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DSUALMH- A new high-resolution dataset for NILM

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Abstract. The optimisation of energy consumption requires a reasonably accurate measurement, so an appropriate and advanced monitoring system of the relevant electrical variables in the electrical installations is of paramount importance. In this context, interoperable and highly configurable devices play a crucial role. A clear example is the OpenZMeter (OZM) which is an open source, open hardware, multi-purpose precision smart meter that can measure a wide range of electrical variables at a high sampling rate and provide processed data on power quality. The aim of this work is to show the use and possible applications of the new high sampling frequency data provided by the OZM device, which are much richer and more accurate than those obtained with other low-cost electrical meters. For this purpose, the opensource tool NILMTK has been used and adapted. Likewise, the use of two of the best known and most widely used algorithms such as Combinatorial Optimisation (CO) and the Factorial Hidden Markov Model (FHMM) has been considered, analysing the results obtained in the experimental study and offering a detailed comparison of the performance of the two different disaggregation algorithms using metrics for the different cases, as well as the incorporation of transients, and the comparison with other public Datasets.

1. Introduction

Given the current energy crisis, the so-called Non-Intrusive Load Monitoring or NILM [1] has come back to the forefront. It consists of estimating the individual consumptions of different electrical appliances connected to a given electrical installation from a single centralised energy meter. Firstly, given this context frameworks such as NILMTK[2], which provides a complete pipeline consisting of converters, evaluation metrics, algorithms [3], etc., reduce the entry barrier for new researchers [4].

On the other hand, it is possible to access sophisticated devices such as the OZM [5], which is an advanced multi-purpose power meter that also behaves as a power quality analyser. It is an open source and open hardware device with IoT capabilities that can measure a wide range of electrical variables at a high sampling frequency (15.625 kHz) including voltage, current or power, as well as harmonics up to order 50.

The aim of this work is to show the potential of energy disaggregation using the data provided by the OZM and adapting the non-intrusive load monitoring tool NILMTK [6] for this purpose. It should be noted that in order to adapt the data from OZM devices to NILMTK, two new converters have been developed, which have allowed the creation of two new datasets (DS): DSUALM and DSUALMH, both in the HDF5 format [7]. These DS include the possibility of considering the use of voltage, current and power harmonics up to order 50, as well as associating the corresponding OZM metadata.

2. Related Work

There are several algorithms for load disaggregation in the literature as well as different datasets available for testing these algorithms. Regarding the existing energy disaggregation methods, they can be classified into three main groups:

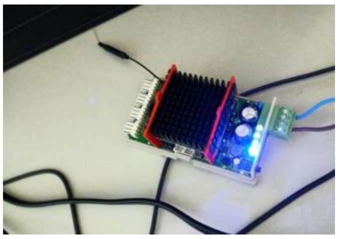

Fig. 1. Overview of the OZM hardware.

- **Optimisation methods** such as Optimized Bird Swarm Algorithm or OBSA [8], genetic algorithms [9] and Particle Swarm Optimization or PSO [10], among others.
- **Supervised methods** such as Bayesian Classifiers [11], Support Vector Machine or SVM [12], the Discriminative Disaggregation Sparse Coding algorithm (DDSC) [13], Artificial Neural Networks (ANN) [14], as well as their extensions.
- **Unsupervised methods**, with the Combinatorial Optimisation (CO) [15], Markov Models (HMM) and their extensions such as FHMM [16], which we will use in this work.

In terms of datasets, there are numerous DS that can be used to test and compare the results offered by different power disaggregation algorithms. The following are some examples of public datasets:

- **IAWE** (Indraprastha Institute of Information Technology) provides aggregated and sub-metered electricity and gas data from 33 household sensors with 1 second resolution over 73 days from a single household [17].
- **REDD** (USA) gives high frequency current and voltage data available for both grid circuits. Power measurements are low-frequency (3 to 4 seconds intervals) from 6 U.S. households over several intervals (between a few days and a few months) over various intervals (between a few weeks and a few months) [18].
- **UK-DALE** (UK) provides 16 kHz aggregate voltage and current meter readings and 6 second submetered power data from individual appliances in 3 UK households, as well as 1 second aggregate and 6 second submetered power data for 2 additional households [17].
- **DEPS** (Escuela Politécnica Superior de la Universidad de Sevilla) provides power, voltage, and current readings at 1 Hz over 6 devices present in a classroom taken over a month [19].

With the new provided DSUALM and DSUALMH Datasets, we intend to offer the research community a rich repository with more than 150 electrical variables taken at a high sampling rate on different everyday applications that will contribute to improve NILM research.

3. Methodology

For the disaggregation process we will use the NILMTK Toolkit. Figure 2 shows the flowchart of the entire process.

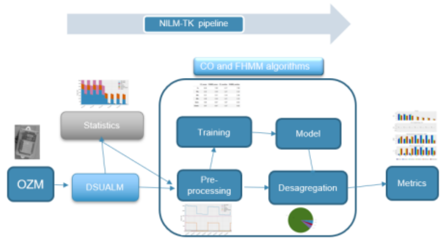

Fig. 2. Flowchart for NILMTK.

A. Dataset development and creation

The models presented in this paper make use of data from recordings of several hours of operation of different devices, using the OZM API, collecting fundamental and secondary electrical characteristics, such as complex harmonic values of current, voltage and power up to order 50.

Fig. 3. Taking measurements with OZM.

The process of creating new datasets starts with the collection of measurements by the different OZM devices installed. Through the API provided, 160 fields are generated with the data obtained. Additionally, these fields must be adapted for use with NILMTK. Specifically, both the data and metadata obtained must be based on the NILMTK-DF format. For this task, it is necessary to develop new converters to perform a series of manipulations to the fields provided in the data files in hdfs or csv format. This process will lead to the creation of the final output data files, which will be saved in csv format.

The next task consists in the conversion of the different csv measurement files pre-processed in the previous phase into a single common file in HDF5 format, which is stored in the "/data/" folder that will also contain all the DS metadata.

Normally, standardised DS formats are used in NILMTK, but given the exclusivity of the data offered by the OZM, a new data format is required, for which we created two functions: convert_ualm (normal) and convert_ualmt (for processing transients). In the directories of the new converters, not only the Python code of the new converters is placed, but also new subdirectories are included in "/metadata/", where the metadata files in yaml format are placed. Figure 4 shows the configuration of all the files needed for the converters, as well as the required directory structure.

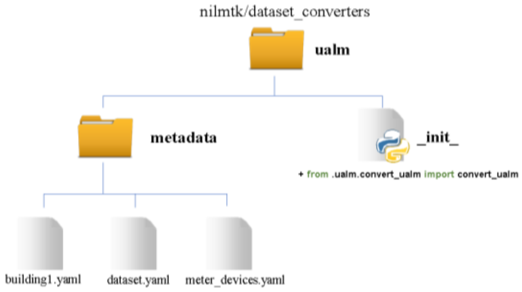

Fig. 4. Metadata file structure.

As each csv file is obtained in the previous phase from the files of the different OZM, it is necessary to number them, with number 1 corresponding to the main meter. To do this, the new function accesses all the aforementioned measurement data files located in the input folder /electricity/", using the labels.csv file, a process that is shown in figure 5.

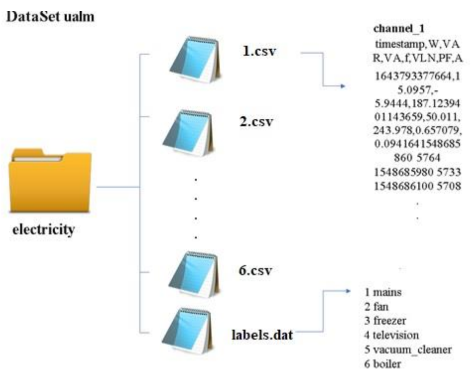

Fig. 5. Structure of data files.

After processing all the measurement files, we proceed to merge them in yaml format, in order to subsequently convert the data structure into a new DS in H5 format. Once the data files are located, the first thing to do is to invoke the DS converter by calling the new function convert_ualm, passing it the path of the metadata and the new name of the DS file that will be generated in H5 format. Once the new DS is created, we can perform a pre-analysis of the data, being especially interesting to represent the voltage, power and current graphs for the different applications.

B. *Data Analysis, Pretreatment and Validation*

Once the new DSs have been generated, NILMTK implementations can be used to perform a quick diagnosis of the DS. It is especially interesting to obtain the voltage profile and the power consumption graph of the appliances (see figure 7).

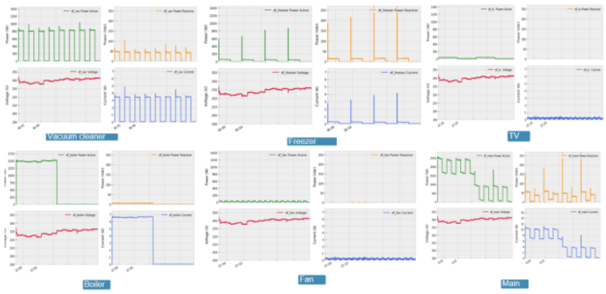

Fig. 6. Representation of the measurements.

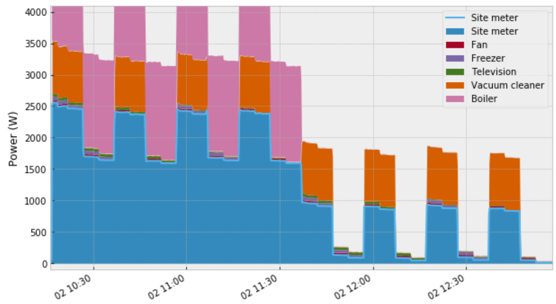

Fig. 7. Power profile.

It is also interesting to know if there are any missing sections or to discard those samples with very low values (by applying filters). Finally, once the data has been analysed, the DS will be divided into a training set, validation set and test set. To train the model we use two of the disaggregation models available in NILMTK, such as the supervised algorithms CO and FHMM, using the data related to the active power of the devices. To do this, in addition to loading the necessary libraries, we will first define the DS, associate the labels associated with the appliances and finally define the training subset.

Once the training model is defined, we will run the two algorithms CO and FHMM in those time intervals (10", 30", 60", 5', 10", 15"), for the three methods (First, Mean and Median), saving the models generated in H5 format. All that remains is to implement the best evaluated model in the validation stage, and thus compare the real signal (GT) with the one predicted by the best model.

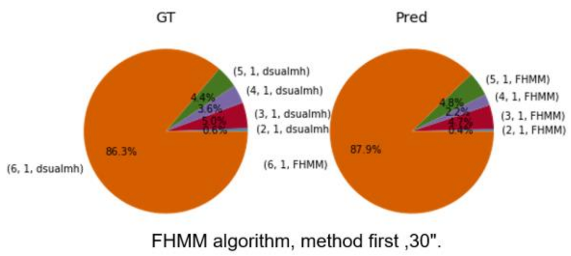

Fig. 8. Comparison of GT with predicted measures.

As can be seen in figure 8, the results are quite acceptable in terms of predictions. For example, for the kettle (in blue) there is only a small deviation of 0.2% from the actual data. Likewise, both the fan (in red) and the light (pink) show minimal variation and the hoover (in orange) only shows a deviation of 1.6%.

4. Results

NILMTK has a calculation engine for evaluation metrics through the use of the MeterGroup for the validation of the results by means of the validation set. For this purpose, it is necessary to run different metrics on the models obtained, such as FEAC, F1, EAE, MNEAP and RMSE, which produce an output like Table 1.

TABLE I.- Main metrics obtained for applications

	fan	freezer	television	vacuum cleaner	boiler
F1	0.679	0.749	0.842	0.989	0.996
EAE	0.000	0.000	0.000	0.000	0.000
MNEAP	0.660	1.815	0.802	0.029	0.022
RMSE	20.600	62.253	24.520	27.240	32.839

A. *F1 and MNEAP Metrics*

As for the F1 metric, the addition of transients allows an improvement for the kettle and the hoover, while maintaining for the fan and freezer, and worsening for the TV.

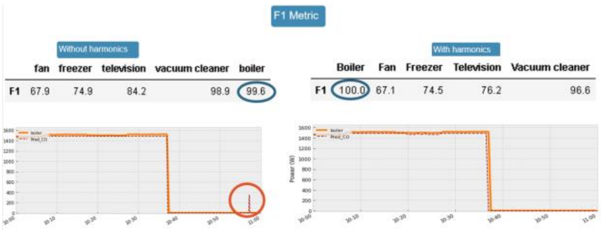

Fig. 9. Comparison with or without transients for metric F1.

With respect to MNEAP, incorporating harmonics improves the performance for the fan and, notably, for the freezer, while maintaining similar values for the rest of the appliances.

B. *RMSE Metric*

In terms of RMSE, the improvement of the freezer clearly stands out (from 62.25 to 35.9) followed by a modest improvement in the TV (from 24.5 to 23.2). Regarding other appliances, the fan remains the same, and both the kettle and the hoover worsen.

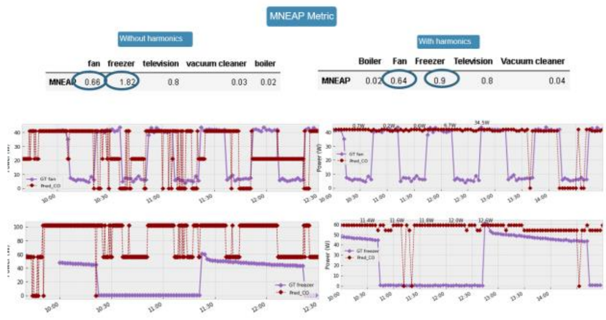

Fig.10. Comparison with or without transients for metric MNEAP.

Fig. 11. Comparison with or without transients for RMSE metric.

C. *Summary of results with and without harmonics*

In general, the incorporation of transients improves all metrics for almost all appliances. Particularly noteworthy are the fan and the freezer. Regarding the TV, it would only get worse for F1, and for the hoover or the kettle, it would only get worse for RSMSE.

TABLE II.- Summary metrics with or without transients Algorithm CO, period 30", method mean

	TR	FAN	FZ	TV	VC	BLR
RMSE	NO	20,6	62,25	24,5	27,24	32,8
	YES	22,19	**35,9**	**23,2**	46	41,8
F1	NO	67,9	74,9	84,2	98,9	99,6
	YES	67,1	74,5	76,2	**99,6**	**100**
MNEAP	NO	0,66	1,82	0,8	0,03	0,02
	YES	**0,64**	**0,9**	0,8	0,04	0,02

D. *Comparison with other DS*

For the IAWE DS, the results show that the most efficient algorithm for this DS is the combinatorial (CO) algorithm using the Mean method and period 10 minutes, compared to only the 10 seconds needed with the OZM data.

	CO_mean	FHMM_mean	CO_median	FHMM_median	CO_first	FHMM_first
1s	11.01	124.36	12.65	117.12	11.46	112.09
10s	11.02	23.09	10.43	22.02	10.31	21.79
30s	10.23	15.35	10.29	15.65	10.24	15.41
60s	9.93	12.88	9.93	12.83	9.81	12.45
5min	9.94	10.38	9.47	10.41	9.48	10.27
10min	9.23	10.02	9.33	10.05	9.27	10.03

Fig. 12. Main metrics obtained for applications in IAWE dataset.

On the other hand, the results obtained for the DEPS DS show a better performance for the CO algorithm, Mean method, but at a sampling time of half an hour, compared to only 10 seconds for the OZM data.

	CO_mean	FHMM_mean	CO_median	FHMM_median	CO_first	FHMM_first
1s	11.08	69.63	10.72	54.70	10.33	59.98
10s	10.52	17.83	10.83	16.95	10.81	16.89
30s	10.69	13.27	10.65	12.92	10.52	13.20
60s	10.17	13.31	10.45	11.57	10.60	12.04
5min	8.84	9.88	8.85	9.97	8.86	9.60
10min	8.16	9.59	8.53	9.33	8.53	9.48
15min	7.61	8.62	7.18	8.64	7.08	7.62
30min	6.60	7.20	7.27	7.87	7.85	7.16

Fig.13. Main metrics obtained for application in DEPS dataset.

Likewise, if we compare GT and Pred for the DS of DEPS, the divergences are very important, ranging between 1.4%, 4.6% and 4.9% compared to 0 and 1.6% for DSUAL.

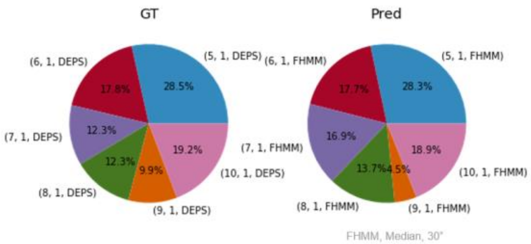

Fig. 14. Comparison of GT with predicted measures for DEPS dataset.

5. Conclusions

In this work, we publish a new set of tools that remove the entry barrier for any researcher who has an OZM (developed by the UGR and UAL) and wishes to access the NILM. A new dataset is also provided which, in addition to being able to include voltage, current and power transients up to order 50, also incorporates the 13-digit timestamp.

The aim of this work is to demonstrate that the new data provided by the OZM improves all the metrics of NILMTK, for which the metrics have been compared between both DS (with or without transients), obtaining better results with their inclusion. Likewise, these have been compared with other public DS, obtaining worse results in other DS in terms of the sampling period required. In addition, the minimum error obtained in the disaggregation in DSUALM stands out, as well as the best values obtained for the MNEAP and RMSE metrics.

Our aim is to continue improving our dataset with the incorporation of new applications, trying to involve the community to join in by applying other algorithms using the new DS or contributing new measures using the new published tools as a reference.

The inclusion of high-frequency measurements, together with the incorporation of transients, improves the results obtained with NILMTK, depending on the application to be considered, which is undoubtedly an interesting aspect to continue working on in future research lines.

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