

Device-Free User Activity Detection using Non-Intrusive Load Monitoring: A Case Study

Andreas Reinhardt
Department of Informatics
TU Clausthal, Germany
reinhardt@ieee.org

Christoph Klemenjak
Institute of Networked and Embedded Systems
University of Klagenfurt, Austria
klemenjak@ieee.org

ABSTRACT

Data collected from smart electricity meters have been shown to contain a wealth of information. Through the application of algorithms for load disaggregation, it is possible to identify the contributions of individual appliances to the electricity bill as well as emitting suggestions to replace inefficient devices. Almost all documented practical use cases of load disaggregation rely on the analysis of appliance operational times and their impact on the monthly electricity bill. However, load disaggregation bears promising potential for other use cases. Recognizing user activities without the need to set up a dedicated sensing infrastructure is one such application, given that many household activities involve the use of electrical appliances. State-of-the-art disaggregation algorithms only provide support for the recognition of one appliance at a time, however. We thus take load disaggregation to the next level, and present to what extent it is applicable to monitor user activities involving multiple appliances (operating sequentially or in parallel) using this technique. For the evaluation of our Non-Intrusive Activity Detection (NIAD), we synthetically generate load signature data to model nine typical user activities, followed by an assessment to what extent they can be detected in aggregate electrical consumption data. Our results prove that state-of-the-art load disaggregation algorithms are also well-suited to identify user activities, at accuracy levels comparable to (but slightly below) the disaggregation of individual appliances.

CCS CONCEPTS

• **Hardware** → **Smart grid**; • **Computing methodologies** → **Machine learning**.

KEYWORDS

smart metering, activities of daily living, activity recognition

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1 INTRODUCTION

The disaggregation of electrical loads, also known as Non-Intrusive Load Monitoring (NILM), is a technique to identify individual contributing appliances from the total electrical power demand of a building. Through the application of NILM, the presence of individual appliances with characteristic consumption signatures can be detected without the need to deploy dedicated sensing devices, and user recommendations how to save energy be provided [4]. Practical use cases beyond the attribution of energy to individual devices are, however, limited by the fact that current NILM algorithms only reconstruct *appliance-level* consumption data. While this enables the identification of inefficient appliances, it does not allow for the detection of more complex consumption patterns, such as the ones resulting from the execution of household activities, where multiple electrical devices are used in conjunction.

Several approaches to infer Activities of Daily Living (ADLs) from electrical consumption data have been presented in recent years, e.g., in [1, 10, 18, 20]. Mostly based on static rules (linking the operation of electrical appliances to the corresponding household activities), these methods have been shown to yield good accuracy levels. The manual linking between activities and appliances, however, not only requires a complete list of the available appliances in the building, but also expert knowledge on the typical household activities in the geographic region of interest. This configuration step is thus error-prone and lacks the potential to be generalized.

In this work we propose a novel approach to overcome this limitation, namely to use existing NILM algorithms to facilitate the detection of household activities from aggregate power consumption data: *Non-Intrusive Activity Detection (NIAD)*. Instead of manually specifying which appliances are used in ADLs, we leave it up to the internal operation of the disaggregation algorithm to identify these relations. This way, existing software for load disaggregation can be easily re-used to identify activities that encompass the activities of more than one appliance, operated simultaneously and/or in sequence. Moreover, as the approach is based on the detection of characteristic consumption patterns, activities can be recognized even when they are performed during unusual hours. The main contributions of this work are:

- (1) We use a trace generation tool to create a dataset comprising nine activities with between one and five involved electrical appliances.
- (2) We provide the generated dataset to a load disaggregation toolkit and evaluate the detection accuracy of the activities using a total of six disaggregation algorithms.
- (3) We discuss the observed results and compare them to the levels at which the involved appliances can be disaggregated individually.

Table 1: List of user activities considered in our activity disaggregation study.

ID	Activity name	Average duration	Involved appliances (+ devices used only sometimes)
1	Breakfast preparation	17 min	breadcutter, toaster, electric stove, coffee maker or kettle
2	Cooking a dinner	41 min	electric stove, kettle (+ microwave)
3	Dishwasher operation	67 min	dishwasher
4	Fridge operation	14 min	fridge
5	Heating a meal	4 min	microwave
6	Ironing while consuming media	113 min	clothes iron, radio or television
7	Vacuuming	12 min	vacuum cleaner
8	Washing laundry	191 min	washing machine
9	Watching TV	156 min	television (+ DVD player)

2 RELATED WORK

The objective of NILM is to identify the operational times and power consumptions of individual electrical appliances from a building’s total power demand. Research on disaggregation algorithms has seen a drastic uptake in recent years. In particular, a strong trend towards the use of neural networks to learn the relation between aggregate and device-level data can be observed [13, 14, 19]. Traditionally, NILM has focused on the detection of individual appliances’ operational times. Inferences about the user behavior that caused these appliance operations, however, cannot be drawn directly.

To overcome this limitation, several works have considered the discovery of ADLs or “household routines” [5] from electrical consumption data. It was demonstrated in [9] that a user’s currently performed activity can be derived from binary indicators about electrical appliances’ operational states, made available through appliance-level power monitors. Similarly high accuracy degrees for differentiating between more than a dozen different ADLs were observed in [18, 20], permitted that consumption data is available for each appliance. These observations are confirmed by [17], where time-of-day information and appliance operation indicators are combined to infer whether a given household activity is currently being executed. ADL identification accuracy levels in excess of 90% were reported in [11], underpinning the practicality of using electrical power consumption as an indicator for household activities.

Operational data about electrical appliances were also used to detect unexpected daily routines in the context of Ambient Assisted Living (AAL) in [2, 3, 8, 15], proving it possible to discover unusual activities from such data. A commonality of all aforementioned approaches is the need for appliance-level data to be available for processing. Even though the application of NILM makes it possible to apply such methods in homes where only aggregate meter data is available [10], the shortcomings of current-generation NILM algorithms (such as documented in [16]) are likely to significantly impact the activity detection accuracy. The NIAD approach we follow in this work does not require to manually define rules that link appliances and activities. Only one method documented in literature follows a similar approach. The activity recognition presented in [1] identifies activities based on the presence of events on the aggregate power consumption signal. The mapping between observed events and corresponding activities is extracted using machine learning tools, and only their semantic annotations need to be defined by human experts. While effectively demonstrating

that certain household activities can be discovered in electricity consumption data, the method still differs from our proposed approach in its reliance on expert data. NIAD, in contrast, will itself discover the relations between appliance usage and ADLs.

3 NON-INTRUSIVE ACTIVITY DETECTION

The detection of ADLs from aggregate electrical power consumption data can be approached in two ways. Most existing methods rely on appliance-level power consumption (collected directly or estimated through the application of NILM) with a rule set that defines what appliances are being used in which ADLs. We propose an alternative method in this work, which we refer to as Non-Intrusive Activity Detection (NIAD). It is similar to the concept of NILM in that it operates on the same type of (aggregate) input data, which can be collected using a non-intrusive load monitoring device. Instead of tuning the underlying NILM algorithm to the disaggregation of individual electrical consumers, however, we train it to recognize the (composite) power data patterns of household routines. In a nutshell, NIAD re-purposes load disaggregation methods to accomplish a different objective.

3.1 Household Routines under Consideration

Many household activities involve the operation of electrical appliances. While electrical power usage is mostly incidental to, e.g., personal hygiene routines (for lighting, ventilation, air or water heating), other activities chiefly rely on the use of specific appliances (e.g., kitchen tools for cooking, HiFi equipment to listen to music). In the present study, we consider the nine household routines listed in Table 1, for each of which we also specify the appliances involved. For the activities using only a single appliance (such as running the dishwasher), the NIAD problem reduces to NILM, i.e., the identification of the appliance’s operation within the aggregate. For composite activities (such as the preparation of meals) their identification becomes more complex due to the varying temporal sequences in which the appliances are being operated, the occasional omission of an appliance’s operation during an activity, and/or the concurrent operation of devices.

3.2 Household Activity Data

No public dataset exists that features (a) household-level aggregate data, (b) appliance-level data, and (c) the required annotations to delineate when individual user activities take place. As a consequence,

we have to resort to the synthetic generation of consumption data in order to investigate the potentials of NIAD. The data used in our study were generated using ANTgen [16], which schedules parametric models of actual appliance consumption in temporal sequences that resemble household routines. The tool was configured to use randomized values for each activity’s synthesis. This way, successive activities not only have different durations, but may also use just a subset of the possible appliances (cf. Table 1). Generated appliance-level traces were subsequently aggregated on two levels: For each household routine, the power consumption readings of the involved appliances were added (**per-activity** data). Moreover, power consumptions of all appliances present in the building were accumulated (**aggregate** data). The former type of data is essential to train the activity detection system; during validation and testing, only aggregate data was used.

3.3 Activity Recognition

In order to assess to what extent current NILM algorithms are suitable to identify household activities, we use the Non-Intrusive Load Monitoring Toolkit (NILMTK) [7]. It compiles a range of state-of-the-art NILM algorithms into a unified framework, which enables comparative studies and automated evaluation runs. By feeding both the per-activity and aggregate data to the NILM algorithms, they can adapt to the characteristics of the activities under consideration. During the testing phase, i.e., assessing to what extent household routines are correctly identified, only aggregate data was provided. NIAD outputs a binary array for each pre-trained activity, of the same length as the input data. It indicates whether the characteristics of a given activity were recognized at each point in time. Evaluations of the activity recognition accuracy thus reduce to a comparison the value of this indicator to the schedule of activities according to the annotations provided by ANTgen.

4 EVALUATION

We evaluate NIAD using NILMTK [6] version v0.4.0dev1 and NILMTK-contrib [7] version 0.1.0, respectively. Out of its available algorithms, we incorporate three traditional disaggregation techniques: *Exact Factorial Hidden Markov Model (FHMM)*, *Combinatorial Optimization (CO)* [12], and *Edge Detection (Hart85)* [12]. Furthermore, we consider three approaches based on deep neural networks: *Denoising Autoencoder (DAE)* [14], *Sequence-to-Sequence Optimization (S2S)* [19] and *Sequence-to-Point Optimization (S2P)* [19]. All neural networks were trained for 30 epochs.

We generate synthetic data for the electricity consumption of a one-person home. Each of the activities listed in Table 1 is scheduled once per day, in order to have a sufficient number of training instances. Even though only a single activity is actively executed by the user at one time, background tasks (e.g., a dishwasher’s operation or the refrigerator’s cooling cycle), frequently occur simultaneously. Synthetic data were generated for a duration of 180 days with a sampling interval of 10 s. We divide our dataset into 144 days (80%) for training and 36 days (20%) to test the disaggregation techniques. To assess the activity detection performance, we compute the F1 score

$$F1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

Table 2: F1 scores for the disaggregation of the activities.

Activity	Traditional			Neural Nets		
	FHMM	CO	Hart85	DAE	S2S	S2P
Breakfast	0.10	0.09	0.02	0.43	0.72	0.90
Cooking a dinner	0.36	0.28	0.07	0.67	0.84	0.88
Dishwasher operation	0.62	0.40	0.08	0.78	0.75	0.82
Fridge operation	0.74	0.59	0.87	0.92	0.97	0.96
Heating a meal	0.03	0.02	0.00	0.52	0.75	0.86
Ironing & media	0.02	0.03	0.01	0.61	0.76	0.74
Vacuuming	0.58	0.22	0.01	0.72	0.94	0.93
Washing laundry	0.31	0.32	0.22	0.55	0.80	0.89
Watching TV	0.14	0.26	0.18	0.70	0.54	0.48

where TP is the number of true positive activity detection results, FP the false positives, and FN the false negatives. The ground truth required to compute this metric is retrieved from ANTgen’s event log file, post-processed to provide a bit array of same shape as the one returned by NIAD (cf. Sec. 3.3). Given the largely different power demands of individual activities, we abstain from using other metrics that rely on absolute differences of power demand (e.g., MAE) for the sake of a fair comparison.

4.1 Activity Detection Results

The F1 scores for the identification of all considered activities are presented in Table 2. With exception of the “Watching TV” activity, it can be observed that S2S and S2P mostly outperform the other methods by large margins. This is well aligned with insights gained in [16], and confirms the enormous potential of neural networks to detect even complex load patterns. It is also of particular note that the traditional NILM approaches considered in our evaluation (CO, FHMM, Hart85) show poor performance when used in conjunction with NIAD. They only reach scores comparable to the neural network-based solutions for the operation of the fridge, yet conversely, this device is a household base load and not actively operated by the user. This indicates that traditional NILM techniques cannot cope with the increased complexity of household routines to be discovered by NIAD, and already reach their limits when applied to conventional appliance disaggregation tasks. In Fig. 1, we illustrate the disaggregation results of activities alongside results obtained when disaggregating the involved appliances individually. It is apparent that NILM techniques employing neural networks (DAE, S2S, S2P) show comparable performance for both cases (see, e.g., Figs. 1a and 1c). Still, it has to be pointed out that S2S and S2P outperform DAE in the vast majority of cases.

Our results also highlight one limitation: The operation of appliances with low electrical power demand (e.g., the radio) or very short and bursty operations (e.g., the bread cutter) were rarely correctly detected. One such device is part of both “Ironing with media consumption” (see Fig. 1d) and “Watching TV” (see Fig. 1b). Even sophisticated NILM approaches like S2S/S2P have difficulties in detecting the activities of such devices with marginal power consumptions. The varying durations and permutations of appliance

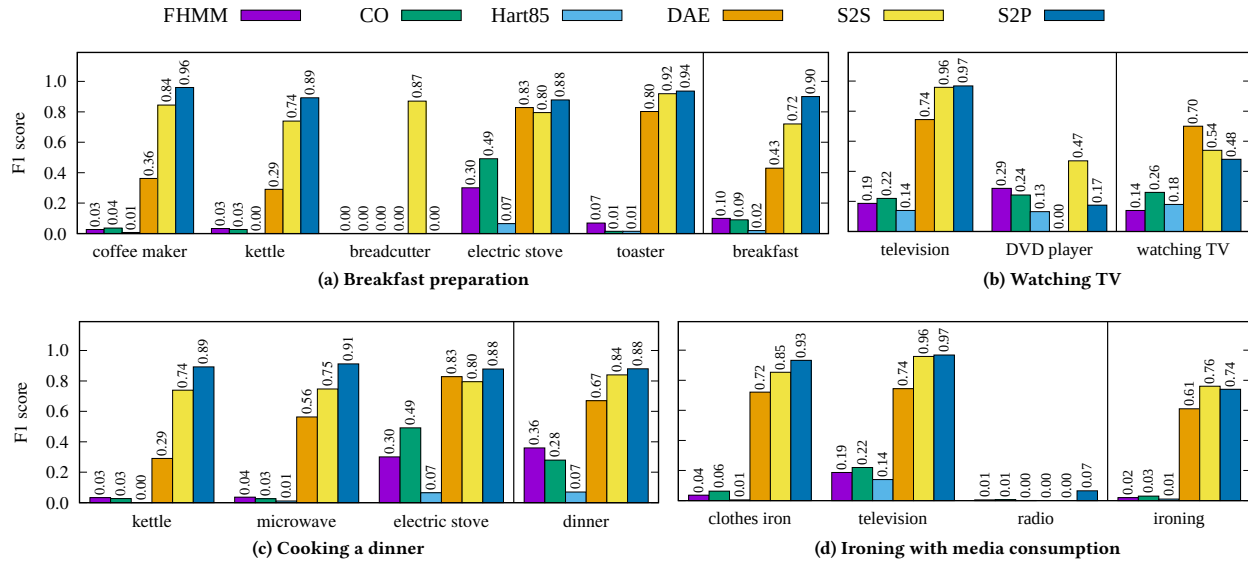


Figure 1: NIAD disaggregation results, in comparison to the individual disaggregation scores of the involved appliances.

operations during the considered activities vastly increase the overall complexity of the disaggregation task. Thus, it is unsurprising to find the activity recognition F1 scores to be below the scores of the individual appliances they comprise. On the positive side, only a single training phase per activity is required in NIAD, whereas a more time-consuming appliance-wise training is needed for NILM.

5 CONCLUSION

Non-Intrusive Load Monitoring is a device-free technique to identify the operational times of individual electrical loads in aggregate consumption data. Corresponding algorithms are, however, not confined to their use for recognizing individual appliances by design. We have presented and evaluated NIAD, a generalization of NILM to the recognition of ADLs, in this work. Our evaluation of its potentials to recognize a set of typical household activities, including composite routines that entail the operation of multiple electrical appliances, have shown that the S2S and S2P methods succeed in discovering household routines in aggregate load data, even when appliances were operated concurrently. This not only demonstrates NIAD's potential to efficiently identify household routines, but also confirms the general viability of NILM algorithms for novel applications of device-free electricity sensing.

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