Event detection and classification for disaggregation of energy consumption metering data

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***Abstract*— One potential solution for stopping global warming lies in addressing the energy efficiency and power consumption of residential buildings. Non-intrusive load monitoring (NILM) emerges as a promising approach to optimize energy consumption by providing detailed insights into individual appliance usage.**

This master's thesis focuses on exploring and evaluating various approaches for event detection and classification within NILM. The research begins by testing the NILMTK toolkit, which offers a comprehensive set of algorithms and tools for energy disaggregation. Building upon this initial investigation, a more recent approach based on deep neural networks is examined. Additionally, a novel methodology centered on leveraging the capabilities of scikit-learn is designed, developed, and presented.

***Keywords*— Non-intrusive load monitoring (NILM), Load disaggregation, Event detection, Machine learning, Energy monitoring**

I. INTRODUCTION

Global warming is a critical issue that demands immediate action. One potential solution lies in addressing the energy efficiency and power consumption of residential buildings. Non-intrusive load monitoring (NILM) emerges as a promising approach to optimize energy consumption by providing detailed insights into individual appliance usage.

NILM is a technique that analyzes overall power consumption to determine the energy usage of individual appliances in a building. Despite being introduced decades ago (1982), NILM has experienced significant growth in the past 10 years. A recent reemergence of this field is attributed to the fact that there has been a vivid deployment of smart meters on a mass scale in recent years. An even more impressive advancement in the field of artificial intelligence (AI) has also contributed to this spike in popularity. Implementing NILM involves combining techniques like signal processing, machine learning, and data analysis. The main challenge of NILM is to distinguish appliance consumption patterns from overall building consumption measurement. To address that issue techniques such as feature extraction, disaggregation, and classification are being utilized. Among the methods primarily used for that task were combinatorial optimization and hidden Markov models. Ongoing research aims to enhance NILM accuracy and applicability, in order to make it a viable solution for energy efficiency optimization and cost reduction in buildings.

The main objective of this dissertation is to experiment and evaluate the feasibility of implementing non-intrusive load monitoring methodologies and performing the load disaggregation in a specific scenario. The special scenario refers to a predisposed set of parameters, assumptions, and datasets that were provided at the beginning of this research endeavor. By employing advanced data analytics and machine learning techniques, the aim is to achieve a comprehensive understanding of energy consumption patterns and identify individual appliance-level load characteristics. Furthermore, an evaluation of the effectiveness of multiple classification and regression algorithms applied in the described process of load disaggregation is being executed.

The content of this thesis is structured in the following order. First of all, an origin of NILM is presented together with a brief demonstration of the process of development of that field. Secondly, a theoretical overview and in depth explanation of the theoretical models that are lying at the core of the non-intrusive load monitoring is shown. Following that an implementation phase is described meticulously in the form of a numerical model. Afterwards comes a presentation of the result and elaboration of obtained values and metrics. The dissertation is finished by a chapter which concludes the main achievements of this study and suggests possible pathways that could be taken as a future work.

II. BACKGROUND

The genesis of the topic of nonintrusive load monitoring is assigned by many researchers to a specific research paper titled "Nonintrusive Appliance Load Monitoring" written by George William Hart, and published in the Proceedings of the IEEE in 1992. It focuses on the concept of nonintrusive load monitoring (NILM) and its potential applications in the field of energy consumption analysis (Hart, 1992).

In (Hart, 1992), the author describes the fundamental principles behind NILM and presents a comprehensive framework for its implementation. The paper discusses various signal processing techniques, such as time-domain and frequency-domain analysis, which are employed to extract appliance-specific features from the aggregate power signal. Feature extraction methods, such as transient detection, steady-state power estimation, and pattern recognition, are explored in detail.

A reemergence of interest in the topic is marked by the publication of (Batra, 2014). This paper marks the beginning of a new wave of NILM development. The authors address the need for a standardized and open-source platform in the field of NILM and present the NILMTK toolkit as a solution. The toolkit provides a collection of pre-processing, feature extraction, and disaggregation algorithms, along with evaluation metrics and visualization tools. It aims to simplify the development and evaluation of NILM algorithms, fostering collaboration and enabling reproducible research.

The paper discusses the architecture and design principles of NILMTK, highlighting its modularity and extensibility. It emphasizes the use of a common data format, facilitating data sharing and comparison between different datasets and algorithms. The toolkit supports various data types, including high-frequency voltage and current measurements, and accommodates both single- and multi-state appliance models. The evaluation metrics and visualization capabilities of NILMTK are discussed, enabling researchers to assess the accuracy and performance of their NILM algorithms. The authors also highlight the toolkit's integration with other open-source projects, such as Pandas and scikit-learn, further enhancing its capabilities and interoperability.

Another NILM implementation is presented in (Kelly, 2015), where a novel approach to load disaggregation based on deep neural networks is being introduced. In specific, three deep neural networks are redesigned and presented in this paper. First is based on a form of recurrent neural network called 'long short-term memory' (LSTM). Second utilizes a neural network which regresses the start and end time as well as the average power drawn by the specific appliance during an activation period. Third is an adaptation of already existing solutions for autoencoders. Furtherly, these three neural networks are tested and evaluated on their accuracy and efficiency metrics. Last but not least, the performance scores of these novel disaggregation algorithms are juxtaposed against the conventional approaches like combinatorial optimization or hidden Markov models.

Nowadays, the research endeavors in the field of NILM are mainly focused on developing new techniques and methodologies for energy disaggregation like event-based disaggregation in (Alcalá, 2017), which brings greater efficiency and accuracy than the previously presented approaches; or an approach based on a convolutional neural network (CNN) that harnesses the pattern recognition capabilities on grey-scale images of current waveforms in (Yang, 2020); or a non-event-based disaggregation introduced in (Zoha, 2020).

Another pathway of research is focused on providing a comprehensive review of state-of-the-art methods or new datasets. Among this second stream it is worth to mention (Sadeghianpourhamami, 2017), which presents the importance of feature selection for the classification of the NILM; or (Gopinath, 2020), which beside presenting opportunities of NILM also shows its current drawback or challenges like: technology immaturity, high algorithmic complexity, or challenges related to collection and processing of gigantic amounts of data necessary for successfully implementing NILM.

III. IMPLEMENTATION

This dissertation focuses on experimentation and evaluation with respect to the feasibility of implementation of a number of approaches that are related to the field of non-intrusive load monitoring and load disaggregation. The first approach is based on the NILMTK toolkit and the academic publication that introduced it (Batra, 2014). The second approach is developed based on neural networks techniques and the basics of its operation are proposed in (Kelly, 2015). Last but not least, an original approach is developed and presented by the author. As a compulsory step, dataset preprocessing and validation had to be performed in the first place.

A. *Dataset preparation*

Data preparation is a crucial step in conducting an in-depth analysis of energy consumption metering data for event detection and classification. To ensure the dataset's suitability for subsequent analyses, a series of steps were undertaken.

The data provided from an external entity was shared in a form of a series of compressed gzip files. Therefore, the first step to be performed in order to have a legible set of data that could be used for the sake of this dissertation was to decompress all the folders.

In the subsequent step, the raw data obtained from a 24-bit Analog to Digital Converter (ADC) required segmentation into meaningful chunks and transformation into real values representing timestamps, voltage, and current measurements of the mains record. This task was accomplished using a specialized parsing function. The parsing script was fine-tuned specifically for the purpose of this thesis, ensuring optimal extraction of relevant information.

Following the initial preprocessing steps, the dataset was converted from its original text format to a more convenient and widely used CSV (Comma-Separated Values) format. This transformation enhanced the dataset's accessibility and facilitated seamless integration of this dataset in the succeeding stages of this research project.

Simultaneously, a separate file containing power consumption recordings per appliance, serving as a reference or 'source of truth' for the experiment, was also parsed into individual files. Each of these files underwent a thorough data continuity check. The focal parameter for data continuity was the timestamp, ensuring a reliable and continuous recording of information saved in the dataset. In cases where missing values were identified, these gaps were filled with zeros to maintain a consistent data structure. Furthermore, any duplicated values were eliminated during this stage.

After performing those steps, the structure of the dataset was as follows: 1 folder containing so called ‘raw data’ or measurements from the mains, which had a resolution of 7.5k samples per second. On top of that there were also additional 4 files each having measurements of specific appliances at 1 sample per minute sampling rate. To proceed with machine learning and load disaggregation experiments a subsampling of data related to mains’ power consumption had to be performed. This way a voltage or current at one point in time in the ‘source of truth’ files would be aligned with the measurement in the file containing 'raw data'. To achieve that a special function was written which iteratively computed Root-Mean-Square of instantaneous voltage, current, and power recorded and subsampled it to 1 sample per minute resolution, which would be perfectly correlated with the per appliance recordings.

Moreover, **Table 1** is provided to enable reaching a better understanding of how the dataset provided for this dissertation differs or resembles the most popular datasets in the field of NILM.

Table 1: A collection of the most popular datasets used for NILM

Dataset	Country	Buildings	Duration	Sampling
REDD	United States	6	2-4 w	I,V: 15 kHz P: 1 Hz OA: 4 s
BLUED	United States	1	1 w	I,V: 12 kHz P,Q: 60 Hz OA: 1 Hz
UK-DALE	United Kingdom	5	655 d	I,V: 16 kHz P,Q: 1 Hz OA: 6 s
PLAID	United States	55	n/a	30 kHz
iAWE	India	1	74 d	1 Hz
DRED	the Netherlands	1	6 m	1 Hz, 1 min
this thesis	Portugal	2	5-7 d	I,V: 7.5 kHz OA: 1 min, 15 min

I=current, V=voltage, P=active power, Q=reactive power, OA=one appliance

These preparatory steps aimed to establish a robust and well-organized dataset, laying the foundation for performing classification and regression experiments and analyses. The transformed dataset, along with the verified appliance-level power consumption recordings, formed the basis for evaluating the accuracy and effectiveness of the disaggregation algorithms employed in this research.

B. *Creating the library with NILMTK toolkit*

In order to effectively utilize the functionalities offered by the NILMTK toolkit, it was essential to prepare and organize the dataset in a specific manner. To accomplish this, a dedicated dataset converter was developed. This step was achieved by drawing inspiration from an existing converter created for the iAWE[1].

The key objective of the converter was to align the column names, structure the data appropriately, and subsequently convert it into the HDF5 data format. By adhering to the converter's instructions and layout, the dataset was transformed into a standardized and compatible format suitable for seamless integration with the NILMTK toolkit.

An additional advantage of utilizing the converter from the NILMTK package was its incorporation of data validation checks and the option for voltage and power normalization if required. This ensured the reliability and consistency of the dataset, enhancing the accuracy of subsequent analyses. As a result of these preprocessing steps, a neatly organized dataset was created, with file '1.csv' containing measurements of the mains' energy indicators, and files '[2, 3, 4, 5].csv' containing data on per-appliance power consumption. These individual appliance-level recordings would later serve as the 'source of truth' during the event detection and classification process.

The structure of the newly created library, representing the organized dataset, is summarized, and presented in **Table 2**. This table provides an overview of the dataset's organization, highlighting the file names, corresponding measurements, and the role they play in the subsequent stages of the research.

Table 2: Organisation of data inside the dataframe.

Equipment name in the Datasheet	Equipment name in "labels.dat"	Input file name
	mains	1.csv
Fridge + Freezer	fridge	2.csv
Oven + Microwave	electric oven	3.csv
Bimby /Kettle /Air fryer	kettle	4.csv
Stove	stove	5.csv

C. *Attempt with NILMTK toolkit*

Despite having successfully converted the dataset to meet the required standards of the NILMTK toolkit, attempts at recreating the combinatorial optimization or FHMM (Factorial Hidden Markov Model) algorithms within the toolkit proved unsuccessful. As a consequence, the approach had to be reconsidered and a thorough examination of available documentation and instructions from various sources followed. As a next step, an endeavor was made to replicate an experiment described in (Batra, 2014). For this attempt it was decided that leaving for the moment the original dataset and utilizing a dataset sourced from within the NILMTK toolkit would be more suited for the task. Regrettably, this trial also concluded with unsatisfactory results.

The lack of success in reproducing the previous methods can be attributed to several factors. Firstly, the challenges faced may stem from the author's limited programming experience, which may have impeded the accurate implementation of the complex algorithms within the NILMTK framework. Moreover, it should be noted that the NILMTK toolkit was developed nearly a decade ago, with the last significant updates or changes to the repository occurring four years ago. This suggests that the toolkit may no longer receive active support or maintenance. Notably, several scripts within NILMTK contain comments indicating that certain sections require further development or improvement, but unfortunately, there appears to be no subsequent follow-up, resulting in unfinished or non-functional code segments.

D. *Attempt with external solution*

The next approach that was tried in order to perform a successful disaggregation involved the implementation primarily developed by Odysseas Krystalakos[2], which is based on NILM disaggregation using neural networks. This proposition drew inspiration from the work and architecture

[1] https://github.com/nilmtk/nilmtk/tree/master/nilmtk/dataset_converters/iawe

[2] https://github.com/OdysseasKr/neural-disaggregator

presented in (Kelly, 2015), providing a promising avenue for further exploration.

The selection of this method was largely driven by the successful recreation of the basic experiment described by the author, in contrast to previous attempts. Encouraged by this outcome, the subsequent step involved replacing the input energy consumption data with the specific dataset provided for this thesis. The possibility for leveraging the dataset that had already been developed using the NILMTK-based converter for the previous experiment was another advantage of this approach. However, despite completing the disaggregation process, the obtained results proved to be unsatisfactory.

E. *Disaggregation with scikit-learn algorithms*

After extensive effort and experimentation with the previous two approaches which unfortunately ended up unsuccessfully, a decision was made to approach the problem from a more mathematical perspective using scikit-learn for disaggregation and put the implementations based on the NILMTK toolkit on the sidetrack.

With a new wave of resolution and through a thorough review of the literature and examining successful implementations in related fields such as image classification, speech synthesis, and pattern recognition, inspiration was drawn for leveraging scikit-learn in this research. The popularity and well-documented nature of scikit-learn made it an attractive choice, as it provided a wide range of classification and regression methods that could be utilized for energy disaggregation. What's more, scikit-learn offers a comprehensive suite of tools for model evaluation and performance assessment. Various evaluation metrics, including accuracy, precision, recall, and mean squared error, were employed to quantitatively measure the performance of the algorithms. These metrics provided valuable insights into the effectiveness of the disaggregation models, allowing for comparisons and informed decision-making.

As the dataset was already well organized and validated several times the decision was made to benefit from that fact and utilize the same CSV files obtained from the previous attempts as input data. The dataset containing the raw recordings from the mains was divided into five subsets to enable the application of the k-fold cross-validation method. This approach ensured that each subset, representing a day's worth of measurements, served as a testing set, while the remaining four days were used for training the classification or regression algorithms. This process was iterated, with each day being used as a testing set, while the algorithms were trained on the remaining data, ensuring a comprehensive evaluation of the models.

In terms of the results obtained from the approach harnessing the functionalities of the scikit-learn, the generated code organizes the output into four distinct folders: 'electric_oven', 'fridge', 'kettle', and 'stove'. Each folder corresponds to a specific equipment or a group of equipment, as explained in the earlier sections of this thesis. The results are presented both numerically and graphically, providing a comprehensive evaluation of the disaggregation process.

A full set of numerical and graphical results of the classification and the regression is available at a designated shared folder space in the google drive[3].

IV. Results

The results of predicted values and performance metrics presented in this thesis are the outcome of the last of the three implementation approaches presented in the previous section.

The metrics that are used to evaluate the results of the performed in this section experiments are:

$$TP = number\,of\,true\,positives$$

$$FP = number\,of\,false\,positives$$

$$TN = number\,of\,true\,negatives$$

$$FN = number\,of\,false\,negatives$$

$$y_i = appliance\,actual\,power$$

$$\hat{y}_i = appliance\,predicted\,power$$

$$\bar{y} = mean\,of\,predicted\,and\,actual\,values$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$AUC = Area\,Under\,[ROC]\,Curve$$

$$mean\,absolute\,error = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$mean\,squared\,error = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

A. *Classification Results*

For the classification of the fridge, the results obtained reveal important insights. A comprehensive analysis is presented in **Table 3**, while **Figure 1** provides a visual representation of the findings. One notable observation is that Logistic Regression exhibits significant deficit in performance when compared to the other classification methods employed in this experiment. This discrepancy highlights the limitations of using a relatively simplistic model like Logistic Regression in scenarios where the dataset contains nonlinear or time series dependencies.

In contrast, the three alternative classification methods employed, namely the Random Forest Classifier, Gradient Boosting Classifier, and SVC, showcase impressive performance metrics. Notably, all three methods surpass the desirable 90% threshold in terms of accuracy, precision, and

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[3] https://drive.google.com/drive/folders/1yhE7LKSrit9tUHhyXU52TMR6T6sFJkFF?usp=sharing

recall. This achievement implies that the overall performance of these models is highly satisfactory for the task. Furthermore, their robustness highlights the fact that they are able to effectively discern patterns and capture dependencies within more complicated datasets like the energy consumption data incorporated in this research.

It is crucial to emphasize that all models achieved an average recall rate exceeding 0.98. This statistic implies that nearly all activation periods of the fridge were accurately detected and correctly assigned as an "ON" state by the classification algorithms. This level of performance further reinforces the reliability and effectiveness of the employed models in accurately identifying and characterizing the operational status of the fridge.

TABLE 3: COMPARISON OF KEY CLASSIFICATION PERFORMANCE METRICS FOR THE FRIDGE.

	$time\_window = 5$			
	AUC	$accuracy$	$precision$	$recall$
$LogisticRegression$	0.87	0.60	0.60	1.00
$RandomForestClassifier$	0.95	0.91	0.91	0.95
$GradientBoostingClassifier$	0.94	0.94	0.91	0.99
SVC	0.88	0.93	0.90	1.00

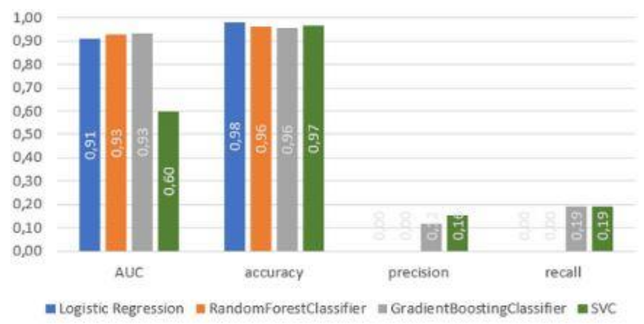

Figure 1: Classification performance of the fridge.

The classification results of the following three appliances (electric oven, kettle, and stove) are presented and discussed at length in the main document of the dissertation.

B. Regression Results

In the context of regression results for the electric oven, kettle, and stove, it is evident that although each of these appliances are different, their load consumption patterns at a resolution incorporated in this research exhibit many similarities. **Figure 2** provides a clear visualization of the electric oven's energy usage, which differs significantly from the previous equipment studied - the fridge. In the cases of the kettle and stove, their energy consumption is predominantly equal to zero, with only occasional instances of usage. By comparing energy consumption patterns of the electric oven, kettle, and stove one can observe the similarities in energy consumption patterns among these three appliances, as they frequently exhibit a continuous, straight line at a level of zero. Occasionally, small peaks in energy consumption are observed in the true values data visualization. Consequently, these three appliances can be discussed collectively as a single group.

The scarcity of non-zero values and the highly unbalanced nature of the dataset is an overarching problem encountered throughout the research conducted for this dissertation, as well as in the field of non-intrusive load monitoring as a whole.

Remarkably, despite the difficulties posed by the challenging dataset, both the Random Forest Regressor and the Gradient Boosting Regressor demonstrate relatively positive performance. This can be observed most prominently when analyzing **Figure 2**, precisely points b) and c). The graphs illustrate that many peak values are accurately recognized, and the predicted values align well with the true values in terms of timing, occasionally even approaching the correct magnitude of the peaks. Of particular interest is the notable superiority of the Gradient Boosting Regressor over the Random Forest Regressor, as evidenced in **TABLE 4**. While both methods exhibit almost identical scores for MAE (0.435 vs 0.438, respectively), the MSE metric highlights the clear advantage (0.700 vs 1.908, respectively) of the Gradient Boosting Regressor.

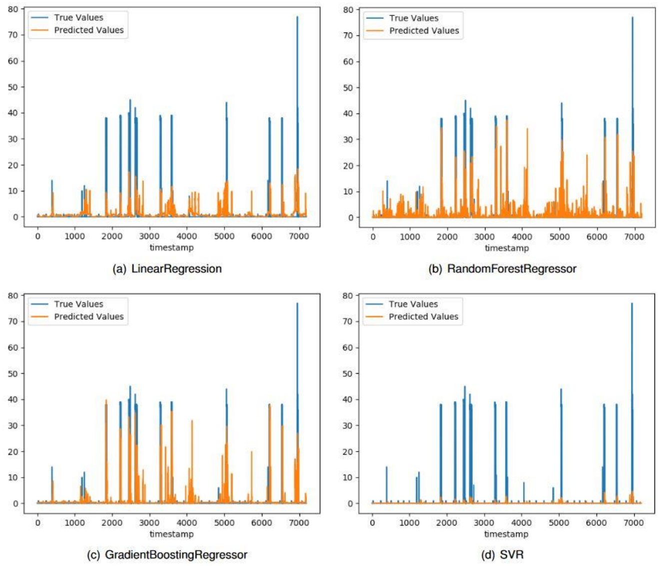

Figure 2: Visual representation of disaggregation of energy consumption of the electric oven based on various regression methodologies: a), b), c), and d).

TABLE 4: COMPARISON OF KEY REGRESSION PERFORMANCE METRICS FOR THE ELECTRIC OVEN.

	MAE	MSE
$LinearRegression$	0.700	2.049
$RandomForestRegressor$	0.438	1.908
$GradientBoostingRegressor$	0.435	0.700
SVR	0.136	0.333

Overall, these findings provide valuable insights into the regression results for the fridge, electric oven, kettle, and stove, providing a plethora of valuable insides on the performance of various regression methods and highlighting the complexities and challenges associated with accurately predicting energy consumption patterns for these appliances.

Taking into consideration all of the above performed and presented experiments, it can be seen that there exists a clear superiority of Random Forest Regressor and Gradient

Boosting Regressor for accurately predicting energy consumption patterns of all of the appliances analyzed in this research. The findings demonstrate the potential of these methodologies to contribute significantly to load disaggregation techniques and improve energy management strategies by providing precise information about appliance usage.

V. CONCLUSION & FUTURE WORK

The first of the achievements obtained on the course of development of this thesis, which was also first in the chronological order is conducting the successful preprocessing and data quality improvement. This included unpacking and decoding the dataset, as well as addressing issues such as outliers and data continuity. The dataset was prepared to meet the standards required for further analysis.

Another aspect that was a considerable obstacle but at the same time it served as a potent reason to exert efforts even stronger was to keep progressing with limited information. Despite encountering limitations in terms of available information about the dataset or clarifications to some parts of it the work was not halted and the progress continued. Complementary information was sought to enhance the understanding and analysis of the data.

Next thing that could be counted as the achievement gained during the process was the implementation of NILM metadata that played a crucial role in converting the dataset into a specific type of a library in the HDF5 format. This process involved aligning the data according to the metadata specifications and instructions inside the NILMTK toolkit. At the end this step facilitated to a great extent a subsequent testing and experimentation with different disaggregation approaches.

Following that the successful disaggregation was performed despite limited power consumption measurements. Regardless of the scantness of the data recording and not so substantial amount of power measurements available, successful disaggregation methods were performed. This poses as an argument in favor of the effectiveness of the implemented approaches. Implementation and evaluation of classification and regression methods was conducted. It was a significant achievement as it compared various artificial intelligence and provided a comprehensive analysis allowing for the identification of suitable machine learning algorithms for non-intrusive load monitoring and disaggregation. Additionally, important parameters such as the size of the time window were evaluated to determine their impact on performance.

Overall, the research efforts in event detection and classification for disaggregation of energy consumption metering data have yielded successful preprocessing techniques, effective disaggregation methods, and valuable insights into the performance and suitability of various machine learning algorithms. The personal growth and learning experiences gained throughout the research further contribute to the significance of these experiments.

A collection of solutions proposed in this dissertation as well as presented pathways for future research demonstrate significant potential for advancing the field of non-intrusive load monitoring and energy disaggregation from metering data. Moreover, these findings offer promising inputs that combined with other research could serve as a potent way of addressing the pressing global issue of global warming, as they promote energy efficiency and empower individuals to actively engage in the development of sustainable energy practices. By collectively working towards this common goal, we can strive to solve the overarching challenge and contribute to a more sustainable future.

A. Possibility of training on more data

One important aspect that could be improved is related to the general size of the dataset. Recording, collecting, and compiling larger amounts of data from households available to the companies or other institutions having access to energy consumption information would bring benefits to the overall implementation of NILM. By working with a richer dataset, it would be possible to train the applied algorithms on a broader range of scenarios, leading to potentially more accurate disaggregation results, at least in theory. Gathering data from diverse households, including those located outside Portugal, could also provide insights into the universality and robustness of the developed techniques. Examining this pathway could also provide a sense of how feasible this solution would be for mass deployment and whether introducing it to a broader market would already be within the reach of private companies.

B. Extending experimentation to more than one household

Another plausible area of future research would be to conduct experiments on multiple and different households, using one house for testing the accuracy of the neural networks and the remaining ones for the training of the disaggregation algorithms. However, it should be noted that this approach has shown some challenges that are documented in the literature. One of such obstacles refers to the issue of similarity of load profiles among different appliances. For example a load profile of the computer could be so similar to the one generated by the air conditioning unit that the disaggregation algorithm yields results no better than a random guess. On the other hand, multiple research papers point out that there are also troubles related to the variability in load profiles even for the same appliances but with slightly different models or manufacturers. Further investigations and experimentation are needed to address these complexities and evaluate the performance of the algorithms in different household contexts.

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