Chapter 1

Introduction

1.1 Building energy consumption

Energy is an essential component of all development programmes. Without energy, modern life would cease to exist\(^1\). However, energy resources all over the world are getting depleted. There are several energy-related problems that the world must solve\(^2\). These energy problems can be grouped under the following three heads: 1) environmental concerns, 2) a large chunk of the population not having access to a modern form of energy, and 3) potential for geopolitical conflict due to escalating competition for energy resources\(^3\).

Carbon dioxide levels, held responsible for climate change, are at their highest in 650,000 years \[2\]. Governments across the world have taken the problem of carbon emissions seriously as evidenced by various climate change conferences\(^4\). Scientists predict that left unchecked, emissions of CO\(_2\) and other greenhouse gases from human activities will raise global temperatures by 2.5\(^{\circ}\)F to 10\(^{\circ}\)F this century. The effects will be profound, and may include rising sea levels, more frequent floods and droughts, and increased spread of infectious diseases \[1\].

Various initiatives have been taken for reducing carbon emissions, across different

\(^{1}\)http://wikieducator.org/Lesson_4:_Energy-Related_Problems
\(^{2}\)http://10unsolvables.org/archives/portfolio/problem-one
\(^{3}\)https://www.amacad.org/multimedia/pdfs/chu_slides07.pdf
\(^{4}\)http://unfccc.int/2860.php
sectors, such as encouraging low carbon and public vehicles in the transportation sector, encouraging programmable thermostats for homes, among others. Reducing emissions not only helps to mitigate the environment related problems, but, also helps meet the demands of a larger population. The buildings sector is particularly interesting from the viewpoint of reducing emissions. Across the world, buildings contribute significantly to the overall energy consumption (Figure 1-1) [18]. In 2004, the total emissions from residential and commercial buildings were 39% of the total U.S. CO$_2$ emissions, more than the transportation or industrial sector. Furthermore, due to rapid urbanisation, the contribution of buildings is only bound to increase [1]. Studies estimate the CO$_2$ emissions from buildings to grow faster than other sectors. Of this energy, residential buildings, or homes, can contribute up to 93% in some countries (like India) [37]. Thus, optimising the energy usage of buildings can be an effective way to reduce carbon emissions.

There are various ways in which the energy consumption of buildings can be reduced. The first category involves constructing energy efficient buildings. For instance, LEED (Leadership in Energy and Environmental Design) certified buildings have been reported to be 25-30% more energy efficient compared to non-LEED buildings [99]. Retrofitting buildings with better insulation material is another example of making buildings more energy efficient. However, such methods often require an expensive and time-consuming audit process. Also, studies suggest that more than half of the buildings that will be existing in 2050 have already been built$^5$.

$^5$http://www.buildingefficiencyinitiative.org/articles/why-focus-existing-buildings
Given the limited role of construction on existing buildings, a significant amount of literature focuses on making existing buildings energy efficient. In fact, some studies go as far as saying that, “Buildings don’t use energy: People do” [58]. Studies indicate that human behaviour plays a very important role in building energy consumption and can be improved to optimise building energy consumption [29]. However, various studies [28, 67] have shown that in general, people have a very limited understanding of their energy consumption. Studies suggest that if people are provided feedback on their energy consumption, they can save up to 15% on their bills [29].

### 1.2 The Value of an Energy Breakdown

Feedback about household energy consumption can be given at various levels and using various interfaces. The simplest feedback on energy consumption is already provided by utilities in the form of a monthly electricity bill. While by itself the monthly bill is not particularly useful in inducing energy conscious behaviour, a large-scale study by a US company called OPower showed savings of 2% if people were simply told how their energy usage fared compared to their peers⁶. Studies indicate that people can save up to 12% if more refined information, such as energy consumption

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⁶https://www.youtube.com/watch?v=4cJ08wOqloc
on a per-appliance basis is made available. Figure 1-2 shows the potential energy savings reported in the literature as a function of granularity and richness of feedback provided [6]. However, it must be noted that these studies may have their own set of flaws and the numbers reported may be hard to realise in practice [66].

**Energy breakdown** is the process of creating an appliance-wise energy consumption from the aggregate energy consumption. Energy breakdown is often synonymously used with the term energy disaggregation. Since energy disaggregation has generally been used in the literature on time series data, we use energy breakdown as a more general term. Energy breakdown can be defined at various resolutions, even at low frequencies at which the notion of time series gets lost. We can break down the monthly energy bill into different appliances. As an example, say, if the total monthly bill is 100 dollars, an energy breakdown approach may be able to suggest that the refrigerator contributed 20 dollars, the HVAC contributed 50 dollars, etc. Energy breakdown can also be defined at a higher resolution (example- 15 minutes). In such cases, the aggregate time series signal (measured in Watts) can be broken into different appliances. For example, if the total power consumption at 11 AM is 300 Watts, an energy breakdown approach would tell that the consumption of fridge is 30 Watts, of HVAC is 200 Watts, etc.

Previous studies [6] have found numerous benefits of an energy breakdown that can be broadly classified into: 1) benefits to the consumer, 2) benefits for research and development, and 3) benefits for utility and policy makers. An interested reader is referred to the following for more information on this topic [6, 38, 61]. Here, we briefly discuss the benefits across the three categories.

### 1.2.1 Benefits to the Consumer

Energy breakdown researchers have often very aptly used the grocery bill example to motivate energy breakdown. Our grocery bills are already itemised and help us to better understand our shopping. Similarly, providing occupants with an itemised bill or their energy breakdown empowers them to better understand their energy consumption. Often, such an energy breakdown may be able to indicate specific
areas (say fridge v/s air conditioning) where the household is consuming or wasting energy. Recommendations can be provided considering the cost of replacing existing appliances with newer ones. Energy breakdown can also help diagnose faults in loads, which can have severe monetary repercussions [96]. It is also envisioned that once the population at large starts understanding the value of energy breakdown, penetration of energy efficient appliances will only increase.

1.2.2 Research and Development

Energy breakdown research allows for a thorough evaluation of energy consumption of different appliances as estimated by manufacturers and their actual usage reported from homes. Such a thorough assessment can help appliance manufacturers to improve their products. Energy breakdown would also help scope the potential of newer and more energy efficient appliances. A great deal of literature focuses on modelling home energy consumption. Such literature will benefit from having a data base of per-appliance energy consumption across a large number of homes.

1.2.3 Utility and Policy

Energy data (and specifically appliance-level) has the potential to improve energy efficiency marketing [6, 22]. Such marketing strategies can segment the customer base for more targeted recommendations. For example, homes having similar air conditioning requirements could be grouped together and provided pertinent recommendations. Furthermore, knowing the energy consumption of different appliances at a large scale can help drive policy making in a data-driven fashion. Energy breakdown can allow a thorough assessment of energy saving potential arising from different policies, such as upgrades, or retrofits, or introducing newer technology. Energy breakdown can also help drive demand response programmes. Knowing the energy breakdown of different homes would allow utilities to offer incentives to lower peak load by allowing users to slack their deferrable loads (such as washing machines).
Figure 1-3: jPlug [39] is one of the many plug load monitors used to measure the power consumption of an appliance [15]

1.3 Techniques for Energy Breakdown

Energy breakdown techniques can be broadly classified into direct, indirect and source separation. We discuss each of these now.

1.3.1 Direct sensing

The goal of direct sensing techniques for energy breakdown is to install a sensor to each appliance for monitoring its power consumption. Generally, appliances or loads can be classified to be plug loads or in-line loads. Plug loads refer to loads that are plugged into the sockets, such as electronics. The other category of loads refers to loads such as lighting, or fans. Various sensors for measuring the power (or energy) consumption of plug loads have been proposed both in industry\textsuperscript{7} and academia [59, 31, 39]. The basic idea of these sensors is to sit in-line with the load and measure the current drawn by the load, and the input voltage available from the power grid. Figure 1-3 shows one such plug load monitor we used in our deployments. As shown in Figure 1-3, the plug load monitor sits in between the load and the socket.

Plug load monitors can give a very accurate energy consumption for plug loads, since they directly monitor the load. However, there are various reasons that make them less attractive for producing energy breakdown at scale. First, these can be expensive. A single plug load sensor may cost up to $200 and may take years to break even. Cost aside, the maintenance effort required in residential sensor deployments

\textsuperscript{7}http://www.onsetcomp.com/products/data-loggers/ux120-018
is significant [52].

For loads, such as lighting, that are not plug loads, power measurement can be done via their corresponding circuit breaker (also called circuit level sensing). For many loads, there is a one to one mapping with a given circuit breaker in the home circuit. Current transformers are wound across a circuit breaker to measure its current consumption. Figure 1-4 shows current transformers used to measure the current in five circuits.

Circuit level sensing, like, plug load sensing requires multiple sensors per home and thus can be prohibitively expensive. Also, if a home does not adhere to uniform circuit specifications, a considerable amount of effort must be spent in finding the mapping between each load and the corresponding breaker.

1.3.2 Indirect sensing

In contrast to direct sensing techniques that directly measure the signal of interest (power/energy), indirect sensing techniques rely on measuring a correlated side channel. Kim et al. [71] develop a system called Viridiscope that leverages the correlation amongst sensor streams, like using a vibration sensor on a fridge to tell if the compressor is running or not, and then using a model to determine fridges power. Similarly, Clark et al. [27] develop a system called Deltaflow that employs energy harvesting sensors and performs computation on the activation of these sensors to determine
Figure 1-5: Indirect sensing approaches measure a correlated side-channel to predict the energy consumption of an appliance. The shown example is from a system called Viridiscop [71] that leverages the sound emitted by a fridge compressor to detect its operation and thus power consumption.

Appliance power draw. Jain et al. [57, 56, 55] install temperature sensors inside a home to estimate air conditioner energy usage. Gupta et al. [48], Chen et al. [25] and Gulati et al. [46, 43, 44] use the electromagnetic interference typically generated by electronic appliances to determine appliance usages. Gulati et al. [45] also proposed the use of radio frequency interference generated by electronic appliances for appliance activity recognition and annotation.

Since indirect sensing approaches do not directly measure power, they are bound to be less accurate when compared to direct sensing techniques. However, they are generally cheaper and easier to install. However, they can only measure the power consumption of loads that have strongly associated side channels, after a complex calibration step.

1.3.3 Source separation

Source separation refers to separating a source into constituent components. In the energy breakdown literature, the term non-intrusive load monitoring (NILM), or energy disaggregation is used synonymously to describe source separation techniques for energy breakdown. The key idea of NILM is to measure the energy consumption of
a home only at a single point, and use statistical techniques to break down the total consumption into appliance energy. The key intuition behind NILM’s working is that different appliances have different electrical signatures [7, 50] that can be exploited to break down the aggregate into its constituents. A smart meter is typically used in an NILM deployment. A smart meter is just like a regular analog electricity meter, but, it can in real time provide the aggregate household energy consumption. A typical NILM installation would have the smart meter connected to the cloud and have a dashboard application to show the users their energy breakdown.

The term non-intrusive load monitoring (NILM) was first coined by George Hart in early 1980s [50]. In recent years, the combination of smart meter deployments [23, 32] and reduced hardware costs of household electricity sensors has led to a rapid expansion of the field. Such rapid growth over the past five years has been evidenced by the wealth of academic papers published, international meetings held (e.g. NILM 2012, 2014, 2016) and EPRI NILM 2013\(^8\), startup companies founded (e.g. Bidgely and Neurio) and data sets released, (e.g. REDD [74], BLUED [4] and Smart* [10]).

We now briefly discuss the field of NILM or energy disaggregation across two dimensions: algorithms and data sets. An interested reader is directed to several surveys and reports for a detailed understanding [103, 109, 6, 83].

**Disaggregation Algorithms**

The seminal work by George Hart presented a simple event-based method for energy disaggregation. Figure 1-6 shows Hart’s algorithm in action [50], applied on household aggregate power. The algorithm finds events (corresponding to step changes in the power signal) and assigns them to different appliances. Appliances turning “on” would produce a positive step change in power and appliances turning “off” would produce a negative step change in power. The efficacy of the algorithm is largely a function of the differences in step changes of different appliances. Figure 1-7 shows a two-dimensional signature space of a house as monitored by Hart et al. [50]. Most of the loads in the signature space show low spread. There also is a sufficient distance between different

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\(^8\)http://goo.gl/dr4tpq
Figure 1-6: Hart's seminal NILM algorithm [50] finds events in the power time series and assigns these to different appliances toggling their state.

Figure 1-7: Hart's algorithm and similar event based methods are accurate if the appliances have distinctive signatures in their power consumption. Figure shows the scatter plot of power consumption of few common household appliances as computed by Hart et al. [50]
appliance clusters. Since, the algorithm would model each appliance to change state causing a step change, appliances were modelled as finite state machines (FSMs). In such FSMs, each transition would correspond to a power delta and different states of the FSM would correspond to different states of the appliance.

Such event-based approaches had the shortcoming of poor performance when more than one appliance would change state at the same time. In such event-based approaches, a wrong or mis-detection would propagate further and cause more errors in disaggregation. In contrast, borrowing from the similar concept of FSMs, novel non-event based methods have been proposed in the literature. Such non-event based methods model each appliance as a hidden Markov model (HMM). Correspondingly, the aggregate household consumption can be assumed to be the sum of the power of individual appliances, forming a factorial structure as shown in Figure 1-8. Extensions of such factorial hidden Markov model (FHMM) have been proposed in the past [86, 87, 104, 106, 14, 17, 80]. With the availability of larger quantities of data, and the availability of other information (such as weather) that can help in disaggregation, new techniques based on deep learning [65] and incorporating context have been proposed [102]. A variety of dictionary learning based schemes [35, 79, 47, 95, 72]
As we increase the sampling rate, more sophisticated features can be used to give more accurate energy breakdown. Figure borrowed from Armel et al. [6].

The basic premise of dictionary learning approaches is to learn “basis” vectors and their corresponding activations.

The above discussed techniques are generally applied on low-frequency data (data sampled once a second to once every few minutes). At such frequencies, the accuracy of low power appliances, and appliances that can not be modelled using FSMs remains poor. Previous literature has proposed approaches that can leverage high-frequency voltage and current signals [6, 51, 40]. While higher resolution data is likely to improve appliance detection accuracy, it comes with an additional hardware and data management cost. Installing such high resolution hardware at scale is currently prohibitively expensive and is unlikely to scale unless the cost comes down significantly in the future. Further, ongoing smart meter deployments involve collecting data at less than once a minute. Affordable and wide scale adoption of such smart metering infrastructure resulted in much of the research in the NILM domain focusing largely on low-frequency data. Figure 1-9 presents a graphical illustration of the impact of sampling frequency on the performance of energy breakdown.

Data sets

In 2011, the Reference Energy Disaggregation Dataset (REDD) [74] was introduced as the first publicly available data set collected specifically to aid NILM research. The data set contains both aggregate and sub-metered power data from six households, and has since become the most popular data set for evaluating energy disaggregation,
<table>
<thead>
<tr>
<th>Data set</th>
<th>Location</th>
<th>Duration per house</th>
<th>Number of houses</th>
<th>Appliance sample frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>REDD MA, USA</td>
<td>3-19 days</td>
<td>6</td>
<td>3 sec</td>
<td>1 sec &amp; 15 kHz</td>
</tr>
<tr>
<td>BLUED</td>
<td>PA, USA</td>
<td>8 days</td>
<td>1</td>
<td>N/A*</td>
</tr>
<tr>
<td>Smart*</td>
<td>MA, USA</td>
<td>3 months</td>
<td>3</td>
<td>1 sec</td>
</tr>
<tr>
<td>Tracebase</td>
<td>Germany</td>
<td>N/A</td>
<td>N/A</td>
<td>1-10 sec</td>
</tr>
<tr>
<td>Dataport</td>
<td>TX, USA</td>
<td>3+ years</td>
<td>1000+</td>
<td>1 min</td>
</tr>
<tr>
<td>HES</td>
<td>UK</td>
<td>1 or 12 months</td>
<td>251</td>
<td>2 or 10 min</td>
</tr>
<tr>
<td>AMPds</td>
<td>BC, Canada</td>
<td>1 year</td>
<td>1</td>
<td>1 min</td>
</tr>
<tr>
<td>iAWE</td>
<td>Delhi, India</td>
<td>73 days</td>
<td>1</td>
<td>1 or 6 sec</td>
</tr>
<tr>
<td>UK-DALE</td>
<td>London, UK</td>
<td>3-17 months</td>
<td>4</td>
<td>6 sec</td>
</tr>
</tbody>
</table>

Table 1.1: Comparison of household energy data sets. *BLUED labels state transitions for each appliance. Table borrowed from [16] and Oliver Parson’s blog.

algorithms. In 2012, the Building-Level fully-labeled dataset for Electricity Disaggregation (BLUED) [4] was released containing data from a single household. However, the data set does not include sub-metered power data, and instead records events triggered by appliance state changes. As a result, it is only possible to evaluate whether changes in appliance states have been detected (e.g. washing machine turns on), rather than the assignment of aggregate power demand to individual appliances (e.g. washing machine draws 2 kW power). More recently, the Smart* [10] data set was released, which contains household aggregate power data from three households, while sub-metered appliance power data was only collected from a single household.

In 2013 the Pecan Street sample data set was released [54], which contains both aggregate and sub-metered power data from 10 households. Now, the data set has been renamed to as Dataport [84] and has data from more than 1000 homes. Owing to the high data quality and the volume of data available, Dataport has now become one of the most used data sets in the community. Later in 2013, the Household Electricity Survey data set was released [108], which contains data from 251 households although aggregate data was only collected for 14 households. The Almanac of Minutely Power dataset (AMPds) [81] was also released that year containing both aggregate and sub-metered power data from a single household. Subsequently, the Indian data for Ambient Water and Electricity Sensing (iAWE) [15] was released, which contains
both aggregate and sub-metered power data from a single house. Most recently, the UK Domestic Appliance-Level Electricity data set [64] (UK-DALE) was released which contains data from four households using both aggregate meters and individual appliance sub-meters. We summarise these data sets in Table 1.1.

1.4 Contributions of This Thesis and Thesis Outline

Having described energy breakdown, its use cases, and pertinent literature, we now describe our contributions towards this thesis. Despite the fact that the field is more than three decades old, its practicality is impeded by three core challenges: 1) it is hard to compare energy breakdown algorithms (specifically NILM), 2) it is hard to ascertain if the energy feedback can be turned into actionable feedback, and 3) current methods require hardware in each home limiting scalability. In this thesis, we provide systems and analytical techniques towards making energy breakdown more practical, by making it comparable, actionable and scalable.

All the previous NILM and home energy data sets were collected from developed countries. We undertook a dense deployment in India and surfaced unique challenges especially pertinent to the Indian settings. Many of the learnings from our study would likely benefit future deployments. We also publicly released our data set called Indian data set of ambient, water and energy [15]. Ours was one of the earliest work showing how energy disaggregation can be improved by using additional contextual data (such as water and ambient conditions). Our residential deployment work is described in Chapter 2.

The extensive home deployment provided us with a personal experience of challenges associated with dense home deployments, as is also experienced by other eminent researchers [52]. We were thoroughly convinced that in order to scale up disaggregation, the way forward is to reduce the number of sensors. This led us to delve deeper into the NILM domain. The first question that we wanted to answer
was- “what is the best NILM algorithm?” However, at that point of time, empirically comparing disaggregation algorithms was virtually impossible. This was due to the different data sets used, the lack of reference implementations of these algorithms and the variety of accuracy metrics employed. To address this challenge, we presented the Non-intrusive Load Monitoring Toolkit (NILMTK) [16, 62]; an open source toolkit designed specifically to enable the comparison of energy disaggregation algorithms in a reproducible manner. This work was the first research to compare multiple disaggregation approaches across multiple publicly available data sets. Our toolkit includes parsers for a range of existing data sets, a collection of preprocessing algorithms, a set of statistics for describing data sets, three reference benchmark disaggregation algorithms and a suite of accuracy metrics. NILMTK has been well received by the community as evidenced by multiple data sets and algorithms contributed by the community, and several awards. NILMTK is described in Chapter 3.

After solving the problem of comparative evaluation metrics, algorithmic implementations and datasets in a standard format, we moved on to exploring deeper into
the actual premise with which we started this journey - how to reduce on the energy consumption. This led us to look deeper into how we can provide informative feedback beyond simple disaggregation. We realised that, while dozens of new techniques have been proposed for more accurate energy disaggregation, the jury is still out on whether these techniques can actually save energy and, if so, whether higher accuracy translates into higher energy savings. In our next work, we developed new techniques that use disaggregated power data to provide actionable feedback to residential users. We evaluate whether existing energy disaggregation techniques provide power traces with sufficient fidelity to support the feedback techniques that we created and whether more accurate disaggregation results translate into more energy savings for the users. Some of our techniques can save up to 25% energy for different appliances. Our work on actionable energy insights from disaggregated data is described in Chapter 4 and illustrated in 1-10.

We realised that existing energy breakdown approaches require hardware to be installed in each home, impeding scalability. While smart meter adoption is happening at a large scale, we are still standing at 43% smart metering penetration in the USA, less than 10% in Africa, and 30% globally. So if we were to act today and provide useful and actionable feedback to everyone, including those who do not have smart meter installed, what can we do? In our work, we present techniques for producing an energy breakdown in a home without requiring any additional sensing. The basic premise of our approach was that common design and construction patterns for homes create a repeating structure in their energy data. Thus, a sparse basis can be used to represent energy data from a broad range of homes. We observed that not only is our work more scalable, it is also more accurate compared to the state-of-the-art NILM algorithms by up to 37%. Our scalable energy breakdown work is described in Chapter 5 and illustrated in 1-11.

We finally conclude in Chapter 6. Overall, this thesis provides systems and techniques towards making energy breakdown more practical across three dimensions: comparability, scalability and actionability.

Our contributions and findings can be summarised as follows:
Figure 1-11: Illustration of our work on scalable energy feedback. Unlike previous approaches shown in (a) and (b), our work shown in (c) does not require hardware in test home.
1. We carried out the first residential building energy deployment outside of the developed world and provided systems and insights for future deployments and studies. We highlighted various aspects of our deployment that are unique to developing countries.

2. We created an open source toolkit called NILMTK for easy comparison of energy disaggregation algorithms. NILMTK provides a complete pipeline from data sets to metrics and has been widely used by the community.

3. We created mechanisms to leverage appliance traces to produce actionable feedback—feedback that can be directly applied to save energy. Our mechanisms can help save up to 10% home energy consumption.

4. We created algorithms to provide energy breakdown in homes without requiring any sensors to be installed. Our approach is not only more scalable, it is also up to 37% more accurate compared to the state of the art approaches.

1.5 Thesis publications

We now enlist the publications that contributed to this thesis.

1.5.1 Chapter 2


1.5.2 Chapter 3


1.5.3 Chapter 4


1.5.4 Chapter 5

