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ECONOMICAL REAL-TIME ENERGY MANAGEMENT FOR MICROGRIDS VIA NILM AND WITH USER DECISION SUPPORT

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by

Ali Adabi

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The Dissertation of Ali Adabi
is approved:

Professor Patrick Mantey, Chair

Professor Michael Isaacson

Professor Joel Kubby

Dean Tyrus Miller
Vice Provost and Dean of Graduate Studies

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Abstract

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by

Ali Adabi

With time-of-use pricing of electrical energy, real-time energy management is being economically incentivized for all. Consumers with renewable sources are among the first to recognize this, and those with the capability to operate in island mode as a micro grid find real-time energy management a necessity.

A real-time energy management system (EMS) requires real-time data that enables immediate identification of electrical loads. Non-Intrusive Load Monitoring (NILM) is the process of identification of loads from an aggregate power interface using disaggregation algorithms, thus providing load data economically.

Application of NILM in residential settings has been hampered by limited data availability. Utility billing smart meters provide very sparse (time) sampling of energy use, yielding data that is not adequate for quantifying fundamental harmonics of the waveform. For research and deployment of NILM, there is a critical need for a low-cost sensor system to collect energy data with fast sampling and significant precision.

We first identify the current status, methodologies and challenges of NILM in residential settings. NILM has advanced substantially in recent years due to improvement in algorithms and methodologies. Currently, the important challenges facing

residential NILM are inaccessibility of electricity meter high sampling data, and lack of reliable high resolution datasets.

We introduce SEADS (Smart Energy Analytic Disaggregation System) which provides a powerful and flexible system, supporting user configuration of sampling rates and amplitude resolution up to 65KHz and up to 24 bits respectively. The SEADS internal processor is capable of implementing NILM algorithms in real time on the sampled measurements.

An Intelligent Energy Management System (IEMS) has been introduced. Since SEADS has the load information instantaneously, it can be part of a real time command and control system of a microgrid. IEMS proposed integrates SEADS into a Decision Support System (DSS). DSS helps consumers make informed realtime decisions, especially when microgrid is operating in the island mode. Prolonging the stay on the battery and renewable sources, can reduce or eliminate the need for use of a local fossil fuel generator. A combination of automatic and user driven load shedding is necessary in a microgrid for interactively responding to the intermittency of renewable sources. This is possible by controlling only a limited number of loads in parallel with using a battery storage system.

To my family,

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Ali Adabi

0.1 Introduction

Non-Intrusive Load Monitoring (NILM) is the process of identification of loads from an aggregate power interface using disaggregation algorithms. Since G. Hart introduced NILM method in detail in 1992 [21], hundreds of studies have been published on the issue of energy monitoring using aggregate data.

Although the studies that have been conducted in recent years have advanced NILM, this area still faces substantial challenges and limitations in its application, especially in terms of training time and recognition accuracy. The widespread use of NILM is especially hindered by the limitations of the ”smart meters” now widely deployed for Automated Meter Reading (AMR) and the data sampling rate these meters use. For research in NILM, there is very little data available at sampling rates that can capture even the low harmonics of the 60Hz signals. Therefore, there is an obvious need for a low-cost sensor system to collect energy data with fast sampling and significant precision.

This thesis describes a cost effective system called Smart Energy Analytic Disaggregation System (SEADS) capable of running real time NILM algorithms via sampling high frequency data. Furthermore, this thesis identifies how SEADS can be part of an Intelligent Energy Management System (IEMS) especially in the case of a microgrid.

The main contribution in this thesis can be summarized as follows:

- SEADS (Smart Energy Analytic Disaggregation System): SEADS hardware system can sample up to 65kHz and 24 bits. Software system includes a high throughput backend with the required API for dealing with high frequency data. SEADS inserts the data into a big table (NoSQL) database, and has the API that can query this data instantaneously (achieved through indexing). SEADS has four layers, Hardware layer (sensors, data acquisition, and networking) Software layer (data analysis, storage), API layer, and Application layer (consumer feedback, demand response, and automation).

- Sampling Rate Range: We find the optimal range of sampling rate for the residential disaggregation to be 4-8kHz. We achieve 72% accuracy on appliances with using only 6 fundamental harmonics (1st, 3rd, 11th, 17th, 27th, and 33rd) and with all 50 harmonics, we can achieve 92% accuracy. We observe higher harmonics above 8kHz fall below the noise floor and can not be used for identification.

- Intelligent Energy Management System (IEMS): An intelligent energy management system is proposed. IEMS integrates SEADS into a decision support system. Decision Support helps the user make informed real-time decisions, especially in the case of outages or operation in the Microgrid Island mode or when facing Time of Use pricing. Automatic or user driven load shedding is essential for a Microgrid to be able to respond to the intermittency of the renewable resources dynamically and economically. In order to do that, we have to control only a few loads. The data gathered from the user, weather, load, generator, and battery is aggregated and fed into a decision support system to help consumers make informed decisions.

SEADS is an important part of the IEMS which provides appliance's state and energy usage. The data gathered through the decision support is fed to the three components, user behavior prediction, modeling and optimization. The data processed through this section make a rule-based decision tree that feeds user rules to the consumers through a UI and automation rules to the automation section. Automation is mainly used for a few appliances that have controllable relays and are connected to the network (for example through SEADS plug) or smart appliances such as smart thermostats.

0.2 Chapters

This dissertation is organized and discussed in the following chapter summaries.

- **Chapter 1. Status of Non-Intrusive Load Monitoring in Residential Settings**

  In this chapter, we discuss the status and challenges of the current NILM in the residential settings. We review studies by researchers in the area of Non-Intrusive Load Monitoring. We characterize applications that can be built on top of a real-time appliance energy monitoring system in residential settings (e.g. consumer feedback, and demand response).

- **Chapter 2. Smart Energy Analytic Disaggregation System (SEADS)**

  In this chapter, the hardware of SEADS has been described and the related work on the topic of NILM is discussed. SEADS design flow and the hardware are described. Hardware of SEADS includes sensors, data acquisition and networking.

- **Chapter 3. Experimentation**

  In this chapter, the software architecture of SEADS is described. Furthermore, the experimental results using SEADS and the required sampling rates are discussed. Software of the SEADS includes a high through put backend with capability of receiving high frequency data. SEADS' modular and modifiable platform enables detection at a variety of sampling rates and amplitude resolution.

- **Chapter 4. SEADS as a part of an Energy Managment System(EMS)**

  In this chapter, the practical uses of SEADS are discussed. SEADS provides a platform for other applications such as demand response and consumer feedback. We divide loads into three categories deferrable loads, marginally deferrable loads, and Non-deferrable loads (Critical Loads). We describe how SEADS and SEAD Plug together can be part of a microgrid control management system.

- **Chapter 5. Decision Support System for a Residential Microgrid**

  In this chapter, an Intelligent Energy Management System (IEMS) is introduced. IEMS receives inputs from the user, load, ambient conditions, solar/wind, generator, grid, and battery. Decision support uses models and an optimization methodology to create a rule base tree. These rules are pushed to the user or automation block. Furthermore, simulation of the batteries in an IEMS has been discussed.

Chapter 1

Status of Non-Intrusive Load Monitoring in Residential Settings

1.1 Why Residential Real-Time Appliance Energy Monitoring?

A real time appliance energy monitoring system can provide realtime visualization or notification to the consumer. This system can be used in variety of scenarios such as consumer feedback, demand response, dynamic pricing and microgrid monitoring and control.

1.1.1 Consumer Feedback

According to the US Energy Information Administration (EIA), the use for electronics and appliances continues to rise while heating and cooling are no longer majority of the U.S. home energy use [1]. Space heating and cooling accounted for more than half of all residential energy usage for decades. However this is changing and energy used for space conditioning has declined, while energy consumption for appliances and electronics continues to rise because of an increase in the number and category of such devices. Non-weather related energy use for appliances, electronics, water heating, and lighting now accounts for 52% of total consumption, up from 42% back in 1993. This increase calls for smarter monitoring devices that can measure electricity of such appliances in a cost effective manner.

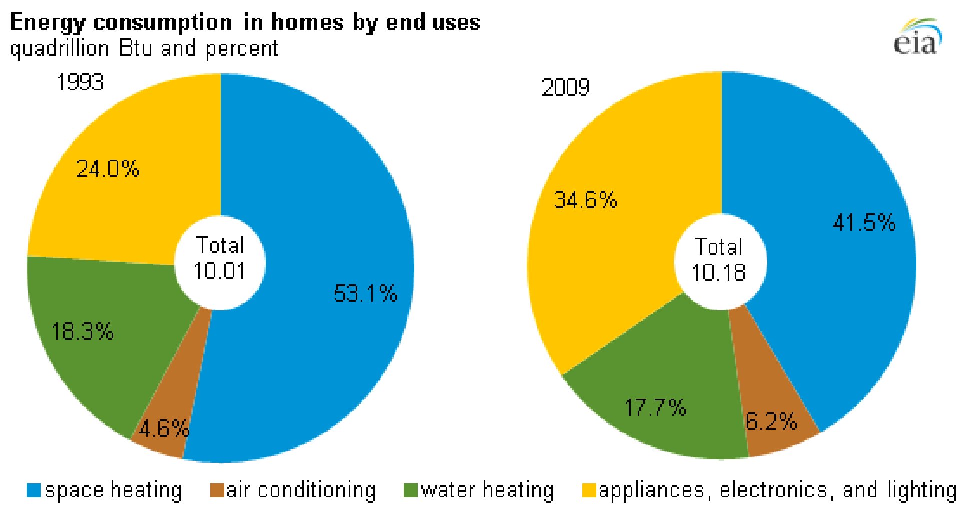


Figure 1.1: Energy consumption in home by end uses according to [1].

Many studies prove effectiveness of the real time consumer energy feedback. More noticeably Ehrhardt-Martinez *et al.* [12] study has shown that appliance direct feedback via automated personal recommendation can result in more than 12% in energy savings for consumers (Fig. 1.2). A typical house in the US consumes close to 11,320 kWh of electricity per year, and 12% of that is equivalent to 1358kWh considering the average rate of 15.2 cents per kWh in California, this saving is equivalent of $207 per year. Therefore, any device that is under this price has only one year of breakeven point (cost effective). According to US Environmental Protection Agency (EPA), the carbon emission per kilowatt hour is 6.8955110^{-4} metric tons CO_2 / kWh, which means the 12% saving equivalent of keeping 0.142 metric tons of CO_2 in the ground per average household.

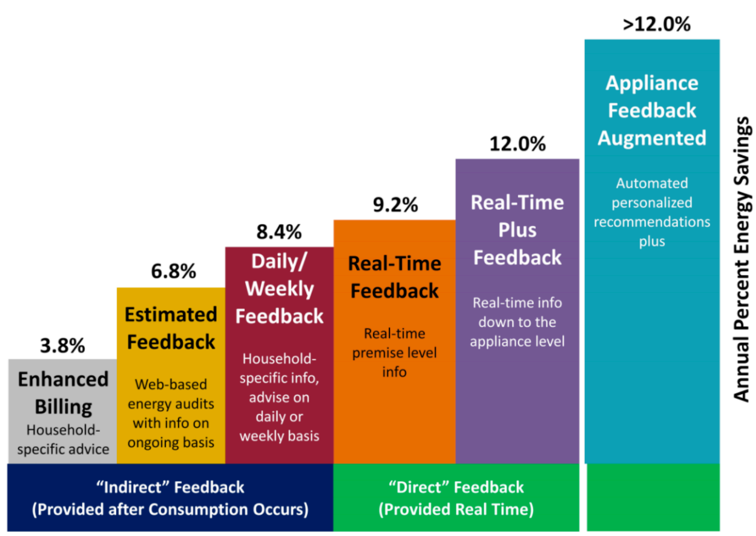


Figure 1.2: Residential saving due to consumption feedback

1.1.2 Demand Response

Demand response provides a framework for consumers to participate in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates. Demand response is a potential resource option for balancing the supply and demand. A real time management systems seem to be an integral part of an agile Demand Response (DR) system. There are two ways for consumers to participate, manual and automatic.

1.1.2.1 Automated DR

The automated demand response is when the user gives the control of its appliances to an aggregator. An aggregator then can shed loads when there is a peak in power usage. An example of it would be automatic control of a thermostat or water heater in an event of an outage.

1.1.2.2 Manual DR

Manual DR is when consumer manually responds to a price signal. Manual DR can be instructed via sending notification to the consumer's smart phones to curtail the load. The user then replies by curtailing the loads or shifting them to a different time when the demand is not as high. Increasing penetration of renewables can create a new challenge in demand response. For example, for PV installations a cloudy day means reduction in energy production by 70%. The system should be fast enough to respond to such sudden changes caused by intermittent sources.

1.2 Why Non-intrusive Load Monitoring (NILM)?

Installing plug load to monitor each appliance is costly and not practical. NILM can help significantly in reducing the cost and burden of installing plug load sensors for monitoring appliances. Other than cost, in many cases, consumers should move heavy appliance in order to install the sensors and in many cases, the antenna can get buried behind the appliance and not be able to communicate to a hub. There is also cost associated with managing and maintenance of all these plug loads which adds to the total costs. Non-Intrusive Load Monitoring provides a single sensor with the goal of monitoring all or most appliances and it is much more cost effective and has less hassle than installing a circuit monitor on every device at home.

1.3 Residential Aproaches

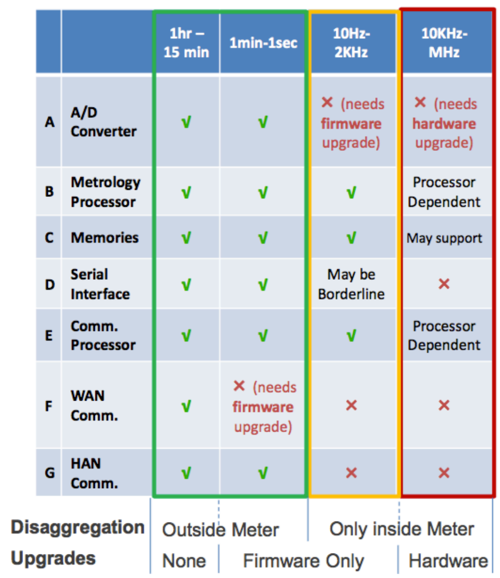
From its inception, NILM has been seen as a tool especially valuable for residential energy use monitoring from data gathered at the revenue meter. With the wide deployment of "smart meters", which provide both data acquisition and networking for Automated Meter Reading (AMR, and the overall system called Automated Metering Infrastructure AMI), there has been growing interest in using this AMR data for NILM. Unfortunately, the data sampling frequency required for billing purposes led to data being provided to the utility – at best – every five minutes and sometimes with as much as an hour between samples. Utilities (e.g. PG&E) also do not make this data available until a day or two later. In California the investor-owned utilities have added the capability in the meter for another link, to the Home Area Network (HAN) in real time, via Zigbee (802.15.4) [9].

This path provides real-time data with a sampling interval at best of 10 seconds. Existing smart meters can provide 1 second data with a firmware upgrade based on [7] as depicted in figure 1.3, however, since they don't broadcast this information over the WiFi (IEEE 802.11) an extra hardware is usually needed to extract this information. Weiss *et al.* [40] discusses a smart meter that sends power measurements through an ethernet port at 1 second and describes NILM algorithms that can achieve device recognition rate of 87%. Even though current smart meter internally sample at more than 2kHz, they do not provide 2kHz data over the HAN link mainly due to small processor memory and buffer size. Therefore, companies such as Pecan Street have chosen to instrument more than 1200 houses with eGauge metering devices which provides simultaneous 1 second data of 12 circuits as well as up to three voltage phases.

1.3.1 State of Monitoring in Residential Settings

The majority of studies on residential NILM can be divided into two main groups: Studies which investigated the low frequency sampling data [6,21,26](frequency $\leq$ 1Hz), and studies which examined the high frequency sampling data (frequency $>$ 1Hz) [19,33].

While identification of loads with unique power requirements (generally large loads such as the oven, HVAC, electric water heater, electric clothes dryer) may be accomplished with low frequency sampling, many devices have similar power requirements and maybe running simultaneously, and identification in these circumstances requires data sampled at higher frequencies to utilize unique "signatures" of the specific devices. There are 30-50 different appliances in a home today [41]. Identifying all these for com-



		1hr – 15 min	1min-1sec	10Hz-2KHz	10KHz-MHz
A	A/D Converter	√	√	× (needs firmware upgrade)	× (needs hardware upgrade)
B	Metrology Processor	√	√	√	Processor Dependent
C	Memories	√	√	√	May support
D	Serial Interface	√	√	May be Borderline	×
E	Comm. Processor	√	√	√	Processor Dependent
F	WAN Comm.	√	× (needs firmware upgrade)	×	×
G	HAN Comm.	√	√	×	×

Figure 1.3: Smart Meter limitation for NILM system integration based on [7]

plete household energy monitoring is a complex task, even with high frequency sampling, and presents significant challenges for training of the recognition algorithm employed. The NILM application needs to be considered in determining what is actually needed in load disaggregation. As an example, an application such as "demand response" where users are expected to change their use to respond to changes in electrical energy pricing (or for "time-of-use" metering (TOU) etc.) it is probably not necessary to fully disaggregate the energy being used. If a user categorizes the loads by the amount of energy used and whether or not they are essential, the disaggregation that identifies the key loads that the user is willing to shed is probably all that is needed in selecting their response to a (short term) change in energy pricing.

1.3.1.1 Low Frequency

Publicly available databases can help in reducing the training needed for NILM algorithms by enabling the creation of generic models of appliances. Therefore, several open Low Frequency(LF) datasets such as the REDD LF dataset[1], Pecan Street Inc. have been released in the last few years. Table 5.1 shows a group of datasets with their *associated number of houses* that were monitored, *period* over which the experiment was conducted and data gathered, *number of circuits* monitored per house, and *the time period* corresponding to each data measurement.

Barta *et al.* [8] are developing a toolkit called NILMTK for processing and analysis of all publicly available LF datasets. This toolkit addresses the problem of

[1]REDD has both high and low frequency data.

Table 1.1: Public NILM Datasets

Dataset	Number of Houses	Period Monitored	Number of Circuits/Appliances	Frequency
Pecan Street Inc.	1295 Houses	4+ years	Various houses	1/60Hz
HES	26 Houses 225 Houses	1 Year 1 Month	each house 13-51 appliance types	1 Hz
REDD	6 Houses	Varies-weeks to months	10-25 individually monitored circuits	1/3-1/4Hz
UMASS	3 Houses	3 months	21-26 circuits	1Hz
EDF	1 Houses	4 years	3 circuits	1/60Hz
Tracebase	–	1883 days	158 instances of 43 appliance type	1 Hz
iAWE	1 Houses	73 days	33 sensors	1Hz
BERDS	1 Industry	1 week	4 appliance types	1/20Hz
PLAID Plugs	56 Houses	1 min	200 appliances	30kHz
BLUEDD	1 Houses	8 days	—-	12kHz

scarcity of an established code base for developers. Furthermore, NILMTK enables comparison of algorithms on heterogeneous datasets with different data type, data rate and meta data. The NILMTK platform promises to accelerate and streamline algorithm development for LF data.

1.3.1.2 High Frequency

High Frequency(HF) current and voltage features are used for appliance monitoring and specifically for appliance event detection(on/off). HF methods generally apply signal-processing techniques which require extra hardware on the circuit mains or the circuit breakers. HF methods can look for steady state or switching transient features. Transient voltage features were initially studied by Patel *et al.* [33] and con-

Table 1.2: High Frequency methods range from 10kHz to 1MHz

Name	Description	Variable	Appliances	Sample rate	Training	Accuracy(%)
Berges et al. (2010) [10]	Signatures	Power , Voltage	17	10kHz	5 days non real time	86
Ford(2009)	Bayesian	Power , Voltage	6	15kHz	minutes	99%
Kolter(2012) [27]	Factorial HMM	Current	9	15kHz	2 weeks	83
Inagaki(2011) [14]	Integer programing	Current , Voltage	42	40kHz	Not reported	80
Patel(2007) [33]	On/Off transient noise	Current , Voltage	40	100kHz	150-350 events	85-95
Gupta(2010) [20]	harmonic analysis	Voltage	94	1MHz	6 months	94

tinued further with EMI analysis by Gupta *et al.* [19]. These EMI based methods showed higher accuracies with shorter training periods. Voltage transient features on data rate above 40 kHz differ from home to home because these features are tied to the specific home's wiring. This suggests that 40kHz and above transients data might not be significant to introduce verifiable and salient signatures across homes. However, HF methods have shown to be more effective in detecting appliances more precisely. Large number of appliances can be recognized in the 10-40kHz ranges. Even though the reported training time varies from study to study [41], a pattern can be drawn that higher sampling rates result in more accurate models which can decrease the training time of the algorithms. Table 1.2 shows a few high frequency studies including the the variables they measured, number of appliances they targeted, sampling rate and the training duration, and the percentage accuracy they achieved.

1.3.2 Challenges for NILM in Residential Settings

One of the challenges in Low Frequency(LF) disaggregation is the lack of accessibility of 1 Hz data through smart meters in the United States. Even though most US installed smart-meters internally sample voltage and current between 1 Hz to 2 kHz, they do not make the data accessible at this rate. Smart-meters generally transmit this data to the utilities at a 15min interval which is accessible by the consumer a day later. Therefore, extra hardware is needed to capture output rate of 5 minutes down to 10 seconds of power data through smart-meters's Zigbee IEEE 802.15.4. On the one hand, installation of smart meters can enable disaggregation, but on the other hand, extra hardware is needed to extract this information. Armel *et al.* [7] recommends US utilities to adopt IEEE802.11 (WiFi) capability to be able to connect to the consumers HAN, eliminating the need for costly hardware equipment for accessing energy usage data.

Currently, most US residential solar powered units are using net metering, which provides a single signed number indicating the net energy generated or consumed. Therefore these smart meters do not report the load's power consumption separately whenever solar generation is active (i.e. day time). This creates an ambiguity in determining if the patterns in the power time-series data are caused by clouds passing above solar panels or if they are due to loads (appliances). Therefore if the solar unit is not instrumented, identifying loads in a net metered home with solar generation during day time is difficult. As the figure 1.4 shows, it is very difficult to detect the loads through the net-metered data.

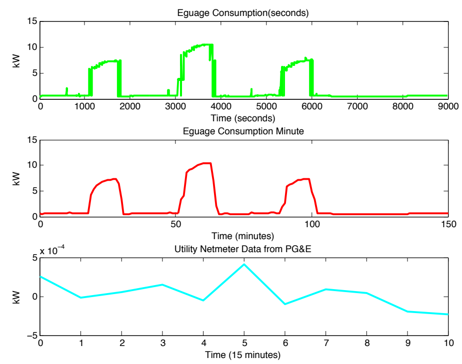


Figure 1.4: Top plot shows the consumption(kW) per second, middle plot shows consumption(kW) averaged per minute and the last plot shows netmeterd data

Gupta *et al.* [18] describes a method for extracting load power usage from net meters by calculating solar generation through meteorological data and the size of solar panels. However, predicting solar generation [11] using a variety of weather models is subject to noise, and errors.

For collecting HF data, additional hardware and installation can be burdensome for the consumers. The sheer sensitivity of this method to various noises of the power line is a limiting factor in this case since it increases the false positive instances. Therefore, the HF accuracies reported in studies should include true positive and espe-

Table 1.3: Low frequency sampling comparison

Algorithms	Description	Sampling Rate	Benefits	Drawbacks
Heuristic End-Use Load Profiler	Analysis large spikes in power draw	every 15 min	Inexpensive	1. Not accurate 2. can't monitor consumer electronics devices.
Concordia University(CU)	A decision tree via pattern recognition	every 16s	Accuracy of about 80%	1. Requires excessive training per appliance (one week) 2. Need to create appliance specific rules limit
Extension to CU method	Using real power data for events	every 16s	Good for big loads detect water heater,refrigerator, clothes washer, stove, clothes Dryer, Dishwasher, Heater	1. long training per appliance (2 weeks). 2. Only monitors big appliance usages
Baranksi method	Optical sensor on power meter	1 Hz	Simultaneous matching increases accuracy	May not be an optimal solution.

cially the false positive data as a metric that requires improvement.

Lack of availability of reliable HF datasets is another challenge. Some of the high resolution public datasets such as REDD HF dataset and BLUEDD used current sensors with 300Hz cut off [41] making their collected HF data above 300Hz ineffective. Recently, a new high resolution dataset called PLAID (Plug Level Appliance Identification Dataset) was introduced to collect individual plug load current and voltage at 30kHz [16]. However the metadata such as the model of the devices was not present in the dataset.

One of the challenges of NILM data-driven approaches is the "cold start" problem. Cold start means that the system cannot draw inferences because of insufficient data about load profile and it's behavior at the beginning. Most approaches in NILM are data driven and generalization of data-driven models consequently requires a significant amount of individual appliance labeled data and the underlying "ground truth".

Collecting this ground truth data requires additional hardware. For example, Schoofs *et al.* [35] introduced an automated electricity ANNOT system for labeling the electrical activity events. Kim *et al.* [25] also used ambient sensors which measure either sound or magnetic field to estimate the electricity usage of various devices which can also serve as a labeling system.

Some other researchers have examined model-driven approaches. For example, Dawei *et al.* [22] described a model-driven classification approach which used prior knowledge about internal circuitry to overcome this problem. Dawei *et al.* focuses on detecting Miscellaneous Electronic Loads (MELs) such as refrigerator, computer, space heater among others, which their use anticipated to grow by 78% by 2030. He tries to fit MELs into a taxonomy which includes Resistive Loads (toaster), Reactive predominant Loads (fan), Electronic loads with/without Power corrections (Laptop/projector), linear loads (LED), phase angle controlled loads (stapler), and complex structure (Microwave). However, the work on how to use this model in NILM cases need to be investigated more with real life datasets and experimental NILM deployment.

Disaggregation error rises as the number of the appliances increase. Both low and especially high-frequency methods suffer from external and internal noise. The external noise might be due to the variation of the utility voltage signal, and internal noise can be due to the appliance itself or other appliances. This noise might be more apparent in the case of using local generation as well. Characterizing the source of this noise could be the key to avoiding errors. As the number of the appliances increases the features of various appliances can override and identifying the appliances might become more difficult.

1.3.3 Future of NILM in Residential Settings

The expansion of public datasets, and smart meters with high resolution output for enabling disaggregation can be seen as a enabling factor in the performance of the NILM. Separate PV monitoring should be added to enable extraction of load data from the net metered data. Accuracies certainly can increase by data and more so via increase in availability of high resolution datasets. If the next generation of smart meters can provide the data to the consumer at a fast sampling rate via IEEE 802.11, NILM algorithms will be able to identify more appliances.

Chapter 2

Smart Energy Analytic Disaggregation System (SEADS)

Non-Intrusive Load Monitoring (NILM) is the process of identification of loads from an aggregate power interface using disaggregation algorithms. We introduce a new NILM system consisting of the required hardware and software capable of disaggregating appliance energy usage. One of the important challenges facing residential NILM stems from the low sampling rates provided through utility owned "smart meters", lack of datasets that capture details of energy waveforms including fundamental frequency harmonics, and cost effective tools to collect and analyze energy data.

Smart Meters are designed for billing Automated Meter Reading (AMR) [7]. AMR requires much less detailed data than is needed for NILM. SEADS' modifiable frameworks enables data acquisition at a variety of sampling rates and amplitude resolutions. SEADS also enables running disaggregation algorithms and classification on-board the processor of an embedded device, which reduces the need for data communication between the metering location and a remote server [6].

Researchers have examined a variety of methods for NILM since G. Hart [21] initially introduced the topic in detail in 1992. These algorithms have gradually improved the accuracy and the detection rate. Majority of NILM studies have emphasized the use of data from "Smart Meters" as this data is available at no cost, and commercially available more capable alternatives are expensive. Most researchers who worked on high frequency data in NILM have relied on commercially available costly DAQs and focused on developing better algorithms and software [17] [20]. Therefore, there is an essential need for NILM researchers to have access to a cost effective, customizable, scalable hardware tool which can provide the current and voltage information in real time. SEADS provides both the required hardware and software platform for a wide range of sampling frequency (1Hz-65kHz). SEADS' customizable data rate allows experimenting and selecting the sampling frequency which is needed for achieving the desired accuracy.

2.1 Related Work

Deployment of smart meters has provided an opportunity for collecting a large amount of energy data. However, the data collected through smart meters is generally provided every five to 15 minutes, for billing data, and is *not* made available to the consumers until the following day. Currently, there is also no standard, cost-effective devices for high frequency sampling data capture for the purpose of NILM. SEADS components price is less than 20 dollars which makes it an affordable unit for use in residential settings. High frequency sampling has been examined previously by Patel *et al.* [33] and Gupta *et al.* [20] among others. Some groups have built tools to disaggregate unique devices from energy data taken at low sampling rates. For example, Open Energy Monitor [3] has introduced an open source platform which can provide real-time energy data for disaggregation. Neurio [2] commercially introduced a device which disaggregates based on the 1 second data. Smappee [4] has also made a similar commercial product, but not many details are available on its internal data, operation or accuracy. A few groups have used smart meters for disaggregation. For example, Weiss *et al.* [39] have claimed success in disaggregation using data from ”smart meters”. They discuss ”smart meters” that can potentially be used for appliance detection and achieves a 87% accuracy. They use a specific ”smart meter” (in Switzerland) which provides 1 second data and most smart meters deployed in the U.S. are incapable of providing data at this rate. To the authors' knowledge SEADS is the only modular system with a modifiable sampling rate of 1-65kHz which is designed for the purpose of disaggregation. SEADS is designed to be a cost-effective system in a small form factor which can be used for detecting electrical activities at home. One of its research goals is to be a data acquisition system which aims at exploring the sampling rate, bit resolution required to achieve accurate disaggregation by means of a top-down approach. SEADS can be installed in a breaker panel and it can also internally compute the FFT of the current and voltage signal and use these to disaggregate appliances on-board in real-time.

Complete NILM systems have also been implemented before. For example, Ruzzelli *et al.* [34] described RECAP, which was the first real time recognition and profiling system for disaggregation under a single framework. RECAP used a commercial product, Episensor ZEM-30 ZigBee, as the energy monitor which was outputting power data every minute. By comparison, SEADS samples faster and provide more fine grained data for disaggregation.

Shenavar *et al.* [38] has also designed a NILM embedded system. However, no details on DAQ has been discussed. He points out that taking 100 samples a cycle should be enough. (5 kHz or 6 kHz)

Zeifman *et al.* [41] mentions one of the drawbacks of harmonic analysis as excessive training for each appliance before classification and monitoring. However, in our preliminary result, we observe salient features that are repetitive and expect no obstacles in training.

Shaw *et. al.* [37] discusses design and implementation of hardware and software tools for nonintrusive electrical load monitoring as well. He reviews, techniques for transient event detection and steady state for monitoring the power consumption of varying loads (e.g., variable speed drives). SEAD System provides a platform for all devices disaggregation including both varying and static loads.

NILM software systems and data processing pipelines are currently under development for disaggregation. Barta *et al.* [8] have developed a toolkit called NILMTK for processing and analysis of all publicly available low frequency data sets. This toolkit addresses the problem of scarcity of an established code base for the developers. The

NILMTK platform promises to accelerate and streamline algorithm development for low frequency data. SEADS platform can be used as a complementary tool to NILMTK for providing data because it is modular and it can provide both low and high frequency sampled data.

Various studies has been preformed on the harmonics. For example, Dawei *et al.* [23] indicated since no harmonics higher than 11th harmonics are needed, a sampling frequency of 1.92 kHz or 3.84 kHz is desired to balance the accuracy and cost. He further suggested one minute of transient waveform is necessary to ensure a robust load identification. Initial testing with SEAD indicates there is no salient and significant harmonics beyond 50th harmonics for most home appliances which can be used for the purpose of disaggregation. MIT's L. Norford and S. Leeb [36] previously examined harmonics and spectral envelope. They found a correlation between 5th and 7th harmonics and real power and described a variety of ways to analyze waveforms. Laughman [29] has studied power signature transients for variable speed drive appliances and used 8kHz sampling to compute the spectral envelope to summarize the time-varying harmonic content. Lee *et. al.* [30] described a method for measuring variable speed drives energy based on their harmonic content. Table 1.2 shows other high frequency NILM studies and their reported accuracy and training time.

2.2 SEAD System Design

Real-time disaggregation of appliances can serve a variety of purposes such as automation, real-time demand response, or consumer feedback. SEADS intention is to serve all of the aforementioned applications. SEADS has been written with two applications in mind. One version is built for the research and the other one is built for consumers. The research version is a data acquisition system with modifiable sampling rate and amplitude resolution, which provides data through USB. The consumer version is similar, except it uses an extra network stack for transmitting *disaggregation results* and *unrecognizable signatures* to the server.

As Figure 2.1 shows the SEADS consumer version consists of four abstract layers. The hardware layer captures data through sensors and processes the data, and applies disaggregation algorithms and sends only the important data to a server. The server layer stores the data and can apply further analysis on the data and provides the resulting information to the outside world through the Interface layer's API. The application layer contains user applications such as data visualization, support for demand response systems, and automation.

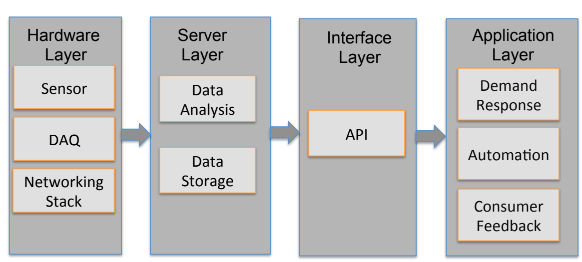


Figure 2.1: SEADS Design Flow Chart

SEADS monitors current and voltage using current transformers and voltage sensors. The data from sampling current and voltage sensors are sent to a processor which is capable of preforming disaggregation on-board or carried over to a server where the data will be processed. Signatures are extracted from a group of appliances. Signatures from the unknown waveforms are matched against the known devices in the server. The candidate matches are subsequently evaluated for correctness of the match using K-Nearest Neighbors (k-NN). The result of the characterization can be pushed over to the SEAD to reduce the need for server call backs. If there is an error in classification detected by the user, the data can also be carried over to the server and a modified algorithm will be deployed to the device. This method of classification on board will reduce the overhead to the server and makes NILM practical. Furthermore, SEADS can provide the RMS value of current and voltage every cycle at 60Hz to every one second. Therefore, SEADS is capable of producing both low and high frequencies at the same time. This enables adoption of hybrid methods that can use both high and low frequencies to be preformed to disaggregate the data. SEADS is also capable of reporting power factor for measuring power quality.

Previously an open source software toolkit NILMTK by Barta *et al.* [8] has been introduced. Currently this toolkit only supports low frequency data disaggregation. None the less NILMTK addresses an important problem and that's sparsity of data and metadata that has been collected. SEADS provide a common platform for the research community to get together and share their data that gets collected by a common tool and format to establish a versatile event based dataset which can be used for disaggregation. The expansion of public datasets, and smart meters with high resolution output for enabling disaggregation can be seen as an enabling factor in the performance of the NILM. One of the challenges of NILM data-driven approaches is the "cold start" problem. Cold start means that the system cannot draw inferences because of insufficient data about load profile and its behavior at the beginning. With a large dataset of events researchers are able to create algorithms needed to overcome the cold start problem.

2.3 Hardware

The SEADS hardware was designed to enable the acquisition of data necessary for the development of high frequency load-disaggregation techniques. This hardware additionally provides a cost effective solution to monitor appliance energy consumption. To ensure that the system is as extensible as possible, modularity exists throughout the system and extends to the hardware implementation. This hardware modularity allows for flexibility in data acquisition bandwidth and the bit rate. Fig. 2.2 shows the data flow through the SEADS Hardware.

The SEADS hardware has two designs:

1. SEADS Research: The research version includes an analog front end, a high-bandwidth data acquisition board and has a USB module which provides power to the board and communicates to the Raspberry Pi or the PC.

2. SEADS Consumer: The consumer version is comprised of an analog front-end, a

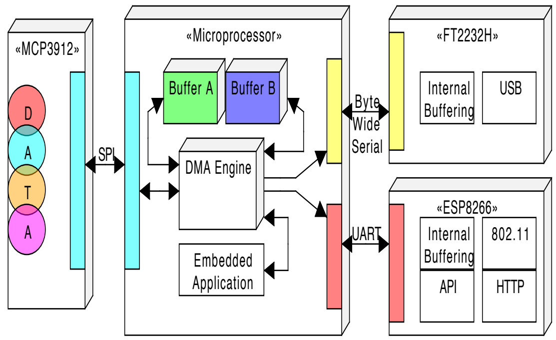


Figure 2.2: Data-Flow Through the SEADS Hardware

high-bandwidth data acquisition board, an IEEE 802.11 module, and with integrated AC/DC power supply for standalone operation.

Figure 2.3 shows the Analog Front-End for standalone operation. Microchip MCP3912 A/D converter is used to provide programmable data rate. This A/D converter provides simultaneous sampling of four channels of data, giving 24-bits of potential accuracy, and supporting maximum sampling rate of 65kHz. Differential sampling from A/D converter helps in reducing the serial physical communication layers like USB, or SPI from influencing sampled data due to ground bounce or switching noise. Each current transformer input has a first-order anti-aliasing filter.

2.3.1 SEADS Research Hardware

SEADS research hardware (Fig. 2.4) is a high-bandwidth USB acquisition board which utilizes a 32 bit PIC microprocessor, and an FTDI (FT2232H) USB FIFO. This board is designed to be able to collect data directly into a PC, streamlining the

Figure 2.3: SEADS Analog Front-End

data analysis and algorithm development. The PIC is chosen for its flexible DMA engine, and sizable amount of RAM, which allows continuous acquisition of data. The processor uses SPI clock rate of 20 MHz.

2.3.2 SEADS Consumer Hardware

The SEADS Consumer Hardware (Fig. 4.4) is a *IEEE 802.11* connected acquisition board. SEADS Consumer Hardware functionality is similar to the *SEADS Research Hardware* except an added a networking stack. ESP8266 has an embedded *IEEE802.11* radio and HTTP stack. Combined with a *RESTful API*, the board can provide RMS current and voltage data along with disaggregated loads.

Figure 2.4: SEADS Reseach Hardware

Chapter 3

Experimentation

Residential loads can be divided into four generic types: resistive loads (toaster,lamp), inductive loads (fans, motors), and loads with solid state switching (computer) and complex loads which are combined resistive, inductive or solid state switching components (refrigerator) [23] [21]. Purely resistive loads generate sinusoidal current waves with insignificant harmonics while inductive loads or appliances with Switching Mode Power Supply can generate significant noise on the fundamental waveform. These appliances can be detected using high frequency methods via steady state or switching transient features.

3.1 Experimentation Results

The SEADS dynamic and modifiable framework allows integration of most NILM methodologies mentioned in Figure 3.1 [32] since it provides both low and high frequency data.

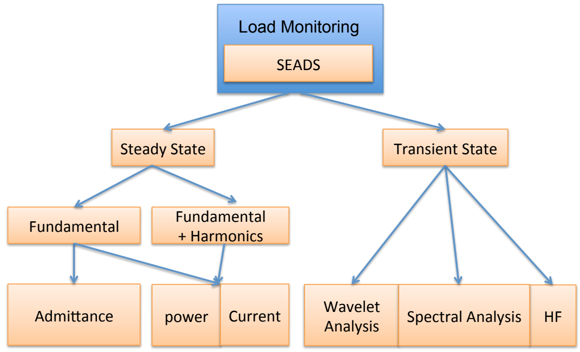


Figure 3.1: SEADS can implement most methods mentioned by [32]

An experiment has been conducted to demonstrate SEADS signatures at 65kHz sampling rate while measuring 1 second data using eGauge at the same time [5]. Figure 3.2 shows a chronological event scenario which has been captured at a kitchen panel. Appliances are turned on for a limited time and their signature has been recorded using both eGauge and a SEAD device. A current transformer has been installed on the kitchen panel to record the high frequency current data via a SEAD device. As Figure 3.2 depicts, and based on G. Hart's [21] "one-at-a-time assumption" many devices can be identified using the 1 second data. However, in real life scenarios appliances can be turned on or off at any time or change states together, and variable loads such as variable speed drives make device identification difficult. Therefore, high frequency data can help disaggregation algorithms by providing a more fine grained epic and unique signatures.

Figure 3.3 shows a microwave normalized current waveform and FFT. Significant noise is observable on the fundamental waveform on the time domain plot.

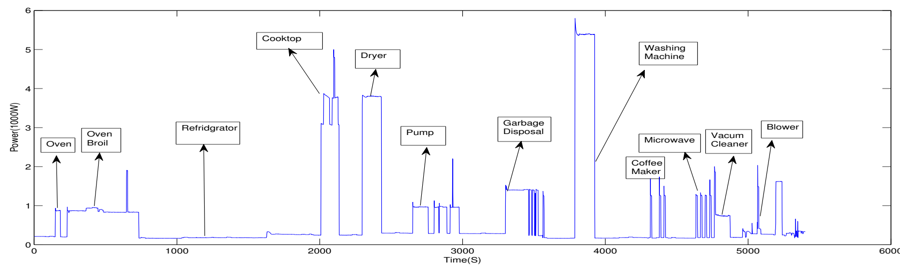


Figure 3.2: Appliances power signatures captured at 1Hz through eGauge

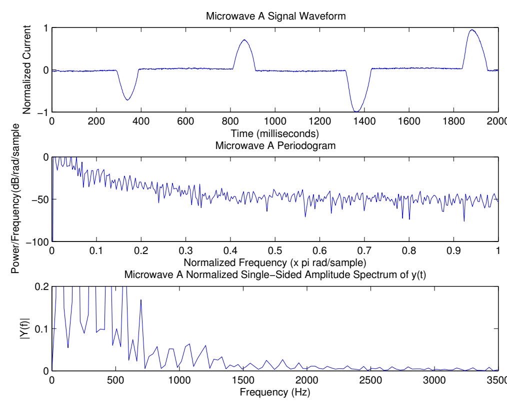


Figure 3.3: Microwave normalized signature time domain, periodogram and normalized FFT captured via SEADS

However, from the frequency plot, one can observe there is a significant harmonics amplitude decrease after 1300Hz such that the rest of the harmonics after this frequency are buried under the noise floor.

Figure 3.4 shows a blower signature characteristics in both time and frequency domain. Inrush current can also be used as a feature here. Furthermore, the 2nd, 3rd, 5th, 7th and 9th have a significant amplitude on the fundamental frequency waveform. The frequency plot shows a significant harmonics decrease after 600Hz.

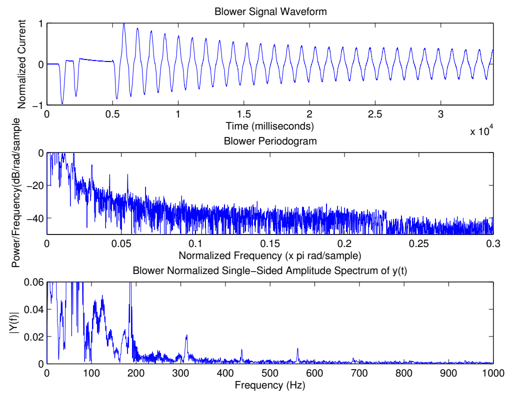


Figure 3.4: Blower normalized signature time domain, periodogram and normalized FFT captured via SEADS

Figure 3.5 shows the signature of a vacuum cleaner which is similar to the blower Figure 3.4 in the time domain because they both use a motor. However, in the frequency domain vacuum cleaner's frequency content diminishes after the third harmonic. Therefore, the amplitude of the harmonics is a feature for differentiating it from blower or the pump.

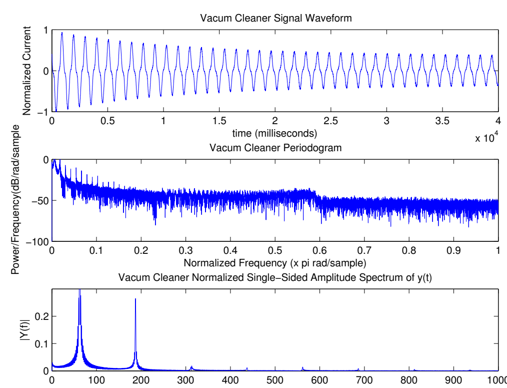


Figure 3.5: Vacum cleaner normalized signature time domain, periodogram and normalized FFT captured via SEADS

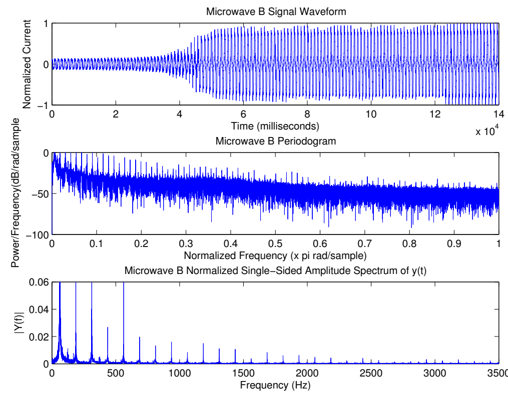


Figure 3.6: Microwave B normalized signature time domain, periodogram and normalized FFT captured via SEADS

Figure 3.6 shows signature of another microwave (Microwave B) which is different from the one shown in the Figures 3.3 and 3.2. The harmonic content of the signal attenuates after 1500Hz and gets buried under the noise floor after 3500Hz.

3.2 Sampling Rate

Various studies have suggested sampling rates ranging from a sample per hour to a sample every microsecond, which is 10 orders of magnitude range. Table 1.2 shows some of the high frequency methods with their acquainted accuracy. Studies suggest sampling rate of 4-8kHz [6, 7] might be sufficient. From our finding, we conclude that sampling *above* the frequencies of 8kHz (4kHz bandwidth) for a typical residential unit does not provide a significant accuracy gain, especially on the current harmonics because the harmonics will be buried under the noise floor in higher frequencies. We also collected 50 appliances' voltage and current harmonic signature and used a tree based classifier, and found the fundamental harmonics 3rd, 11th, 17th, 1st, 27th, and 33th, in order are important harmonics for device identification. As in our test, we were able to classify appliances with 72% accuracy, using only this 6 harmonics. Using a combination of all of the first 50th harmonics, we were able to identify appliances with 92% accuracy. These results also suggest that sampling above 8kHz might not be required.

Figure 3.7 shows the that refrigerator has significant detectable harmonics.

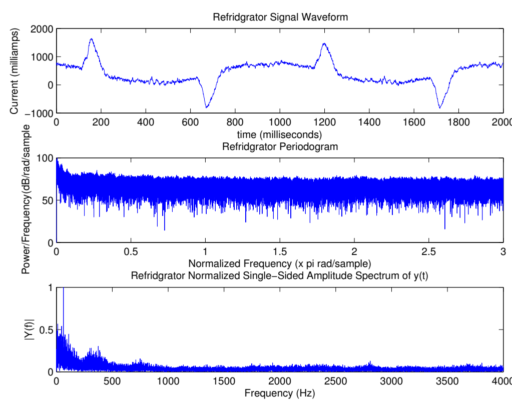


Figure 3.7: Refridgrator

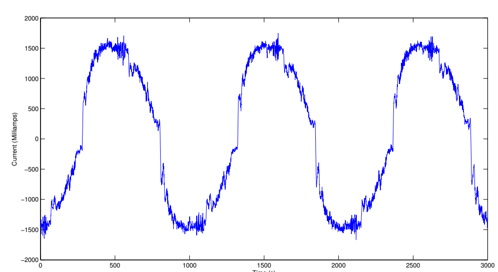


Figure 3.8: Microwave Kitchen

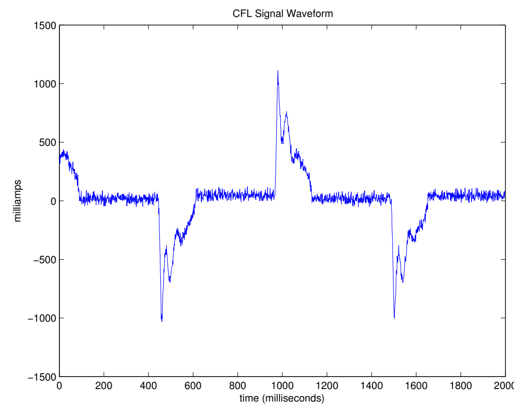


Figure 3.9: CFL Waveform

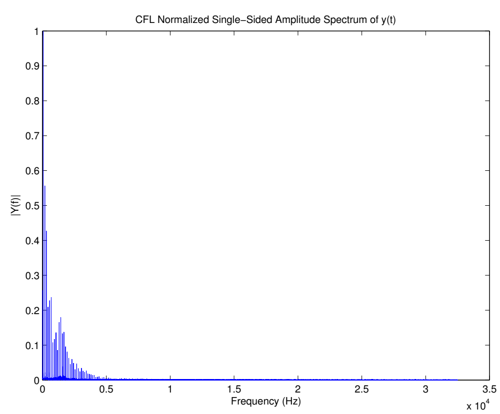


Figure 3.10: CFL Normalized FFT

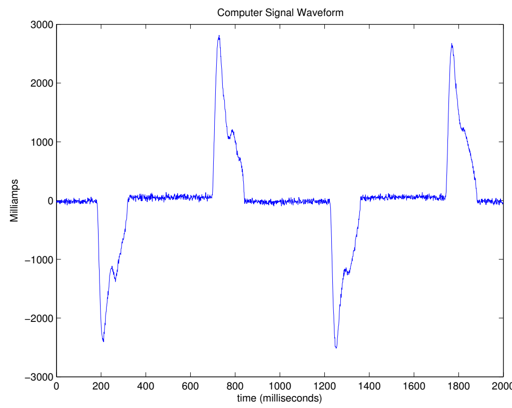


Figure 3.11: Computer Waveform

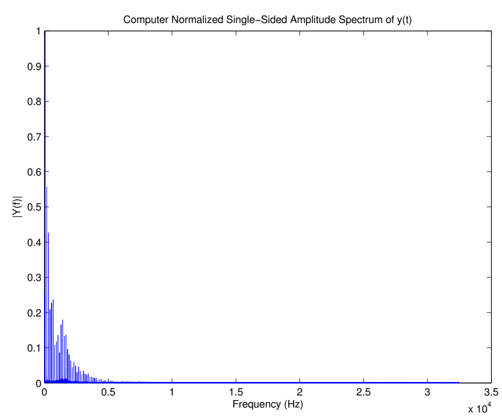


Figure 3.12: Computer Normalized FFT

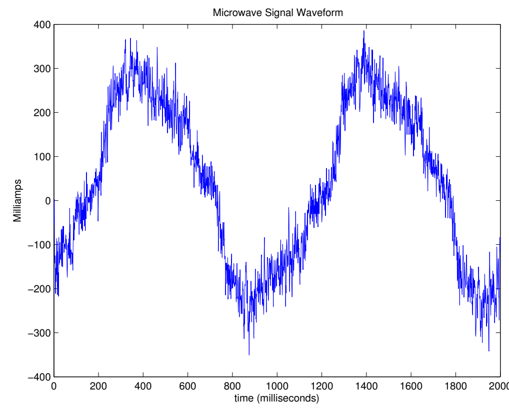


Figure 3.13: Microwave Waveform

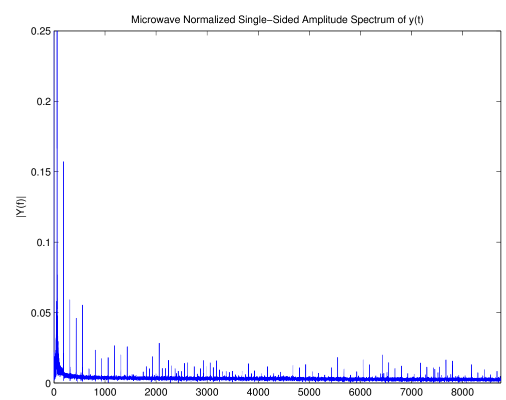


Figure 3.14: Microwave Norm FFT

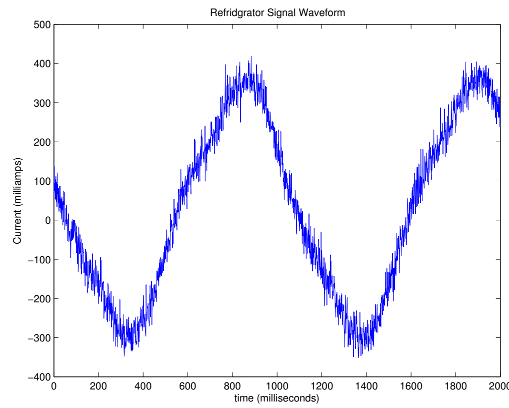


Figure 3.15: Refridgerator Waveform

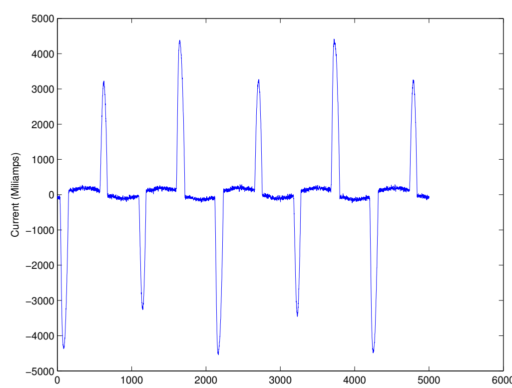


Figure 3.16: Kitchen Microwave

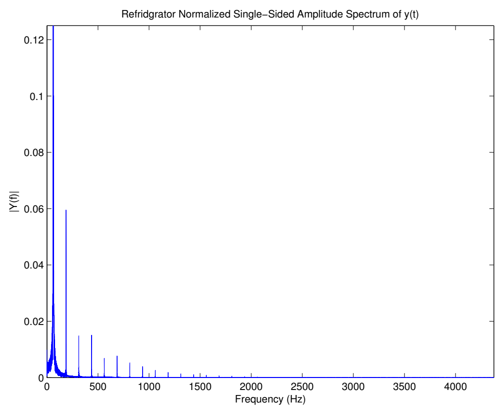


Figure 3.17: Refridgrator Norm FFT

Chapter 4

SEADS as a part of an Energy Managment System(EMS)

4.1 Introduction

Effective home energy management requires data on the current power consumption of devices in the home. Individually monitoring every appliance is costly and inconvenient. Non-Intrusive Load Monitoring (NILM) promises to provide individual electrical load information from aggregate power measurements. Application of NILM in residential settings has been constrained by the data provided by utility billing smart meters. Current utility billing smart meters do not deliver data that supports quantifying the harmonic content in the 60 Hz waveforms. Research in NILM shown the need for a low-cost sensor system to collect energy data with fast sampling and significant precision to demonstrate actual data requirements. Implementation of cost-effective NILM in a residential consumer context requires real-time processing of this data to identify individual loads. This chapter describes a system providing a powerful and flexible platform, supporting user configuration of sampling rates and amplitude resolution up to 65 kHz and up to 24 bits respectively. The internal processor is also capable of running NILM algorithms in real time on the sampled measurements. Using this prototype, real time load identification can be provided to the consumer for control, visualization, feedback, and demand response implications.

Consumers need a cost-effective Energy Management System (EMS) for their homes, to fill a variety of needs. Management of loads supports conservation efforts, and can provide warning of unusual or unwanted energy use. When the local utility implements Time-of-Use (ToU) pricing, an EMS is essential in aiding the effective response of the consumer.

Central to EMS is real-time information on what devices at any moment are on and what energy they are consuming. Nonintrusive Load Monitoring (NILM) makes possible the use of one (or a few) measurements of energy at an electrical panel, and from disaggregation of those measurements, consumption by individual devices is determined.

The energy use data provided by current utility smart meters, as deployed widely in the US, provide data that is sparsely sampled in time (i.e. every 15 min). This data is not adequate for quantifying harmonics of the 60 Hz, and this information on the higher harmonics can greatly improve performance of NILM [6, 7]. Consumer concerns regarding privacy argue against utilities capturing data that can be used to identify individual loads on the customer side of the meter [31]. Consumer deployment of electrical energy monitoring devices to implement NILM also suffer from their low sampling frequency data interfaces, which limits the amount of data that must be managed or communicated, but which also cripples NILM [6] [7].

In a growing number of utilities, consumers are faced with ToU pricing, in an attempt by utilities and the PUCs to implement load shifting to reduce peak load and to respond to the variability of energy supply with a growing use of intermittent renewable sources. Utilities employ a variety of rate structures, from fixed rates with tiers, to scheduled variable pricing with tiers, or more dynamic pricing such as critical peak pricing or market pricing. If a consumer had real-time information of electrical energy use at their home, with identification of use by individual appliances, and with this information immediately available on a smart phone or other personal display, then the consumer could be guided in management of their appliances in response to changes in energy pricing, or to a potential energy shortage. For example, if via NILM, the consumer is made aware that their clothes dryer is running and that the current price of energy is very high, they could defer that use until the price drops.

Consumers have some flexibility in their timing of energy use; some are essential at the moment, others can be run later when energy costs are less. We divide loads into three categories [1] in terms of flexibility of usage as shown in Figure 4.1:

- *Deferrable loads* [15]: Appliances which can be rescheduled to run at different times such as dishwasher, laundry washer, dryer, electric heating, electric water

[1] Some of these categorizations depend on consumer preferences, for example, some consumers might consider coffee maker or microwave as non-deferrable loads.

heater, electric vehicle charging, electric oven, coffee maker, microwave, etc.

- *Marginally deferrable loads*: Appliances which deferring their schedule can cause significant inconvenience to the consumers such as microwave, electric range, and electric HVAC on a hot/cold day.

- *Non-deferrable loads (Critical Loads)*: Appliances that their schedule cannot be altered or deferred such as refrigerator, modem, router, medical equipment such as CPAP etc.

Use of NILM in a home with an EMS, and with suitably equipped appliances, makes possible automatic shedding of nonessential loads during times of peak prices. In the suite of prototype devices in our project is a *plug load monitor* with an internal relay that can be remotely operated via WiFi from the central EMS controller. A *plug load monitor* can give real time power consumption, voltage and current information at high sampling rates for the device at that outlet(Figure 4.3). The data can be used to evaluate the behavior of an appliance or even detect an appliances possible failure [13]. In addition, the data from a plug monitor can be used to help NILM disambiguate devices. For example, a refrigerator's data from a plug monitor will allow that refrigerator data (which is continually running) to be subtracted from the aggregate data, and this simplifies the task of NILM in training and recognizing other appliances.

Use of an EMS to manage generation and loads when the residence operates as a microgrid, with its own (renewable and / or fossil fuel) generation, and potentially battery storage, adds requirements that can be met by the EMS. This is most challenging when the micro grid is disconnected from the grid, operating as an island. Details of the EMS are beyond the scope of this chapter. However, the data obtained by the prototype instruments described here, and the NILM resulting from that data, are also key to the cost-effective EMS for the microgrid, as depicted in Figure 4.2.

At the center of the proposed EMS is a smart, cost-effective circuit monitor prototype with data acquisition (DAQ) and with a processor for realtime algorithm implementation (Figure 4.4).

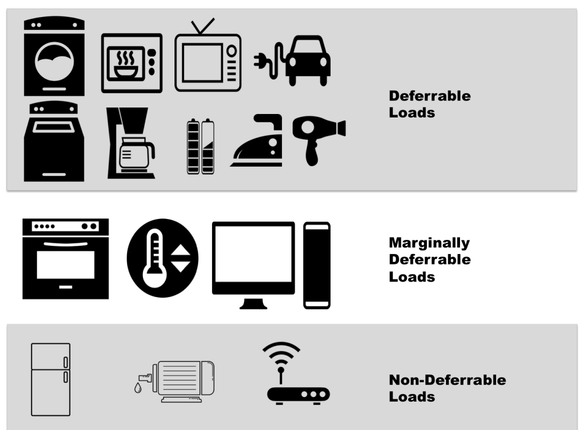


Figure 4.1: Load schedule flexibility categorization

4.2 System Architecture

Our NILM system architecture is depicted in Figure 2.1. The system contains four abstraction layers. The hardware layer is designed to sense and process signals such as voltage or current. Capturing the current signal is achieved using current transformers, and the current signals are digitized via a 24 bit Analog to Digital (A/D) converter

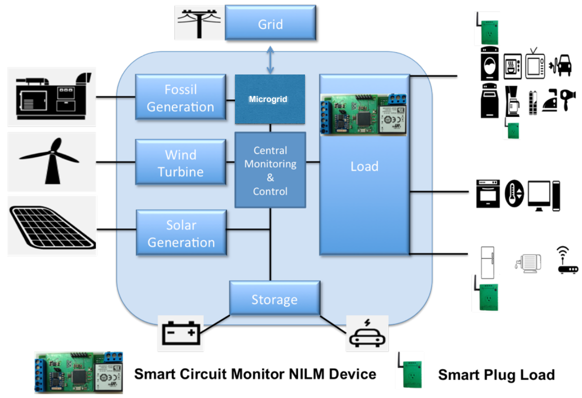


Figure 4.2: Instrumentation of a residential microgrid

Figure 4.3: IEEE 802.11 connected plug load capable of meausring power information and shedding loads

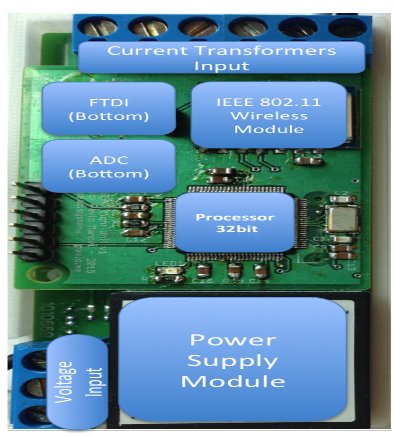


Figure 4.4: Circuit monitor is part of the proposed NILM system which can implement realtime disaggregation on board

with an effective sampling rate of 65 kHz. (Lower sampling rates are obtained by digitally anti-aliasing and down sampling.) Processing includes running the Fast Fourier Transforms (FFTs) and also running disaggregation algorithms, performed on-board via a 32 bit microprocessor. When the algorithms are successful in recognizing devices based on their known signatures, the results of the recognition (including confidence and time stamps) are communicated to the server. Classification methods used in the local microprocessor include k-Nearest Neighbors (k-NN) algorithms. If local recognition is not successful, the data are sent to the server for further processing, and can also be sent to the consumer's smart phone for manual classification. Other values reported to the server include the RMS value of current and voltage along with the power factor. These can be computed as frequently as once each cycle of the 60 Hz. The processing capabilities of the hardware layer are such that signals at a range of sampling rates can be created and be processed simultaneously. The server layer supports further analysis for unrecognized devices, and provides information to the outside world (the application layer) through the interface layer, whose Application Programming Interface (API) supports outside applications (i.e. the EMS) which can include automation, visualization, and demand response.

4.3 Discussion

The experiment shown here demonstrates the capability of the system, and what it offers over devices which report power at one second intervals. Three devices: a vacuum cleaner, a leaf blower, and a microwave, with each consuming the same amount of power, look indistinguishable when their power is sampled at the rate of 1 Hz. When monitored by our prototype, as shown in Figures 4.5, 3.4, 3.3 they are very different when the frequency content of the current waveforms is analyzed.

Various methodologies can be used to automatically identify these devices, such as harmonic analysis, wavelet analysis, spectral analysis and other high frequency methods. However, in terms of practicality, harmonic analysis with classification methods such as k-NN, or tree based classifications seem to be sufficient [36].

To the authors' knowledge the system described in this chapter is the only modular system with a modifiable sampling rate of 1-65 kHz which is designed for the purpose of energy disaggregation [24]. The system has been designed to be cost-effective in a small form factor which can be used for detecting electrical activities at home. One of its research goals is to be a data acquisition system which aims at exploring the sampling rate and bit amplitude resolution required to achieve accurate disaggregation using a top-down approach.

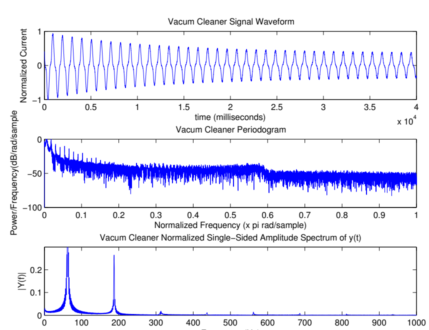


Figure 4.5: Vacuum cleaner normalized signature time domain, periodogram and normalized FFT captured by the system

Chapter 5

Decision Support System for a Residential Microgrid

An **Intelligent Energy Management System (IEMS)**, a Decision Support System (DSS) for operation and control of a residential microgrid, is introduced in this chapter. Complete design and implementation of such an IEMS DSS is clearly beyond the scope of this work. Here we develop an architecture for this DSS and specify component modules, and provide some details on roles and tasks associated with the various modules. Then, via simulation, we demonstrate the potential economic and operational value of such a DSS in both grid-tied and island mode.

The IEMS (DSS) receives inputs from SEADS about details of the electrical loads, and from other sensing devices it receives available energy from local solar/wind generation, fossil-fueled local generation, state of batteries and thermal storage, state of the grid connection, ambient conditions, weather prediction, etc. With this information and by rules it contains, implemented as a decision tree, the IEMS is able to autonomously respond to changing conditions including loss of grid connection, changes in loads, etc. When the user engages with the IEMS, its decision tree output become recommendations to the user, and the IEMS will allow users to override the autonomous actions. To illustrate the role of the IEMS, several scenarios are simulated showing the responses implemented by the IEMS to changing conditions. For example, with the IEMS in autonomous mode, when the grid connection is lost, the IEMS will follow rules via the decision tree and shed loads as appropriate (least-essential first) to maximize the time the micro grid can operate without starting the fossil-fueled local generation (and thus minimize fossil-fuel consumption and pollution.)

An IEMS is essential for the effective and economical operation of a microgrid in island mode. It is the agent for automatically implementing actions desired by the user in all situations that are covered by the decision tree. When the microgrid is connected to the local utility via its distribution grid, these decisions have economic impacts, and can have significant impact on the consumers energy bill from the utility. When in an island mode, the operation of the IEMS must result in a local balance of sources and loads.

5.1 Microgrid

A Microgrid is a low voltage (e.g. 120/240 volts) distribution energy system with its own local energy generation, such as solar and wind, and fossil-fuel generator (mechanical or fuel-cell), and potentially with electrical energy (and thermal energy) storage. A micro-grid does not require connection to the power grid to serve its local loads, but grid connection is usually more economical than operation without grid connection: island mode.

The Consortium for Electric Reliability Technology Solutions (CERTS) defines the microgrid concept *as an aggregation of loads and microsources which are operating as a single system with the majority of the microsources providing the required flexibility. This flexibility and control enables a microgrid to present itself to the bulk power system as a single unit while meeting its local needs for reliability and security* [28].

A balance between generation and load is critical for the operation of the microgrid, since microgrids can be either connected to the grid or be disconnected from the grid. Two general conditions are discussed: grid connected and islanded. For these two different modes of operations there are four scenarios that are needed to be considered.

1. Grid-connected:

    (a) Local generation exceeds load: If the renewable generation exceeded the load requirements of the micro grid, the distribution grid can absorb the excess energy, thereby acting as the storage component much like batteries and/or thermal storage.

    (b) Load exceeds generation (Fig. 5.2): If the load exceeds local generation in grid-connected mode, the grid provides the required electricity. If the utility uses peak-time pricing, it might be financially beneficial to shed laxity loads to balance generation and load. Battery and thermal storage can be used for providing further flexibility.

2. Islanded (off-grid):

   (a) Generation exceeds load (Fig. 5.4): If the generation exceeds the load in the island mode, the excess energy may be absorbed by charging attached storage batteries, electric vehicle batteries, etc, or by adding load. Loads with thermal storage (e.g. electric water heater) can absorb excess generation by increasing the temperature of the water in them.

   (b) Load exceeds generation (Fig. 5.3): If the load exceeds generation in the island mode, the loads are shed according to their laxity. Least essential loads are shed first, but defining this order is a user preference that may change with situations and local conditions. If load shedding of loads with laxity does not achieve balance, electrical energy can be drawn from the batteries. If additional generation is required, it may be added by activating the fossil-fuel generation.

5.2 Inteligent Energy Management System

The variability of renewable energy generation presents a continuous challenge for a micro grid in island mode, when it must dynamically manage generation, storage

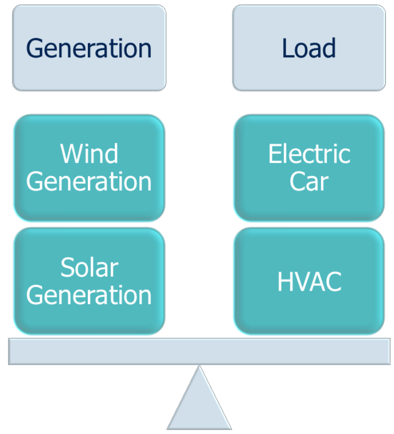


Figure 5.1: Grid connected when load matches generations

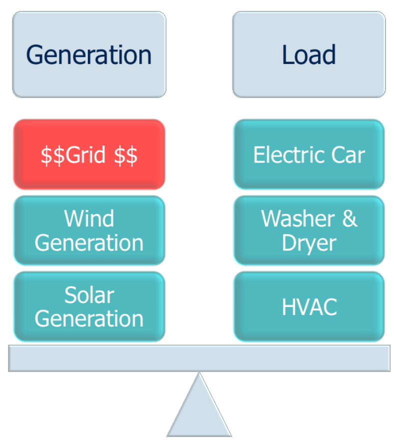


Figure 5.2: Grid connected when load exceeds generations

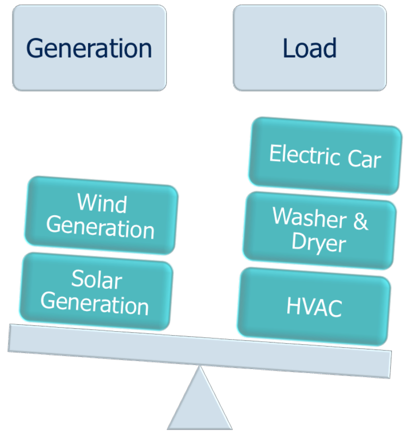


Figure 5.3: Island mode when load exceeds generations

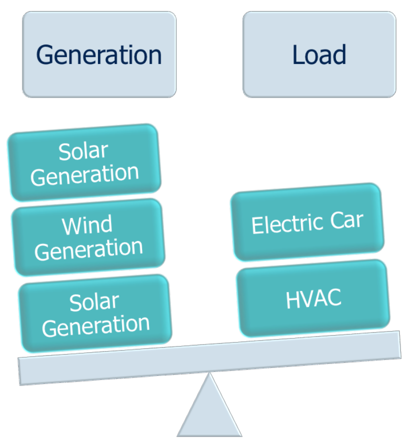


Figure 5.4: Island mode when generation exceeds load

and loads to maintain voltage and frequency in the microgrid. Automation of this management is achieved via that Intelligent Energy Management System(IEMS). It provides real-time control of the micro grid, and engages the consumer in making decisions and changing rules under unexpected conditions, operation as a decision support system for the consumer. The Table 5.1 lists requirements for the IEMS DSS, in both On-Grid and Island modes. Note that many of the tasks of the IEMS DSS in On-Grid mode are necessary to be able to respond immediately and correctly to a loss of grid connection, going to Island mode.

The IEMS utilizes information on the load, energy usage, and the cost of maintaining the system to ensure resources are consumed intelligently. The IEMS should learn and become "smarter" over time thus becoming better-matched to user behavior pattern preferences. Fig. 5.5 shows the components of the proposed Intelligent EMS system.

5.2.1 IEMS Functional Modules

The IEMS is a real-time decision support system to engage a user / consumer in the operation, management and control of a microgrid. The IEMS has four domains that make up this human/machine system: 1) User, 2) Energy loads served in the micro grid, 3) energy sources, i.e. Generation, and 4) Energy storage. These are the horizontal rows in the IEMS diagram 5.5.

For each domain there are functional modules that implement functions related primarily to that domain. Many of these functional modules interact, and the IEMS

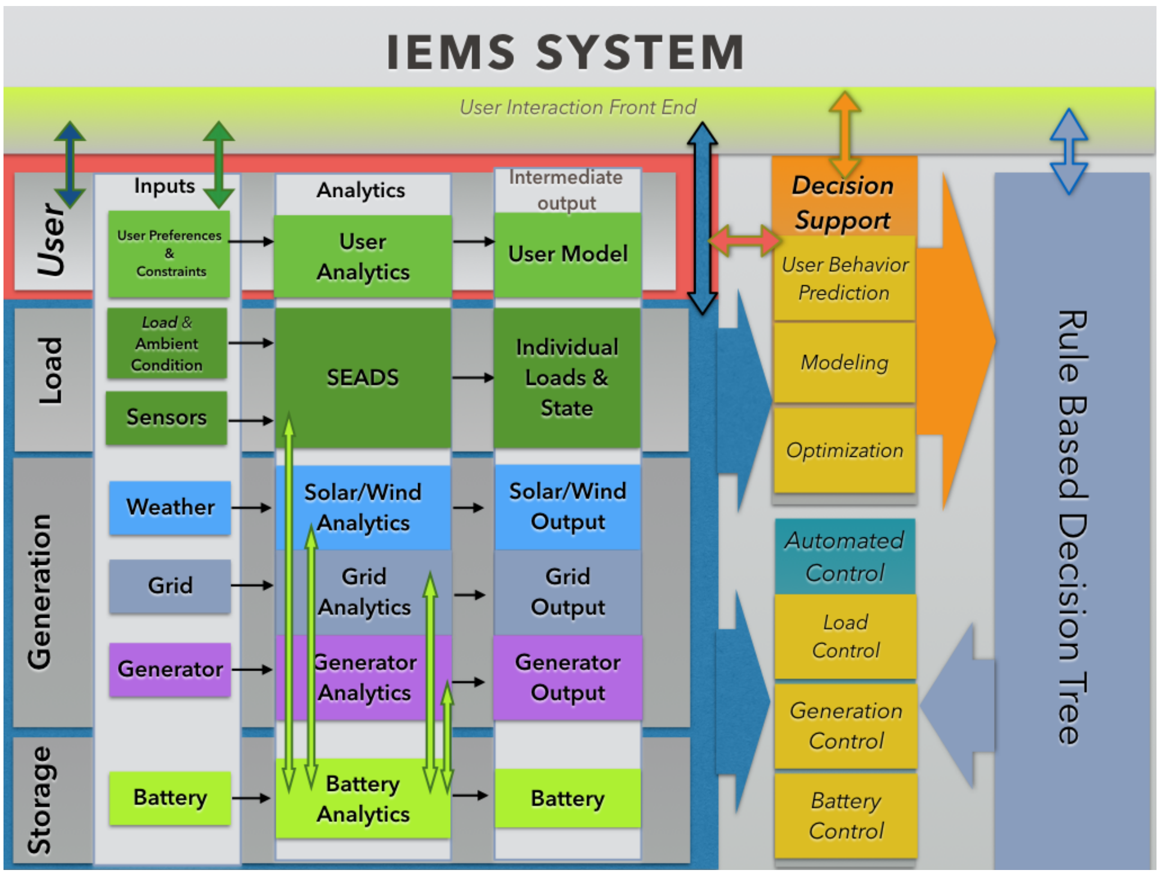


Figure 5.5: IEMS

Table 5.1: Requirements for the IEMS DSS

On Grid	Off Grid
• Continuously monitors all loads and output of renewable generation, and state of energy storage and presents this information to the consumer on demand. • Predicts from load characteristics and usage patterns when current loads will complete their cycle (e.g. dishwasher, clothes washer) • Determines costs of individual loads for energy from utility, with TOU, Tiered and Critical Peak pricing. • Provides recommendations to the consumer of possible energy saving by better load management (e.g. by disconnecting devices using significant stand-by power.) • Controls loads appropriately equipped dispatchable loads (i.e. loads with laxity) to maintain desired conditions while minimizing costs. (e.g. HVAC, electric water heater, various water pumps) • Alerts consumer when the consumer has started a dispatchable load at a time when its operation will be at higher electrical rates than are available at other times. • Predicts from local weather conditions and forecasts the output of renewable energy generation. • Prepares system for potential island operation, based on weather forecast or input from the consumer, to have batteries charged, pending dispatchable loads run, etc.	• Controls loads, energy storage and local generation to maintain microgrid operation, balancing generation and load. • Manages storage based on inputs from weather and forecast, from consumer input and information from the utility to predict the expected duration of the island operation (grid outage). • Determines [1] if available renewable generation is exceeding loads (including that from charging batteries and thermal storage) and alerts consumer, suggesting other dispatchable loads that might be run to exploit this excess. (Example: Now is a good time to finish the drying of clothes or a to run the load of dishes in the dishwasher.) • Determines when it necessary or desirable to start operation of the fossil-fuel backup generation. • Alerts consumer to provide input to the IEMS on immediate conditions and on special needs that may influence scheduling of dispatchable loads. • Alerts user when it detects (possibly inadvertent and ill-advised) starting of dispatchable loads by the consumer. • Estimates available fuel available for fossil-fuel generator (from data on its energy production) and forecasts the energy still available from that source without refueling, and provides recommendations on load shedding and management to prolong this energy production.

must support user interaction and input to many of them.

The following describes the IEMS domains:

1. **User:** The user choices examples are the desired temperature range/limit of the HVAC thermostat, and the temperature of the water heater.

   Example of the user preferences scenarios include the user:

   - Setting of the HVAC thermostat to a certain temperature during the day and certain temperature during the night.
   - Adding an appliances to the critical loads list (e.g. refrigerator, dehumidifier, network-enabling devices such as modem, router, or etc).
   - Changing the temperature range of the water heater.
   - Identifying certain loads (e.g. washer and dryer) as deferrable loads.

   Preference limits are enforced by the IEMS as constraints. Thus algorithms will only provide results or recommendations that meet the given user constraints. For example, if a user wants the refrigerator to be always running, this is considered as a hard constraint and the refrigerator is not a sheddable load (i.e. no laxity). The user preferences and constraints are entered into the system through a **User Interaction Front End**. There is significant information is presented to the user through the **Decision Support**. For example, in the case of an outage, the IEMS will show the user the amount of energy he/she can save by deferring the dishwasher to a later time. User preferences and constraints are fed to the user analytics module. User analytics collect, process and compare all the user constraints to ensure these settings are coherent and consistent. Users can enter exceptions to these rules, overriding them in case of an unusual event, such as family gathering (when the number of people in the household is more than usual).

A typical (default) user behavior profile is set at the default when the user initiates use of the system. The default profile will have rules for a wide range of situations. The IEMS learns over time more information about the user and adapts, changing its rules accordingly.

The user information processed through the user analytic section generates a model of the user's preferences and patterns of use. This model interacts with the decision support system and will contribute to the user behavior prediction and modeling.

2. **Load:** The load functional module gets the data from *high frequency* sampling of current/ voltage sensors, and from ambient conditions obtained from the temperature sensors and load initial condition. Other load functional module input data include the *low frequency* (1 second) power aggregate data from SEADS low frequency measurement (SEADS provide both low and high frequency measurement). SEADS is the system described in chapters 3 and 4 has an important role in the IEMS. SEADS, provide the individual load information for the IEMS system. It uses NILM methods to disaggregate loads. SEADS outputs are individual loads, both energy usage and state. The user load patterns can be learned through statistical analysis of individual load data that is gathered via SEADS.

3. **Generation:** The generation block inputs are weather data (e.g. wind speed, temperature, weather condition, solar radiation), grid data (e.g. price of electricity, power consumption, state of grid connection), and generator information (e.g. the amount of fuel, cost).

   - **Weather:** Weather data is fed to the Solar/Wind analysis module. Its role is to predict future output of renewable generation. The weather analysis is essential in preparing the user and system for the possible disruption in service (i.e. from grid to island). For example, if a storm is heading towards the microgrid, higher winds, and lower solar production are expected. The system can prioritize having batteries fully charged and alert the consumer to see the generator has enough fuel for the possible disruption in service. The Solar/Wind analytic makes a series of short-term (1s-15min) and long term (days ahead) predictions for the solar/wind output. The output of this process is fed to the decision support system module and the battery analysis module.

   - **Grid:** Grid input data include the price of electricity and instantaneous power consumption. This data is fed to the Grid Analytics module, where it gets combined with the Time of Use (TOU) pricing and Critical Peak Pricing (CPP). The output of the Grid Analytic module is the price of the electricity from the grid vs. time.

   - **Generator:** The main data required for running the generator are cost, minimum running period (e.g. 30 minutes), the ramp up time (e.g. usually less than 1 minute), the fuel capacity, and max power generated.

4. **Battery Storage:** The battery module guides capacity, charging or discharging according to battery specification and battery State of Charge (SOC). The battery analytic module interacts directly with generation and load blocks.

   The battery storage block needs to:

   - Recognize the state of the loads from the SEADS. For example, if there is a large need of power to run large a appliance, battery analytics module can evaluate and deploy a discharging strategy to supplement and meet the demand.
   - Interact with the Solar/Wind Analytics module. For example, if Solar/Wind block find production surpasses the load, system needs to strategize the best way to deploy the excess power generation (e.g. charge batteries or heat water).
   - Interact with the grid and use the rate structure (i.e. TOU and Tiers) of the grid electricity in order to devise battery charging or discharging plans.

   Other than charging via energy from the grid or renewable sources, the battery could also get charged through the generator if the goal is to reduce the amount of the generator run time. For example, if the generator is about to run for a period of outage that extends into the night, charging the battery during the evening and discharging the battery at night, can reduce the amount of cost (and pollution) associated with running a standby generator over night. Another added benefit of using the battery over night is cutting the noise especially if the generator is loud during the night (i.e. not to bother the household members or neighbors).

5.2.1.1 Decision Support

Decision Support System (DSS) module serve as the control center for the management, operations and planning of the microgrid in both on-grid or off-grid mode. The DSS creates a rule-based decision tree that can be used for automatic control of appliances or can be manually managed by the user through the **User Interaction Front End**. Decision Support acquires data from various modules such in *User, Generation, Load, Storage*, and *User Interaction Front End*. The DSS includes three modules, User Behavior Prediction, Modeling and Optimization.

- **Behaviour Prediction:** Predicting the user behavior can be useful in creating good algorithms for estimating the user's power consumption behavior. Knowledge of user's consumption behavior pattern can help in devising battery strategies, which are particularly important for operating in the island mode. For example, knowing what group of appliances are run when the user wakes up and how much use energy they use, can be beneficial in estimating how long the system can last on the battery when the microgrid is operating off-grid. User behavior prediction can estimate the time that the system can run on battery and guide users what they can do to maximize this this time. This can reduce the need of the Microgrid operating in an off-grid mode to operate on generator and therefore reduces cost, noise, and carbon emission.

- **Modeling:** The user, load, generation, and the battery blocks (Fig. 5.5) all produce output data for a variety of scenarios on a day to day basis. Since the number of scenarios that can happen is difficult to predict, having a modeling procedure is essential in being able to deal with unexpected circumstances. For example, instead of asking the user questions or presenting him/her with many options (which makes user participation difficult), IEMS should utilize the *user model* to answer questions such as what would a simulated user (based on the model) do in such scenario, therefore reduces the need to overwhelm users with questions. The goal of modeling is to combine user, load, generation, and battery model in creating a comprehensive model. This model can answer many questions such as: Which appliances consumer is going to use? How much energy will these appliances use? What is the duration of this appliances' runtime especially if the solar generation is reduced? Should the battery produce power or use the generator?

- **Optimization:** The goal of the optimization module is to minimize the electricity cost function while maintaining a balance between generation and load. Section 5.4 discusses optimization in more details.

5.2.1.2 Automation

The automation block applies the rules from a Rule Based Decision Tree to automatically control the load, generation and battery.

- **Load Control:** The load control module develops signals to control loads via a SEAD plug or smart appliances (such as smart thermostat), based on the decision tree created in the optimization problem addressed in the optimization section.

- **Generation Control:** The Generation Control module uses the rule based decisions and analyzes the amount of generation needed in the system. The objective here is to never curtail renewable generation. Instead, the excess generation should be directed to the battery, or to thermal storage.

- **Battery Control:** The battery control acts upon information gathered from the load and generation blocks. The battery management strategies consider the optimization constraints mentioned in the section 5.4. The battery charging can be a load if generation exceeds loads. The battery can smooth the effect of the variability of energy into the system (caused by renewable generation) and facilitates integration of the renewable generation.

5.2.1.3 Rule Base Decision Tree

Rule based decision tree is created by the decision support, and it consists of two sets of commands: automated and user driven. Automated commands such as changing the thermostat temperature within the users' preferences do not require user involvement. User driven rules are such as scheduling a dryer to an off-peak time is an example of user involvement. Automated rules are fed to the automation block, while user driven ones are fed to the user block through a *User Interface*.

5.2.1.4 Front End (Graphs and Apps)

The user Front End module provides a user friendly interface to engage the consumer with IEMS. Questions that are posed to the user should be presented elegantly, giving user the ability to interactively and efficiently view the information. Users should be able to inform the system about his/her preferences in a practical, and user-friendly manner.

5.3 Load Sheding

The need for a micro grid to shed loads can be the result of various situations where load reduction is needed. One of the most important of these is in the transition from on-grid to island mode. On-grid the available energy is limited only by the capacity of the service provided by the grid connection. When in island mode, this changes drastically, and then is the capacity of the renewable sources and batteries. If a fossil-fueled generator is part of the micro grid, it may not be desired to start it immediately. The generator takes some time to start, and it uses fuel. A micro grid temporarily and for a possible short time in island mode may be able to serve loads, or at least critical and uninterruptible loads, for energy provided by the renewable sources and / or batteries. Shedding of non-essential loads may make this possible.

Fig. 5.6 gives a list of common appliances, their power requirements, and some categorization as candidates for load shedding. At the top are devices that should automatically turn off in event of loss of grid power. Newer models of laundry washers and dryers, dishwashers, and ovens, thanks to their electronic controls, turn off due to a loss of power and require restarting by the user. In our work we expect that any HVAC (e.g. heat-pump) and electric water heater will be modified to also turn off when power is lost. Using guidance from the IEMS, and possibly controlled through signal from the IEMS, the user will decide when to restart these loads. ,

Some appliances (e.g. dishwasher, laundry, microwave or other oven) take some interval of time to complete their cycle or task. We label these "interval operated", and expect that the user would want to prioritize or schedule their completion when adequate power is available, would resume their operation under user control, guided by the IEMS. Those labeled "non-interval" have a variable amount of time for their use by the consumer, and again the consumer use of these in island mode will be guided by the IEMS.

The "uninterruptible loads" are those that the consumer identifies as priorities, and that are not to be shed. The refrigerator or freezer, computer networking and internet modem, or some electrical medical equipment, would belong in this category. The IEMS prioritizes these and runs them from the renewable sources, battery power, and if need by by starting the back-up generator.

Fig. 5.6 categorizes load data of average power consumptions in a sample all electric home. In terms of Load Control, three categories of loads are identified:

APPLIANCE	AVERAGE POWER (ON) KW	CONTROL	
HEAT PUMP	7	Auto Controlled	
AIR CONDITIONAR	5.23		
PUMP	1.159		
WATER HEATER	3.8		
WASHING MACHINE	0.722	User Controlled	Interval Operated
DRYER	5.486		
DISH WASHER	0.533		
COFFEE MAKER	1339		
OVEN	3.64		
MICROWAVE	1.343		
BROIL	3.8		
COOK TOP	1.4		None-Interval
BLOWER	0.96		
GARBAGE DISPOSAL	1.497		
VACUM CLEANER	1.267		
REFRIGRATOR	0.172	Uninterruptible Load	
ESSENTIAL LIGHTING	0.300		
NETWORKING	0.5		

Figure 5.6: Loads

- Auto-controlled
- User-controlled
  - Interval Operated
  - Non-Interval Operated
- Uninterruptible load

5.4 Optimization

The optimization module solves an economic dispatch problem via an integer programming softwares such as *AMPL* and a solver such as *CPLEX*. A set of optimization equations has been formulated for the purpose of minimizing operational costs of a microgrid in both on-grid and off-grid mode while maintaining a balance between energy production and consumption. This optimization can be preformed on a day ahead basis or every hour, every minute, or second. When on grid, the objective function is described in equation 5.1 and the goal is to minimize:

$$C_{Off-grid} = \sum_{t=1}^{T} CF_{Generator} * P_{Generator} + CF_{Battery} * P_{Battery} - P_{Solar} \tag{5.1}$$

where T is typically a 24 hours period with granularity e.g. $T = 86400 second$, $T = 1440 minute$, and $T = 24 hour$. where $CF_{Generator}$ is the cost of running the generator, $P_{Generator}$ is the power produced by the generator, $CF_{Battery}$ is the cost of running the battery, $P_{Battery}$ is power delivered or absorbed by the battery and P_{Solar} is power generated or expected to be generated by the solar cells.

When on grid, the objective function is described in equation 5.2 and the goal is to minimize cost of running a microgrid in an on-grid mode (minimizing $C_{On-grid}$).

$$C_{On-grid} = \sum_{t=1}^{T} CF_{Generator} * P_{Generator} + CF_{Battery} * P_{Battery} + CF_{Grid} * P_{Grid} - P_{Solar} \tag{5.2}$$

With constraints:

Equations 5.3 and 5.4 balance the generation and load under any circumstances.

$$\sum_{n=1}^{N} P^{n}_{d-load,t} + \sum_{n=1}^{M} P^{n}_{ui-load,t} = Pgrid,t + P_{battery} + Pgenerator + Psolar \tag{5.3}$$

where N are the number of deferrable loads, M are the number of uninterruptible loads, $P^{n}_{d-load,t}$ are the deferrable loads and $P^{n}_{ui-load,t}$ are the uninterruptible loads.

$$\sum_{n=1}^{N} P^{n}_{d-load,t} = Pgrid,t + P_{battery} + Pgenerator + Psolar - \sum_{n=1}^{N} P^{n}_{ui-load,t} \tag{5.4}$$

The limits of power a generator can put out is given by:

$$P^{min}_{generator} \leq P_{generator,t} \leq P^{max}_{generator} \tag{5.5}$$

The limits of the power from the grid (i.e. capacity of the grid connection) are:

$$P^{min}_{grid} \leq P_{grid,t} \leq P^{max}_{grid} \tag{5.6}$$

The limit of of power a battery can produce are:

$$P_{battery}^{min} \leq P_{battery,t} \leq P_{battery}^{max} \tag{5.7}$$

The limit of State of Charge of a battery (SOC) is:

$$SOC^{min} \leq SOC_{t-1} + \Delta SOC_t \leq SOC^{max} \tag{5.8}$$

Where SOC_{t-1} is the state of the charge of the battery at the time $t-1$, SOCt is the state of charge at time t , SOC^{max} is the maximum state of the charge of the battery and SOC^{min} is the minimum amount of battery charge.

5.4.1 Grid Connected Case Study with Batteries and Time of Use

Based on CERTS definition, a grid connected Microgrid should have the flexibility to operate as a single system. One of the important components providing flexibility in a microgrid is a battery storage system. A residential grid connected microgrid has been studied to examine the role of a battery in a grid connected mode. For the purpose of studying the cost analysis, the E6 rates from PG&E (Fig. 5.7) are used. Several commercial batteries are discussed. The size and power of the batteries correspond to the data that was published by the company about the battery specifications. Batteries which are considered for this study are *iCan* from *PomCube*, *PowerWall* from *Tesla*, and a Vehicle to Grid battery (e.g. *Nissan Leaf*). The data used for this study comes from a year worth of 15 minute net-metering data from PG&E and 15min solar data from the inverter from a test home. At first an off-peak changing and on-peak discharging battery storage control strategy in the grid connected configuration was studied.

One idea is to charge the battery during the off-peak hours when the price of electricity is low and release the charge during the peak hours when the price of electricity is high. During the summer time the peak hours with E6 rate are from 1pm to 7pm Monday through Fridays. Partial Peaks are from 10AM to 1PM Monday through Friday and 7pm to 9pm Monday through Friday and from 5pm to 8pm on Saturday and Sunday. All other times are off peak hours. Fig 5.8 shows the cost saving for a variety of battery sizes using this strategy. It can be observed that with the current cost of the batteries, rate structure and strategy, that would be a long payback period for the battery (e.g. Tesla Battery). During the winter the difference between off-peak and peak is not as high as the summer so the savings in winter would be less dramatic.

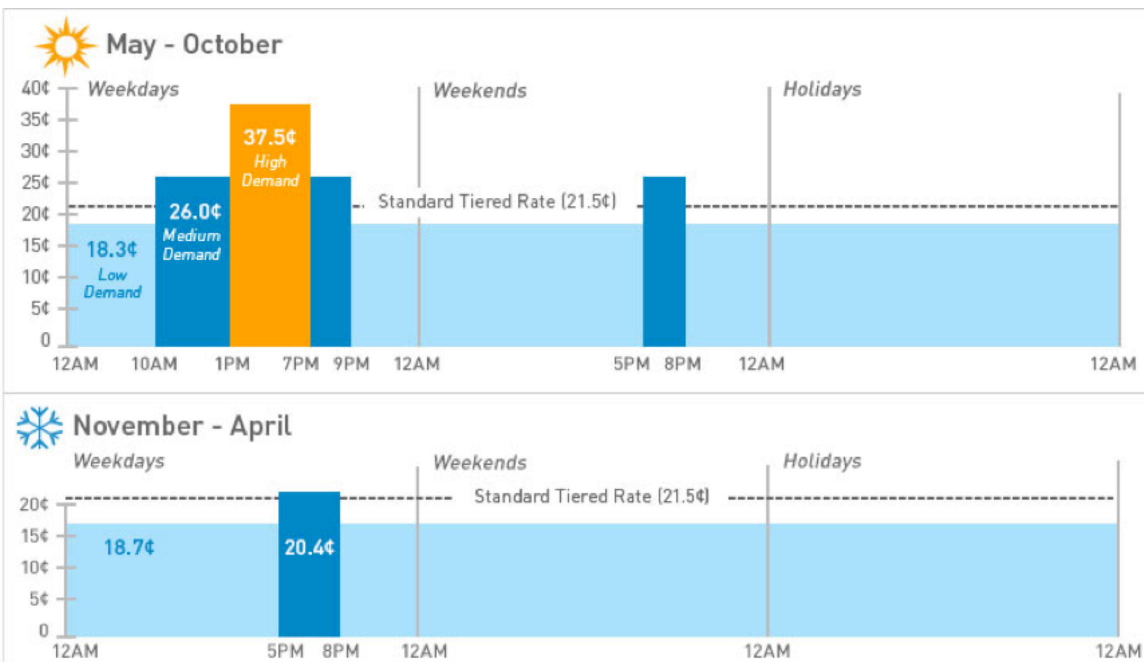


Figure 5.7: PG&E E6 rate

	BASE	2.2KWH ICAN .5KW	7KWH TESLA 3KW	20KWH V2G 10.88KW
YEARLY BILL($)	390.31	349.19	270.40	47.75
PERCENT DECREASE	0	10.54%	30.72%	87.77%

Figure 5.8: Shows the effect of adopting a "buy low" (off-peak), "sell high" (on-peak) battery strategy for a grid-connected microgrid

A different strategy for charging and discharging the battery was then considered. In this strategy the battery absorbs power when there is an excess amount of power via renewable generation, and discharges when there is an insufficient amount of power in the system. Using this strategy with iCan battery storage, we see that the yearly bill only reduces by 1 percent, which is not significant. With this strategy, battery goes through 964 cycles within a year. With a battery life of 5000 cycles for this kind of battery, it would not out last 5 years of usage. As the experiments mentioned, with the current rate structure incentives and the strategies mentioned, and the cost of the batteries, the payback time of the batteries is over 10 years (if the battery lasts).Therefore, we conclude the most important role of a battery storage in a residential microgrid is operation in the Island mode and ensuring that *critical loads* are running at all the time. These *critical loads* in the microgrid studied (as shown in Fig. 5.6) are refrigerator and computers and the networking stack (400W).

5.5 Microgrid Simulation

A Matlab Simulink simulation model has been created based on the real data from a microgrid (Fig 5.9). The inputs of the simulation are load and solar power usage information. The simulation runs are conducted on a secondly basis in a 24 hour timeframe. In the simulation model, the parameters are set such that the real power that flows to/from the grid is zero. In the Island mode of the microgrid considered, power generation comes from the solar PV generation and a storage battery. The battery's State of Charge (SOC) generally operates within 50% to 95% of the maximum charge capacity. The battery uses energy to charge when the renewable electricity generation exceeds demand of the loads. The model is set that microgrid does not depend on the grid power for consumption and the required power is provided by the renewable generation and battery.

A winter day with relatively high electricity consumption has been considered for studying the role of the battery in an all electric home. The total electricity consumption on this day was 59.4kWh. As Fig 5.10 shows, the heat pump and water heater together are responsible for 65% of the consumption. About 43% (or 25.7kWh) of this consumption is that of heat pump and about 22% (or 20.40kWh) of total consumption is due to the water heater. Drying a a washer-load of clothes consumes 4.2kWh of electricity, while the washing of this load uses 0.6kWh. On this winter day, there were three

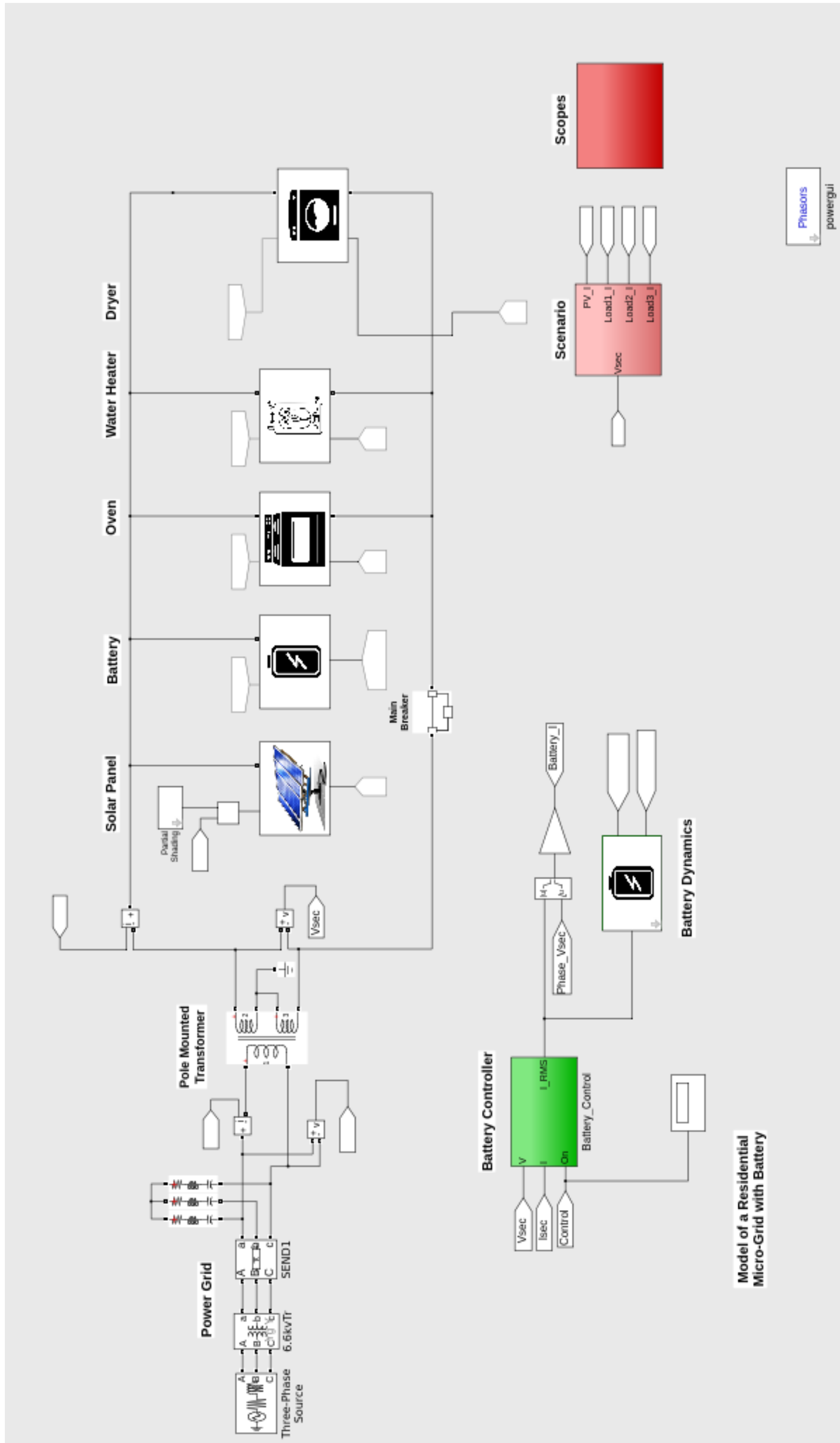


Figure 5.9: Microgrid residential simulation model

loads in the dryer (contributing to 22% of total consumption) and two loads of washer (contributing to only 2% of consumption) were completed. On this day, the rest of the consumption (11% or 6.6kWh) originates from the refrigerator, television, computers, cooktop, etc. Maximum power used during this day reaches 17kW.

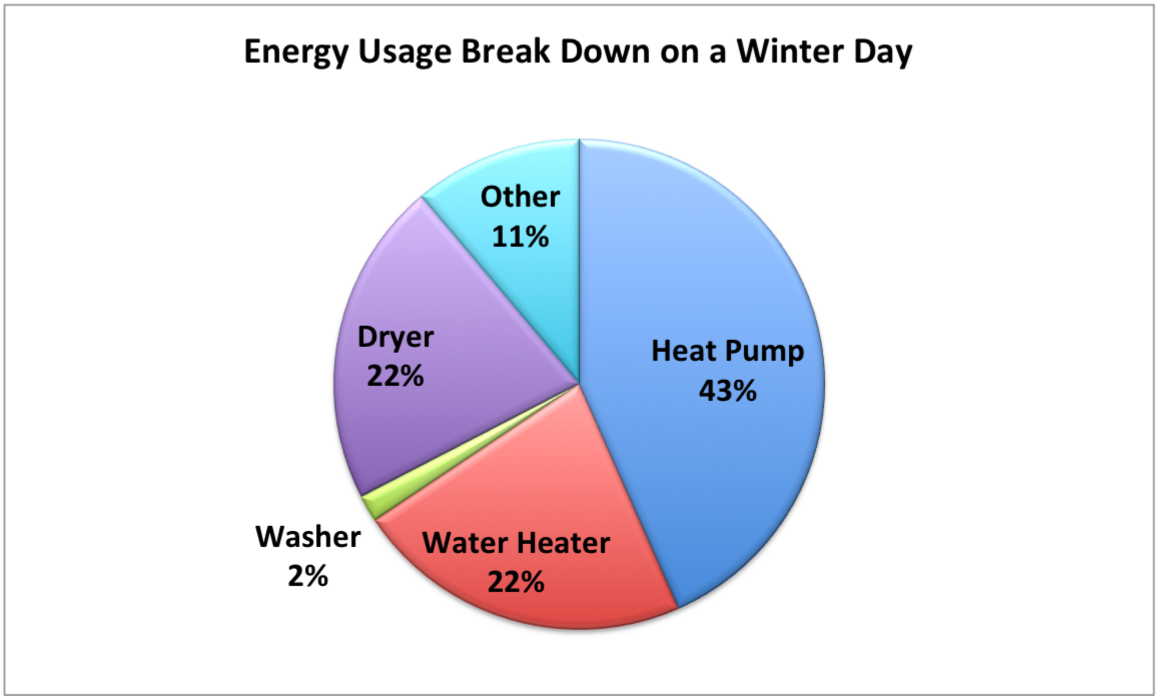


Figure 5.10: Energy consumption pie chart in a winter day shows the energy used by the heat pump and water heater together make up 78% of the total energy consumption

Fig. 5.11 shows the breakdown of appliance power data used as input for the simulation model depicted in Fig. 5.9. The graph titled Panel 1 shows the heat pump power signature. During the night heat pump is mostly on. The graph titled Panel 2 shows the water heater. The water heater is mostly off during the night and on during the day. Panel 3 graph shows most of the energy used in this panel comes from the dryer and washing machine. Panel 3 is the kitchen panel and supplies a variety of appliances such as a refrigerator, microwave, laundry, and a television which use a low amount of energy are in the "base-load".

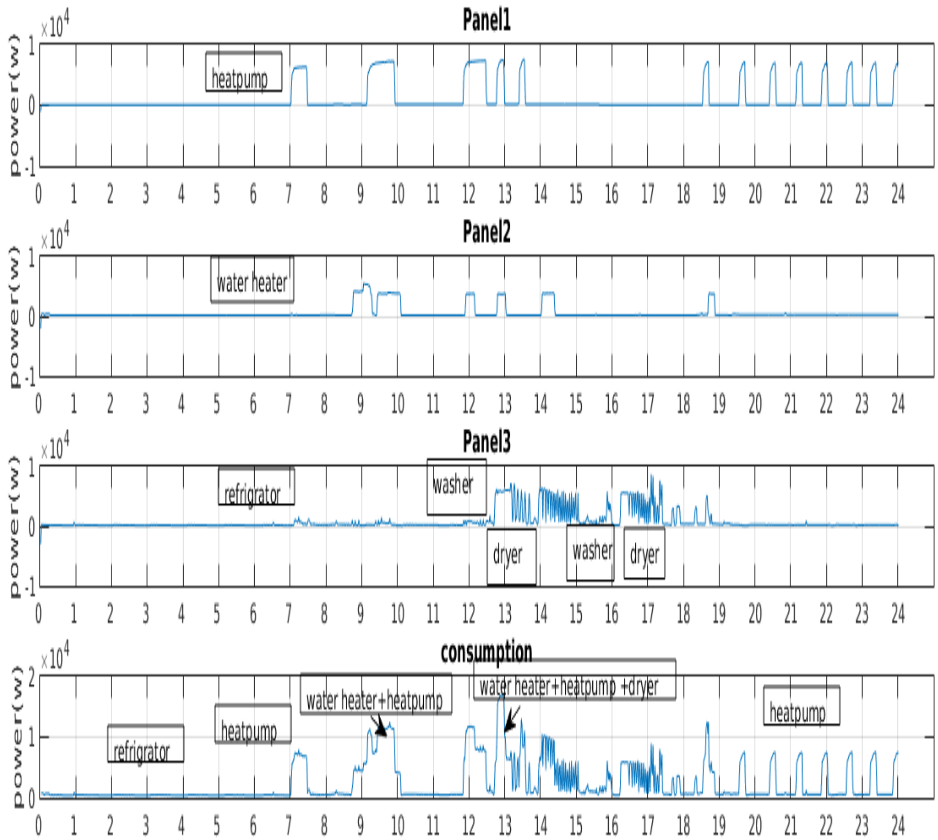


Figure 5.11: Appliances breakdown on three circuites

In the first baseline case of the simulation, we used load and generation inputs from a real day. Fig. 5.12 shows the existing condition without any load shedding over a 24 hour (x-axis) window. Without load shedding the battery size needs to be 28kWh with 6kW peak output to be able to supply the energy used on this day. The

State of Charge (SOC) of the battery declines throughout the 24 hours from 80 % to 60%. Table 5.2 shows summary of analysis of all cases discussed in the simulation. As table 5.2 shows the demand mean during this day is 2.5kW while the max demand reaches 17kW.

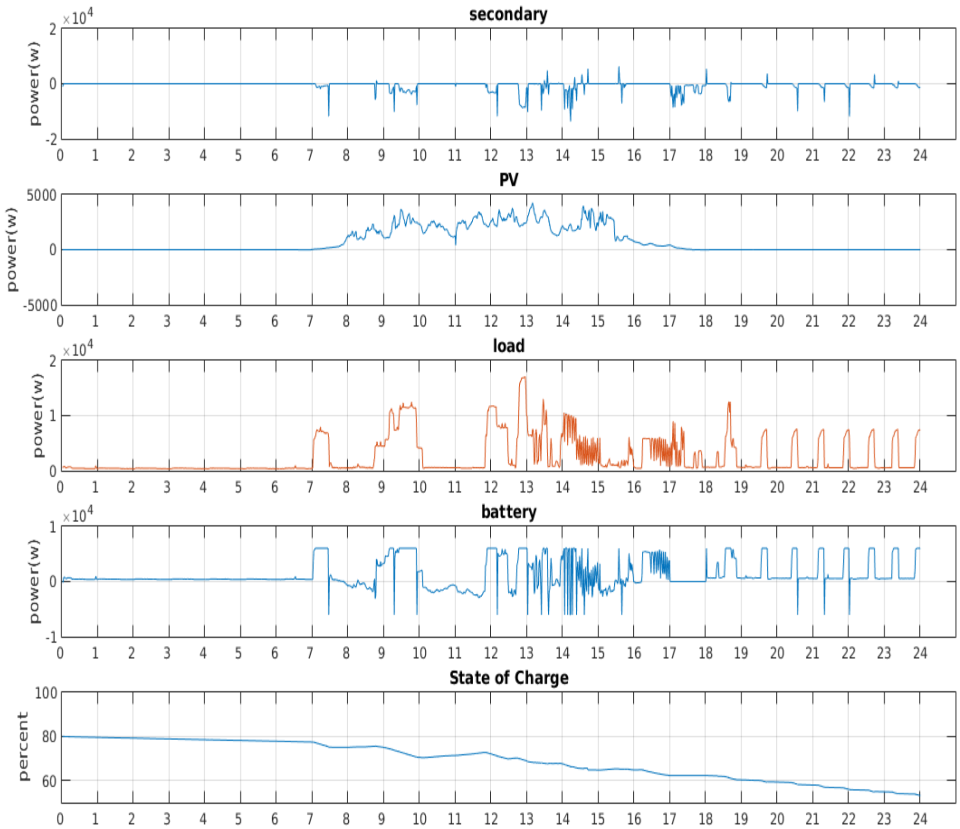


Figure 5.12: Shows the baseline case without doing any load sheding

In the second simulation, we shed the two big loads, namely the heat pump and water heater and otherwise kept the same settings of the previous simulation. Fig. 5.13

shows the effect of shedding the heat pump and water heater on the microgrid. The load graph in Fig. 5.13 has two charts overlaid on top of each other. The orange curve corresponds to the consumption in the baseline case. The blue curve corresponds to the total load when the water heater and heat pump are shed. The SOC of the battery starts at 80% charge and it reaches 85% during the day before declining to 80%. The battery curve shows the effect of the shedding water heater and heat pump on the battery's power consumption. As Table 5.2 shows, the batteries net flow to the power system is -0.5kWh. This means that the battery is charged with 0.5kWh during the day, after providing back up during the 24 hour period. The max battery power output to the system is 5.5kW which mainly to support use of the clothes dryer during this period.The total demand during the day reduced to 20.4kWh from the baseline of 59.5kWh (66% reduction). The max demand during the day reduced to 8.7kW, from the baseline of 17kW (51% reduction). The mean demand during this day is also reduced to 0.84kW.

In the third case of the simulation, apart from shedding the water heater and heat pump, loads such as the dryer and washer are shed to keep the essential base load such as refrigerator, networking, and computer running. Fig. 5.14 shows the effect of transitioning to the base load (400W) on the battery power, SOC, and the secondary. The battery charges steadily from 10am to 6pm to 95%. The blue curve in the load graph stays constant under the baseline load depicted in orange. The Table 5.2 shows battery could gain (if it had adequate capacity) a net charge of 14kWh during this day (running on base load). Now, if the battery capacity is 6.4kWh, the extra amount of charge (the rest 7.6kW) needs to get dumped into a dump load such as a water heater

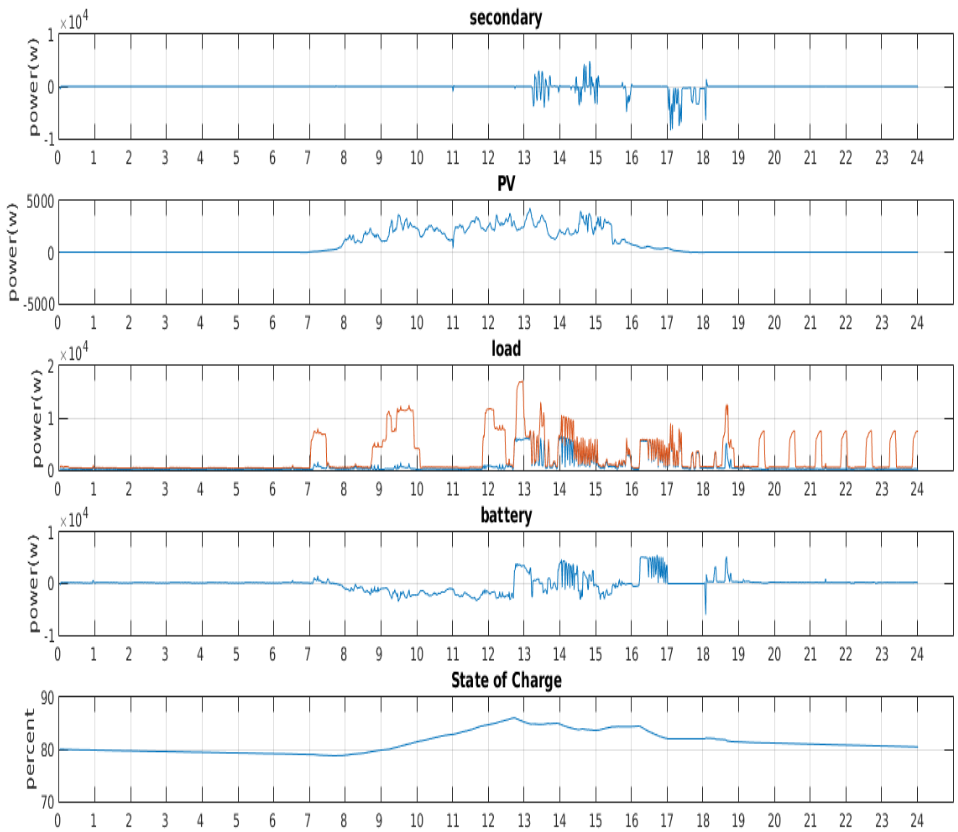


Figure 5.13: Shows the effect of shedding the heat pump and water heater on the microgrid.

or the heat pump or PV output can possibly get reduced. If the battery is fully charged at 7kW and the system receives extra amount of power flow at the variety of rates (due to variations in solar power 0..4kW), the battery can be set to the discharge mode to provide the complementary amount of energy needed to keep the quantized loads such as the 4kW water heater or a 7kW heat pump running.

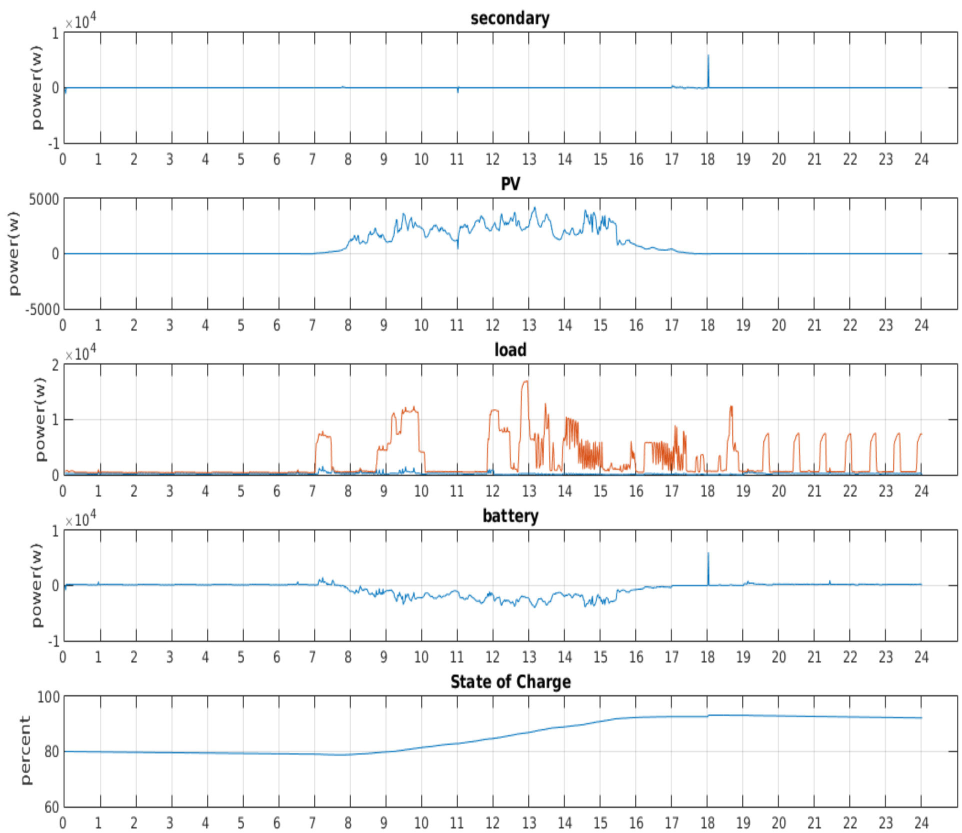


Figure 5.14: Shedding load to base load (400W) shows battery charges to 95% during the 24 hour period

Table 5.2 shows the simulation results for three modes of microgrids operation

Table 5.2: Tracebased simulation of comparison of three modes of operations in a microgrid

Mode	Battery (kWh)	Battery Min/Max (KW)	Demand (kWh)	Demand Max (kW)	Demand Mean (kW)
Without load shedding	29.8	6.0	59.5	17.0	2.5
Shed water heater & heat-pump	-0.5	5.5	20.4	8.7	0.84
Base load (400W)	-14.0	-4	4.4	.5	0.4

and interaction with the battery:

1. Baseline without load shedding
2. Shedding water heater and heat pump
3. Running only the base load (400W)

5.5.1 Grid Connected Cost Benefit Analysis and Opportunities of DSS and IEMS

As mentioned in the section 5.2 and section 5.5, IEMS is essential in the island mode operation of a Microgrid. However, an IEMS can be important in the grid connected mode as well. In this section, we provide cases and suggest opportunities where IEMS can be important in reducing consumers' electricity bill. A real-time decision support recommendation system can provide users with the opportunity to engage in their electricity consumption decisions. The IEMS can guide users in making load scheduling decisions needed with the Time of Use rate structures.

Figure 5.15 shows, flowchart of a role that IEMS's DSS and SEADS can play in a grid connected microgrid.

1. User starts an appliance.
2. SEADS detects that appliance.
3. IEMS presents user alternative options and cost saving of postponing scheduling the load.
4. User makes a decision.
5. IEMS learns.

Assumption and goals:

This study uses the load sizes described in section 5.3. PGE's E6 rate structure was described in section 5.4.1. The goal here is to achieve consistent saving of at least

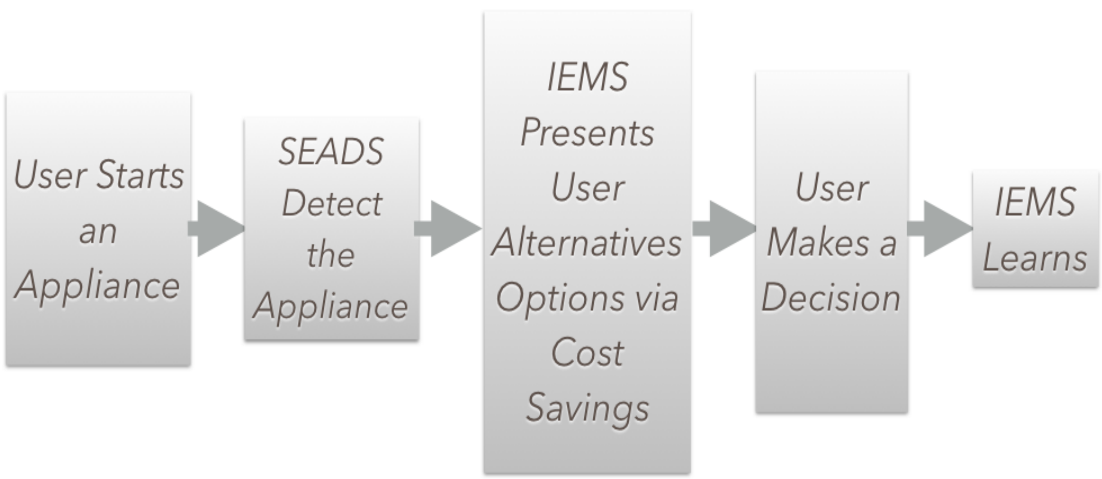


Figure 5.15: The flow chart of how the DSS can help consumers in the grid connected mode.

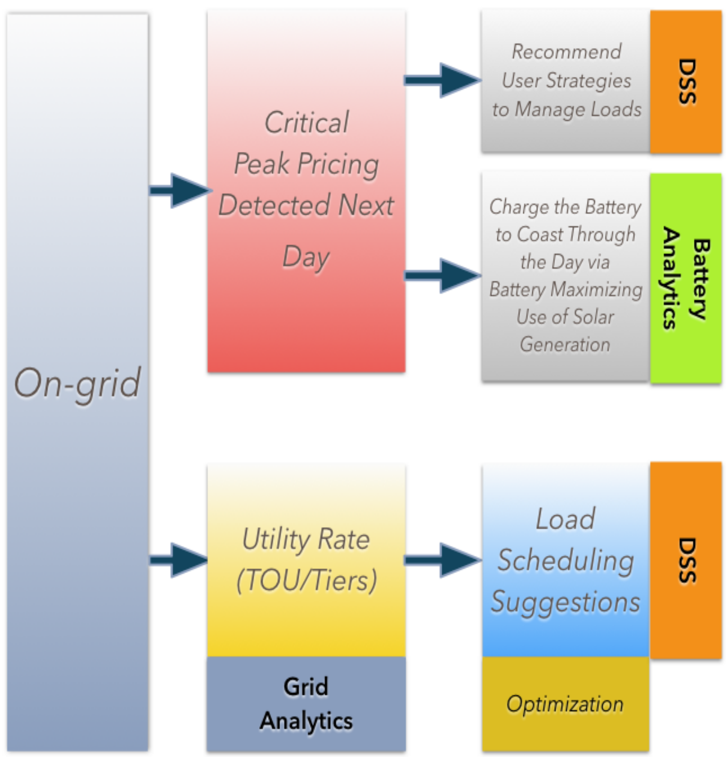


Figure 5.16: IEMS On-Grid Fow Chart

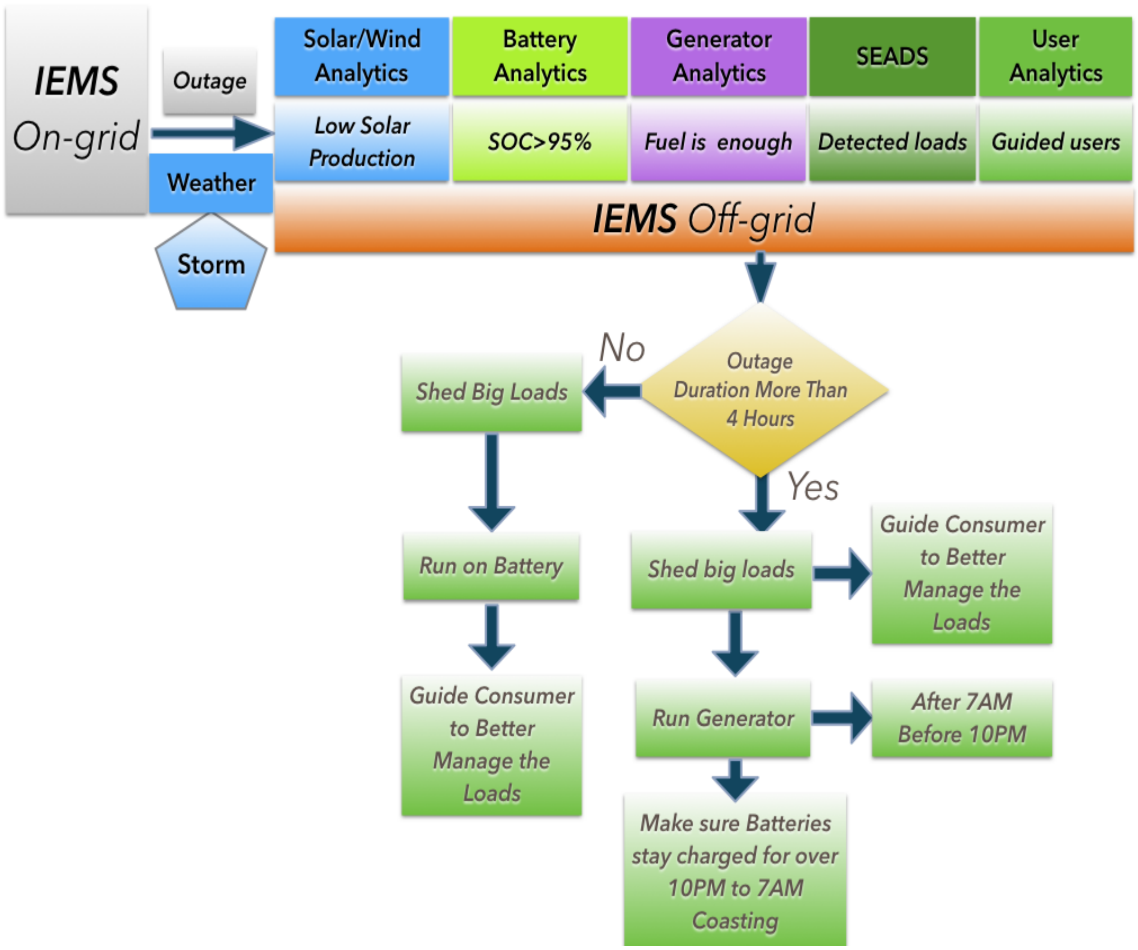


Figure 5.17: IEMS Off-Grid Flow Chart

50 cents per day which will be equivalent of \$182.5 per year. Here are 10 ways that IEMS can save on a grid connected circuit.

On the winter days:

1. Reduce the heat pump run time by 30 minutes (reduce heat possibly when the occupants are away or early in the evening)

2. Reduce the water heater run time by 45 minutes

3. The combination of 1 and 2, meaning reducing run time of the heat pump by 15 minutes and water heater by 22.5 minutes.

4. Move 4 cycle of washer dryer loads from on-peak to off-peak (only 2 cents difference in winter, but this transition still will make the 50 cents) .

Summer days:

5. Reduce the air conditioner run time during peak time by 7.5 minutes.

6. Reduce the water heater usage by 11 minutes during peak time.

7. A combination of 5 and 6, meaning reducing the air conditioner run time by 3.25 minutes and the water heater by 5.5 minutes during the peak time.

8. A load of washer dryer costs \$1.875 in the peak hour, this drops to \$0.9 dollar if you move it to off-peak and save \$0.9.

9. A load of washer and dryer costs \$1.3 in the partial peak hour, and this drops to \$0.9 dollar saving 40 cents when moving it to an off-peak hour.

10. An hour of oven on a peak time cost $1.34 during the peak time if reduce the oven run-time by 22 minutes consumer can save 50 cents.

In addition to the strategies outlined above, an IEMS with SEADS can detect what appliances are failing/ or are inefficient and recommend users to buy a new appliance. There are many ways a recommendation system and a decision support can help consumers save on grid IEMS recommender DSS system with TOU rate structures.

Chapter 6

Conclusion

In this thesis we have explored the requirements for cost-effective control and operation of small scale (e.g. single residence) micro grid with local renewable energy sources supplying its energy. Real-time identification of significant (power of 1KW or more) individual loads was determined to be essential to this work. This was addressed by disaggregation of data obtained from measurements of voltage and the input current to a utility panel, via non-intrusive load monitoring or NILM.)

We examined the potential of NILM using data from utility smart meters as many have suggested, and demonstrated by experimentation that this data (as obtained from smart meters of U.S. utilities) is inadequate for effective NILM. We then showed that sampling at a sampling rate of 8 KHz for the current and voltage measurements is required, and with this sampling rate we obtained appliance overall recognition rates of 92% and higher for the recognition of the significant loads. The results show by using a tree-based J48 classifier and with data on the frequency content that includes the fundamental (60 HZ) component and the 3rd, 11th, 17th, 27th, and 33rd harmonics, we can achieve 72% accuracy in appliance identification, and when using all the harmonics below the 50 we can achieve 92% recognition accuracy.

We designed and built instrumentation (SEADS) that captures this data at an electrical panel at this 8 KHz sampling rate, and that SEADS can also implement NILM within the device situated in the panel, and thus reduce data transfer from the panel by sending results of recognition, and only sent sample sequences when signatures are encountered that are not recognized. Finally, we developed an architecture for an Intelligent Energy Management System / Decision Support System (IEMS) which uses this NILM real-time information, other available data on ambient conditions, input from users including their preferences, to automate control of a micro grid with local renewable energy sources . Scenarios were presented of the logic of the IEMS and of the actions that the IEMS will take under several and representative conditions in both on-grid and island mode, and especially for the transition from on-grid to island.

Some key results include the establishment of the 8KHz sampling rate, the prototyping of affordable metering hardware for capture of the required data, development and limited prototyping of the architecture of a software system that takes this data from its capture (A/D) through its uses in efficient operation of the micro grid. The context of this work, using real data from an actual all-electric home with local generation via a 5.4 KW (24 panel) solar array, demonstrated that load shedding of major loads is critical when the micro grid moves from grid attached to island mode. It also was shown that the two major loads on this micro grid that need minor modification to make them sheddable are the HVAC (heat pump) and the electric water heater. It was found that most other loads that are significant (e.g. clothes dryer, dishwasher, microwave, oven) are self-shedding, In that their electronic controls cause them to shut off when power is lost and require user action to restart. And the other significant loads are directly operated by the user (e.g. cook top, vacuum cleaner) and thus alerting the user to a switching from grid connection to island can be expected to result in the user immediately shedding these loads.

We demonstrated that the IEMS, fed with data from NILM implement by SEADS, can support engagement with consumers in managing their energy use, on-grid, when responding to Time-of-Use (TOU) and other variable pricing of energy from the utility grid, and can lead to lower electric utility bills. Another consumer benefit of this combination of SEADS and the IEMS is in appliance energy monitoring, which can alert consumers to changes in energy use, while accomplishing the same result, that may be due to incipient failure of the appliance (e.g. refrigerator or HVAC) and might enable the user to take corrective action that would avoid more significant costs later. Enabling consumers at their individual residences to operate off-grid in a island mode encourages deployment of solar arrays and other renewable energy, plus local storage , and this can brings significant benefits to consumer and to the electrical distribution grid. In our vision, consumers would continue to operate primarily as grid connected, but can also operate disconnected, albeit at potentially higher cost, but with significantly increased reliability. Reliable electrical power is essential to modern life. Total dependence on our aging and overloaded electrical grid leads to decreased reliability, and increased vulnerability to disruption and long outages from natural causes or other events. In the long run, we envision the electric distribution grid of today being replaced by a federation of micro grids, resulting in significant positive impacts on the environment, and on electric energy resilience.

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Appendix A

Ancillary

A.1 Plots

Fig. A.1 shows the price of electricity during 25 days during month of January.

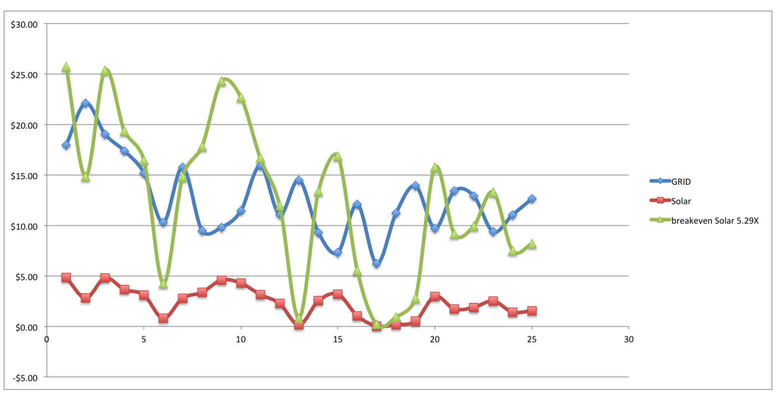

Figure A.1: Price of electricity and solar

Fig. A.2 shows the statical analysis of Frequency, Voltage, Current, and Power.

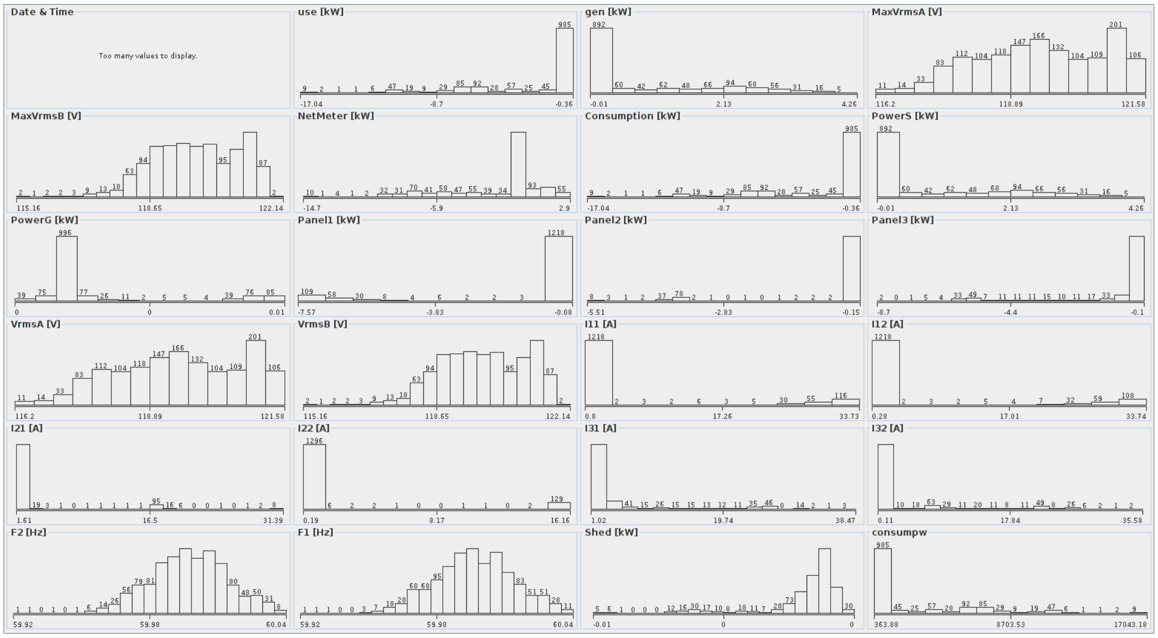

Figure A.2: Statical analysis of Frequency, Voltage, Current, and Power

A.2 Signatures

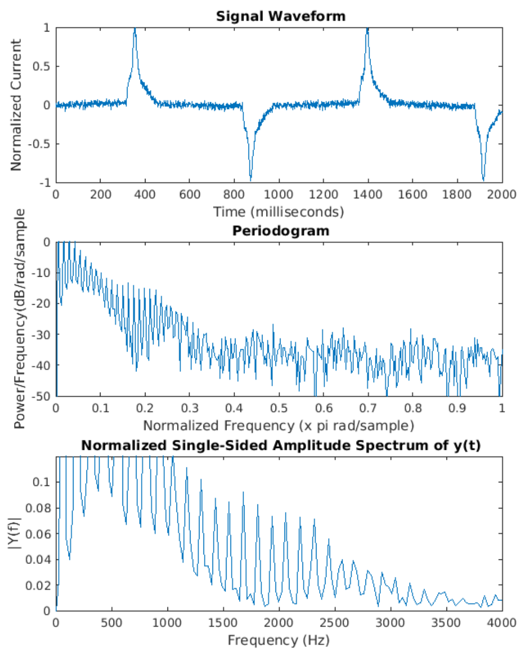

Figure A.3: Router