Results from Non-intrusive Load Monitoring

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Non-intrusive load monitoring (NILM) refers to the determination of the electrical load composition through a single point of measurement, e.g. at the main power feed. In this article we shortly review NILM techniques, position the CSEM approach and provide results from recent work.

NILM requires load curve data acquisition at an adequate rate so that distinctive load patterns can be identified. As the number of exploitable data features increases with the sampling frequency, the latter mainly determines the number of appliances that can be identified, see also Table 1 hereafter.

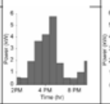
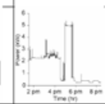
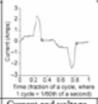
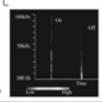
Data Frequency Analyzed	1 hr – 15 min	1 min – 1 s (1 Hz)	1-60 Hz	60 Hz-2 kHz	10-40 kHz	>1 MHz
Data Appearance						
Data Features Used by Algorithms	Visually observable patterns; duration and time of appliance use	Steady state steps/ transitions of power	Steady state steps/ transitions of power	Current and voltage, providing low order harmonics	Current and voltage, providing medium order harmonics to identify type of electrical circuitry in appliance	Current and voltage, providing very high order harmonics to identify both transients & the background noise of appliances
Appliances Identified	Differentiates ~3 general categories: loads that correlate with outdoor temperature, loads that are continuous, and loads that are time-dependent	Top <10 appliance types: Refrigerator, ACs, Heaters, Pool Pump, Washers, Dryers etc.	10-20 appliance types	Not known, see text for more details	20-40 appliance types: Toasters, Computers, etc. along with larger loads identified at lower frequencies	40-100 specific appliances: e.g., differentiates between 2 lights; requires separate power consumption data stream

Table 1: Survey derived from approximately 40 studies [1] showing exploitable data features and number of identifiable appliances as function of data acquisition frequency.

The disaggregation into individual appliances is based on statistical approaches, which try to identify known appliance signatures in the aggregated load curve. In general we can distinguish supervised and unsupervised approaches. Supervised approaches, which include optimization (sparse representation, dictionary learning, nonnegative matrix factorization, etc.) and pattern recognition (support vector machines, neuronal networks, hidden Markov models (HMM), Bayesian networks, etc.) techniques, require – often rather large – labelled data bases for training. Unsupervised approaches are based on parametric or probabilistic models that are used by feature detection models (e.g. on/off events) in combination with clustering approaches.

The NILM approach investigated at CSEM is unsupervised and exploits sparse signal decomposition based on the Orthogonal Matching Pursuit (OMP) algorithm with rectangular shaped boxcar atoms, see also Figure 1. The signal decomposition is based on active and reactive power on all three phases and has been mainly applied to 1 Hz signals.

A benchmarking study of the CSEM algorithm conducted last year was based on data from the publicly available data bases ECO (Switzerland) and DALE (UK), which both contain labelled data. The study revealed the following major points:

- In general, an average energy detection error of about 6.5% and event detection precisions above 95% have been observed.
- The currently used parametric models are not yet well suited for all encountered situation, such that the resulting energy estimation errors are then above 10%.

Concerning the second point, it is anticipated that tuning of the model parameters combined with some adaptations of the algorithm framework will allow to cope with such situations so that the performance observed in the first point can then be achieved in all situations.

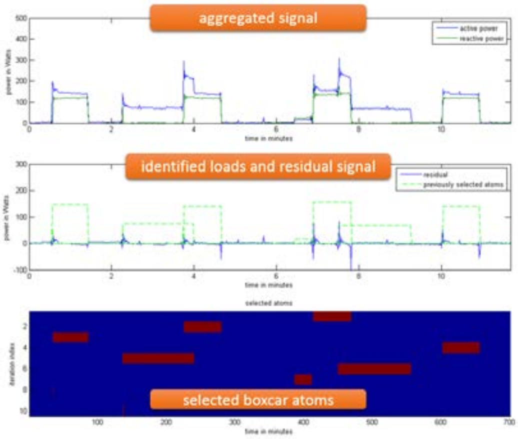


Figure 1: Illustration of CSEM's OMP-based disaggregation approach.

In early 2016 the CSEM NILM approach has also been applied to detect heat pumps at household level. Data sampled at 1 Hz from three households was analyzed for a duration of two weeks. The results from the benchmarking were confirmed with an average error of the daily energy consumption of 6.13%. For the activation events (e.g. turning an appliance ON) a recall [2] of 96.4% and a precision of 99.1% were observed, whereas for the deactivation events (turning an appliance OFF) recall and precision were 96.4% and 98.8%, respectively. The study then investigated the effect of an increased sampling period (SP). For SPs of 30 seconds and 1 minute the average energy error decreased only slightly to 6.63 and 7.53%. A similar behavior was observed for the events statistics (see also Figure 2) which shows that reduced sampling frequencies down to about 1/60 Hz are possible.

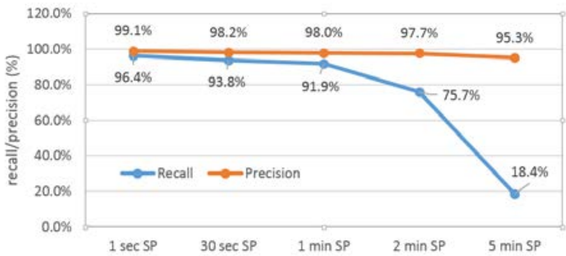


Figure 2: Heat-pump activation event detection statistics.

The above example illustrates the performance of the patented CSEM approach, which is currently continuously extended to include new appliances.

[1] K. Carrie Armel, *et al.*, "Is disaggregation the holy grail of Energy Efficiency?", Precourt Energy Efficiency Center PTP-2012-05-1.

[2] "Recall" is defined as the percentage of the number of all detected true positive events w.r.t. to all relevant positive events, whereas precision is the number of true positives w.r.t. all detected events.