Training Free Non-Intrusive Load Monitoring of Electronic Appliances Battery Charging with Low Sampling Rate

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Training Free Non-Intrusive Load Monitoring of Electronic Appliances Battery Charging with Low Sampling Rate

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Under the Supervision Of

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DECLARATION

itledWe do hereby declare that the thesis t" Training Free Non-Intrusive Load Monitoring of Electronic Appliances Battery Charging with Low Sampling Rate" is submitted to the Department of Computer Science and Engineering of BRAC University in partial fulfillment of the completion of Bachelors of Science in Computer Science and Engineering. We hereby declare that this thesis is based on results obtained from our own work. Due acknowledgement has been made in the text to all other material used. This thesis, neither in whole nor in part has been previously submitted to any University or Institute for the award of any degree or diploma. The materials of work found by other researchers and sources are properly acknowledged and mentioned by reference.

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The final report is satisfactory and it's all materials are also acceptable and ready for the submission to the Department of Computer Science and Engineering,BRAC University.

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PREFACE

Numerous people have supported us during the development of this dissertation, and our undergraduate experience more generally. A few words' mention here cannot adequately capture all our appreciation.

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ABSTRACT

Non-intrusive load monitoring (NILM) is a convenient method to determine the amount of energy consumed by individual electrical appliances of our household and operate them by analyzing the composite load measured directly at the main circuit panel or electric meter of the building. A significant reduction in the energy wastage can be achieved through this approach. A lot of remarkable researches were developed to establish the theory of NILM and introduced its innovative applications. However, forthcoming deployment of electronic vehicle battery (EVB) will challenge NILM systems as the previous methods are not suitable for recognizing the variable characteristics of it. In this paper, we propose an improved algorithm to disaggregate EV charging signals from aggregated real power signals. The proposed method can effectively mitigate interference coming from air-conditioner (AC) and detect EVB signals effectively under the presence of AC power signals. The results demonstrate that the EVB charging load is recognized as well as other traditional appliances.

Index Terms— NILM-Non Intrusive Load Monitoring, EVB, Training Free, Load, Low Sampling rate.

ABBREVIATION

EVB- Electronic Vehicle Battery

NILM- Non-Intrusive Load Monitoring

NIALM- Non-Intrusive Appliances Load Monitoring

ALM- Appliances Load Monitoring

REDD- The Reference Energy Disaggregation Dataset

BLUED- The Building-Level Fully labelled Energy Disaggregation dataset

HAN- Home Area Network

ILM- Intrusive Load Monitoring

AMI- Appliances Load Monitoring

FSL- Finite State Load

CVD- Continuously Variable Devices

CC- Constant Current

CV- Constant Voltage

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CHAPTER 1

Introduction

1 .1Motivation

In today's world, the usage of current and voltage is increasing but the measurement of energy consumption is not measured and thus electricity and money cannot be saved from this. Decreasing energy consumption and cutting costs are important in new era. Especially in residential areas, it is hard to decrease the usage of current and voltage and to save money and energy as they don't have any idea about the power or energy consumption of each house or flat. If a method or process that can detect the energy or power consumed by each house or flat, it will be a great save for everyone. Actually people get the aggregated bill at the end of a month, they don't get the disaggregated bill or disaggregated power consumption list. If one can get the disaggregated energy system and real-time power consumption list, various studies have shown that it can save 12-15% current and money at the same time. Moreover, others suggest that even more power or energy can be saved if accurate, real-time, disaggregated power information is available to consumers.

Now-a-days, interest in home automation system and application is increasing. People are becoming more conscious than before and are interested in saving power for future. There is a growing consciousness in people that can be seen about renewable energy and ecological reasons for reducing energy or power consumption. Even, it is showed that there is also a growing number of companies interested in providing consumers with more detailed electricity consumption feedback and commercial electricity monitors: The Energy Detective (TED), PlotWatt, Bidgely, and Opower, to list a few.

Non-intrusive load monitoring (NILM) or Non-intrusive appliances load monitoring (NIALM) is a useful process that can define the changes in current and voltage and operation of individual appliances based on analysis of complex load measured at the entry of a house [4].

If we can figure out the individual load being used in every appliance at our household, it will assist us with managing bills and with power quality monitoring. A significant reduction in the energy wastage can be achieved through this approach. This is not basically a modern approach as two decades ago G. W. Hart [1] first developed the idea of non-intrusive load monitoring; it is an ancient approach of NILM to collect the signals or metering. Later a lot of remarkable researches were developed to establish the theory of NILM and introduced its innovative applications. However, the increasing use of electronic vehicle battery (EVB) will challenge NILM systems as the previous methods are not suitable for recognizing the variable characteristics of it. Although several researches are going on to establish more accurate approach to EVB load disaggregation, we are proposing an improved algorithm for training free NILM for low sampling rate.

The idea behind NILM is to help people to know how much power they are consuming and where that power is going [1]. Today, many cars have real-time gas mileage feedback, but there is no system for real-time power consumption in the house. Before this feedback for cars was available, the only indication of gas consumption was how frequently one had to refill the tank. Increased fuel prices have spurred advancements in internal combustion engines that have not only improved their efficiency, but have also sought to instruct the user on how to drive more efficiently. This is the type of impact that NILM systems could potentially have in the home. Instead of paying the vague monthly power bill, consumers can take control of the situation and be surer of where their money is going and exactly what they are paying for.

We now turn to a review of NILM literature and provide some historical context for the problem. Following the literature review we briefly discuss the main contributions of this thesis, then we present some ways in which the work in this thesis may be used in practical settings, and we close the introduction by providing an overview of the structure of the thesis.

1.2 Literature Review

NILM or Non-intrusive load monitoring may have various name such as NIALM (Non-intrusive Appliances Load Monitoring) or NALM. We will present a short history about NILM. NILM (Non-intrusive Load Monitoring) was first proposed by G. W. Hart [1] as a method for disaggregating electrical loads by examining only the appliance specific power consumption signatures within the aggregated load data. The data is acquired from the main electrical panel outside the residence. It is considered to be non-intrusive as the method avoids any equipment installation inside the building. The goal is to partition the whole-house building data into its major constituents. Actually NILM is a method that provides consumers estimates of device-level energy consumption based on aggregate measurements usually taken at the main circuit panel or electric meter.

In 1989, F. Sultanem also began to work on a design of a load monitor for NILM [2]. Sultanem presented a similar study on NILM with a general classification of household appliances in terms of their particular function and structure.

In 1995, a new approach for NILM was presented by Steven B. Leeb [3]. It uses transient signatures of appliances for load disaggregation, the so called transient approach. Recently, Liang et. al. [19] has proposed to combine different algorithms as well as appliance features using committee decision mechanisms (CDM) to improve the overall disaggregation accuracy. It is important to mention that the performance of the above mentioned classifiers are highly dependent on the feature sets, the type and number of target appliances being used in the experimentation. Cole[16] presented a data extraction method and a steady-state load identification algorithm for NILM. The algorithm developed by Cole can be used for load switching between individual appliances when one or more appliances are switched on or off. However, this algorithm requires an extended period of time to accumulate real power (P) and reactive power (Q) data, and cannot recognize any appliance power consumption that does not change.

In 2005, Lee presented an estimation technique using unique harmonic signatures to monitor variable-speed-drive (VSD) power consumption in a NILM system. Furthermore, to indicate the time-varying nature of VSD power demand makes it difficult to keep the track of the ON/OFF status of other constant loads [21].

Wichakool et al. presents further improvements to the solution for the problem of variable power electronics by using a spectral estimation method and a switching function technique [24]. A summary and presentation of the latest achievements in this line of work can be found in Shaw et al [23].

The above research has provided the fundamental theory of NILM and introduced its innovative applications. However the forthcoming deployment of electric vehicles (EVs) within the general electrical load will challenge NILM systems as the previous methods are not suitable for recognizing the variable characteristics of the Electrical Vehicle Battery (EVB) charging load. As a CVL it does not have any steady-state and hence the steady-state approach is not applicable. Although the transient approach is capable of identifying some CVLs, such as induction motors and fluorescent lamps, it is not capable of identifying EVB charging load because the transient pattern of the EVB is determined by the charger type and the state of charge (SOC).

1.2.1 Datasets for NILM

By taking datasets, different data can be compared and difference between those datasets can be seen. There are many datasets exist for collecting data for different purposes, but there are three most important and specifically made for NILM. Those datasets are described below briefly.

REDD or The Reference Energy Disaggregation Dataset was the first public dataset for specially made for NILM researchers and released in 2011 [18]. It holds data from six houses in the Boston, Massachusetts area with aggregate energy or power consumption and power on the subcircuits in the house reported at 1 Hz; higher frequency aggregate current and voltage are also available. There is another important dataset known as the Trace base repository [22]. It does not provide any aggregate measurements, but it has over 1,000 power traces sampled at 1 Hz across more than 100 individual devices. This dataset does not contain any aggregate data, so disaggregation may be easy for this dataset, and the responsibility of this dataset is to recognising the devices that hold data. Parson uses Trace base in to train generalized usage models and applies these to the REDD dataset. The Building-Level Fully labelled Energy Disaggregation dataset or BLUED [20] was first released in 2012 and contains current and voltage sampled at 12 kHz for one house for a week along with approximately 2,400 ground truth time stamped events indicating device activity. The BLUED dataset was collected by a group at Carnegie Mellon

University in Pittsburgh, Pennsylvania. It differs from the REDD dataset in that BLUED contains extensive time stamped and labelled events on the device level.

However, though other datasets exist and they vary in number of houses collected, length of collection, extent of submetering for ground truth, and sampling rates yet these three are the most known and most important dataset for NILM approach. It's obvious that we will use one of them for our work and research.

1.2.2 Supervised and Unsupervised Process

Supervised means that need training or supervision to do work and Unsupervised means no need of supervision or training to do work [4]. For load disaggregation, many processes are supervised, in other words, process of load disaggregation needs training to gather aggregated loads and disperse those data. Many researchers find it difficult to divide the assemble data without any training. Most approaches of load disaggregation are supervised, only few of them are unsupervised. For home appliances, unsupervised process may have an advantage of separating data from assembly.

As there are users specified appliances are present in the home, user interaction may be needed and without user interaction this process cannot collect any data regarding power or energy load. There are some recent works that has advocated unsupervised approaches that consider the whole home signal without labeling, and automatically separate different signals. To facilitate supervised approaches and to aid in evaluating all approaches, REDD or The Reference Energy Disaggregation Dataset [18] includes as much "supervised" or "trained" information as possible: we monitor each individual circuit in the home (especially important for huge loads that cannot be easily monitored or measured by a plug load) as well as many large plugs piles as is practical.

NILM actually needs training or supervision for receiving or collecting data from household appliances. But it is a successful system in which apart from training needed, it is a system in which user interaction is needed. We will use training free NILM for electronic appliances battery charging with low sampling rate.

1.3 GOALS

To provide an efficient method for load monitoring is our goal. This method or process should be useful unlike the previous or existing methods invented by the researchers. Most of the previous methods are not as much effective as it should be, we want to make this process effective and useful to all and it will be easier to know how much power or energy is consumed by us and thus the bill will be less or complication free unlike present situation. Our aim is to make a proficient work for energy consumption by each house and use without supervision NILM for home appliances.

1.4 THESIS LAYOUT

The rest of this thesis paper is well structured as:

Chapter 2 contains related work or previous work, Chapter 3 is about Load Monitoring, Chapter 4 is on Load Analysis, Chapter 5 discusses about the challenges, Chapter 6 explains our proposed method, Chapter 7 shows the experimental results and the output, Chapter 8 is about the concluding part of our work with future of our model, Chapter 9 includes the references.

CHAPTER 2

Related Work

For metering, there were some methods or processes such as ALM or Appliances Load Monitoring, AMI or Advanced Metering Infrastructure, HAN or Home Area Network and ILM or Intrusive Load Monitoring. These are some smart greed technologies for current or power consumption. They are applied in a residential building area to provide intellectual power metering service to home inhabitants. Before these technologies were invented, the power metering had been mostly focused on to electricity suppliers. By obtaining and guessing information of energy or power consumption and claim of home dwellers, the suppliers can improve security, consistency, and effectiveness of their own services. However, as the infrastructure of user level's load monitoring service by AMI and HAN is recognized, the users are more accessible to access to the data of their energy or power consumption. For instance, the information can be sent to load monitoring devices that are sealed to the users, which are part of smart technologies such as a computer monitor, a television, or a cell phone. Then, it makes the users who can recognize their energy or power consumption as well as have knowledge on performance of their electrical home appliances.

Additionally, the methods of load monitoring provide awareness of energy or power consumption to the users and indicate them to act beneficial responses in order to decrease their energy or power consumption. Since these load monitoring techniques become broadly being used, may be the consumers will claim more complete and constant load monitoring data or information. The demand or claim will include not only the total energy or power consumption in real time but also the operation time or the duration of each electrical home appliance. ILM or ALM is a smart greed technology to monitor load of power or energy such as current and voltage. But these smart greed technologies cannot monitor these loads without any training or supervision.

Our proposed method with NILM or Non-Intrusive Load Monitoring system will monitor the loads of power or energy without any training or supervision and it will be effective for home appliances and will be easier for calculating the bills for the energy or power consumed by the users from residential area or sector. Throughout an area, our method will count power consumed by each house separately and it can help the service provider and the users in all way round. This will be effective and useful to everyone.

2.1 Data Collection

Collecting publicly available data is very important for a research, without collecting data, dataset cannot be compared with other dataset and thus an effective result cannot be shown. Data is necessary for testing algorithms and comparing performance results against other research. For NILM research, BLUED or The Building Level Fully Labelled Dataset is the most suitable dataset for power consumption. At first, we will show a primer on AC power to explain the reader with the basic concepts for understanding how power consumption is monitored. And then there will be a discussion about how ground truth can be obtained for NILM dataset. Data collection for research is an important step because the evaluation of NILM algorithms and research depends on knowing the actual operation of the electronic devices being monitored.

CHAPTER 3

Load Monitoring

Load Monitoring refers to the detection of load such as current and voltage in each house [11]. Load of current, voltage or energy can be measured by meter system. By monitoring or detecting the load used by each house, it would be easy to count on the bill and power consumption by each house or area. Actually, every device in any home will be counted on and a proper detection will be measured through load monitoring.

3.1 NILM

NILM is the short form of Non-Intrusive Load Monitoring, it was first proposed by G. W. Hart [1] as a method for disaggregating electrical loads by examining only the appliance specific power consumption signatures within the aggregated load data. The data is acquired from the main electrical panel outside the residence. It is considered to be non-intrusive as the method avoids any equipment installation inside the building.

Appliance Load Monitoring or ALM refers to the load detection of current or voltage of a home. Actually, there are two major approaches to ALM, known as Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM) [4]. Literally, ILM and NILM are referred to as distributed sensing and single point sensing methods individually. Because the ILM approaches have the requirement of one or more than one sensor per appliance to perform ALM, whereas NILM just have the requirement of only a single meter per house or a building that is to be monitored or detected. Though the Intrusive Load Monitoring or ILM method is more correct in measuring appliance-specific power consumption compared with NILM, the real drawbacks includes high costs, multiple sensor configuration as well as installation complexity favoring the use of NILM especially for the case of large scale deployments [4].

From the above discussion and scenario, it is clear that ILM does not need any training or supervision and NILM needs supervision or training. But without training or supervision, NILM can monitor the load of a house or building. We will work with the training free Non-Intrusive Load Monitoring or NILM. Load profiling techniques classify devices by the changes in steady state load caused by their being turned ON and OFF. The approach is to decay the load profile into a complex of single appliances features, i.e., representative pairs of ON/OFF events. For instance, periodic spikes in energy use are visible in homes with electric furnaces during cold weather. NILM algorithms can extract the expected furnace load from the load profile to expose other, possibly smaller, appliance loads. These type of techniques use appliance models and information learned about a habitation over time to rebuild behavior from a single aggregate signature. NILM approach will detect the overall power consumption of a building or home.

3.2 NILM Working Procedure

NILM is an approach that detects the energy or power consumption of home appliances of a house or a building may be. A Non-Intrusive Load Monitor (also known as NILM) or Non-Intrusive Appliance Load Monitor is made to observe an electrical circuit that contains a number of appliances which can switch on and off autonomously. The goal is to partition the whole-house building data into its major constituents. According to Hart [4], This problem can be formulated as follows: The power signals from the active appliances aggregate at the entry point of the meter as P(t) is shown below mathematically defined as

$$\mathbf{P(t) = P_1(t) + P_2(t) + \ldots. + P_n(t)}$$

Where P_i is the power consumption of individual appliances contributing to the aggregated measurement and n is the total number of active appliances within the time period t.

The task of the NILM is to decompose P (t) into appliance specific power signals in order to achieve disaggregated energy. By an advanced investigation of the current and voltage waveforms of the total load, the NALM or NILM estimates the number and nature of the individual loads, their individual energy consumption, and other relevant statistics such as time-of-day variations. No access to the individual components is necessary for installing sensors or making measurements (Zoha et. al. [4]). This can provide a very convenient and effective method of gathering load data compared to traditional means of placing sensors on each of the individual components of the load. The resulting end-use load data is extremely valuable to consumers, energy auditors, utilities, public policy makers, and appliance manufacturers, for a broad range of purposes. For instance, if a monitor is placed outside a home, it can be detected or seen through the monitor that how much current or voltage are going inside the house, and how much energy is consumed by each house.

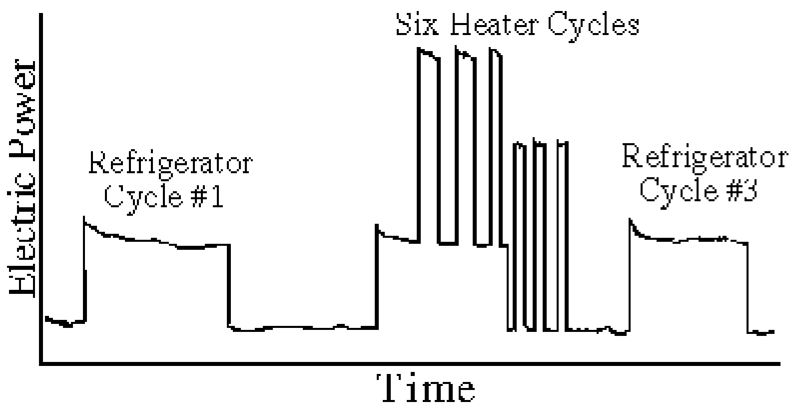


Figure 1: Power Consumption Measurement

In the above figure, it has been shown and described how NILM or NIALM approach works to monitor or detect the total load of energy consumed by each house and building. This permits very easy installation, removal, and maintenance compared with traditional intrusive load monitoring techniques that require “submetering” and interior wiring. The NILM or NALM detects the total load, checking for certain ``signatures" which provide information about the activity of the appliances which constitute the load [23]. For example, if the residence contains a refrigerator which consumes 250 W and 200 VAR, then a step increase of that characteristic size indicates that the refrigerator turned on, and a decrease of that size indicates the turn-off events. Other appliances have other characteristic signatures. The devices or appliances must show the total difference between on and off switches or modes and the total load can be measured if the difference between the on and off mode is known. How it works can be shown from the above figure. From the above figure, power consumption can be measured which plots total or may be real power consumption vs. time for a single-family home over a two-hour period. In this figure, in between two hours, the total load shows activity due to a refrigerator and a heater of a home. Two different-sized step changes are clearly present, given that characteristic signatures of the refrigerator and the heater. The refrigerator cycles on and off three times, the heater six times. By measuring the total load outside the home, it is not difficult to find these step changes and measure their size. Knowing the time of each on and off event, the total energy consumption of the refrigerator and the heater are easily determined. The total power consumption can tell us or show us more information about appliances of a home, that information may not be known now to us. Total load can be measured easily and without any complex issue.

Now-a-days, many companies or organization make or involve simple software with complex hardware to measure data for load monitoring (Anderson et. al [20]). Actually, it has been happening for years from when the approach for load detecting was invented. A monitoring point at each appliance of interest and wires (or sometimes power-line carrier techniques) connecting each to a central data-gathering location provide separate data paths, so the software merely has to tabulate the data arriving over these separate hardware channels. The NILM or NALM approach reverses this balance, with simple hardware but complex software for signal processing and analysis. Only a single point in the circuit is instrumented, but mathematical algorithms must separate the measured load into separate components. In many load-monitoring applications, this is a very cost-effective trade-off, which is a major advantage of the NALM. Through NILM approach, the traditional way of monitoring or gathering data through a process is changed as NILM has simple hardware and complex software to do the work.

Moreover, in order to observe the total load used by each and every house or building NILM approach is an effective approach. Every single devices or appliances will be counted to measure the total load, and individually every appliance will show their total usage of power or energy in considerable hours. As it’s a smart metering system for home appliances and it can reduce the total power or energy consumption by 5-15%, it will be an effective system or approach to the smart or digital world. To generate appliance specific power consumption, we first need to know load analysis and appliance signatures.

CHAPTER 4

LOAD ANALYSIS

4.1 Load Survey

At present, there are various kinds of electrical appliances in operation. It is almost impossible and impractical to obtain a complete database for all of them. Ina previous research, a wide variety of typical electronic appliances used for domestic purpose has been investigated. For our further work, we are relying on those previous studies to determine the types of electronic appliances available for domestic usages. In our household, total load generally means the power consumed by all the appliances in operation. Since appliances are wired in parallel connection simply inside the power box, the total load equals the sum of the power consumed by individual appliances. According to Hart [1], these appliances can be categorized in different categories based on their operational states. The common appliances in our houses are known as Finite State Machine or FSM as their operational states are finite and these types of Loads are known as Finite State Load (FSL).

Finite State Loads (FSL): Various types of FSLs of appliances operation at house at present can be two state of multi state. We are going to discuss them briefly below.

- ON/OFF: These are the common appliances in our house used for common purposes. The operational state diagram of these appliances is the simplest with only two states of operation; one of them is ON and the other one is OFF. For an example: Electric Kettle.

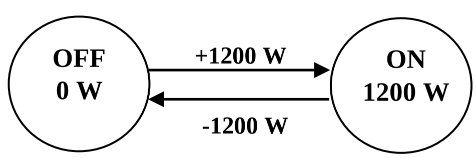


Figure 2: A generic 1200 W two-state electric kettle

The state diagram of an electric kettle is the simplest. The circles indicate individual state, which is defined by an operating power level. The arrows indicate the possible state transitions, and are labeled with the power change which is observed to accompany the state transition.

- FINITE MULTIPLE STATES: There are few appliances with a finite number (more than two) of operating states. In between ON and OFF there are few alternative operational states based on the type of appliance. For an example, refrigerator is an appliance with three operational states; one is OFF and the other two are running states in different operation.

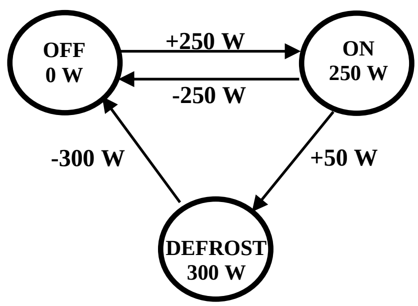


Figure 3: A multi-state refrigerator with defrost.

At one point refrigerator alter between normal running conditions and the alternative condition of defrost, which requires additional power.

Continuously Variable Devices (CVD): The main characteristics of these appliances are they often draw variable power. Hence, these appliances have no fixed number of states. Our modern day appliance EVB falls under this category. Therefore, it is very challenging for the NILM methods to disaggregate this type of appliance from the aggregated load measurements. Electric vehicles employ rechargeable batteries, which are normally charged through the charger converting mains electrical power, AC, to the required DC. In the charging procedure, most of the power is consumed by the battery. Constant current - constant voltage (CC-CV) is a traditional method for charging EVBs. Olivier Tremblay et.al [5] developed a generic battery model, based on which the charging profiles of different types of EVBs are obtained. Fig. 3 shows the Tremblay electronic vehicle battery model.

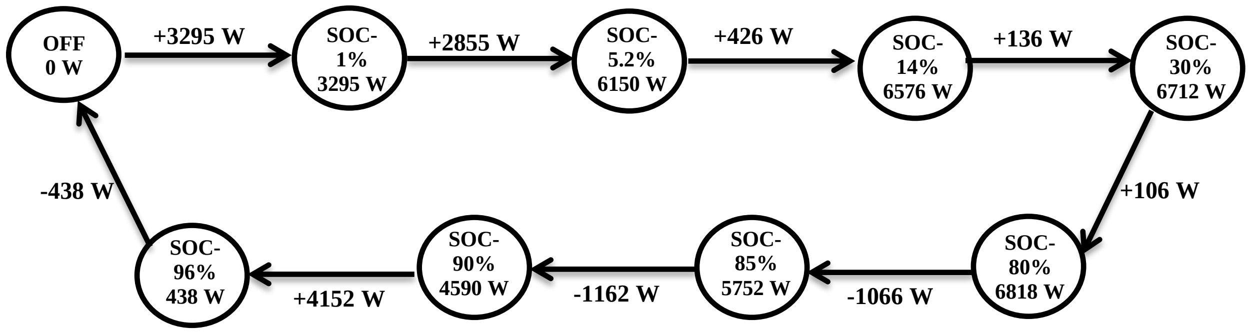


Fig.4: A lithium-ion EVB being charged by CC-CV method at C/3.

The charging process could be considered as a dynamic system, in which no steady states or state transitions exist, but one in which constant change occurs.

4.2 Appliance Signatures

The measurement of an appliance that provides information about its nature and operation are defined as its appliance signature [23]. It is necessary to establish an appliance signature database as the signatures provide good references for load disaggregation and recognition. The advantage of this signature is that the phase angle between current and voltage allows the positioning of an appliance’s power use in a two-dimensional power space (P-Q) and each appliance's signature could be located in the plane as an operational point [6]. An EVB, charging by the CC-CV method for example, initially consumes high levels of power before it starts decreasing in a controlled manner, as the SOC of the batteries increase. The envelope of the power waveform located in the plane is called the power profile which is a significant feature to recognize the load of EVB.

CHAPTER 5

CHALLENGES

Our big challenge of disaggregating an EV charging load from aggregated power signals is mitigating interference from AC. As shown in Fig. 5, an EV charging load signal can be characterized as a square wave of a high amplitude (higher than 3 kW) and a long duration (longer than 30 minutes but generally shorter than 200 minutes) [7]. According to Perez et. al, AC power signals usually exhibit two kinds of waveform patterns [25]. One pattern resembles a spike train with very short durations (e.g. the train of waves from the 1st to 700-th minutes. Another waveform pattern resembles a rectangular waveform of a high and slowly fluctuating amplitude and a long duration (e.g. the two lumps from the 700-th to 1200-th minutes.

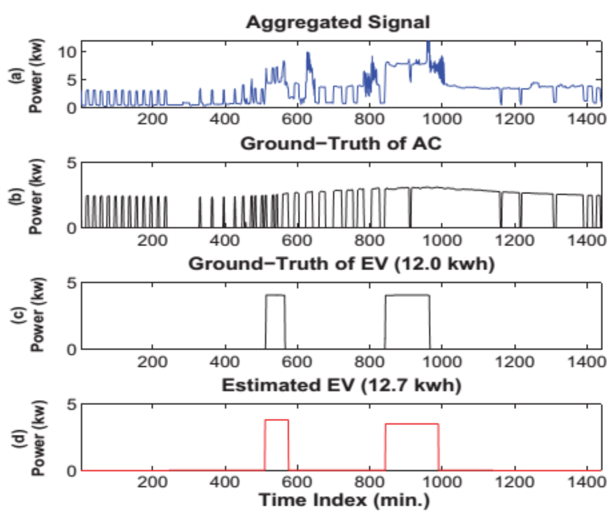


Figure 5: Energy disaggregation by the proposed algorithm. (a) An aggregated signal of one day. (b) The ground-truth of AC. (c) The ground-truth of EV (energy consumption is 12.0 kWh). (d) The estimated EV power signal (estimated energy consumption is 12.7 kWh). The energy estimation error (defined in Section IV) is 5.8%, and the MSE is 0.178.

This waveform pattern can seriously affect disaggregation performance of EV charging load signals due to the difficulty of distinguishing the AC waveform pattern from EV charging load signals, especially in the presence of other appliances' power signals and highly fluctuating residual noise. For notational convenience, this kind of AC waveforms will be called as AC lumps.

Another challenge lies with the aggregated data themselves of being real power signals sampled at 1/60 Hz [6]. At this sampling rate, many useful appliance signatures such as transient characteristics available from high sampling rates no longer exist, which limits pattern recognition tools to render accurate disaggregation results.

The third challenge is the lack of ground-truth of EV charging load signals for each house and its large variation across different houses. To obtain the ground-truth of EV charging load signals in a given house, it requires installing sub-meter sensors to record these signals. However, it is unpractical to install such sub-meter sensors in every house. Thus,while disaggregating EV charging load from aggregated power signals in a given house, there is no training set (i.e. a collection of ground-truth of EV charging load signals in the house) available to train an algorithm. On the other side, EV charging load signals have large variation across different houses. For example, EV charging load signals could have different amplitudes (although always higher than 3 kW), different width (i.e., charging duration), and different appearance time from house to house. As a result, an algorithm working well for a given house may perform poorly for another house. In summary, a practical algorithm should work well for various houses and every season (especially the summer), and should not require training sets. But due to the above issues, to achieve high disaggregation accuracy of EV charging load is truly challenging.

CHAPTER 6

PROPOSED METHOD FOR EVB LOAD DISAGGREGATION

We present a novel method of load disaggregation specifically for Electronic Vehicle Battery (EVB) used in our household. In our method, we focused on mitigating the interference coming from Air-conditioner (AC), detecting the accurate EV charging and estimating the power consumed by EVBs under the presence of the AC power signals. Besides, our proposed method does not require any training and it does not demands heavy computational load. It also delivers high estimation accuracy and works well for data recorded at lower sampling rate (1/60 Hz)

We choose one-day aggregated power signal of a household (taken from the Pecan Street Database [9]) to illustrate our disaggregated data. From the aggregated signal at first, a rough estimation of the EV charging load signal was obtained by applying a threshold. For a given aggregated signal *x(t)*, a threshold T_{low} was applied.

$$\underline{x}(t) = \begin{cases} \mathrm{x(t)} & \mathrm{x(t)} \geq \mathrm{Tlow} \\ 0 & \mathrm{x(t)} < \mathrm{Tlow} \end{cases}$$

Where Tlow $\triangleq$ max $\{2.5, \frac{1}{2|\mathrm{x(n)}>2|} \sum_{n:x(n)>2} x(n)\}$, and |x(n) > 2| counts the number of sampling points whose amplitude is larger than 2 kW. After the initial thresholding, the segments information of $x(t)$ can be obtained such as the locations of a start-point and an end-point of each segment.

Now we have already discussed that, AC (Air-conditioner) usually exhibit two kinds of waveform patterns. One pattern resembles a *spike train* with very short durations such as 1st to 700-th minutes. Another waveform pattern resembles a rectangular waveform of a high and slowly fluctuating amplitude and a long duration; the two lumps from the 700-th to 1200-th minutes. Therefore, many AC spikes are found in the thresholding result which needs to be removed. For that operation, we could set another threshold to remove all spikes whose duration is shorter than the threshold. However, it is not easy to find a suitable duration threshold to remove all these spikes due to the varying nature of AC spike duration. In addition, the duration of AC spikes gradually increases from morning to later afternoon and gradually decreases from later afternoon to midnight. Based on this observation, we have designed the following filter to remove these spikes. It first finds segments, which are called 'seeds' and labeled as 'spike to remove' with duration shorter than T_{seed} = 20 (minutes). Then, from each 'seed', the filter searches the nearest segment *forwardly*, checking whether the segment's duration is shorter than $D \triangleq (1+\eta)D_{cur}$ and whether the gap between the 'seed' and the nearest segment is no more than $3D_{cur}$, where D_{cur} is the duration of the current 'seed' and η is a duration extension parameter (η = 1.2 in our algorithm). If this search condition meets, this nearest segment will be labeled as '*spikes to remove*' and will be set as a new 'seed'. Using this new 'seed', the filter repeats the same *forward* segment searching to the nearest segment. Similarly, the filter searches *backwardly* as well. In the end, after completing the whole search range, all segments labeled as '*spikes to remove*' are removed from $x(t)$. We adjust another threshold T_{spike} to prevent a segment of larger duration from removing such that all removed segments have duration no more than T_{spike}. In our algorithm the value of T_{spike} is 90 minutes. However, the filter does not remove all segments which have duration no more than T_{spike}. It removes a segment only if its duration does not increase sharply compared to its surrounding segments' duration. If a segment with a long duration is surrounded by very short segments, even if this long segment has duration shorter than T_{spike}, it will not be removed. The reason is that this segment can indicate a waveform of EV, dryer, or oven. So, it requires further examination to identify.

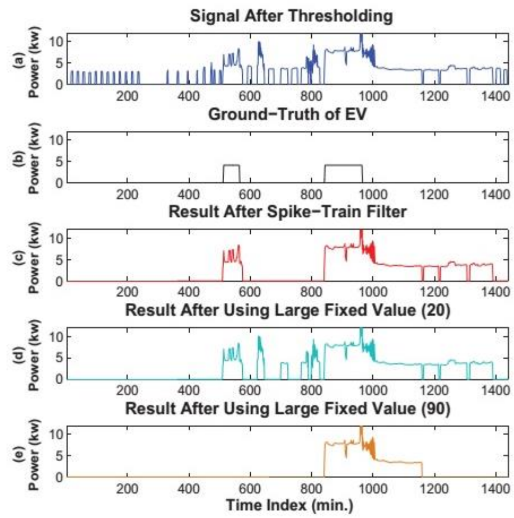
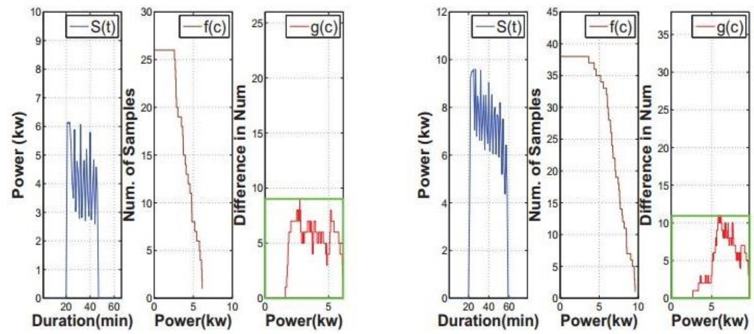


Figure 6: Results after using the spike-train filter and the fix-value thresholding method.

After filtering AC spike train, we move on to take care of residual noise. Residual noise is basically the mixture of errors from fluctuation of power signals, loss in power lines, and power signals of appliances with low amplitude. We have already obtained location information of each segment in thresholding stage. The amplitude of residual noise can be estimated around each segment from that information. For each segment, using the minimum value of N_b points immediately before the segment and the minimum value of N_a points immediately after the segment, the amplitude of the local residual noise can be estimated by averaging the two minimum values. The residual noise removal can be obtained by subtracting the segment by its associated local residual noise amplitude. In our algorithm $N_b = N_a = 5$.

After removing residual noise, there are only a few segments remaining in the filtered aggregated signal. At this point, we will classify every segment into one of three types designed by Zhang et.al [10].

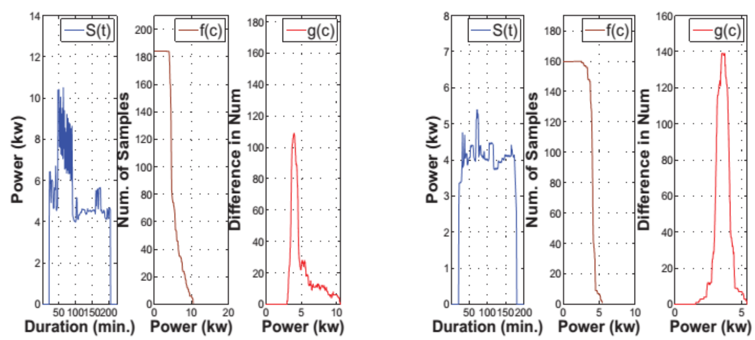
1. **Type 0:** First type are segment belongs to a dryer/oven waveform, or belongs to an EV waveform fully overlapping with a dryer/oven waveform which has almost the same duration as the EV waveform. If the segment belongs to a dryer/oven waveform, it can be simply removed since it is not an EV waveform. If the segment belongs to an EV waveform, it should have very high amplitude since a dryer/oven waveform has high amplitude like an EV waveform (generally higher than 5 kW).



(a) (b)

Figure 7: Two typical segments of Type 0. (a) Shows a dryer wave. (b) Shows an EV wave completely overlapped by a dryer wave which has the same duration as the EV wave.

2. **Type 1:** This type of segment either belongs to an EV waveform or an AC lump or an EV waveform overlapping with waveforms of non-AC appliances with relatively shorter durations or an AC lump overlapping with waveforms of other appliances. We can calculate the approximate width and height of the segment, decide whether it is an EV waveform, and then reconstruct the EV waveform.



(a) (b)

Figure 8: Two typical segments of Type 1. (a) Shows an EV wave overlapped by a dryer wave with short duration. (b) Shows an EV wave contaminated by fluctuation of residual noise.

3. **Type 2:** This type of segment belongs to an EV waveform overlapping with an AC waveform, which is probably also overlapping with other appliances' waveforms. For example, the first two segments shown in Fig. 8 are respectively an EV waveform overlapping with an AC spike train and an EV waveform overlapping with an AC lump and a dryer waveform.

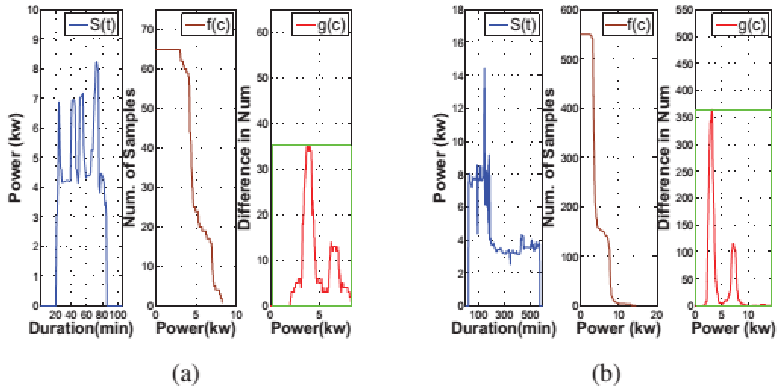


Figure 9: Two typical segments of Type 2. (a) Shows an EV wave overlapped by an AC spike train, where the EV wave is the bottom part of the segment. (b) Shows an EV wave overlapped by an AC lump and a dryer wave, where the EV wave is in the top part of the segment.

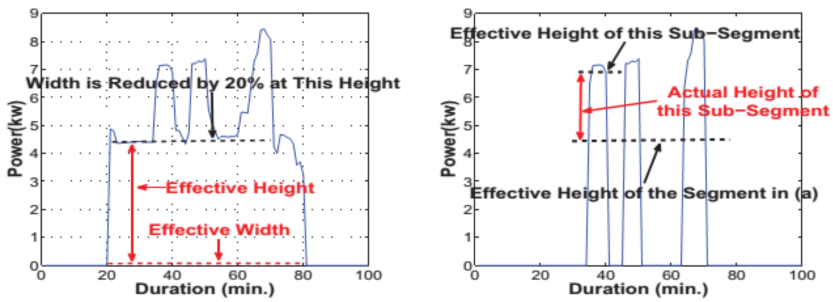
We will be calculating using the following cumulative counting function in order to classify a given segment *S(t)*:

$$f(c) = \langle S(t) > c \rangle$$

Where *c* is an amplitude threshold from 0 to *max(S(t))* and the operator $\langle S(t) > c \rangle$ counts the number of sampling points in *S(t)* with an amplitude greater than *c*. For example, if *c*=0, then *f(c)* is the total number of all nonzero samples in the segment. If *c*= *max(S(t))*, then *f(c)*=0.

When calculating the gradient of the cumulative function *f(c)*, we can find that there are two prominent peaks for Type 2 segments. This is because both an AC waveform and an EV waveform can be approximated as square waves, and a square wave can result in sharp drop in *f(c)* when *c* is equal to the height of the square wave. Similarly, there is one prominent peak in the gradient of *f(c)* for Type 1 segments and no prominent peak for Type 0 segments. Thus, the number of prominent peaks in the gradient of the function suggests which type an observing segment belongs to. To find prominent peaks, we search peaks with mutual distance larger than 2 kW and peak height larger than *0.2max(g)* where *g* is the gradient of *f*. The Matlab command findpeaks can finish this task easily. If there is one peak, the segment is classified as Type 1 (Fig.7). If there are at least two peaks, further calculate the area under the normalized gradient function $g_n \triangleq g/max(g)$. If the area is larger than 35% of the square area with the same width and height as g_n (e.g. the green square area in Fig.6 and Fig.8), then the segment is classified as Type 0 (Fig.6); otherwise, it is classified as Type 2 (Fig.9).

The next step of our algorithm is energy disaggregation. To disaggregate energy, we need to define the effective height and effective width of each segment. The effective width is the width of a segment at bottom. The effective height is defined as the height at which the segment's width becomes only 80% of the bottom width. The calculation of the effective height and width is illustrated in the following figure.



(a) A segment (b) Sub-segments of the segment in (a)

Figure 10: (a) Calculation of the effective width and height from a segment. (b) Calculation of the actual height of sub-segments of the segment in (a). The sub-segments are obtained by thresholding the segment.

If a segment belongs to Type 0, then we first determine its effective height. If its effective height is smaller than 5.5 kW, this segment is classified as a wave of dryer/oven. If larger than 5.5 kW, the segment is classified as a fully overlapping waveform of an EV and a dryer/oven. For the latter case, it is impossible to accurately estimate EV waveform's height. However, considering the fact that an EV waveform has constant and very stable amplitude from day to day, the EV waveform height can be assigned with a height estimate at another time of the same day or another day. Thus an EV square wave is reconstructed using the height and the calculated effective width. If a segment belongs to Type 1, the effective height and width can be simply calculated, and then its square waveform can be reconstructed accordingly. However, if the width is very large, e.g. larger than 250 (minutes), the segment will be removed since an EV waveform generally exhibits a constant amplitude for no more than 2-3 hours. More likely, these long waveforms could be AC lumps or other appliances' waveforms. Besides, if a candidate waveform has an effective height lower than 3 kW or is surrounded by a number of AC spikes, then it is treated as an AC lump as well. If a segment belongs to Type 2, this segment can be considered to include both an EV waveform and an AC waveform. Thus it needs to be determined whether an EV waveform occupies the top part or the bottom part of the segment. First an additional threshold T_{high} will be used to obtain the sub-segment information of the top part. For the proposed algorithm, $T_{high}=T_{low}$ +2.5(kW) is set. From the first step, using this threshold a number of sub-segments in the top part can be obtained as shown in Fig. 9(b).

Then we calculate the effective width. If the width is larger than 250 (minutes), then the bottom part is more likely to be an AC lump due to the EV duration characteristic mentioned before. Thus, EV waveforms belong to the top part. Similarly, the effective width and the actual height of the actual height of a sub-segment is calculated as the effective height of the sub-segment subtracted by the effective height of the associated segment. Each sub-segment (with duration longer than 20 minutes) are calculated to reconstruct an EV square waveform. If the width is less than 250 (minutes), then the sub segments are analyzed. The proposed spike-train filter is used to remove the sub-segments. As a result, the following two cases are considered.

1) If the filter can remove all sub segments, then the top part is an AC spike train, while the bottom part is an EV waveform. We can calculate the effective height and width of the bottom part to reconstruct the EV waveform.
2) If the spike-train filter cannot remove all sub-segments, then each remained sub-segment needs to be analyzed one by one. The actual height of each remained sub-segment and the effective height of the segment need to be calculated. Whichever (sub-segment's actual height or the segment's effective height) is closer to an estimated EV height at another time of non-overlapping observation; it will be identified as an EV waveform.

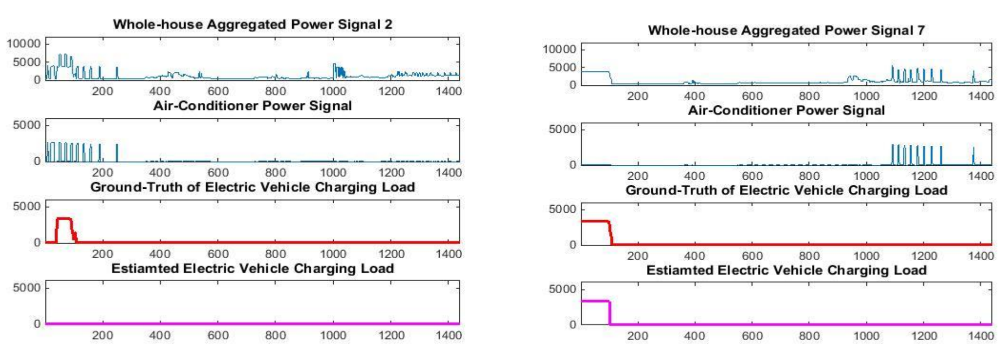
Our algorithm uses a number of default values such as the amplitude and width of EV charging load signals. However, it is worthy emphasizing that these default values are based on general knowledge of EV charging load characteristics, and do not rely on a specific type of EV. For example, although the amplitude of EV charging load signals is changing from house to house, the amplitude is always larger than 3 kW. The proposed algorithm utilizes the amplitude range information, but not any exact amplitude number. In the next section the proposed algorithm will be applied to a number of houses with robust performance across different houses and different seasons. This indicates the default values used in the algorithm do not affect practical use.

CHAPTER 7

EXPERIMENTAL RESULTS AND EVALUATION

Our proposed algorithm was tested through a simulation process. The aggregated power signal came from the Pecan Street Database, which collects raw power signals recorded from hundreds of residual houses in Austin, Texas. Eleven houses using EV were randomly chosen from the database. Each house data contain aggregated power signals of about one year. Each aggregated power signal is generally a combination of about twenty power signals of various appliances, such as EV, AC, furnace, dryer, oven, range, dishwasher, cloth-washer, refrigerator, microwave, bedroom-lighting, and bathroom-lighting. The ground-truth power signals of these appliances are also available in the database. Thus the database is very suitable to test algorithms' performance in practice.

We have also compared the result provided by the simulation using our proposed method with Hidden Markov Model [11], another algorithm for energy disaggregation of various residential appliances. Since HMM was not specifically designed for EV charging, and it requires extensive training and a large computational load, we have decided to compare our method with it to emphasize on the energy consumed by EVBs in a house. Based on our algorithm we had run some simulations and as a result, the following plots were drawn.



(a) (b)

Figure 11: Energy disaggregation by the proposed algorithm. (a) Shows the whole-house aggregated power signal at second hour, AC power signal at second hour of the day, Ground Truth of EVB and estimated load of EVB. (b) Shows

the whole-house aggregated power signal at seventh hour, AC power signal at seventh hour of the day, Ground Truth of EVB and estimated load of EVB at seventh hour of the day.

The eleven houses are listed in Table I. Note that some houses have wrong ground-truth of EV power signals or bad recordings of aggregated signals in some months. Thus we remove the data of these months. The remained data have total 125 months. The sampling rate is 1/60 Hz. Since the HMM algorithm requires training, for each house its ground-truth power signals of EV and AC of two weeks were used as the training set. Note that our proposed algorithm does not need this training period. Three performance indexes were used. One is the averaged estimation error of monthly energy consumption, defined as

$$\mathrm{Err1} = \frac{1}{N}\sum_i \sum_j \frac{|E_{\mathrm{true}}^{i,j} - E_{\mathrm{est}}^{i,j}|}{E_{\mathrm{true}}^{i,j}} \times 100\%$$

Where E_{true} is energy consumption of the ground-truth EV power signal in the j-th month of the i-th year, and E_{est} is energy consumption of the estimated EV power signal in the same month, and N is the total month number in the calculation. A related performance index is the averaged estimation error of monthly energy consumption in kWh, defined as

$$\mathrm{Err2} = \frac{1}{N}\sum_i \sum_j |E_{\mathrm{true}}^{i,j} - E_{\mathrm{est}}^{i,j}| \quad (\mathrm{kwh})$$

The third performance index is the averaged normalized mean square error (MSE) in estimating EV charging load signals, defined as

$$\mathrm{MSE} = \frac{1}{N}\sum_i \sum_j \frac{(X_{\mathrm{true}}^{i,j} - X_{\mathrm{est}}^{i,j})^2}{(X_{\mathrm{true}}^{i,j})^2}$$

Where $X^{i,j}_{true}$ is the ground-truth EV charging load signal in the j-th month of the i-th year, and $X^{i,j}_{est}$ is the estimated EV charging load signal in the same month. The results are presented in Table I, which shows that the proposed algorithm significantly outperforms the HMM algorithm. For the proposed algorithm, the averaged estimation error of monthly energy consumption is only 7.5%. Or put in another way, the error is only 15.7 kwh/month in average. In this experiment, the average monthly energy consumption of EV charging load is 208.5 kwh/month, and the average monthly total energy consumption of a house is 1109.9 kWh/month. Therefore, the estimation error of the proposed algorithm is well acceptable.

House	Month Range	Err1	Err2(kWh)	MSE	Err1	Err2(kWh)	MSE
370	2012-10 to 2013-09	8.00%	11.70%	0.31	135.50%	192.20	1.51
545	2012-09 to 2013-09	5.60%	10.80%	0.13	89.10%	156.80	1.06
1782	2012-05 to 2013-09	7.00%	13.90%	0.17	28.80%	79.30	0.42
1801	2012-07 to 2013-08	11.70%	24.50%	0.29	76.20%	156.50	0.96
2335	2012-06 to 2013-05	9.60%	20.30%	0.30	26.00%	58.00	0.47
3036	2012-08 to 2013-09	5.90%	20.30%	0.12	3.90%	12.90	0.17
3367	2012-11 to 2013-10	5.90%	9.90%	0.16	47.60%	81.30	0.63
6139	2012-10 to 2012-05	10.10%	21.10%	0.05	2.60%	5.00	0.09
7863	2012-09 to 2013-09	9.20%	20.90%	0.08	101.20%	236.00	1.02
8669	2012-09 to 2013-08	3.10%	8.60%	0.15	26.70%	78.40	0.3
9934	2012-10 to 2013-10	7.00%	12.30%	0.27	38.80%	73.10	0.46

Table I. Performance Comparison of our Proposed Algorithm and Hmm Algorithm. The Last Row of The Table Gives The Performance (Mean±Standard Variance) Averaged Over All Months And All Houses.

In contrast, for the HMM algorithm, the averaged estimation error of monthly energy consumption is 55.6%, or $12.56/month. In fact, the poor performance of the HMM algorithm is mainly due to the estimation error in summer, when AC becomes the strongest interference. From the results, one can see the HMM algorithm does not provide any meaningful estimation for these four months; the averaged estimation error of monthly energy consumption of EV charging is 152.7%, or $34.11/month, and the averaged normalized MSE is 1.81. (A meaningful disaggregation result should have normalized MSE much smaller than 1.)

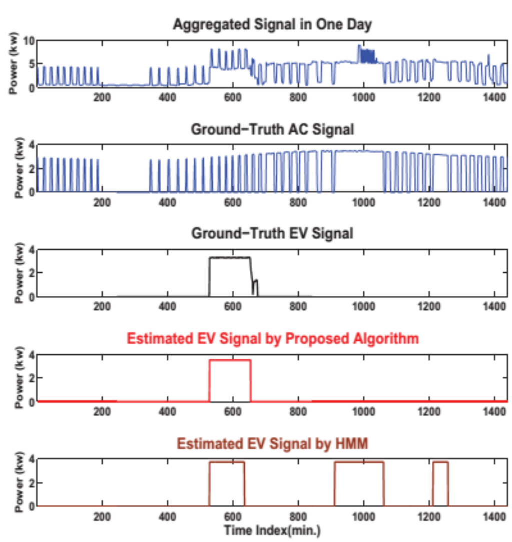


Figure 12: The estimation performance of our proposed algorithm and the HMM algorithm

Figure 12 shows an example of the estimated EV charging load signals by the two algorithms. One can see the HMM algorithm treats some AC lumps as parts of the EV signal, and thus makes large errors. In contrast, the proposed algorithm correctly identifies and disaggregates the EV charging load signals from the aggregated signals.

CHAPTER 8

CONCLUSION AND FUTURE WORK

CONCLUSION

Our works were based on previous works on the same problems. However, our algorithm for non-intrusive energy disaggregation of electronic vehicle charging has given a real aggregated power signal. It does not require training, demands a light computational load, and renders a high energy estimation accuracy. These advantages were illustrated by experiments on the real world data with a low sampling rate (1/60 Hz) delivering superior performance even under the presence of air-conditioners.

FUTURE WORK

In this thesis,we studied the the load monitoring for electric vehical battery based appliances aspects were not taken in account while we did this. Our lot of mostly used in our house. A algorithm might have significant result in terms of HMM algorithm but its' accuracy is not more than95 .%For better results ,we are planning to work further on this algortihm. Besides, oad the l consumed by specific electronic vehicles such as laptops, cellular devices can be disaggregated as well by working further.

CHAPTER 9

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