2019 27th European Signal Processing Conference (EUSIPCO)

Improving Energy Disaggregation Performance Using Appliance-Driven Sampling Rates

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***Abstract*—This paper proposes a new appliance-driven selection of sampling frequencies for improving the energy disaggregation performance in non-intrusive load monitoring. Specifically, the methodology uses a machine learning model with parallel device detectors and optimized device dependent sampling rates in order to improve device identification. The performance of the proposed methodology was evaluated on a state-of-the-art baseline system and a set of publicly available databases increasing performance up to 6.7% in terms of estimation accuracy when compared to the baseline energy disaggregation setup without device dependent sampling rates.**

***Index Terms*—Non-intrusive load monitoring (NILM), Energy Disaggregation, Device Classification.**

I. Introduction

In the last decades the need for accurate and fine grained monitoring of electrical energy consumption within residential and industrial environments has become a crucial issue. Rising energy consumption needs, the establishment of smart grids and demand management [1], as well as the fluctuation of power generation due to an increasing percentage of renewable energies enhancing these issues [2]. These changes are challenging for network operators and power generation facilities, since power-needs are becoming less predictable and unstable [3]. Furthermore, with the ability to provide real-time information through smart-metering and determining detailed household energy consumption, consumer privacy concerns are arising and energy data protection becomes prominent [3]. To address those challenges detailed, cost-effective and privacy concerned analysis of power consumption on device level is necessary [4].

Energy disaggregation is the task of extracting energy consumption at appliance level based on one or multiple measures, trying to identify the device specific operating patterns from the aggregated measure [5]. When using one sensor only this task is referred to as Non-Intrusive Load Monitoring ($NILM$) as introduced by [6]. $NILM$ formulates the energy disaggregation as a single channel source separation problem, where the goal is to find the inverse of the aggregation function to determine the per device consumption by a cost effective and privacy conserving single channel measurement at the main power inlet of households and buildings. In general this problem is highly under-determined when using one sensor only, therefore either knowledge-based [7], [8] or data-driven [9], [10] models are used to find the best separation.

Solving the $NILM$ problem for data-driven approaches can be briefly described as follows: pre-processing of the aggregated signal (e.g. filtering or sampling), framing (e.g. constant or variable frame length/edge detection [11], [12]), feature extraction and classification as illustrated in Fig. 1. For training the classifier a variety of public available databases with a wide range of sampling frequencies (f_s) are used. These databases can be categorized into Low Sampling Frequencies (LSF) for $f_s \leq 5Hz$ and High Sampling Frequencies (HSF) for $f_s \geq 1kHz$ respectively [13].

Current $NILM$ methods based on probabilistic models and machine learning (ML) usually train one classifier/detector (e.g. k-Nearest-Neighbors ($KNNs$) [14], Artificial Neural Networks ($ANNs$) [15] or Support Vector Machines ($SVMs$) [16]) with a set of features extracted from the aggregated raw data. The selection of features depends on the sampling frequency, hence steady state features (e.g. active or reactive power) are used in case of LSF [4], [13] and transient features (e.g. harmonic spectrum or transient energy) in case of HSF [15] [17]. The choice of frequency and features aims to optimize the overall detection accuracy.

In this study device dependent sampling frequencies are introduced in order to increase device detection Accuracy (ACC) and reduce the Root-Mean-Square-Error ($RMSE$) for energy disaggregation. The rest of the paper is organized as follows: In Section II the proposed signal processing architecture using appliance-driven sampling rates is presented. In Section III the experimental setup is described while the results of the experiments are given in Section IV. The paper is concluded in Section V.

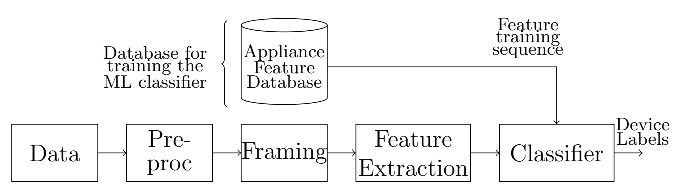

Fig. 1. Baseline machine learning based system for non-intrusive load monitoring. (Look-up-table is denoted as LUT)

II. Proposed Architecture

$NILM$ energy disaggregation can be formulated as the task of determining the power consumption on device level based on the measurements of one sensor, within time windows (frames or epochs). Specifically, for a set of $M-1$ known devices each consuming power p_m with $1 \leq m \leq M$, the aggregated power P_{agg} measured by the sensor will be

$$P_{agg} = f(p_1, p_2, ..., p_{M-1}, g) = \sum_{m=1}^{M-1} p_m + g = \sum_{m=1}^{M} p_m \quad (1)$$

where $g = p_M$ is a 'ghost' power consumption noise usually consumed by one or more unknown devices. In $NILM$ the goal is to find estimations $\hat{p}_m, \hat{g}$ of the power consumption of each device m using an estimation method f^{-1} with minimal estimation error and $\hat{P}_M = \hat{g}$, i.e.

$$\hat{P} = \{\hat{p}_1, \hat{p}_2, ..., \hat{p}_{M-1}, \hat{g}\} \leftarrow f^{-1}(P_{agg}) \quad (2)$$

$$s.t. \ \underset{f^{-1}}{\operatorname{argmin}} \{(P_{agg} - \sum_{m=1}^{M} \hat{p}_m)^2\}$$

The architecture presented in this paper proposes one detector per device with an additional device dependent look-up-table (LUT) for detection thresholds (Th) and sampling frequencies (F_S) as shown in Fig. 2. Thresholds are used for ML techniques performing regression (e.g. ANN) producing a device-specific detection score (i.e. a probability for the existence of that device). The classification stage is followed by a mapping of the detected devices to one of their corresponding states of operation similar used in [18]–[22]. The novelty of the proposed architecture with respect to the state-of-the-art signal processing is the appliance-driven selection of optimal sampling frequencies and thresholds for each of the M devices.

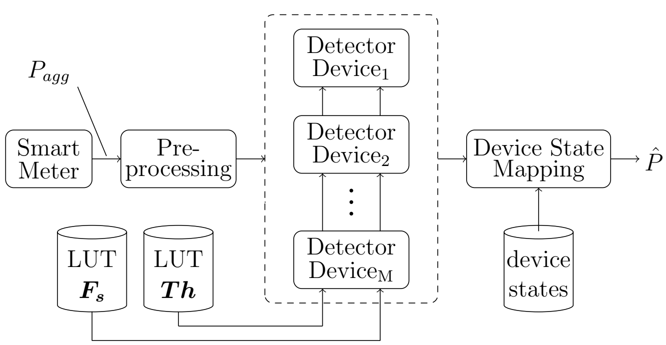

Fig. 2. Block diagram of the $NILM$ architecture using optimal per device frequency selection for appliance-driven device detection

To find the best frequency for the m^{th} device in a specific set of training samples $Y_{train}(f_s, Th)$ and their corresponding ground-truth labels $X_{train}(f_s, Th)$ the device dependent frequency f_s^m must be optimized according to Eq. 3, while thresholds are optimized according to Eq. 4. In Eq. 3-4 $f_{s,opt}^m$ is the optimal frequency and Th_{opt}^m is the optimal threshold for the m^{th} device of a specific database, CL is any machine learning classifier (e.g. KNN, ANN or SVM) and PF is a performance metric (e.g. ACC or $RMSE$) measuring performance on the training samples Y_{train} and X_{train}.

$$f_{s,opt}^m = \underset{f_s}{\operatorname{argmax}} \ PF[CL(Y_{train}(f_s), X_{train}(f_s))] \quad (3)$$

$$Th_{opt}^m = \underset{Th}{\operatorname{argmax}} \ PF[CL(Y_{train}(Th), X_{train}(Th))] \quad (4)$$

The extracted set of optimal frequencies $\boldsymbol{F_s} = f_{s,opt}^{1...M}$ and threshold $\boldsymbol{Th} = Th_{s,opt}^{1...M}$ for each device depends on the chosen performance measure. Classification accuracy (ACC) can be chosen to identify working patterns and time dependent device behaviour. Estimation accuracy E_{ACC} according to [23] and $RMSE$ can be selected to assign energy between a set of devices identifying the distribution of energy within a household under consideration of the per device drawn power at each instant in time [24].

The selection of optimal sampling frequency for each device affects the devices' power consumption signature in the time domain as well as the device's representation in the feature space. A characteristic example of the effect of different sampling periods T_s on the aggregated active power P_{agg} is illustrated in Fig. 3. As can be seen in Fig. 3 transient events (mainly power spikes with short duration caused by appliances as kettles or boilers) are getting eliminated by increasing the sampling period (marking 1 in Fig. 3), while devices with steady-state working routines (as for example fridges or freezers) are not affected by the down-sampling (marking 2 in Fig. 3).

Literature already reports many approaches utilizing a wide variety of different sampling frequencies in the range of $0.1Hz$ up to $10kHz$, showing that the choice of sampling frequency, features and method of edge-detection are having a significant influence on overall detection accuracy [14], [25]. However, to best of our knowledge, device specific sampling frequencies have not been reported in literature. Therefore the appliance-driven sampling rate selection is evaluated.

III. Experimental Setup

The $NLIM$ architecture with the appliance-driven sampling presented in Section II was evaluated using the datasets and classification algorithms presented below.

A. Datasets

For testing and training three public available databases namely, ECO [24], UK-$DALE$ [26] and $REDD$ [23] are evaluated, each of them consisting of different datasets containing power consumption recordings from different houses. Only the ECO-3 datasets was excluded as it contains only the aggregated signal and not the power consumption on device level making it impossible to train the model of the proposed architecture. Common in all three databases is their low sampling period (from 1sec to 6sec) and the consideration of active power samplings only. Furthermore all three databases were recorded within the last decade making them representative for nowadays households in terms of monitored devices [23], [24].

In this setup only active power samples from the aggregated signal P_{agg} were used including the ghost power consisting

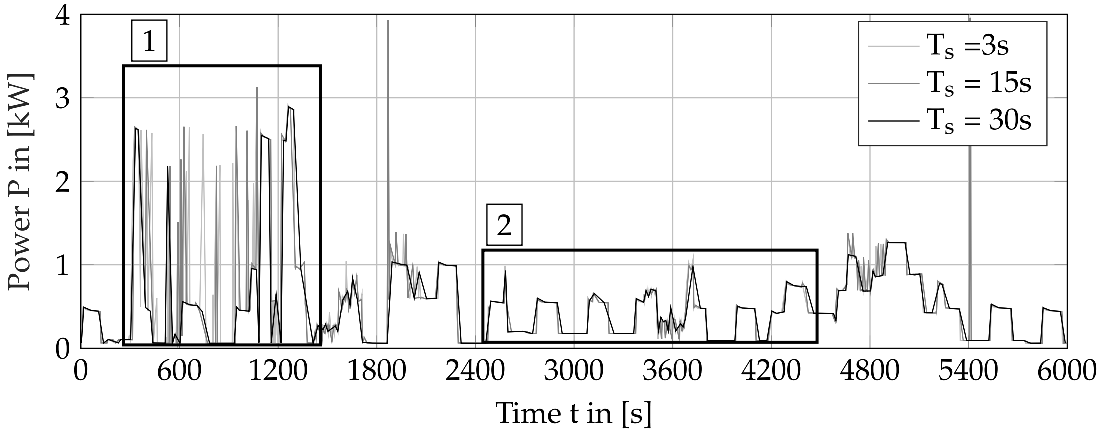

Fig. 3. Example of the influence of down-sampling on power consumption signatures in the aggregated signal

of unknown devices and the interference between devices on the same power line. Further no artificial aggregated data was created by selecting a subset of appliances and summing their power consumption in order to evaluate performance in real conditions as proposed in [27].

B. Pre-processing and Feature Extraction

During the pre-processing the active power samples from the aggregated signal were framed with a constant frame length of $n_{frame} = 10$ samples per frame and a 50% overlap (i.e. 5 samples) between respective frames while features are calculated for each frame respectively. For every frame mean value, standard deviation, Root-Mean-Square (RMS) value and peak-to-rms value were calculated and chosen as features for classification. In detail mean value and RMS value were chosen to incorporate steady-state appliance signatures and standard deviation as well as peak-to-rms value to account for changes in appliances states [28]. Furthermore no pre-processing (e.g. device specific filtering or interpolation) was used to prevent possible effects and interferences from the down-sampling. As classifier a 5-NN nearest neighbour technique similar as in [14], [29] was implemented and devices with power consumption of less than $25W$ were excluded from classification and added to the ghost power. For the purpose of comparability each model was trained with the sampling frequency the database was recorded ($T_{s,ECO} = 1s$, $T_{s,UK-DALE} = 6s$, $T_{s,REDD} = 3s$). In order to avoid overlap, each dataset was equally split into two subsets, one for training and one for evaluating the proposed architecture. To prevent interpolation all database were down-sampled with a set of constant factors $n_{down} = [1, 2, 5, 10, 20]$ and optimal sampling frequencies for each device were stored during the training phase. The testing was carried out selecting the optimal sampling frequency according to Eq. 3 separately for each device.

IV. Experimental Results

All experimental results were generated with the same baseline system as described in Section IV. Classification accuracy was evaluated in terms of percentage of a device to be working or not (Eq. 5), hence binary classification was applied and every device was modelled as one-state device only. In Eq. 5 TP are the true positives, TN are the true negatives, FP are the false positives and FN are the false negatives. $RMSE$ and E_{ACC} (Eq. 6 and Eq. 7) were evaluated taking into account the estimated power $\hat{p}_t^m$ and the ground-truth consumption p_t^m for the m^{th} device, where T is the number of frames and M the number of devices. Since equidistant sampling is applied Eq. 6 and Eq. 6 are also a measure of assigned energy.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{p}_t^m - p_t^m)^2} \tag{6}$$

$$E_{ACC} = 1 - \frac{\sum_{t=1}^{T}\sum_{m=1}^{M}|\hat{p}_t^m - p_t^m|}{2\sum_{t=1}^{T}\sum_{m=1}^{M}|p_t^m|} \tag{7}$$

Experimental results were determined in three steps and results are shown in Table I and Fig. 4 respectively. At first the ACC, E_{ACC} and $RMSE$ values were calculated for every dataset and every device using the sampling frequency at which the database was recorded. As a second step the sampling frequency was optimized according to Eq. 3 and the device detectors were updated with the optimal thresholds according to Eq. 4. Finally the performance with the optimal sampling frequency for each device was determined.

In Table I the column 'Base' gives the per dataset performances for the base sample frequency and the column 'Opt' gives the per dataset performance for the specific optimal sampling frequency respectively. As shown in Table I choosing the optimal device sampling frequency improves classification accuracy, estimation accuracy and root-mean-square-error in

TABLE I
ENERGY DISAGGREGATION PERFORMANCE IN TERMS OF ACC, E_{ACC} AND $RMSE$ VALUES FOR DIFFERENT DATASETS (UK-DALE IS LABELLED AS UK) USING THE SAMPLING FREQUENCY OF THE DATASET ('BASE') AND THE OPTIMAL DEVICE DEPENDENT SAMPLING FREQUENCY ('OPT')

Dataset	**ACC in [%]**		**E_{ACC} in [%]**		**RMSE**	
	Base	Opt	Base	Opt	Base	Opt
ECO-1	86.8	**87.4**	60.3	**67.0**	10.6	**9.5**
ECO-2	89.3	**89.9**	54.6	**59.4**	10.0	**9.3**
ECO-4	82.5	**83.8**	61.7	**64.0**	37.0	**36.1**
ECO-5	90.0	**90.6**	68.9	**69.9**	17.5	**17.0**
ECO-6	91.9	**92.2**	68.0	**70.4**	9.0	**8.7**
UK-1	97.8	**97.9**	74.7	**77.6**	4.4	**4.0**
UK-2	90.5	**91.0**	66.5	**67.8**	18.3	**17.6**
UK-3	96.9	**97.2**	52.5	**58.9**	45.0	**42.3**
UK-4	89.4	**90.6**	56.7	**59.9**	24.4	**23.2**
UK-5	89.6	**90.7**	64.4	**67.5**	11.5	**11.0**
REDD-1	92.0	**92.6**	62.2	**68.7**	13.4	**12.5**
REDD-2	97.5	**97.5**	71.9	**73.0**	7.0	**6.6**
REDD-3	91.6	**92.4**	62.1	**67.6**	15.1	**13.8**
REDD-4	91.9	**92.5**	68.0	**69.6**	8.1	**7.7**
REDD-5	87.7	**89.4**	55.9	**57.9**	27.3	**25.6**
REDD-6	93.7	**94.4**	68.4	**71.1**	23.4	**21.6**

all evaluated dataset when selecting the optimal sampling frequency for each device. The improvements are up-to 1.7% for ACC values, up-to 6.7% for E_{ACC} values and up-to 11.5% for $RMSE$ values.

As shown in Fig. 4 reducing the sampling frequency maximizes both the E_{ACC} and the $RMSE$ for the majority of the evaluated devices. In detail Fig. 4 illustrates devices with noticeable change of E_{ACC} and $RMSE$ scores with respect to different sampling frequency values, namely the dryer, washing machine (WM), freezer and fridge. It also illustrates devices with no significant improvement such as the kettle, stereo, laptop and the ghost-devices. The improvements in case of the fridge and the freezer are due to their iterative working routine which is unchanged for days or weeks, since they are never manually turned off completely. In this case down-sampling does not disrupt this working routine pattern or the appliance signature in the feature space, while it eliminates appliances working in parallel increasing the detection accuracy for the fridge and the freezer. In general, reducing the sampling frequency improves detection accuracy for medium power consumption devices with iterative working routines since their appliance signatures become more prominent in the feature space through a reduction of other devices working in parallel. The washing-machine or the dryer show improvements as well, as these devices operate in cycles (repeated washing or heating cycles) as well. In contrast to the fridge and the freezer the operating cycles of the WM and dryer are in the order of hours thus only marginal down-sampling does not affect those cycles. For devices with none-repetitive patterns (e.g. the electronic devices or ghost power) or for devices having single events with huge power peaks in the order of seconds (e.g. boiler or kettle) no significant improvement was found. The sampling frequency dependent E_{ACC} and $RMSE$ scores for eight different devices are illustrated in Fig. 3.

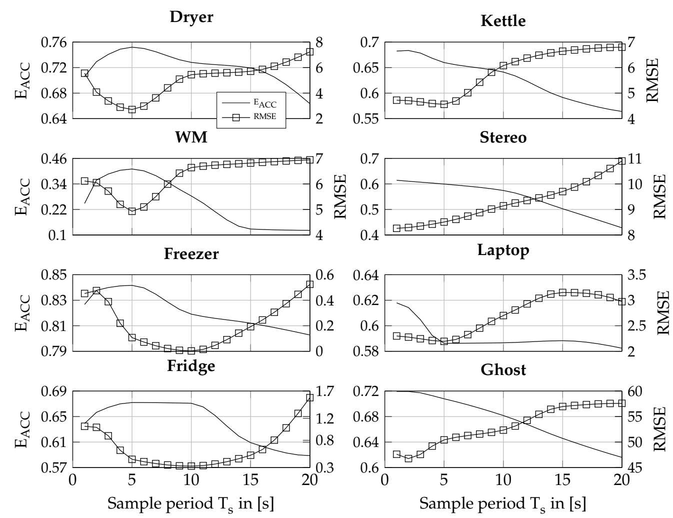

Fig. 4. E_{ACC} and $RMSE$ scores for eight devices of the ECO database for different sampling period values

As shown in Fig. 4 both E_{ACC} and $RMSE$ values are affected by changing the sampling period. There is an absolute performance increase for the devices in the left column, since the estimation accuracy is increasing and the root-mean-square-error is decreasing inverse proportionally. Further the fridge and the freezer (similar devices) show similar patterns with an optimal sampling period at approximately $T_{s,opt} = 10s$, while same holds for the dryer and the washing machine with an optimal sampling period at approximately $T_{s,opt} = 5s$. The larger optimal sampling period for fridge and freezer is due to their endless working routine (only manual shut-down) while dryers and washing machines operate in the order of hours. Further all devices show drastic performance decrease with over-excessive down-sampling.

V. CONCLUSION

This paper presents an appliance-driven selection of optimal sampling frequency to improve energy disaggregation in non-intrusive load monitoring. The proposed methodology leads to optimal device detection accuracies, estimation accuracies and $RMSE$ values independent of the sampling frequency at which the database was recorded. The presented approach works with a state-of-the-art $NILM$ baseline system with optimal device dependent sampling frequencies. Average pre database improvements for estimation accuracy are up to 6.7% and $RMSE$ values are decreasing up to 11.5%. Similar results could be found in all three tested database, with three different base sample frequencies.

ACKNOWLEDGEMENT

This work was supported by the UA Doctoral Training Alliance (https://www.unialliance.ac.uk/) for Energy in the United Kingdom.

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