Highlights

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- The paper presents an experimental overview of the application of NILM-API, which was released with nilmtk-contrib, on three publicly available data sets, draws conclusions and highlights on future research directions.

- A detailed overview on the energy disaggregation problem is presented. Here, we have shown the advantages of the NILM API through which algorithmic comparisons can be defined with relatively little model knowledge.
A Comprehensive Review on the NILM Algorithms for Energy Disaggregation

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\textbf{ABSTRACT}

The housing structures have changed with urbanization and the growth due to the construction of high-rise buildings all around the world requires end-use appliance energy conservation and management in real time. This shift also came along with smart-meters which enabled the estimation of appliance-specific power consumption from the building’s aggregate power consumption reading. Non-intrusive load monitoring (NILM) or energy disaggregation is aimed at separating the household energy measured at the aggregate level into constituent appliances. Over the years, signal processing and machine learning algorithms have been combined to achieve this. Incredible research and publications have been conducted on energy disaggregation, non-intrusive load monitoring, home energy management and appliance classification. There exists an API, NILMTK, a reproducible benchmark algorithm for the same. Many other approaches to perform energy disaggregation have been adapted such as deep neural network architectures and big data approach for household energy dis aggregation. This paper provides a survey of the effective NILM system frameworks and review the performance of the benchmark algorithms in a comprehensive manner. This paper also summarizes the wide application scope and the effectiveness of the algorithmic performance on three publicly available data sets.

1. Introduction

There has been immense research on developing technological solutions in order to address the energy requirements which are rising exponentially and thereby making the challenge of energy conservation harder day by day. The increasing energy demands not only affects a country’s economy but also comes with significant negative implications on the environment. Hence, the only effective way to conserve energy now is to encourage its efficient usage. A fine-grained monitoring of energy consumption and communicating the same to the consumers can help in the noteworthy reduction of energy wastage [33], [9]. The problem was originally studied by Hart [13] in the early 1980s and due to the availability of larger data sets in recent years, smart meter roll outs, and amidst climate change concerns, there has been a renewed interest among researchers in this field. The main objective of energy disaggregation is to offer detailed energy sensing and to provide information on the breakdown of the energy consumed, which would moreover enable the automated energy management systems to depict appliances with a high rate of energy consumption, allowing them to devise energy conservation strategies such as re-scheduling of high power demanding operations for the off-peak times[40]. Furthermore, companies would be able to develop a better understanding of the relationship between appliances and their usage patterns. There are two primary approaches to energy dis aggregation, specifically Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM). Intrusive load monitoring consists of measuring the electricity consumption of one or a few appliances using a low-end metering device, particularly requiring one or more than one sensor per appliance, whereas NILM just requires only a single meter per house or a building that is to be monitored. Non-intrusive load monitoring (NILM) or energy disaggregation is aimed at separating the household energy measured at the aggregate level into constituent appliances. The presence of nilmtk-contrib [5], an open-source, reproducible state-of-the-art energy disaggregation implementation has unfolded the means for comparisons of the different algorithms executing energy disaggregation. It has also enabled researchers to assess the generality of NILM approaches as it can be applied to multiple data sets accessible online. The versatility of NILM API makes experimentation in this field easy by lowering the entry barriers and making the implementation generic irrespective of the datasets and algorithms which helped to progress research in this area.

1.1. Scope and Contribution of This Paper

There has been a good number of research and publications in energy disaggregation, non-intrusive load monitoring, home energy management and appliance classification. In the recent past, machine learning strategies for NILM have attracted a lot of recognition due to breakthroughs in research disciplines such as computer vision. NILM algorithms are trained and tested on energy consumption data sets. Such data sets include aggregate-level energy readings from smart meters as well as appliance-level energy readings from measurement equipment such as smart plugs. In the course of the years, a vast number of publicly-available data sets have been released. With NILMTK, an open-source toolkit was designed specifically to enable the comparison
### Table 1
Articles included in systematic literature review

| Subject                                                                 | Purpose                                                                 | Discussion on framework | Discussion on NILMTK-API | Related dataset references | Algorithm implementation | NILMTK-API implementation | Empirical analysis | Future research prospects |
|------------------------------------------------------------------------|------------------------------------------------------------------------|--------------------------|--------------------------|-----------------------------|--------------------------|--------------------------|---------------------|--------------------------|
| Non-Intrusive Load Monitoring System Framework and Load Disaggregation Algorithms: A Survey[34] | presents a general NILM framework and reviews publicly available data sets. | Yes                      | Yes                      | Yes                         | No                       | No                       | No                  | Yes                      |
| A Survey on Non-Intrusive Load Monitoring Methodologies and Techniques for Energy Disaggregation Problem[11] | an overview of the NILM system and its associated methods and techniques for energy disaggregation problem followed by the review of the state-of-the-art NILM algorithms. | Yes                      | Yes                      | Yes                         | No                       | No                       | No                  | No                       |
| Building power consumption datasets: Survey, taxonomy and future directions[17] | survey, study and visualize the numerical and methodological nature of building energy consumption datasets. | Yes                      | No                       | Yes                         | No                       | No                       | No                  | Yes                      |
| On performance evaluation and machine learning approaches in non-intrusive load monitoring[23] | aims to determine the accuracy as well as the generalisation abilities of existing NILM algorithms on the data sets REDD, UK-DALE, and Dataport. | Yes                      | Yes                      | Yes                         | No                       | No                       | No                  | Yes                      |
| Prospects of Appliance Level Load Monitoring in Off-the-Shelf Energy Monitors: A Technical Review[12] | indicates a trend towards the incorporation of appliance-level e-monitoring and load dis aggregation, along with requirements to implement load disaggregation in the next generation e-monitors. | Yes                      | No                       | Yes                         | No                       | No                       | No                  | Yes                      |
| An Overview of Non-Intrusive Load Monitoring: Approaches, Business Applications, and Challenges[39] | survey of NILM system framework and advanced load disaggregation algorithms, reviews load signature models, presents existing datasets and performance metrics. | Yes                      | Yes                      | Yes                         | Yes                      | No                       | Yes                 | Yes                      |
| Literature Review of Power Disaggregation[18] | reviews the current state of the algorithms and systems of NILM. | Yes                      | No                       | No                         | No                       | No                       | Yes                 | Yes                      |
| Load Disaggregation Technologies: Real World and Laboratory Performance[27] | reviews recent field studies and laboratory tests of NILM technologies. | Yes                      | No                       | No                         | Yes                      | No                       | Yes                 | Yes                      |
| Proposed Comprehensive review on energy disaggregation | reviews of the state-of-the-art techniques, implements NILMTK, presents analysis and draws conclusions | Yes                      | Yes                      | Yes                         | Yes                      | Yes                      | Yes                 | Yes                      |
of energy disaggregation algorithms in a reproducible manner [5]. Performance evaluation and comparison of NILM algorithms remain open research challenges for several reasons [23] [30] [16]. Table-1 is a tabular representation of the literature review compiled from similar survey papers which contains synthesised information about the purpose of research and their major findings in this field. It can be observed that the prospects of NILM application are both, wide and versatile. There have been multiple attempts to devise the generalisation abilities of existing NILM algorithms in order to incorporate the methodology to appliance-level monitoring and disaggregation. It is also challenging to collect and store data at the required sample rates in order to make data sets available for these algorithms. This paper provides a concise and clear overview of the NILM framework and the NILMTK-API by implementing the API on three publicly available data sets and comparing the observed results.

The main contributions of this survey article are as follows:

1. This paper presents an up to date outline of NILM framework and its related strategies and methods for the energy disaggregation problem.
2. The paper presents an experimental overview of the application of NILM-API, which was released with nilmtk-contrib, on three publicly available data sets, draws conclusions and highlights on future research directions.
3. A detailed overview on the energy disaggregation problem is presented. Here, we have shown the advantages of the NILM API through which algorithmic comparisons can be defined with relatively little model knowledge.

1.2. Organisation of this paper

The remainder of this paper is structured as follows. First, we provide a brief background on the load monitoring approaches which is followed by a formal introduction to the energy disaggregation problem and a discussion about the available implementations and their general framework. We then introduce the State-of-the-art Disaggregation Techniques, the NILMTK-contrib repository, and provide an overview of the supported algorithms. Next, we describe the benchmark data sets, including the features taken into consideration for the experiment API. We then demonstrate the value of this implementation through an empirical comparison, before summarising our analysis.

2. Background on Load Monitoring Approaches

Load monitoring and identification is a tool for evaluating the electrical energy usage and operating condition of individual appliances, based on the analysis of the composite load measured from the main power metre in the house. They can supply the customer and the utility with information such as the type of load, the detail of the electricity consumption and the operating conditions of the appliances. Load monitoring is essential for energy management solutions as it gives us statistical insights on appliance energy consumption and their patterns which can be used for load scheduling and optimal energy utilisation.

2.1. Intrusive Load Monitoring

It consists of measuring the electricity consumption of one or a few appliances using a low-end metering device. The term intrusive, here, means that the meter is located in the habitation, typically close to the appliance that is monitored. The Intrusive load monitoring system may well be a standard metering system that measures the energy consumption of an appliance by connecting power meters to each appliance within the household. Therefore, it requires entering the house, thus the system is remarked as intrusive. It provides accurate results, however, imposing high costs and an elaborate installation which usually requires wiring and data storage units for the households concerned [1]. Intrusive load monitoring techniques could also be direct or indirect monitoring techniques [35]. Direct monitoring techniques which are called physical intrusive signatures measure the electrical characteristics of each appliance’s power demand. The physical intrusive signatures are generated by a tiny low device attached to the power cord of an appliance for measuring the energy consumption by the appliances. Whenever the appliance is switched on, the device sends a signal to the data collector indicating the operating state of the appliances. The power drawn by the appliance is often calculated by measuring the electromagnetic field generated by the flow of current through the wire. This technique provides accurate measurement, but it is not cost effective [35].

2.2. Non-Intrusive Load Monitoring

It consists of measuring electricity consumption using a smart meter, typically placed at the meter panel. Relying on a single point of measure it is also called one-sensor metering. The qualification of non-intrusive means that no extra equipment is installed in the house. With NILM, the appliance signatures are superposed and, for comprehending the contribution of single appliances, they have to be separated. This operation is called disaggregation of the total electricity consumption. Non-intrusive load monitoring is a convenient means of determining the energy consumption and therefore the state of operation of individual appliance supported analysis of the aggregate load measured by the main electric meter in a building. NILM is a process of analysing changes within the voltage and current going into a building and deducing what appliances are utilized in the building also as their individual energy consumption [1]. It’s called non-intrusive because it does not require intruding into the house or consumer premises when measuring the energy consumption of various appliances. Smart meters with NILM technology are utilized by companies to survey the particular uses of electrical power in different homes. NILM is taken into account for the cost-effective alternative to intrusive monitoring techniques. The thought of analysing the power flow to see household appliances and report on
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their operating condition started when George W. Hart was collecting and analysing load data as a part of a residential photo-voltaic system [13]. The basic monitoring principle is to acknowledge a step change in active and reactive power within the total load produced by altering the operating state of the various customer’s appliances. A NILM is installed temporarily to analyse the characteristics of the appliances which may be used in suggesting ways of reducing consumption and costs.

3. The Energy Disaggregation Problem

The housing structures have changed with urbanisation and immersed the development of high-rise buildings all round the world which needs end-use appliance energy conservation in real time. This shift also came together with smart-meters which enabled the estimation of appliance-specific power consumption from the building’s aggregate power consumption reading. Almost two decades back, Hart proposed a method for the dis aggregation of electrical loads by examining only the appliance specific power consumption signatures within the aggregated load data. This method is considered to be non-intrusive as it avoids any equipment installed inside the customer’s property. The aggregated data is acquired from the main electrical panel outside the building or the residence. The goal is to partition the whole-house building data into its major constituents. Non-Intrusive Load Monitoring (NILM) is an attractive method for energy dis aggregation, as it can discern devices from the aggregated data acquired from a single point of measurement.

3.1. General Framework of NILM

Non-Intrusive Load Monitoring (NILM) is an attractive method for energy disaggregation, as it can discern devices from the aggregated data acquired from a single point of measurement.

As mentioned in the nilm toolkit[5][4], the model on which NILM works is as follows: For an observed time series of aggregate measurements $Y = (Y_1, Y_2, ..., Y_T)$, where $Y_t \in \mathbb{R}^+$ represents the energy or power (active) measured in Watt-hours or Watts by an electricity meter at time $t$. This signal is assumed to be the aggregation of energy consumed by the component appliances in a building. In the following, we assume there are $I$ appliances, and for each appliance, the energy signal is represented as $X_i = (x_{i1}, x_{i2}, ..., x_{iT})$ where $x_{it} \in \mathbb{R}^+$. The main readings can then be represented as the summation of the appliance signals and $E$, where $E$ is an error term. The aim of the energy disaggregation problem, i.e., NILM, is to recover the unknown signals $X_i$ given only the observed aggregate measurements $Y$. Figure-1 demonstrates one such scenario where a high-rise building H contains multiple apartments which are all equipped with a smart meter (SMX, where X is the apartment number) and the building itself has a smart-meter aggregator (SM0) that is connected to the electricity service. This building can be considered as a meter-group. If the electricity consumption data for this building is collected and sampled at a given rate, then applying NILM to this meter group will give us the appliance-wise energy consumption patterns for this group.

4. State-of-the-art Disaggregation Techniques

The energy disaggregation problem was introduced by George Hart in the early 1980s[13]. Owing to the efforts towards energy conservation and emission reduction, there has been extensive research in this field which also got boosted due to smart meter roll outs across different countries. There are more than 10 publicly available datasets from across different geographies to support significant research activities. The growing interest in this field has led researchers to try and implement various algorithms for solving the energy dis aggregation problem, involving neural networks, big data, soft-computing and statistical methods as shown in Figure-2.
Many methods used probabilistic procedures to explicitly model the energy consumption of an appliance using a hidden Markov model (HMM) [25], [29], [38], [37]. There are both supervised and unsupervised approaches to the problem including signal processing methods that use appliance’s features for the purpose of disaggregation [14], [19]. Another class of methods utilizes soft-computing techniques to solve NILM by employing fuzzy clustering [31], [26], and [32]. Additionally, there is also a set of algorithms based on factorization procedures leveraging the low-rank structure of energy consumption to perform energy disaggregation [3], [8], and [24]. The open-source API for non-intrusive load monitoring toolkit (NILMTK), was released in 2019 in order to facilitate easy comparison of NILM algorithms in a reproducible fashion and was meant to be the source library for energy dis aggregation, data set parsers, and reference benchmark algorithm implementations. The nilmtk-contrib [6] lessens the barrier to entry for algorithm developers and simplifies the definition of algorithm comparison experiments by rewriting the disaggregation API and implementing a new experiment API, along with a number of functional improvements to the toolkit’s installation process, data set parsers, and documentation.

4.1. Neural Networks

Neural networks are being successfully applied to a variety of load scenarios and have achieved better scores in terms of accuracy as well as producing generalization for unseen houses [22], [15]. Recurrent neural networks and Long Short Term Memory are the most popular neural network algorithms. There also exists an RNN based approach for NILM on small power office equipment [2].

4.1.1. DAE

Autoencoders are simple neural architectures which are closely related to principle component analysis and if the activation function used within the autoencoder is linear within each layer, the latent variables present at the bottleneck (the smallest layer in the network) directly corresponds to the principal components from PCA. They are unsupervised machine learning algorithms that project the data from a higher dimension to a lower dimension using non-linear transformation while trying to preserve the important features of the data and removing the non-essential parts. The encoder function of the network compresses or down samples the input into a fewer number of bits and maps the original data to a latent space, which is present at the bottleneck whereas the decoder function tries to reconstruct the input using only the encoding of the input and maps the latent space at the bottleneck to the output. The denoising autoencoder is a specific deep neural network architecture designed to extract a particular component from noisy input. They work by adding some white noise to the data prior to training but compare the error to the original output when training thereby forcing the network to not become overfit to arbitrary noise present in the data. Hence, it subtracts the noise in order to produce the underlying meaningful data. Well-known applications of a DAE include removing grain from images and reverb from speech signals. It has been used for NILM by considering the mains signal to be a noisy representation of the appliance power signal, where the mains reading is assumed to be the sum of the power consumption of the target appliance and noise. Since DAE denoises on a per-appliance basis, it needs multiple trained models to dis aggregate a group of appliances. Besides, the DAE here receives a window of the mains readings of fixed length and outputs the inferred appliance consumption for the same time window. The architecture of the network remains as that was proposed in nilmtk-contrib.

4.1.2. RNN

Recurrent Neural Networks are used to process sequences such as a time series prediction or natural language processing. It takes one element at a time while retaining the memory of previously encountered states, working on the principle of saving the output of a particular layer (or state) and feeding this back to the input in order to predict the output of the layer. Therefore, at each element the model considers not only the current inputs but also what it remembers from the preceding elements. This enables the network to learn long-term dependencies from a series of events which means that the model can take the entire context into consideration while making a prediction. An RNN contains a layer of memory cells and the network is in the form of a chain of repeating modules of a neural network. RNNs, however, suffer from the problem of vanishing gradients and exploding gradients. The gradients carry information used in the RNN, and when the gradient becomes too small, the parameter updates become insignificant whereas a gradient explosion occurs when large error gradients accumulate, resulting in very large updates to the neural network model weighing during the training process. These challenges can be solved using LSTMs (Long Short Term Memory), that are widely used memory cells which maintain a cell state as well as a carry for ensuring that the signal is not lost during the processing of a sequence. It also has a chain-like structure but with multiple communicating neural network layers which decide the amount of data that is required to be retained, the significance of the data to be remembered and the part of the memory cell that impacts the output at the given time-step. Moreover, RNNs are a type of neural network that allows for connections between neurons of the same layer which makes RNNs well suited for sequential data, as in NILM. The employed RNN model receives a sequence of mains readings and outputs a single value of power consumption of the target appliance. The network also utilizes long short-term memory (LSTM) units to overcome the vanishing gradient problem by storing values in their built-in memory cell. The architecture of the network remains as that was proposed in nilmtk-contrib.

4.1.3. Sequence-to-Sequence

The sequence to sequence learning model is a deep learning concept which is used to convert from one sequence to another. It contains an encoder RNN to understand the input
sequence and a decoder RNN to decode the thought vector thereby constructing an output sequence. An encoder network condenses an input sequence into a vector, and a decoder network unfolds that vector into a new sequence. The common denominator between encoder and decoder architectures in the sequence-to-sequence model are Recurrent Neural Networks. In the encoder, a new word of the input sentence is fed at each step of recurrence which is exploited by the next state in the sequence in the subsequent step. The decoder starts by receiving as input the final state generated by the encoder, that ideally contains all the information stored inside the input sentence and thereafter the RNN carries it to each successive step which aims to predict the output by using a discrete probability distribution and the loss function. Here, the main idea is to learn a regression map from the mains sequence to the corresponding target appliance sequence. The seq2seq model is defined by the regression $x_t : t + W/1 = f(y_t : t + W/1, Q) + E$, where $f$ is a neural network. The architecture of the network and other hyperparameters remain as they were proposed in nilmtk-contrib [5].

4.1.4. Sequence-to-Point

Sequence to point learning (seq2point) models the input of the network as a mains window, and the output as the midpoint element of the corresponding window of the target appliance. The intuition behind this method is that the midpoint of the target appliance should have a strong correlation with the mains information before and after that time point. Seq2point learning could be viewed as a non-linear regression. The architecture of the network and other hyperparameters remain as they were proposed in nilmtk-contrib.

4.1.5. OnlineGRU

Gated Recurrent Unit (GRU) is a new generation of Neural Networks that attempts to reduce the computational demand while maintaining the same performance by replacing the LSTM units by light weight Gated Recurrent Units (GRU) and optimising the recurrent layer sizes to reduce redundancy as well as minimising the risk of a vanishing gradient. They are a solution to short-term memory with internal mechanisms called gates that can regulate the flow of information. These gates learn which part of the data is important and pass relevant information down the long chain of sequences. GRUs are similar to LSTM except that they do not have the cell state and use the hidden state to transfer information. It also only has two gates, a reset gate and update gate. The reset gate determines how much of the past knowledge to forget whereas the update gate decides what information to throw away and what new information to add. The working of GRU continues such that when the reset gate is near to zero, the hidden state is constrained to disregard the past hidden state and is reset with the current input. This permits the hidden state to discard any information that’s found to be insignificant within the future. This result permits a more compact representation. Whereas the upgrade gate controls how much information from the past hidden state will be exchanged to the current hidden state. The actuation of the GRU at a specific time may be a straight addition between the past actuation and the candidate activation, where an update door chooses how much the unit overhauls its activation or content. The Online GRU model receives the last available mains readings $y_t : t + W/1$ as input and uses them to calculate the power consumption $x_t (t + W/1)$ of a single appliance $j$, for the last time point. The architecture of the network and other hyperparameters remain as they were proposed in nilmtk-contrib.

4.2. Big Data

A good deal of big-data approaches have popped for energy disaggregation with the application of data analytics in smart meters [36] such as Neighbourhood NILM which works on the intuition that ‘similar’ homes have ‘similar’ energy consumption on a per-appliance basis [7] and a scalable three-level learning framework for smart cities that matches the hierarchical nature of big data generated by smart cities with a goal of providing different levels of knowledge abstractions [28].

4.3. Soft Computing

Feature extraction and pattern recognition tasks for non-intrusive residential electrical consumption using fuzzy logic have proven to be feasible. There are soft computing techniques to identify the behavior of each of the devices from aggregated consumption records [31]. A fuzzy classifier with the Fuzzy C-Means (FCM) clustering and optimization algorithms to identify the energizing and de-energizing statuses of each appliance, has also been proposed [26].

4.4. Bayesian Procedures

Bayesian algorithms are being used for event detection and identification of the individual contribution of appliances. Findings for event detection method based on cepstrum smoothing [10] and LSTM models [20] along with a modular way to address multi-dimensionality issues that arise when the number of appliances increase [21] have been devised.

5. Datasets and Algorithms

5.1. Data sets Considered

5.1.1. REDD

The Reference Energy Disaggregation Data Set (REDD), is a freely available data set containing detailed power usage information from several homes, which is aimed at furthering research on energy dis-aggregation. REDD is the first public energy dataset released by MIT in 2011. REDD contains high and low-frequency readings from 6 households in the USA recorded for short period (between a few weeks and a few months). This data set is widely used for the evaluation of NILM algorithms.

5.1.2. UK-DALE

UK-DALE is an open-access data set from the UK recording Domestic Appliance-Level Electricity at a sample rate of
16kHz for the whole-house and at 1/6Hz for individual appliances. The data set contains 16 kHz current and voltage aggregate meter readings and 6 second sub-metered power data from individual appliances across 3 UK homes, as well as 1 second aggregate and 6 second sub-metered power data for 2 additional homes. An update to the data set was released in August 2015 which has expanded the data available for house 1 to 2.5 years.

5.1.3. IAWE
The Indraprastha Institute of Information Technology recently released the iAWE dataset, which contains aggregate and sub-metered electricity and gas data from 33 household sensors at 1 second resolution. The data set covers 73 days of a single house in Delhi, India.

5.2. Algorithms Considered
For the purpose of this experiment, five neural network based algorithms have been utilised, namely: DAE, RNN, Sequence-to-Sequence, Sequence-to-Point and OnlineGRU, all of which have been described in detail in section 4.1 of this article.

5.3. Experimental Scenario
The tests were run on a machine with GeForce GTX 1660Ti/PCIe/SSE2 GPUs with Intel® Core™ i7-9750H CPU @ 2.60GHz × 12 and 16 GB RAM. The sample period was 60 seconds. All neural algorithms were trained for 5 epochs with a batch size of 32.

5.4. Results and Discussion
For each data set, the network was trained for a period of 30 days based on the data and tested on the subsequent 20 days using the nilmtk-contrib API to predict the energy
Table 2
MAE against Ground Truth for Iawe

| Appliance     | WindowGRU | RNN   | DAE   | Seq2Point | Seq2Seq |
|---------------|-----------|-------|-------|-----------|---------|
| Washing machine | 66.726196 | 65.665489 | 65.275597 | 65.736549 | 65.298805 |
| Fridge        | 53.850956 | 68.835884 | 51.917274 | 36.775997 | 54.116047 |
| Computer      | 24.112394 | 24.148933 | 24.64801 | 24.25812 |
| Air conditioner | 169.634262 | 139.516449 | 139.706543 | 120.483185 | 141.557159 |
| Television    | 1.347255  | 1.353503 | 1.347071 | 1.475708 | 1.449378 |

Figure 4: Predicted energy consumption: REDD

- **Washing machine**
- **Fridge**
- **Light**
- **Sockets**
- **Microwave**

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Table 3
MAE against Ground Truth for REDD

|             | MAE- Redd | Window | GRU | RNN | DAE | Seq2Point | Seq2Seq |
|-------------|-----------|--------|-----|-----|-----|-----------|--------|
| washing machine | 49.6175   | 60.6615 | 49.5411 | 47.5141 | 52.3023 |
| fridge       | 59.6225   | 68.3849 | 63.5401 | 55.8036 | 63.5203 |
| light        | 30.1285   | 32.4357 | 31.2249 | 31.2457 | 31.5573 |
| sockets      | 0.8704    | 0.8887  | 0.9399 | 0.8279 | 0.8832  |
| microwave    | 28.5983   | 28.5997 | 34.9981 | 21.9992 | 24.8032 |

Figure 5: Predicted energy consumption: UKdale

A negatively-oriented score, which means lower values are better. It effectively describes the magnitude of residuals and does not indicate the under performance or over performance of the model. Each residual contributes proportionally to the total amount of error, meaning that larger errors will contribute linearly to the overall error. It is noticeable from Table-2 that there is no clear winner in the case of iAWE and the mean absolute errors are very high which could be because the data set is based on a single housing facility. The mean absolute errors remain similar in cases of washing machine, computer and television with the reported errors being the minimum for television. The case of air conditioner reports the maximum observed error from all three scenarios which is greater than 100 for all five algorithms.
and varies largely for every algorithm. The performance of Sequence-to-Sequence and DAE remains similar across all five appliances with DAE performing the best for the television and Sequence-to-Sequence performing the best for the washing machine. It can also be observed from Figure-3, the difference in the load cycles of different appliances.

It is evident from Table-3 that none of the algorithms in consideration perform the best overall in the case of REDD although Sequence-to-Point leads in four of the five most used appliances. This could be due to the dissimilar usage trends of the appliances that the graphs clearly demonstrate in Figure-4, hence, signifying the energy consumption patterns of the appliances. The mean absolute errors are the lowest in this case making it a preferred data set to base our conclusions on.

The mean absolute errors in for the sockets remain less than 1 which is the minimum error reported by an algorithm in all three scenarios. The errors show maximum variation in the case of the washing machine followed by the fridge. There is little variation in the reported values of mean absolute error for the sockets which is again followed by the light. The performance of WindowGRU and RNN is comparable across light, sockets and microwave but differ largely in cases of the washing machine and fridge.

Table-4 shows that Sequence-to-Sequence performs the best for most cases of UK-Dale and the mean absolute errors, although high, are similar for nearly all appliances. The predictions from the graph indicate how some appliances have clearly defined usage patterns (as seen in Figure-5) whereas others are used on a daily basis. The mean absolute error stays the lowest in the case of microwave with 16.60 being the minimum as reported by RNN. It can also be noticed that the mean absolute error for the fridge remains similar across all five algorithms followed by little variation in the case of light and shows the maximum variation for the washing machine.

Different appliances use different quantities of energy and, thus, compared to a high energy consumption load, the errors measured relative to low energy use might be less significant. Furthermore, some end devices operate less frequently than others, so if a statistically substantial number of run times is not recorded, metric results may not be indicative of efficiency. In view of these problems, it is recommended that every metric assessment reflects some leveling of the use of energy or other basis for appropriate comparisons of results across different end uses which could be a fixed energy usage per end use, a fixed number of real events per end use, or a fixed period that is capable of capturing a variety of conditions.

6. Conclusion and future work

In this paper, we demonstrated how nilmtk-contrib provides an interface to energy disaggregation problems and also the API through which algorithmic comparisons can be defined with relatively little model knowledge, thus enabling empirical evaluations to be easily generated. Therefore, increasing the rate of progress within the field and supporting the progress of research in NILM.

Our experimental results carried out on three publicly available data sets namely IAWE, REDD and UKDale do not indicate the presence of any patterns in the output. This could be a result of the large differences in the data sets. Although, it suggests that the API can be used for data sets from different geographies.

With the need for energy and resources rising each day, careful and efficient utilisation is the only way to conserve it and energy dis-aggregation can be an essential element in the conservation of energy since it elaborates the energy usage tendencies. The trends observed in the energy-usage patterns from a household can be used for the purpose of security as an anomaly in them might represent a sign of appliance failure or illegal use of supplied electricity. The appliance usage patterns can also be used to calculate and control the amount of carbon emissions.

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