate signal
- For each load, the HMM captures the temporal relations in the signal. The DNN is used to infer the state sequence from the aggregate signal.

2.2 Architecture of HMM

- Parametrization of the HMM of load k

$$
\begin{aligned}
s_k(n) &\in \{1, \cdots, M_k\} \\
\underline{\pi}^k &= [P(s_k(1)=1), \ldots, P(s_k(1)=M_k)]^T \\
p^k_i &= p(\underline{x}_k(n)|s_k(n)=i) \sim N(\underline{\mu}^k_i, \mathbf{C}^k_i) \\
\tilde{p}^k_i &= p(\underline{x}(n)|s_k(n)=i) \\
\mathbf{A}^k &= [P(s_k(n)=i|s_k(n-1)=j)]_{ij}
\end{aligned}
$$

- The joint probability distribution of the sequences is

$$
\begin{aligned}
p(\{s_k\}, \{\underline{x}_k\}, \{\underline{x}\}) = &\ \underline{\pi}^k_{s_k(1)} p^k_{s_k(1)} \tilde{p}^k_{s_k(1)} \\
&\cdot \prod_{n=2}^{N} p^k_{s_k(n)} \tilde{p}^k_{s_k(n)} \mathbf{A}_{s_k(n), s_k(n-1)}
\end{aligned}
$$

2.3 Architecture of DNN

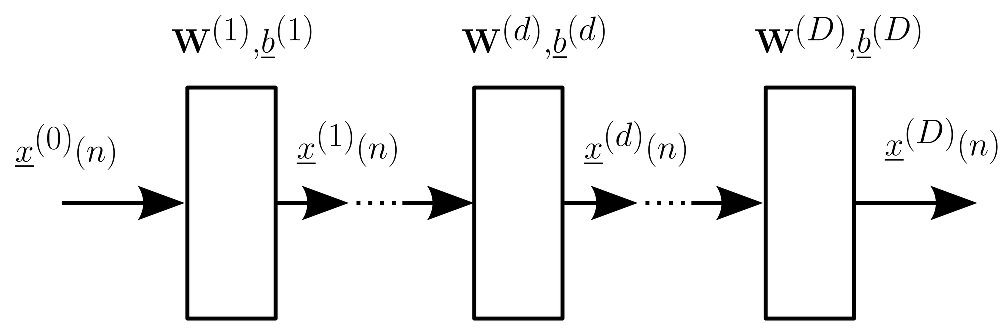


Abbildung 2: *Architecture of the D-layer DNN*

- DNN can model very complex conditional density functions
  - Input: current observation plus context in block of length B

$$\underline{x}^{(0)}(n) = [\underline{x}^T(n-B), \ldots, \underline{x}^T(n+B)]^T$$

  - Mapping:

$$
\begin{aligned}
\underline{a}^{(d)}(n) &= \mathbf{W}^{(d)} \underline{x}^{(d-1)}(n) + \underline{b}^{(d)},\ 1 \le d \le D \\
\underline{x}^{(d)}(n) &= \Phi^{(d)}(\underline{a}^{(d)}(n))
\end{aligned}
$$

  - Output:

$$
\begin{aligned}
\underline{x}^{(D)}(n) &= [f_1(\underline{x}^{(0)}(n)), \ldots, f_{M_k}(\underline{x}^{(0)}(n))]^T \\
f_i(\underline{x}^{(0)}(n)) &= P(s_k(n)=i|\underline{x}^{(0)}(n))
\end{aligned}
$$

- The DNN is trained to approximate

$$\tilde{p}_{s_k(n)} \sim \frac{P(s_k(n)|\underline{x}^{(0)}(n))}{P(s_k(n))}$$

2.4 Inference and signal extraction

- Infer the state sequence from the aggregate signal, using the state posteriors estimated by DNN

$$P(\{s_k\}|\{\underline{x}\}, \underline{\lambda}_k) = \frac{1}{Z} \underline{\pi}^k_{s_k(1)} \tilde{p}^k_{s_k(1)} \prod_{n=2}^{N} \tilde{p}^k_{s_k(n)} \mathbf{A}_{s_k(n), s_k(n-1)}$$

- Reconstruct the power consumed by load k from the state sequence

$$\hat{\underline{x}}_k(n) = \underline{\mu}^k_{s_k(n)}$$

2.5 Supervised training

- For a given training sequence $\underline{x}^t_k$ of load k, maximize

$$p(\{\underline{x}^t_k\}|\underline{\lambda}_k) = \sum_{\{s_k\}} \underline{\pi}^k_{s_k(1)} p^k_{s_k(1)} \prod_{n=2}^{N} p^k_{s_k(n)} \mathbf{A}_{s_k(n), s_k(n-1)}$$

  over parameters $\underline{\lambda}_k$ of the DNN-HMM
- Infer the most likely state sequence $\{\hat{s}^t_k\}$ for given $\{\underline{x}^t_k\}$ and all possible $\{\underline{x}^t\}$
- Optimize over the DNN parameters in order to minimize

$$
\begin{aligned}
J(\{\underline{x}^t_k\}, \{\underline{x}^t\}) &= -\sum_{n=1}^{N} \log\left(\sum_{i=1}^{M_k} \mathbf{A}_{i, \hat{s}^t_k(n-1)} \tilde{p}^k_i p^k_i \mathbf{A}_{\hat{s}^t_k(n+1), i}\right) \\
&= -\log \prod_{n=1}^{N} p(\underline{x}^t_k(n), \underline{x}^t(n)|\hat{s}^t_k(n-1), \hat{s}^t_k(n+1))
\end{aligned}
$$

3. Experiments and results

- Extract the major loads fridge (FR), dishwasher (DW), microwave (MW) and kitchen outlets (KO)
- Reference Energy Disaggregation Dataset (REDD) containing 18 loads used

$$E_k = \frac{1}{F_s} \sum_{n=1}^{N} x_k(n)$$

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

$$\mathrm{NAD} = \frac{\sum_{n=1}^{N} |\hat{x}_k(n) - x_k(n)|}{\sum_{n=1}^{N} |x_k(n)|}$$

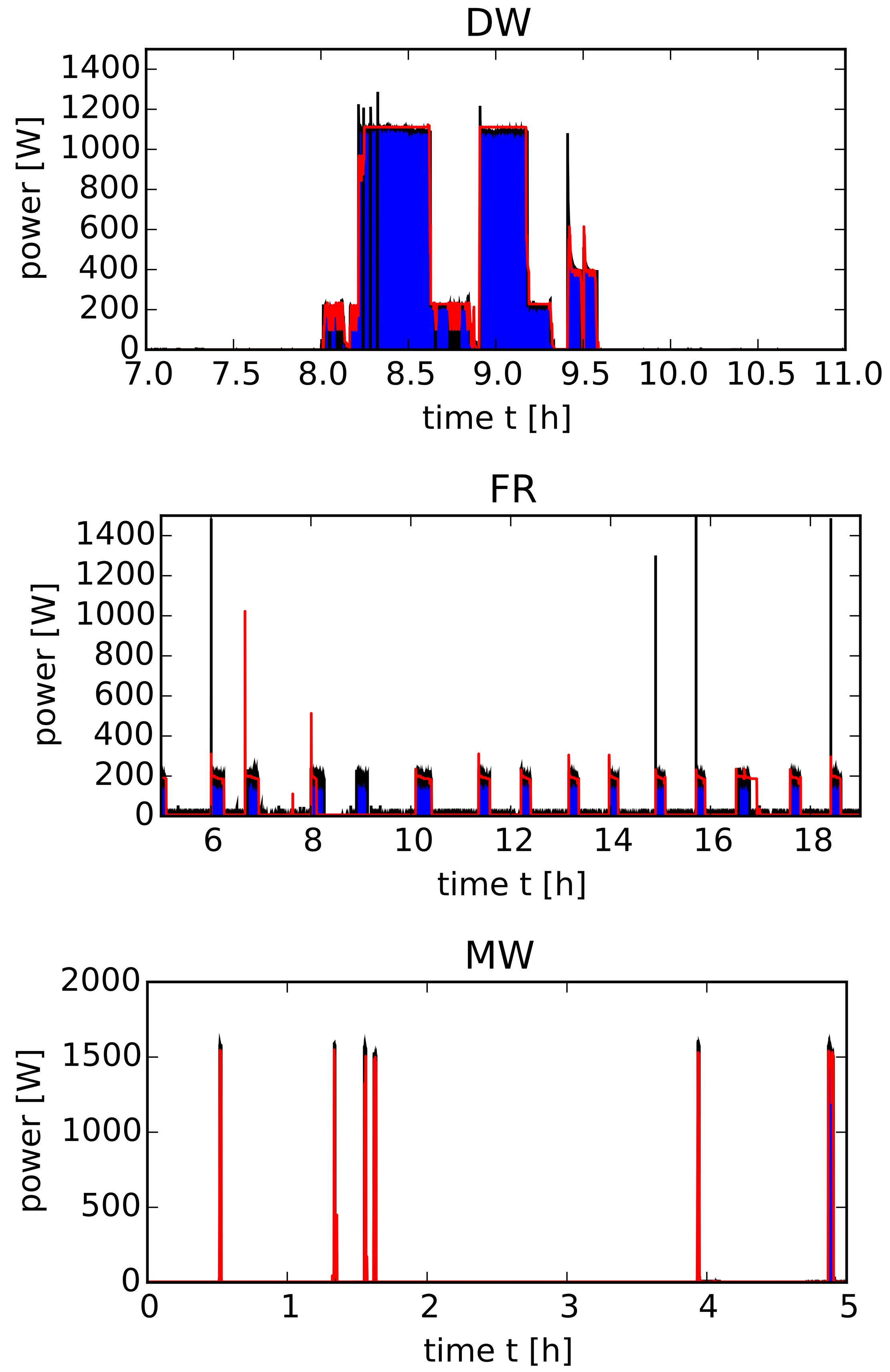


Abbildung 3: *Ground truth (filled blue) and extracted (red) signals.*

Appl.	E_t	$\hat{E}_t$	NAD	Gain
FR	4.30	4.26	0.14	10.5
DW	0.93	0.94	0.08	21.1
MW	1.66	1.49	0.27	13.1
KO	0.35	0.34	0.22	21.0

Tabelle 1: *Power based metrics*

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