# NoFaRe: A Non-Intrusive Facility Resource Monitoring System

Matthias Kahl(✉), Christoph Goebel, Anwar Ul Haq, Thomas Kriechbaumer, and Hans-Arno Jacobsen

Technische Universität München (TUM), Munich, Germany
matthias.kahl@in.tum.de

**Abstract.** The aim of this paper is to present the idea and starting points for an innovative facility resource monitoring system, which will be realized in a recently started research project: NoFaRe. NoFaRe's goal is to enable low cost monitoring of electrical devices in buildings using advanced Non-Intrusive Load Monitoring (NILM) techniques and evaluate its value in facility management based on Building Management System (BMS) prototypes. Low-level device monitoring in buildings is a necessary first step to realize a new generation of BMS that will allow for higher service and efficiency levels in various dimensions of facility management. The general goal of NILM algorithms is to obtain information on the behavior of single appliances based on aggregate measurements, such as smart metering data, which allows for reducing the required amount of sensors and communication infrastructure. The NoFaRe project will on the one hand explore innovative NILM concepts to fulfill BMS application requirements while minimizing hardware cost. On the other hand, it will contribute innovative BMS applications based on device-level monitoring and contemporary communication infrastructure.

**Keywords:** Electricity metering · Building Management Systems · Non-Intrusive Load Monitoring

## 1 Introduction

Modern information technology is about to fundamentally change the way facilities are managed. Many buildings already incorporate increasingly sophisticated Building Management Systems (BMS) that integrate building control with improved sensors and better data collection and presentation capabilities. However, these systems currently only allow for simple, decoupled control of building services, such as lighting, ventilation, heating, and cooling. Their architecture and Application Programming Interfaces (APIs) are not standardized, and often proprietary: only the BMS vendor can add functionality. Moreover, most of the devices that are used within contemporary buildings are not directly monitored or controlled via information systems because this would require the deployment


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of prohibitively expensive monitoring and control infrastructures. Still, increasing BMS coverage could lead to an entire ecosystem of innovative applications in the building sector, which could be further facilitated by opening up BMS APIs to third party application development. The final step toward smart buildings would then be to bring the human in the loop, i.e., enable individual but coordinated control of building services based on actual user feedback.

In this paper, we present the motivation, scope, and starting points of a new research project, NoFaRe, that will contribute to the realization of next generation BMS. NoFaRe will investigate innovative ways to realize device-level monitoring in buildings without adding sensors to every device, but infer the status of devices by applying machine learning methods to aggregated power signals, which has recently been referred to as Non-Intrusive Load Monitoring (NILM). It will also explore ways to integrate NILM capability into innovative BMS applications that can take full advantage of it.

The following Sect. 2 provides an overview of the state-of-the-art in BMS and NILM. Section 3 describes the scope of NoFaRe and how we plan to contribute to the technical landscape. Section 4 concludes our paper with a short summary and outlook.

## 2 Technical Landscape

### 2.1 Building Management Systems

Buildings can be viewed as complex cyber-physical systems consisting of many controllable elements, e.g., doors, windows, blinds, elevators, air conditioning units, lighting, fire protection, and various appliances. Although we are nowadays still used to controlling most of these elements manually, the degree of building automation is steadily increasing. BMS are software systems for monitoring and controlling the state of building elements. They rely on corresponding hardware, in particular sensors and actuators connected to a central server via a communication network. The visible part of a BMS typically includes a graphical user interfaces that allows building managers to remotely monitor relevant building functions and adjust controls whenever necessary.

Every building is unique, and so is its existing or potential management system. Apart from this unchangeable fact, however, there are more reasons for the abundance and heterogeneity of contemporary BMS. For instance, the building equipment for different functional areas, such as air conditioning and lighting, is often sourced from different vendors. Furthermore, the same company that provides a certain type of building equipment usually also develops and installs the corresponding BMS for monitoring and controlling the equipment. Thus, one often finds a separate BMS for different functional areas. When buildings get updated, even the equipment within the same functional area may become more heterogeneous, which can then results in several BMS per building function. Apart from certain communication protocol standards like BACnet, LonWorks, KNX or Modbus, which are typically used for the communication between a BMS and the sensors and actuators connected to it, little BMS standardization has happened so far. As a result, the different BMS within a building usually coexist as separate siloed systems. They are neither interoperable nor standardized [1].

The goal constraints of BMS are as diverse as the different functional areas they support. For instance, air conditioning systems are expected to sustain a comfortable indoor room climate, whereas lighting systems control the level of illumination in different areas of the building based on the need of its occupants. While these constraints should be met at all times, BMS should allow building managers to minimize cost, including maintenance and energy costs.

In both areas, i.e., the adherence to constraints and the maximization of building management goals, there still remains significant room for improvement. Given the energy and cost footprint of buildings, improvements in building control are a highly relevant research topic. In particular, the importance of information technology in buildings is quickly increasing. Current smart building research efforts proceed into several directions to improve the situation:

- Standardized BMS that could spur application innovation [1].
- Innovative control methods, in particular for indoor climate [2].
- Personalized control of building services [3].
- Sensor networks to increase measurement capability in buildings [4].

### 2.2 Non-Intrusive Load Monitoring

NILM was introduced by Hart and Schweppe in the late 1980's [5]. Their approach is based on continuously observing changes in the real and reactive power consumption measured at a single point in a circuit and detecting appliance on/off switching based on unique load signatures. This was sufficient to identify the state of small residential loads with a limited number of states at accuracies up to 85 % [5]. Hart's seminal work has spawned several follow-up studies investigating the feasibility of NILM in different settings using various methods, including work on more complex loads found in the commercial and industrial context [6]. Recently, several NILM frameworks featuring test data sets have been published [7,8]. Different NILM approaches can be classified according to the type of sensors and data granularity [9]. Table 1 contains pointers to recent NILM studies, including their data characteristics.

### 2.3 Research Gaps

In summary, both BMS and NILM are research areas that are attracting increasing attention in the computer science community. Furthermore, we believe that both topics are interrelated: NILM could allow for low-cost device-level monitoring, which could turn out as key enabler of next generation BMS. We believe that this connection has so far not been sufficiently appreciated. Rather, NILM research has so far focused on accurate disaggregation, but not deployment cost, usability, or concrete applications to building management. It is thus particularly interesting in our opinion to explore which innovative BMS applications could be enabled with NILM, which NILM algorithms are best suited for which

**Table 1.** Overview of Household Electricity Datasets

| Dataset | Year | Project / University | Duration | Households | Aggregate Sampling |
|---|---|---|---|---|---|
| REDD [10] | 2011 | MIT | 3–19 days | 6 | 1 s & 15 kHz |
| BLUED [11] | 2012 | CMU | 8 days | 1 | 12 kHz |
| Smart* [12] | 2012 | UMass | 3 months | 3 | 1 s |
| Tracebase [13] | 2012 | Darmstadt | N/A | 15 | N/A[a] |
| IHEPCDS [14] | 2012 | University of California, Irvine | 4 years | 1 | 1 min |
| Sample [15] | 2013 | Pecan Street | 7 days | 10 | 1 min |
| OCTES [16] | 2013 | EU | 4–13 months | 33 | 7 s |
| HES [17] | 2013 | DECC, DEFRA | 1/12 months | 251 | 2 min |
| AMPds [18] | 2013 | Simon Fraser U | 1 year | 1 | 1 min |
| iAWE [19] | 2013 | IIIT Delhi | 73 days | 1 | 1 s |
| BERDS [20] | 2013 | University of California, Berkeley | 7 days | 1 | 20 s |
| UK-DALE [21] | 2014 | Imperial College | 3–17 months | 4 | 1–6 s & 16 kHz |
| GREEND [22] | 2014 | AAU Klagenfurt | 1 year | 9 | 1 s |
| ECO [8] | 2014 | ETH | 8 months | 6 | 1 s |

[a] Available at device level.

application, and how actual NILM processes and system architectures could look like. In our opinion, more prototype-based research is needed to answer these questions and reveal practical challenges.

## 3 NoFaRe Project Scope

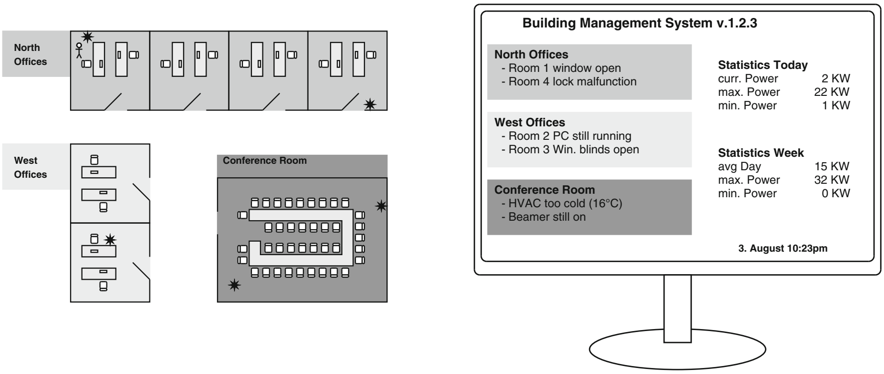
The NoFaRe project will address the research gaps mentioned above by developing a new NILM system including a self-designed smart meter box, the *NoFaRe Box*. The *NoFaRe Box* will be composed of a single-board computer equipped with a LAN/WiFi interface, a memory card, and one or multiple 16bit A/D converters for conducting circuit measurements at high frequencies of up to 44.1 kHz. Our NILM system will allow for device detection, type classification, state inference, and power disaggregation in an industrial, commercial, or private building environment. It will include a web-based management frontend that will allow for carrying out all necessary configuration, training and appliance registration tasks. Furthermore, we plan to design innovative BMS applications that leverage the NILM capabilities provided by the NoFaRe system. The targeted BMS features include the following:

***Energy Saving.*** NILM capability can help to detect unnecessary energy consumption, e.g., by correlation of device-level consumption or benchmarking. It can also help to accurately identify inefficient devices and provide feedback to the responsible occupant or manager.

***Maintenance Support.*** NILM can help to detect anomalous device behavior, which could be an indication of required maintenance. This feature can help to save manual inspection cost and increase service levels.

***Energy Accounting.*** Device-level energy monitoring can pave the way toward energy billing according to actual consumption, possibly down to the level of individuals.

***Safety.*** The ability to monitor single devices can enable new safety applications, ranging from the detection of potentially dangerous appliance states to detecting unauthorized access to buildings or machinery.




(a) Floor plan. NILM events shown as stars.

(b) BMS frontend. Event classification with localization.

**Fig. 1.** Outlook to future BMS using NILM techniques

Figure 1(a) and (b) show how NILM capability combined with floor plans can yield valuable information without the requirement to install expensive additional sensors.

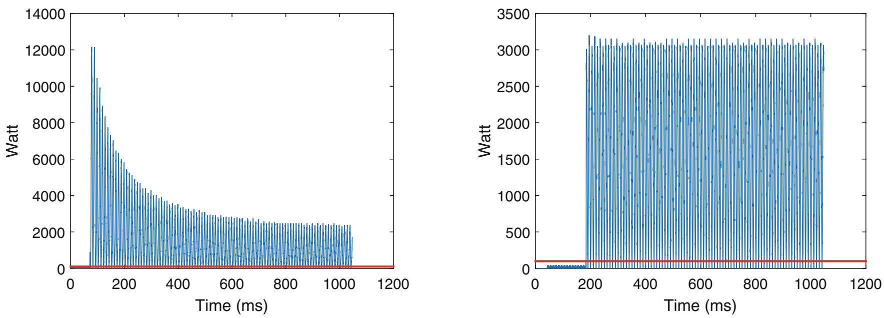
### 3.1 Specific NILM Challenges

Based on the state-of-the-art of NILM, we will develop our own methods and corresponding architectures. One of our starting points is pattern recognition using high frequency current and voltage signals. We will develop methods that are able to determine the state of devices by detecting their characteristic influence on the current and voltage measured by the corresponding *NoFaRe Box*. In the following, we outline several challenges that we expect during the project:

***Data Acquisition.*** Many highly useful appliance characteristics can only be observed at very short time scales. A good example of such a characteristic is the startup transient and inrush current, a very short but significant increase of the current as it energizes a devices. To measure such short time characteristics, it is necessary to obtain high frequency measurements. Sampling current at 1 Hz, as it is done in many NILM studies, is definitely insufficient for this purpose. Since we plan to make use of existing computer sound cards, the goal is a sampling frequency of up to 44.1 kHz.

***Feature Extraction.*** To distinguish appliance classes (e.g., distinguishing hair dryers from television sets), discriminating features are necessary, which will be stored in the so-called feature space and used for the NILM tasks described in the following. A major challenge consists in finding features that are good representatives for one class but also offer a good discrimination against other classes. The extraction process of these characteristics is usually called *feature extraction* and uses all discriminating characteristics of the appliances.

***Appliance On/Off Detection.*** To recognize an appliance based on its electricity signals, it is necessary to know if the appliance is switched on. On/off detection, i.e., the task of determining whether a particular appliance is currently in use (consuming power), is a necessary precondition to perform other NILM tasks, in particular disaggregation. A basic approach to detect whether an appliance is switched on is edge detection [5], which checks the power curve for step-like changes. A simple power threshold can indicate the inrush, as shown in Fig. 2. The method assumes that each device is consuming a measurable amount of power. We expect that reliable detection of multi-state appliances, such as dishwashers or dimmable lights, will require further work in the area of reliable edge detection.




(a) Inrush of a hoover. (b) Inrush of a kettle.

**Fig. 2.** Inrush comparison between a hoover and a kettle. The different characteristics are clearly visible. The *switch on* threshold is shown as red line (Colour figure online).

***Appliance Identification.*** In building management, a number of appliances is usually known to be present. Appliance identification then refers to selecting those appliances from an existing list that are currently consuming power. Several studies have shown that this task can be carried out with relatively high accuracy [22].

***Appliance Classification.*** Classification means assigning an appliance characteristic to a typical appliance class, e.g., washing machines, television sets, hairdryers etc. This task requires a set of typical characteristics for each class, which forms a distinguishable subspace in the feature space. A prerequisite for appliance classification is a well developed appliance taxonomy, which can be constructed manually, or automatically using clustering techniques. The work of [23] presents an approach to classify appliances using a clustering method based on their voltage-current (V-I) trajectory. Appliance classification becomes relevant if appliance identification fails because the observed characteristics do not match any registered appliances.

***Disaggregation.*** The task of determining the individual consumption of several devices consuming power concurrently based on aggregated signals is referred to as disaggregation. A basic disaggregation approach is to first measure the amount of power that an individual device consumes over time and combine this information with edge detection. Many more sophisticated disaggregation methods have been evaluated, e.g., Factorial Hidden Markov Model (FHMM) [10]. Due to its complexity and potential impact, disaggregation can certainly be considered as one of the most demanding NILM tasks at the moment.

***Privacy Preservation.*** NILM raises many privacy concerns because it potentially allows for tracking human behavior. In fact, NILM is not limited to determining what happens in a household, e.g., sleeping, being away, cooking, watching television. It even allows for going further, e.g., identifying the television program currently being watched [24,25]. An important challenge of NILM is therefore to preserve privacy according to legal requirements, i.e., certain information must not be used without the consent of the concerned individuals and must be effectively protected from other uses. In NoFaRe, we will therefore pay close attention to the secure processing and transmission of potentially revealing data.

### 3.2 A Tentative Appliance Identification Algorithm

Figure 3 shows the flow chart of a tentative appliance detection algorithm. We present it here to show how several NILM tasks can be combined into a continuous process that could later run on the *NoFaRe box*.

The algorithm as two parallel loops. The first loop continuously acquires the current and voltage from the A/D converters and observes their characteristics. If this observation indicates that a device has just been switched on, feature extraction starts in a new thread. Based on the extracted features, the algorithm then tries to identify the added appliance based on the devices previously registered by the user. If this appliance identification is successful (based on a corresponding confidence threshold), the identified user-registered appliance is added to the list of *currently running* appliances. If the appliance identification is not confident, an appliance classification step will be triggered to assign the new device to a device type present in the local *appliance type* data base. Since multi-state appliances, like washing machines, can be certainly recognized after

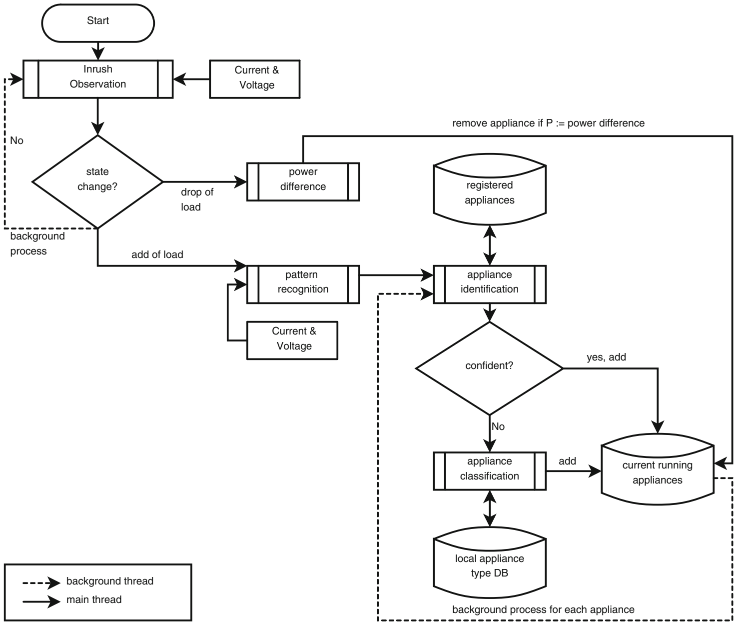



**Fig. 3.** Flow chart visualization of the *NoFaRe* appliance detection algorithm.

some time has passed, it is necessary to continuously repeat the classification step in a second, parallel loop.

### 3.3 Preliminary Experiments and Results

First experiments with the proposed algorithm for appliance detection, based on their startup transient characteristics, yielded promising results. The experimental setup is based on *House 1* of the UK-DALE dataset [21]. We have implemented an automatic inrush recognition based on short time load changes to find the actual startup of the appliances. The rough positions are manually retrieved from the 6 s data set [26] and a 15 s window is extracted from the 16 kHz dataset [27] for further automated analysis. After finding the exact startup time and extracting the first 500 ms, we extract 5 discriminating features of 12 different appliance types from around 10,000 samples. Based on 10-fold cross validation, the classification accuracy lies consistently above 85 % with a 5-nearest neighbor classifier.

## 4 Conclusion

In this paper, we have introduced the idea of integrating NILM technology into the BMS landscape. NILM can enable new BMS that take advantage of high resolution monitoring capability at lower cost compared to dedicated sensor networks. In the NoFaRe project, we intend to evaluate the presented concept by developing a corresponding system architecture. A core element of our prototypical system will be the NoFaRe box, a low-cost single-board computer that will measure electricity signals at high frequency and perform continuous device detection. Since the NoFaRe project is still in an early stage, we have only presented preliminary evaluation results. However, we have placed NoFaRe within the current technical landscape, detailed its expected contribution, and described several challenges which we expect to face during the project.

## References

1. Dawson-Haggerty, S. et al.: BOSS: Building Operating System Services. In: Proceedings of the 10th USENIX Conference on Networked Systems Design and Implementation. ACM, pp. 443–458 (2013)
2. Aswani, A. et al.: Reducing transient and steady state electricity consumption in HVAC using learning-based model-predictive control. In: Proceedings of the IEEE 100.1 (2012), pp. 240–253 (2011). doi:10.1109/jproc.2011.2161242
3. Krioukov, A. et al.: A living laboratory study in personalized automated lighting controls. In: Proceedings of the Third ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings. ACM, pp. 1–6 (2011). doi:10.1145/2434020.2434022
4. Jiang, X. et al.: Experiences with a high-fidelity wireless building energy auditing network. In: Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems. ACM, pp. 113–126 (2009). doi:10.1145/1644038.1644050
5. Hart, G.W.: Nonintrusive appliance load monitoring. In: Proceedings of the IEEE 80.12, pp. 1870–1891 (1992). doi:10.1109/5.192069
6. Lee, K.D., et al.: Estimation of variable-speed-drive power consumption from harmonic content. IEEE Trans. Energy Convers. **20**(3), 566–574 (2005). doi:10.1109/tec.2005.852963
7. Batra, N. et al.: NILMTK: an open source toolkit for non-intrusive load monitoring. In: Proceedings of the 5th International Conference on Future Energy Systems, pp. 265–276 (2014).doi:10.1145/2602044.2602051
8. Beckel, C. et al.: The ECO data set and the performance of non- intrusive load monitoring algorithms. In: Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings, pp. 80–89 (2014). doi:10.1145/2674061.2674064
9. De Paola, A. et al.: Intelligent management systems for energy efficiency in buildings: a survey. In: ACM Computing Surveys (CSUR) 47.1, p. 13 (2014). doi:10.1145/2611779
10. Kolter, J.Z., Johnson, M.J.: REDD: a public data set for energy disaggregation research. In: Workshop on Data Mining Applications in Sustainability (SIGKDD), vol. 25, pp. 59–62. Citeseer, San Diego (2011)
11. Anderson, K. et al.: BLUED: a fully labeled public dataset for event- based non-intrusive load monitoring research. In: Proceedings of the 2nd KDD Workshop on Data Mining Applications in Sustainability (SustKDD), pp. 1–5 (2012)
12. Barker, S. et al.: Smart*: an open data set and tools for enabling research in sustainable homes. In: SustKDD (2012)
13. Reinhardt, A. et al.: Electric appliance classification based on distributed high resolution current sensing. In: 37th Annual IEEE Conference on Local Computer Networks, Workshop Proceedings, pp. 999–1005 (2012). doi:10.1109/lcnw.2012.6424093

14. Lichman, M.: UCI machine learning repository: individual household electric power consumption data set (2013). http://archive.ics.uci.edu/ml
15. Pecan Street Inc., Sample Data Set (2013).http://pecanstreet.org/projects/consortium (online accessed 02 June 2015)
16. European Union. Opportunities for Community Groups Through Energy Storage (OCTES) (2013). http://octes.oamk.fi/final (online accessed 02 June 2015)
17. Zimmermann, J.-P. et al.: Household electricity survey: a study of domestic electrical product usage. In: Intertek Testing & Certification Ltd (2012)
18. Makonin, S. et al.: AMPds: a public dataset for load disaggregation and eco-feedback research. In: Electrical Power & Energy Confer- ence (EPEC). IEEE, pp. 1–6 (2013).doi:10.1109/epec.2013.6802949
19. Batra, N. et al.: It's different: insights into home energy consumption in India. In: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings, pp. 1–8. ACM (2013). doi:10.1145/2528282.2528293
20. Maasoumy, M. et al.: Berds-Berkeley energy disaggregation data set. In: Proceedings of the Workshop on Big Learning at the Conference on Neural Information Processing Systems (2014)
21. Kelly, J., Knottenbelt, W.: The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes. In: Scientific Data (2015). doi: 10.1038/sdata.2015.7. http://www.doc.ic.ac.uk/dk3810/data/
22. Monacchi, A. et al.: GREEND: an energy consumption dataset of households in Italy and Austria. In: CoRR abs/1405.3100 (2014). doi:10.1109/smartgridcomm.2014.7007698
23. Lam, H.Y., Fung, G.S.K., Lee, W.K.: A novel method to construct taxonomy electrical appliances based on load signatures. IEEE Trans. Consum. Electron. **53**(2), 653–660 (2007). doi:10.1109/tce.2007.381742
24. Greveler, U., Justus, B., Löhr, D.: Hintergrund und experimentelle Ergebnisse zum Thema Smart Meter und Datenschutz. In: Fachhochschule Munster-University of Applied Sciences Technical Paper (2011)
25. Enev, M. et al.: Televisions, video privacy, and powerline electromagnetic interference. In: Proceedings of the 18th ACM Conference on Computer and Communications Security, CCS 2011, pp. 537–550. ACM, Chicago (2011). ISBN: 978-1-4503-0948-6, doi:10.1145/2046707.2046770
26. UK-DALE: disaggregated (6s) appliance power and aggregated (1s) whole house power (2015). doi:10.5286/UKERC.EDC.000001
27. UK-DALE: high speed (16 kHz) aggregated whole house current/voltage (2015). doi:10.5286/UKERC.EDC.000002