Electric Vehicle Transportation Center

Electric Vehicle Interaction at the Electrical Circuit Level

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Introduction

The objective of the Electric Vehicle Interaction at the Electrical Circuit Level project was to investigate electric vehicle (EV) charging as a means of mitigating transient over-voltages (TOVs) on the circuit level electric utility distribution grid. A transient time domain model of a sub-circuit service area was developed to simulate TOV mitigation using EV charging equipment and wireless sensor networks on a residential sub circuit with PV power generation.

The project began with a literature review of EV charging technology and over-voltage mitigation. Then a transient time domain model of a sub-circuit service area was developed to simulate transient over-voltage (TOV) mitigation using EV charging equipment and wireless sensor networks on a residential sub circuit with photovoltaic (PV) power generation. Reports were written on both of the literature reviews and research results are presented on the transient time domain modeling effort. These reports are posted on the EVTC website and the citations for these three reports are as follows:

1. Schwarzer, V., Ghorbani, R., (2015). Current State-of-the-Art of EV Chargers (HNEI Rep. No. HNEI-01-15). Honolulu, HI: Hawaii Natural Energy Institute, University of Hawaii at Manoa.
2. Schwarzer, V., Ghorbani, R., (2015). Transient Over-Voltage Mitigation and its Prevention in Secondary Distribution Networks with High PV-to-Load Ratio (HNEI Rep. No. HNEI-02-15). Honolulu, HI: Hawaii Natural Energy Institute, University of Hawaii at Manoa.
3. Eshraghi, A., Sariri, S., Schwarzer, V., Ghorbani, R., (2016) Islanding Detection and Over Voltage Mitigation using Wireless Sensor Networks and Electric Vehicle Charging Stations (HNEI Rep. No. HNEI-08-15). Honolulu, HI: Hawaii Natural Energy Institute, University of Hawaii at Manoa.
4. Sariri, S., Schwarzer, V., Ghorbani, R., (2017) Electric Vehicle Interaction at the Electrical Circuit Level (HNEI Rep. No. HNEI-15-16). Honolulu, HI: Hawaii Natural Energy Institute, University of Hawaii at Manoa.

In addition to the above four reports, the major project effort was taking data, conducting analysis and writing a paper that presents a real-time data acquisition system for the collection and storage of power data that will allow the study of demand response in an urban area, which can be applied to the efficient use of EV charging stations, referred to as EV supply equipment (EVSE).

Electric Vehicle Interaction at the Electrical Circuit Level

Shawyun Sariri
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1.0 Abstract

A large growth in energy demand has increased renewable energy penetration into existing power grid infrastructures, as well as spurring increased research into demand response programs. But before implementing an efficient demand response program, it is first necessary to understand the power usage behaviors of a consumer. This paper presents a real-time data acquisition system for the collection and storage of power data that will allow the study of demand response in an urban area, which can be applied to the efficient use of electric vehicle supply equipment (EVSE). Demand response programs are an ideal alternative to costly energy storage and spinning reserves. Detailed power consumption data is necessary to study proper demand response programs and implement efficient control decisions. A pilot system has been implemented on the island of Oahu in Hawaii to prove the feasibility of a data collection system in an urban environment. The pilot program has deployed a smart metering device that is collecting power data at a high resolution and transmitting it in real-time to a server for load forecasting analysis. There were two purposes to this study. The first being to study and investigate the feasibility of implementing real-time data acquisition on a large scale as it relates to the study of present and future demand response programs. And the second being the utilization of a bottom-up approach to collect and analyze data for usage in load prediction and forecasting in combination with demand response techniques.

2.0 Background

A 2013 report by the American Society of Civil Engineers (ASCE) rated the American electrical grid a "D+", on an A to F scale [1]. Operation failures were deemed as a main source of outages across the country due to power congestion in transmission lines. Utility companies are relying on a grid infrastructure that still has components from the 19th century. Expanding US energy capacity after 2020 will be a main concern for the utilities, and one way to alleviate some of the pressure of capacity expansion will be to increase consumer side power generation using renewable resources, but the addition of more generation comes with logistical issues, especially when transmitting power generated from stochastic sources. Rather than invest large amounts of money replacing the current grid infrastructure, the ASCE suggests research in smart grids and real-time forecasting as alternatives. Smart grids will be necessary in areas containing dense populations such as large urban centers.

With a majority of the world population living in urban areas by 2030 [2], cities themselves will need to become large power generators. This is because in times of peak power draw, factors such as lengthy transmission lines and lack of fuel supply can have crippling effects on a large urban populations, as was the case in 2014 during the US Polar Vortex [3, 4]. Cities have been turning to distributed generation (DG) as a way to become more self-sufficient in regards to power generation [5]. This is because many DG units now allow for more reliability, increased efficiency and cost effectiveness as well as an opportunity to use renewable generation sources [6]. Hybrid renewable systems being used as distributed generation (DG) provide a way for utility companies to move peak loads and deliver reliable power transmission [7].

The US Energy Information Administration (EIA) produced a report, dated August 2013, describing the current characteristics of distributed generation (DG) systems in the US as well as present and future costs of installing renewable generation infrastructure. The report stated that in 2008 a crystalline based photovoltaic system cost approximately $8200/kW, but by 2020 it was estimated to cost around $4000/kW [8]. As the price of renewable generation decreases, the more it will penetrate into the current grid infrastructure.

Utilizing DG can allow a more reliable and cost-effective solution to consumers, and in cases where renewable generation sources are installed, a more maintainable and ecofriendly alternative to fossil fuels [6]. However, with more DG generation becoming interconnected with the current grid infrastructure, and DG sources potentially feeding power back into the current grid system, utilities will need to be able to better monitor different points within the grid to ensure grid stability. As renewable energy generation becomes more abundant and affordable, distributed generation use will only increase and become more entwined with current grid infrastructure, necessitating a need to collect data in order to analyze and predict grid states in real-time. To do this, smart meter devices will be needed to collect large amounts of grid data to be analyzed. Thus contributing to the development and maintenance of demand response programs.

Utility companies today are needing to evolve from their historic position of producing energy, to managing energy production not only from the supply side, but from the consumer side as well. The topic of this paper revolves around the implementation of a pilot system that allows a power producer to collect large data and analyze it in order to create cost effective energy management strategies.

2.1 Current Electric Vehicle Charging Station Research

EVSE research has also delved into the topic of load forecasting for EV charging stations. FeiXiang et al. determined that if 20,000 petrol based buses in Beijing were replaced with similar electric buses, the electric buses would require 3% of the power supplied to the city of Beijing. The research determined that the use of EV charging stations, and therefore the ability to forecast usage, is closely related to the habits of users. For example, A/C usage is related to weather conditions, whereas the charge of an EV can be related to when a consumer must be at their workplace. FeiXiang et al. suggests that multiple types of charging stations will need to be deployed to meet EV demand; Fast Charging Mode (charge above 90% within minutes, high current), Normal Charging Mode (residential, slow charge most commonly used at night, low current), and Quick Change of Battery (changing out batteries to be charged and replaced with a charged battery). Forecasting models needed for EVSE load predictions are complex and non-linear [29].

In addition to load prediction, the cost of energy associated with EVSEs is also a concern for EV integration into the current grid infrastructure. Li et al. has proposed the use of a dynamic break-even analysis theory to determine the price of electricity at an EVSE. It was determined that government involvement is needed to promote the development of EVs and the corresponding charging stations [30]

Research presented in this paper can provide a basis to better test theoretical solutions against real life results when it comes to predicting factors that affect EVs and EVSEs. For example, our system can monitor the volume and vehicles that frequent a specific EVSE, which will grant the capability to understand EV usage within a certain part of a city at specific times, and adjust loads accordingly to avoid potential blackouts during times of peak usage. There is a need to understand how EVs interact with the current grid infrastructure and the ability to understand the limits of the current power grid. Smart grids are a proposed solution to better integrate new components into the current power grid infrastructure.

2.2 A Smarter Grid

The transition to a "smarter" grid will grant utilities the ability to become more proactive in how they manage power supply in the transmission infrastructure. In the past, utility companies have needed to increase spinning reserves, and invest in generators with faster start up times to counter intermittent generation created by renewable energy sources [9, 10]. Demand response is an option to alleviate the issues that come with renewable energy penetration, and are an alternative to costly large scale energy storage [11]. Even though there has been research into the feasibility of renewables into the current grid infrastructure [12], utilities and policymakers find themselves still requiring ways to understand the benefits and drawbacks of demand response programs [13].

The North American Electric Reliability Corporation categorized demand response as a "subset" of Demand-Side Management (DSM), which looks to create efficient energy programs focused on the consumer end (node) of power consumption [14]. Many current grid infrastructures have a utility generating energy at a plant, and sending it through a network to the consumer [15]. In a demand response program, the consumer has a direct connection to the utility, whether it be through Direct Control Load Management (DCLM), or and Interruptible Demand. DCLM involves the utility having the ability to remotely turn on/off, or cycle devices within a home, or business, thereby reducing demand on the consumer side. Interruptible demand is an agreement between the consumer and the utility where the utility can request that a consumer curtail their energy use during peak hours, or have the ability to remotely trip devices within the consumers property as long as notice is given beforehand. In exchange, a consumer will receive discounts and/or credits towards their energy bills [14].

Other demand response programs involve consumer rate programs that are time-based. Time-of-Use Rates (TOU) involve power prices set at certain rates depending on the time of day, utilities hope that consumers will notice high rates that correlate to peak hours, and therefore reduce their demand during these time periods. Critical Peak Pricing (CPP) uses preset rates which are made available when the power grid incurs a large stress, or an unforeseen event that requires energy curtailment within the power grid. Real-Time Pricing (RTP) provides prices that change hourly, or from day to day, to wholesale and retail markets, with the hope that high demand for power will be reduced when power is at its price peak.

DCLM and Interruptible Demand are just two examples of demand response programs where incentives are introduced to curtail energy usage, but require further investigation and research into long-term effects. TOU, CPP and RTP are three time-based demand response programs that involve consumers adjusting power demand based on price rates, however, like the incentive based programs, the time-based approaches also require further research to assess long term reliability. The North American Electric Reliability Corporation (NERC) stated a need to acquire experience in demand response programs, and to understand how consumers interact with the proposed DSM programs.

Grids are currently monitored by workers that must physically go to points on the grid, whether that involves reading meters, or searching for equipment failures [15]. A worker cannot provide real time information describing multiple sections of the grid in real-time, instead, this task must be automated, so that a utility, or consumer, can be proactive and participate in a demand response program to curtail peak loads.

Because of the island's geography and dense population, Oahu provides an ideal location to understand renewable energy penetration into an existing power grid, and how it relates to demand response programs. Several factors allow for Oahu to be the location to implement the pilot system, these factors include high solar radiation on the island, access to a dense urban populations, and Oahu being an isolated power grid. In 2015, the Hawaii state legislature voted to have 100% energy generation from renewable sources by 2045 [17]. Hawaii's commitment to alternative energy sources allows for a continued study of an urban area with high renewable energy generation, and the effects of this generation on demand response.

2.3 Demand Response and the Electric Vehicle

Ninety-five percent of private transport is dependent on oil, and is responsible for 50% of the oil consumed around the world [31]. However, personal vehicles are on the road only 4-5% of the day, while 90% of personal vehicles are parked during the peak hours of traffic, making them ideal to be utilized as battery storage devices [32].

Companies have looked to EVs as a way to create mobile storage devices that would aid in balancing the intermittency of renewable energy sources within the grid [31]. The area of highest potential looks to be in the use of already existing EV fleets, such as hybrid buses, that would provide ancillary services when connected to the grid. Analyzed battery powered fleets have shown potential for high market value for vehicle to grid systems (V2G) among a variety of different electric power sources [32]. The requirements of V2G would be; on-board precision metering of the vehicle, control connections that allow the vehicles to communicate with grid operators, as well as a power connection between the vehicle and the grid [32].

The battery powered fleets would be focused towards regulated ancillary services that partake in grid control. Mainly, the control of frequency and voltage in local areas. Ancillary regulation would enable the ability to match generation and load, maintain interconnection frequency, and balance the actual and scheduled power flows, all within the respective control areas [32]. The reduction of voltage deviations and power losses can be accomplished by coordinating the charge schedules of plug-in hybrid vehicles by flattening peak power demand [33]. Electric buses are ideal because they have high battery capacity and high power potential. The predictive routes of buses allow for predictable load scheduling. The economic analysis of demand response has led to the study of different tariff methods, [35] suggested several price schemes for EV charging within smart grids that involve single, bi, tri, tetra tariff and real-time pricing [35].

Another strategy for demand response utilizes plug-in EVs (PEVs) to supply demand-side management services in smart grids. V2G capable PEVs can communicate with the grid, return energy to the grid, and store energy [34]. PEVs within the grid would be treated as individual agents tasked with solving optimization problems at the local level to find a global solution. The PEVs can, "enhance energy infrastructure resilience, enable renewable integration, and reduce economic costs for consumers and energy providers." The first step in the proposed load shaping strategies has a PEV solving a local optimization problem based on a price signal and then communicating its response to an aggregator. The second step involves the aggregator updating the price signal to reach minimal load variance [34].

One study of EVs as they relate to demand response has focused on the charging stations themselves as a way to create a hierarchal demand response for EVs. One such study by [36] suggested a deadline-aware, two-level market mechanism. The charging stations lead the market and EVs follow to determine their respective strategies. The solutions converge to equilibrium where no user can improve their respective gains by changing their strategy.

The following sections will discuss the development and implementation of a smart metering system for the purpose of collecting and analyzing data for usage in load prediction and forecasting as it relates to the usage of demand response programs for energy management in a grid.

3.0 Smart Power Meter (SPM) Pilot System

A pilot program has been created at the University of Hawaii that currently involves monitoring aggregate power usage from 9 homes on the island of Oahu using a smart power meter (SPM). The system will allow the ability to collect and analyze data as it relates to load prediction and demand based power management. As more EVs enter the market, it will be necessary to understand and analyze how the power aggregation of EVs impact the larger power grid system as a whole. An outline of the demand response logic as it pertains to the pilot system is displayed in Figure 3.1.

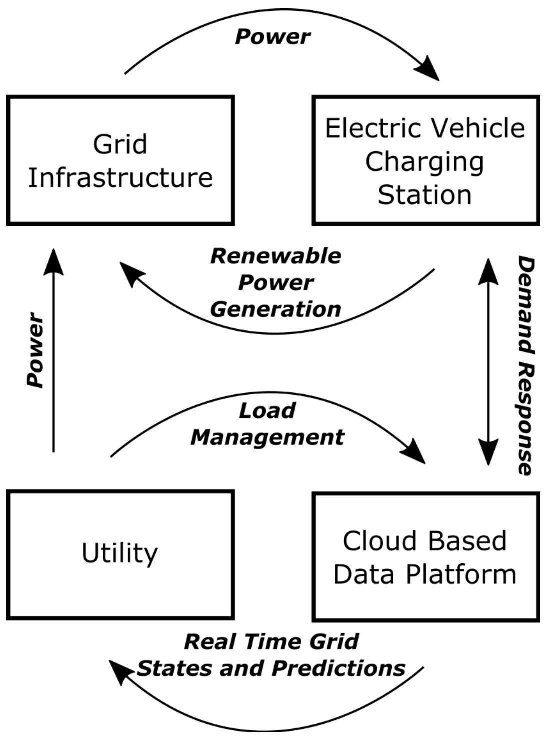


Figure 3.1: The system demand structure for a data collection system is presented. A cloud based platform will store and analyze data collected from a home, or business, in real-time, allowing for quick control decisions in demand response programs. One, or several EVCSs, can be analyzed within the urban environment by monitoring the amount of power consumed through the charging station using SPMs.

Previous devices that measure power consumption have been used in research, however, most studies do not offer high frequency data with the resolution to detect small transient changes [16]. Current research on the pilot system collects and analyzes data at higher resolutions. A 1Hz resolution, or better, will provide a good sampling rate for large data collection and the ability to see transient patterns in power usage, such as the warming of a stove, or the brightness of a television. The pilot system has shown different devices within a home display a specific power profile signature when their power draw is monitored. This signature can be thought of as a *power fingerprint*. Having the ability to determine device usage from power data allows cost efficiency in power monitoring because rather than installing a power monitoring meter on each device within a building, software can instead analyze and determine which devices on a property are in use based on the power signatures found within an aggregate power data set for an entire home, or business.

Power producers will be able to monitor a node and understand which devices can be cycled during peak loads to relieve grid pressure, especially in high energy consumption areas like urban centers. The pilot system provides the foundation for a power utility to better understand how consumer behaviors affect the grid as a whole. Understanding when specific devices are in use allows for some load prediction and scheduling. For example, a UK-based utility company found that millions of kettles are cycled around 5pm, knowledge such as this allows a utility to know when to cycle specific loads within home [34]. Aggregating these cycling patterns with the loads of other houses in a neighborhood, or region, can allow the ability to maintain grid stability throughout sections of a power grid. Components, challenges and scalability of the pilot system will be discussed in the following sections.

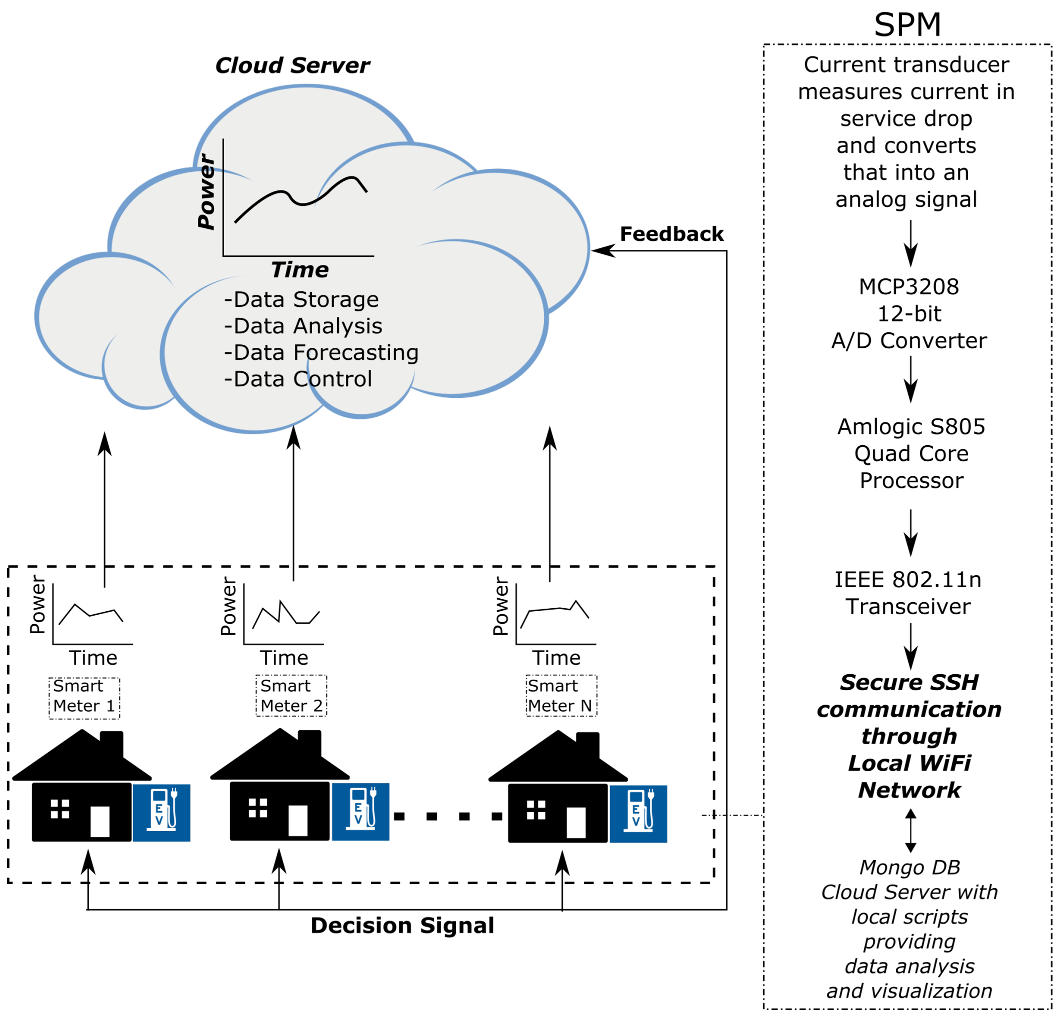


Figure 3.2: The setup of the proposed system, which was developed at the University of Hawaii, implements a SPM to monitor and transmit data from a circuit box. Transmitted data is then transmitted to a server for analysis. The current server can be scaled to cloud storage, so that more nodes can participate in the pilot program and provide more data for load forecasting analysis. Just as the individual power consumption of homes can be analyzed within the cloud server, so can the power consumption of EVCSs.

Most buildings have circuit breaker boxes, so a preexisting interface is already in place to install the SPMs. The device collects data at a frequency of 60Hz and implements one-second intervals to send the data through a local WiFi network to a remote cloud server using a secure shell (SSH) tunnel. Data storage, analysis, forecasting and control can all occur within the cloud. The cloud server will have the ability to convey control signals based on analysis of the power data to the consumer, where an installed client can cycle devices in accordance with demand response programs to reduce peak loads. The SPMs will allow the ability to collect data on EV charging, which can be used to analyze the EVs impact on overall power consumption in the grid. Figure 3.2 illustrates the overall pilot system.

3.1 Data Acquisition

The data acquisition is performed by a power metering device at the local consumer level. The device can fit within a circuit breaker box, is non-invasive, and allows for easy installation, setup and maintenance while delivering accurate power measurement, data preprocessing, and server communication. The SPM is powered through the circuit breaker box. Two current transducers, one connected to each service drop wire within the circuit breaker box, measure current signals, and sent to a MCP3208 12 bit analog digital converter (ADC), which collects data at 80 kilo-samples-per-second (kSps). A SPM installed in a residential circuit breaker box is shown in Figure 3.3.

Figure 3.3: A SPM meter developed at the University of Hawai'i is installed in the circuit breaker box of a home taking part in the pilot project.

An Amlogic Quad Core processor computes the power consumption for each phase. Power is calculated assuming a constant AC voltage entering a home, in the US, this would be 120V. The median power pertaining to one second of collected data is obtained for each phase, and sent to the cloud server for storage and analyzing. Figure 3.4 describes data collection and transmission on the consumer level.

3.2 Communication

After the power data is collected and preprocessed by the SPM, the data is then transmitted to a remote server using a secure SSH tunnel via a local WiFi network. When scaling the pilot system, SSH tunnels will be replaced with virtual private networks (VPN). The advantage of this communication setup is that the SSH tunnel provides an added layer of security for what is confidential information. While the utilization of a preexisting local WiFi connection takes advantage of an already existing network, thus eliminating the added cost of building a new communication infrastructure. Data is stored directly into a MongoDB database. Because data is being sent from multiple locations, each data set needs to be identified by the node it originated from, this is accomplished when the SPM assigns a node identifier to each outgoing data set. When there is a disturbance in the WiFi connection, or a communication delay, the SPM will buffer until a connection is reestablished to minimize data-loss. Even though the SPM transmits data at a rate of 1Hz, bandwidth and storage requirements are kept minimal. Each database query consists of just three integers, using 24 bytes of data per second on a 64 bit system. Households are currently transmitting approximately 2MB/d. The island of Oahu has a population of approximately 991,788 with an average of 3 people per household, which would give 330596 households [18]. 661GB of power data would be sent to the servers each day at a rate of 7.65MB/s.

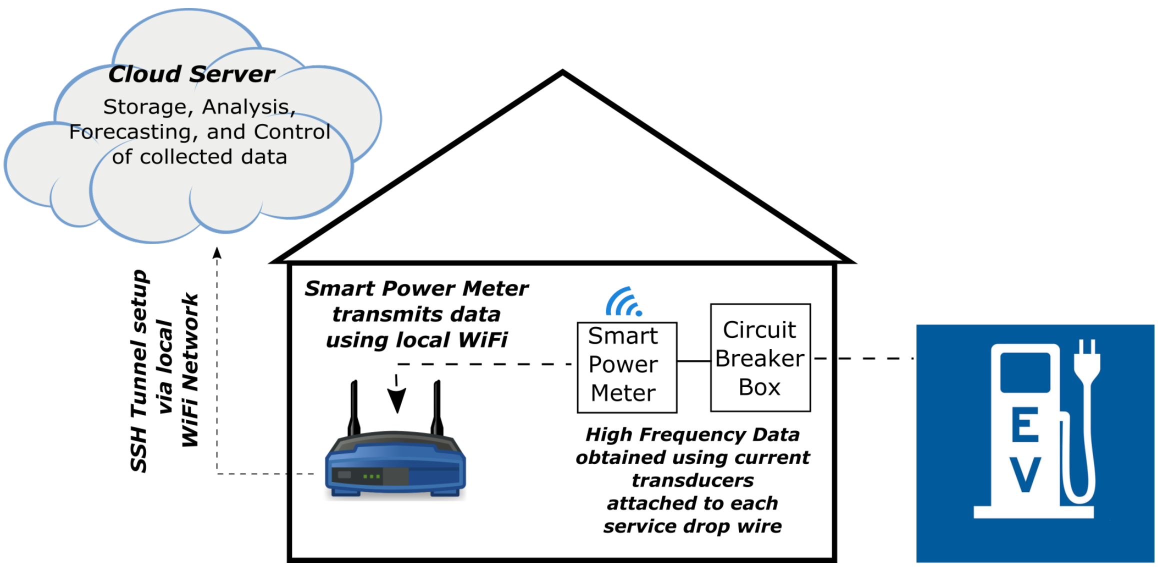


Figure 3.4: Utilizing preexisting WiFi connections within a home allow for a cost effective solution for data transmission. Circuit breaker boxes are usually located in a remote area of a building, so it is necessary to utilize a wireless connection to allow for a robust system to monitor and transmit data from a node. A secure SSH connection allows for safe and reliable transmission of data to a server in real-time. The pilot system structure was developed at the University of Hawaii.

3.3 Data Storage/Analysis

The MongoDB database on the cloud server, is a document based open-source database. It is utilized as a multiuse agent that acts as a central node where large amounts of power data is collected, streamed, and queried for data analysis of real-time system states and forecasting.

Document based databases yield high scalability and data storage flexibility, which aids in the analysis of large complex urban centers, which may have numerous amounts of contributing factors. Streams of real-time and recent data, as well as data queries for historical data must be performed as efficiently as possible to create predictions that will analyze data in real-time, thus allowing for fast and efficient conclusions and decisions. Data can be analyzed to understand when a large amount of EVSEs are in use, and how much power they consume relative to other loads connected to the grid. These conclusions will be utilized in future work to create control decisions to be sent back to the consumer where devices within a property can be controlled using a client. Thus granting the ability to create forecasts that enable efficient demand response programs to be implemented, which will reduce peak loads and ensure reliable power transmission within the grid infrastructure.

3.4 Control

Future work revolves around enabling the cloud server to analyze real-time and historic data in order to determine, and send control decisions for demand response programs. Smart control decisions enable the ability to better ensure grid stability and power transmission reliability. These commands include, but are not limited to, ON/OFF commands, as well as time constraint commands. The control clients executing the commands will have the ability to send feedback data to the cloud. The server itself can be utilized by the consumer as an interface to monitor power consumption, or override control decisions.

4.0 Scalability

A large and flexible database is necessary for bulk amounts of data being collected from an urban center. MongoDB is a “NoSQL” cloud database where large data collection will be stored and analyzed when the pilot system is scaled.
A “NoSQL”, or “non SQL” database is an alternative to the relational databases that use the Structured Query Language (SQL). There are alternative “NoSQL” databases such as Apache Cassandra and Couchbase, but recent studies have shown MongoDB to be more efficient in terms of reduced latencies when it came to read and update workloads [23]. MongoDB contains a document database architecture, which provides the flexibility needed for scalability as the pilot system grows to include more nodes.

The use of a single server would lead to scalability issues as more data is collected and processed, MongoDB overcomes these issues with the potential to add more servers to accommodate large data as well as the utilization of automatic sharding, meaning that data is spread throughout multiple servers. Automatic sharding permits data to be accessed easier, and managed faster [24]. MongoDB utilizes a flexible data model, which allows the opportunity for easier development and scalability. This is because MongoDB does not use a rigid database schema, which determines how data is logically grouped.

Rather, documents within MongoDB are assigned a primary key (id), which allows for a flexible schema where data can be easily queried. Because factors that are not originally in a prediction algorithm may later prove to be of importance, a flexible schema allows newly identified factors to easily be integrated into a preexisting data structure within the database [25]. The “NoSQL” database MongoDB also takes advantage of bucket streaming URI (Uniform Resource Identifier), which is based on chunked transfer encoding. The streaming transfers permit data to be sent directly to the cloud server whenever data is available for transfer. This is because data is not buffered and saved to an isolated file, thus allowing for faster data transmission to the cloud servers [26].

There are drawbacks to using MongoDB, one being that the database performs poorly when it comes to aggregate functions, such as medians, modes, and sums. However, current research has not deemed this to be a problem when implementing algorithms into the cloud server. MongoDB also struggles with non-key values, but this too has not been deemed an issue in current research related to the pilot system. Because MongoDB is a “NoSQL” database, its implementation will require less effort than a SQL database due to the fact the schema in a "NoSQL" database is not as rigid. And because "NoSQL" databases have only recently gained in the popularity they have today, there is less support and literature as compared to a SQL database, which in many industries is considered a standard [25].

5.0 Data Analysis and Results

For initial studies, data from August 15 to November 15 was available, obtained from a total of 9 nodes. Each service drop wire in the circuit breaker box is measured and the data is then sent to a server where data can be queried. Figure 5.1 provides data queried from the system server, which shows the power consumption of a node for one day. The power measured from each service drop wire is plotted and referred to as circuits one (red) and two (black).

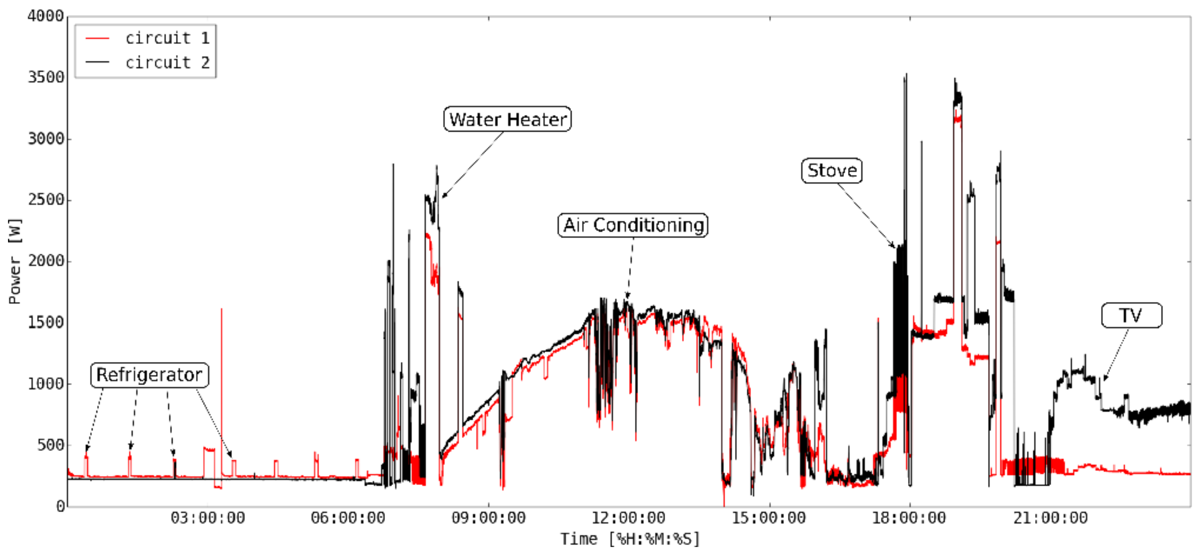


Figure 5.1: Devices produce specific power signatures when in use. It can be observed when certain devices are cycled. The cycling of loads within a node displays the behavior and patterns of a consumer that can be used to predict and schedule power generation. Installing a node within a home with an electric vehicle will allow the ability to recognize when an EVCS is in use.

The large increases in loads displayed in Figure 5.1 correspond to unique device signatures throughout the day, which are labeled in the figure. In the displayed example, from midnight to 7am, the only signal that stands out is the refrigerator cycling, which is due to the fact no other major loads are present at the respective time interval. During the day air conditioning is the dominant load, which correlates to the heat in Oahu at midday. Evening loads are dominated by consumer electronics such as TV.

Detailed power profiles over extended time periods grant an observer the ability to understand the energy needs of a consumer and predict when to schedule loads. Such is the case in Figure 5.2 where a week of data has been plotted.

The node displays a clear pattern of power consumption throughout a week. Dominant loads throughout the day are shown in blue and green, correlating to air conditioning and dinnerrelated activities, respectively. The family exhibits a fixed pattern of power consumption throughout the week that can be used for load prediction. Air conditioning loads dominate the day while cooking related activities dominate evening loads. The two main load patterns stemming for air conditioning and cooking are repeated daily throughout the week. Nighttime loads are reduced to a bare minimum because of inactivity at night.

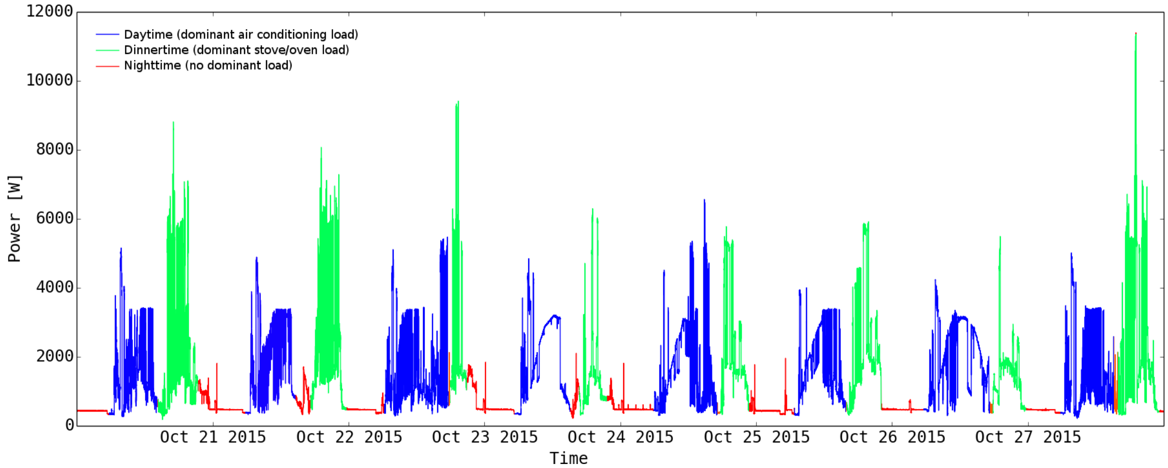


Figure 5.2: One week of total power consumption is plotted for one family home. Consumer pattern behavior is evident from the increases in power consumption.

Self-learning algorithms, such as Artificial Neural Networks (ANN), can be taught to detect power fingerprints in large data sets such as those shown in Figures 5.1 and 5.2. Knowing which devices are in use, and when, will allow for scripts installed on a server to calculate optimal load schedules to cycle devices, such as water heaters, an EVSE, and air conditioning units within a node. Being able to distinguish when, and how often, a consumer uses a device will enable a power provider the ability to shed peak loads while not creating an interruption to a consumer's power usage. The capability to cycle a load can be automated, so that a client within a home can obtain decision signals from a cloud based server and implement the signals in real-time.

In order to deploy proper demand response programs within a grid, it is important to first understand consumer behavior in greater detail. The pilot system has already proven the feasibility of using high frequency to gather power consumption data at a node, however, to implement proper load scheduling, it is necessary to understand which devices in a node are in use and when.

5.1 Bottom-Up Approach

A bottom-up approach was taken in analyzing power signature data. Data such as Figure 5.1 exhibits that it is possible to identify certain devices in an aggregate power signal produced by a node. Each of these devices displayed a unique power signature when plotted in the time domain, which allowed the ability to create a rough estimate of when and how long certain devices were in use. Consumer behavior can be viewed on a broad scale as a repeating pattern of habits, which allows power data from a node to then be classified as the combination of repeating separate loads composed of unique characteristic signatures that pertain to individual devices. So to implement a bottom-up approach, it is important to study individual devices in order to understand the characteristics displayed by their respective power signatures, and how these power signatures could be found in the aggregate power data from a node.

A research group at Darmstadt University cycled 43 devices that are commonly found in a home, and measured the power draw of each device with respect to time [20]. The power consumption of all 43 devices provided signatures that contained certain characteristics when plotted that could be categorized in one of five categories shown in Table 5.1 below.

Table 5.1 shows that many power signatures from devices contain characteristics, which grants the ability to categorize appliances, thus allowing a preliminary factor in identifying devices. However, five categories are not enough to identify a specific device directly, so it was necessary to further analyze the device power signatures to understand potential methods to recognize a specific device in an aggregate data plot. Figure 5.3 displays a power signature for one of the measured devices over an extended period of time, a water boiler.

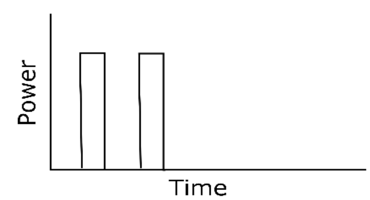
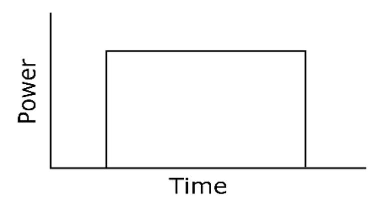
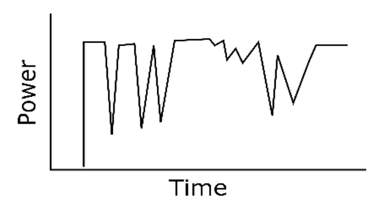
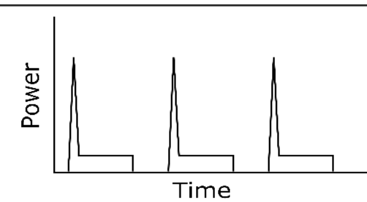
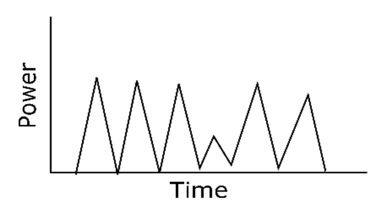
Type of Load	*Device Examples*	*Signal Plot*
Single Peak Loads Devices that create power plots with one, or more rectangular load peaks	Vacuum Cleaners Cooking Stove Kettle	
Stable Time Dependent Loads Devices that are used for extended periods of time and can be considered stable loads	Lamps Water Heater Microwaves	
Stochastic Time Dependent Loads Devices that are used for extended periods of time but, can increase and decrease power usage during cycling	TVs Computers Audio Systems	
Cyclic Loads Devices that are known to cycle throughout the day	Refrigerators A/C Systems	
Periodic Loads Devices that display various load peaks within a short amount of time	Printers	

Table 5.1: It was determined that the power signatures of the 43 measured devices can be categorized into five main categories shown in the table. Each type of signal plots differently when transferred to the frequency domain, which allows for a factor of differentiation when categorizing signals. It will be necessary to monitor an EVCS to understand how the signal plot for its respective power consumption behaves.

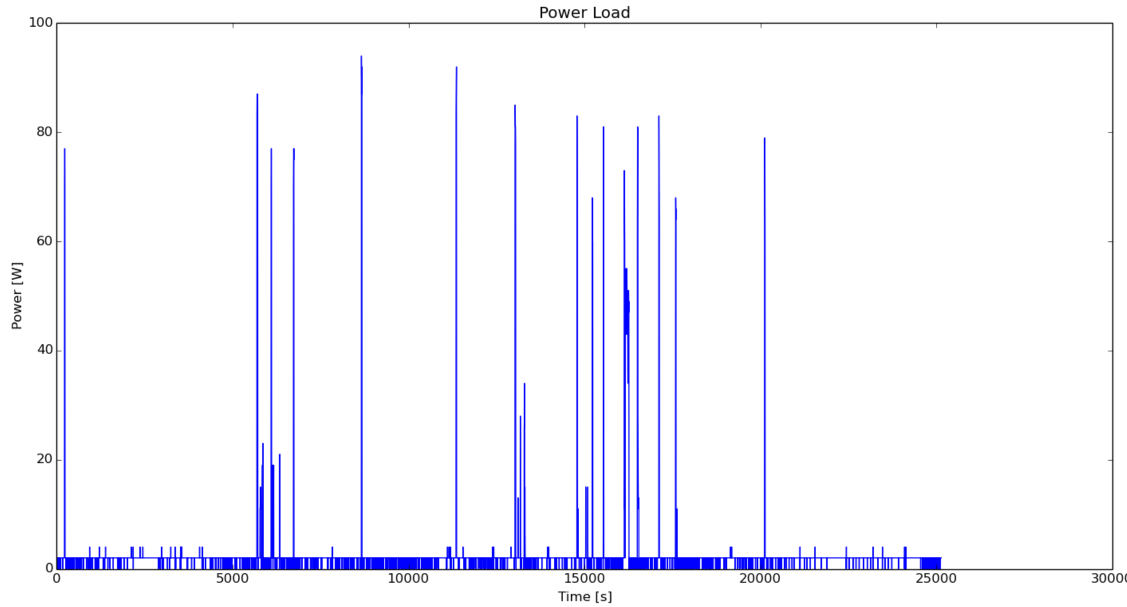


Figure 5.3: The cycling of a water boiler is shown. All the measured devices displayed unique power signatures when plotted in the time domain.

To better understand if there were unique characteristics that defined the power signature, it was necessary to narrow down the data set to a few individual peaks to locate small transient changes in the power draw that may be distinct to a device. Figure 5.4 provides a closer look at selected peaks from Figure 5.3.

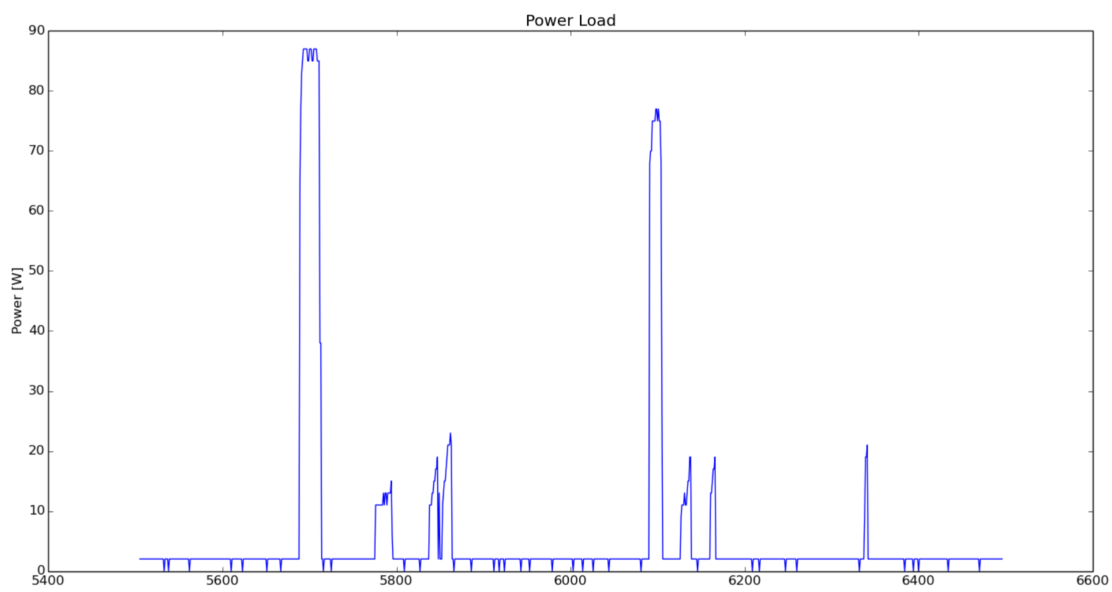


Figure 5.4: A closer look at the peaks within the plotted power data from a water boiler reveal unique transient changes, namely at the various power signal peaks.

A closer look at the power peaks allow the ability to investigate small transient changes in the power signature. Figure 5.5 demonstrates narrowing the focus to an individual peak.

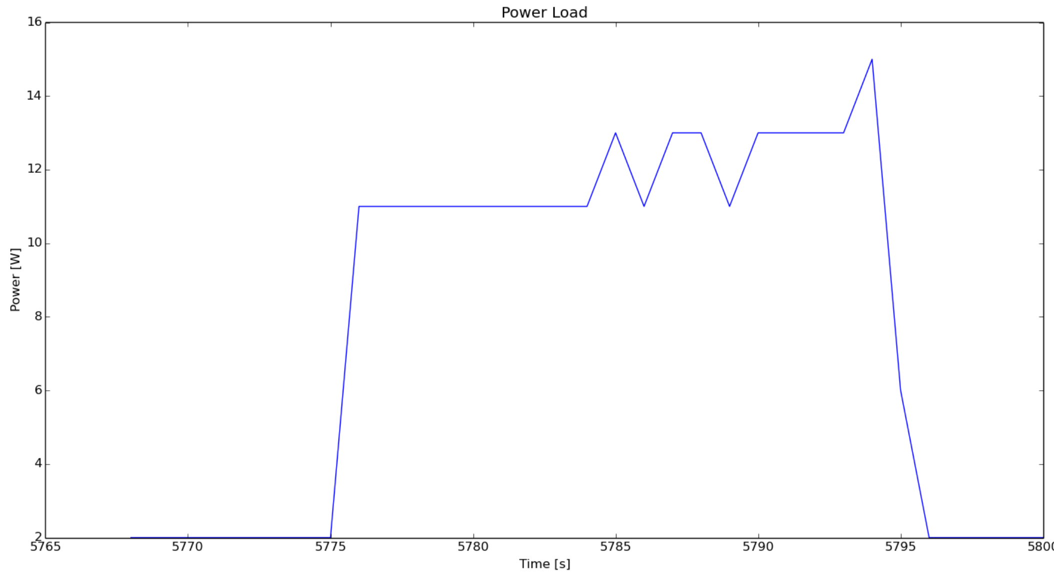


Figure 5.5: A particular pattern in the power data is observed when focusing on an individual peak, which can be used as a factor to classify the water boiler in a device database.

An example of another measured appliance, a refrigerator, is shown in Figures 5.6 and 5.7.

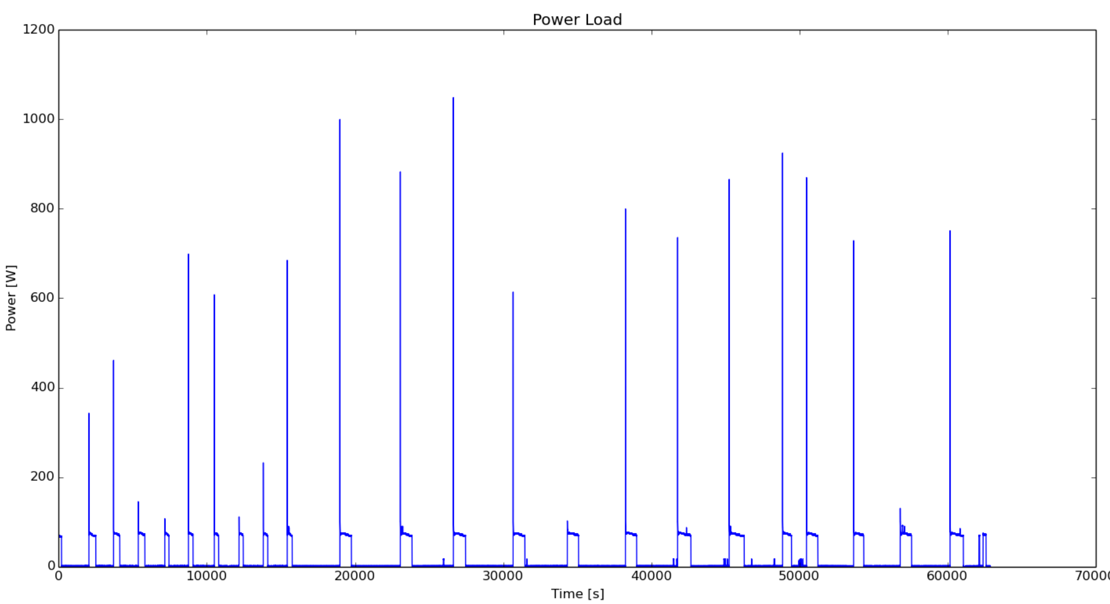


Figure 5.6: The power load data for a refrigerator is plotted to display differences between the power signatures of measured devices such as the water boiler in Fig. 5.3.

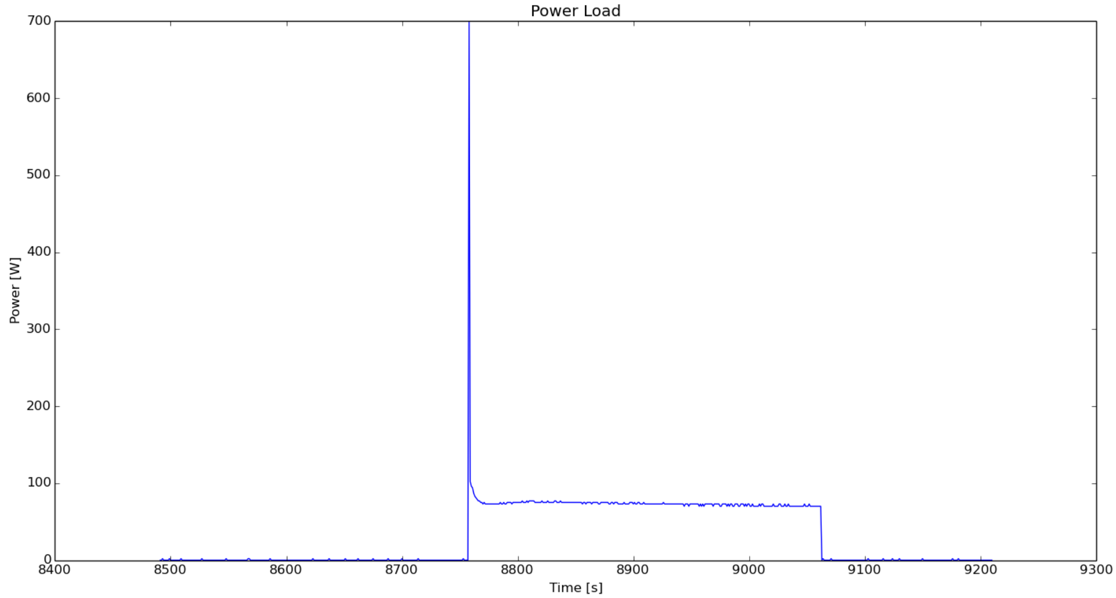


Figure 5.7: When focusing on a peak in the plotted power data for the refrigerator, it can be seen that there are defining signal characteristics unique to the device, as was the case with the water boiler in Fig. 12. The unique characteristics were deemed as a factor in recognizing devices in a large collection of power data.

After determining that a power signature for a device displayed unique transient characteristics, it was then necessary to implement a method to further analyze the data, namely investigation into a technique to differentiate multiple device signatures from an aggregated data set obtained from a node. Recognizing specific loads in a node grants a power producer the ability to implement proper load scheduling throughout the day based on the pattern usage of various devices within a node. Many EVs are charged in the evening, knowing exactly when and how much power is consumed will allow efficient nighttime load scheduling.

Initial research has focused on the combining of two unique power signatures, like those in Figures 5.5 and 5.7, from two different devices. Once the power signals of the devices were combined, techniques were implemented to recognize individual devices in an aggregated signal. Figure 5.8 displays the power signatures of two devices. Figure 5.9 displays an example of two device signals being combined to form one load.

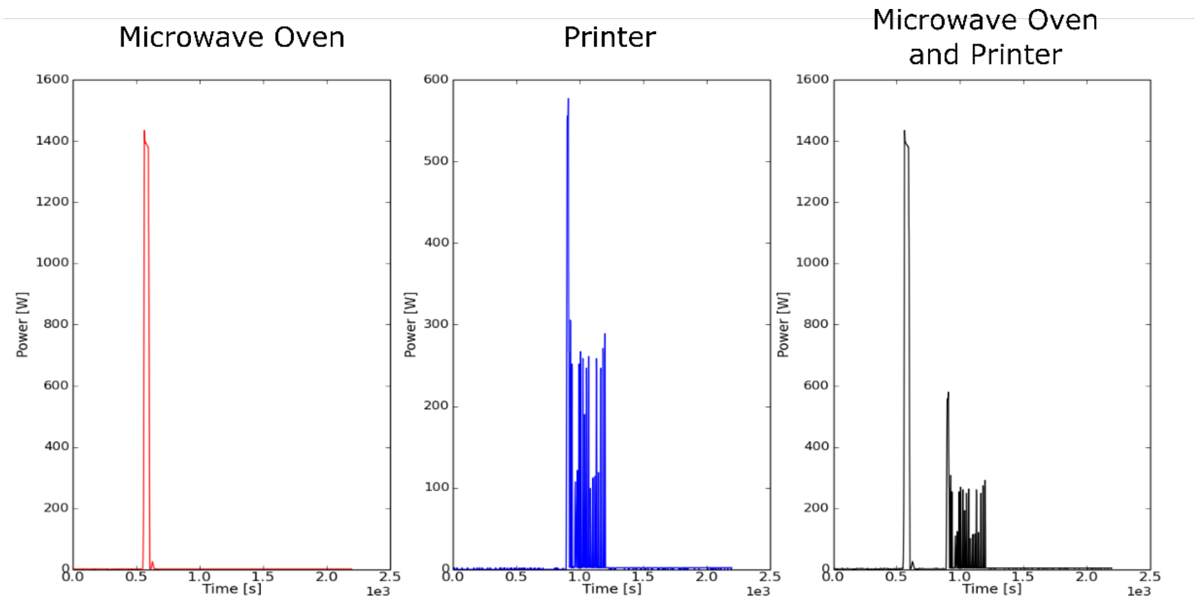


Figure 5.8: Two devices can be combined to create a time dependent plot that features both signals, in this case a microwave oven and a printer, however it can be seen that the devices were recorded at different times, so it is necessary to combine the signals into one aggregated signature.

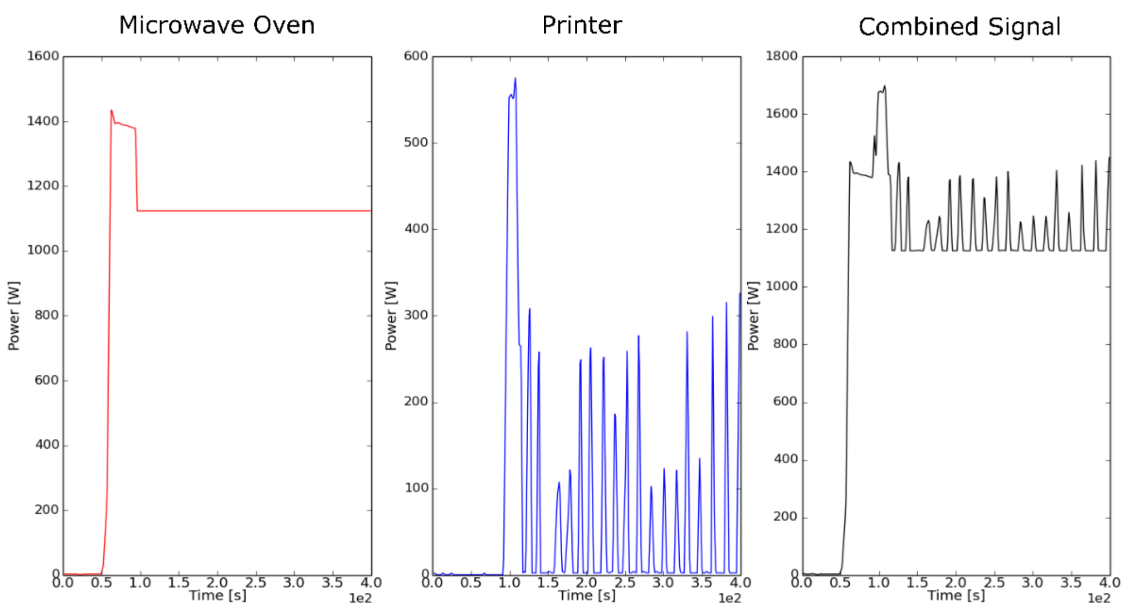


Figure 5.9: Aggregating two device signals allows the ability to analyze how the unique characteristics of signals correlating to specific devices interact with each other. Studying this interaction allows the ability to understand techniques for sifting specific devices from a large power set produced by a node**.**

To further analyze the power data, Fourier based methods were chosen as a first step in analyzing the power signatures of various devices. Fourier transforms have applications used for the analysis of square waves, as well as periodic signals [21]. Figures 5.5 and 5.7 demonstrate that when various devices are cycled, and the power signatures are plotted in the time domain, they bare similar characteristics of repeating square wave forms. Fourier analysis also approximates a function into a sum of trigonometric sets, which could aid in identifying certain devices. Because Fourier analysis breaks a larger set into a sum of sinusoids, it may be possible to correlate certain devices to specific frequency thresholds. Taking into account the theory of square wave forms and the summing of trigonometric sets, Fourier analysis was deemed as a viable first step in determining if a large set of power data from a node could be broken down into a sum of individual signatures that pertain to specific devices. Analyzing the power signatures in the frequency domain allowed the ability to determine if certain devices had higher energies at specific frequencies that would grant the ability to organize devices based on which frequency their signal energy was most influential.

An initial Fast Fourier Transform (FFT) was performed on each device signal as well as the combined signal. Row two of Figure 5.10 displays this analysis.

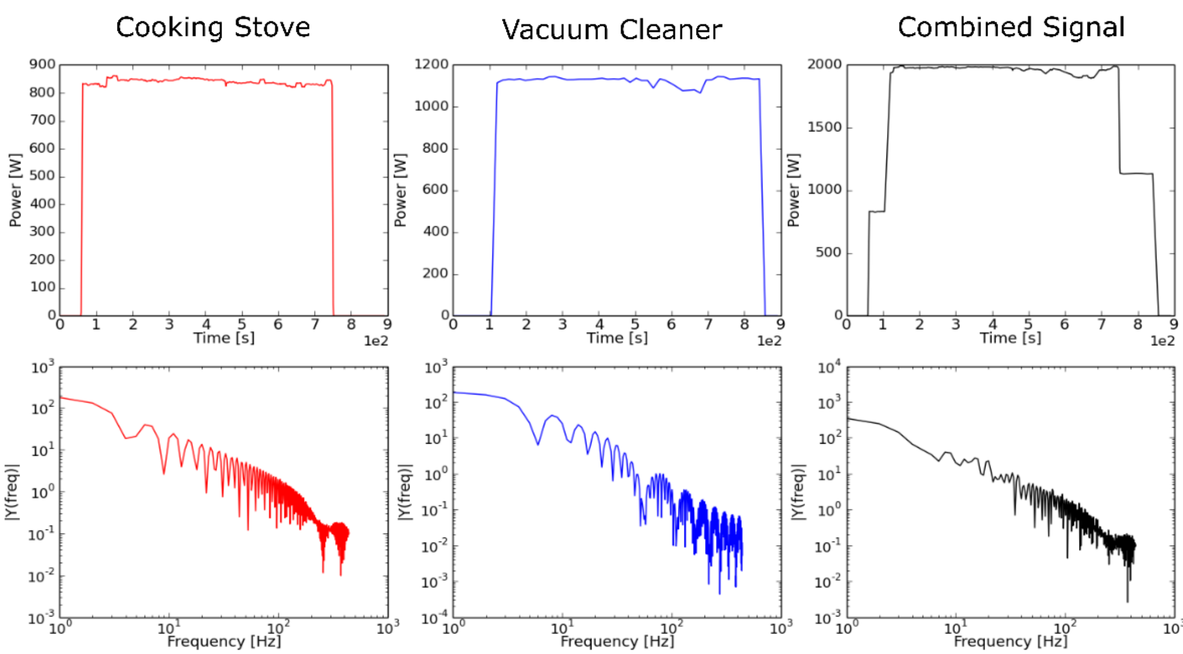


Figure 5.10: Once two device signals are combined they can then be analyzed in the frequency domain to better understand if the signals exhibit a specific characteristic pattern.

As can be seen in Figure 5.10, FFT analysis provides two plots with unique characteristics, however, Fourier analysis alone has disadvantages when applied to power data like that of Figure 5.7. These disadvantages come from the fact that Fourier analysis is better suited for non-stochastic and stationary signals [22]. So to better distinguish the signals, another analysis, known as power spectral density analysis (PSD) was performed on the power signature data. PSD can implement Fourier based methods to plot what can be considered a *random* time signal in the frequency domain, allowing the ability to determine what frequencies within the signal contain the largest energy densities relative to the surrounding ambient signals. If periodicities exist in the spectrum, PSD will allow them to be observed, these periodicities can then be used to classify devices into categories. Using PSD, transient variabilities from the time domain can be found in a frequency domain. Figure 5.11 highlights these variabilities.

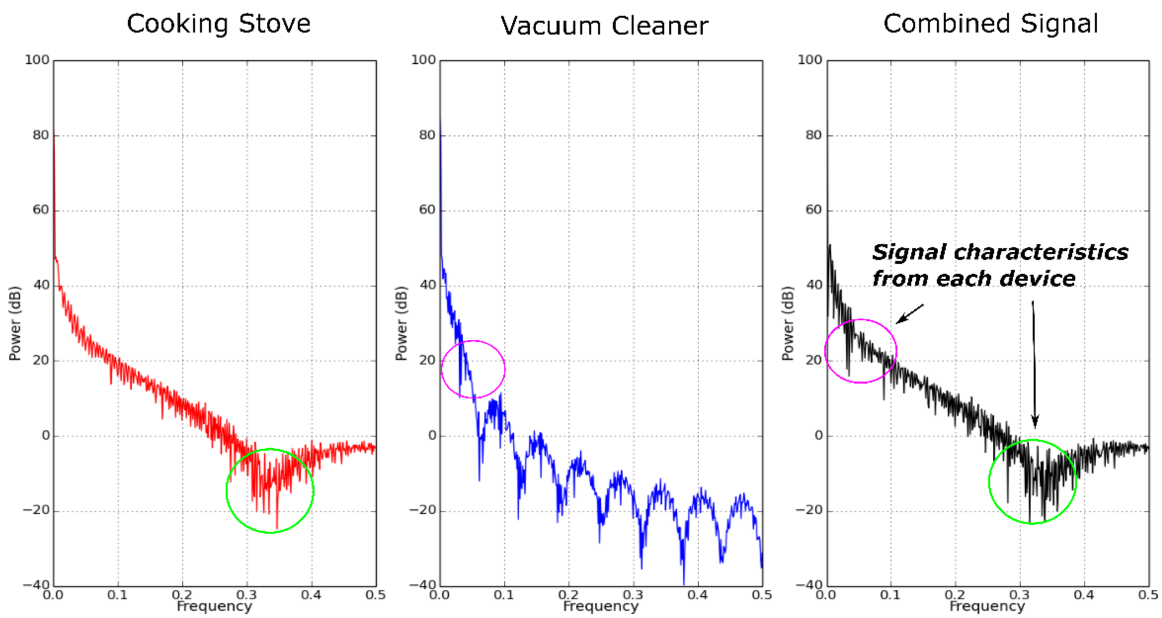


Figure 5.11: The implementation of PSD granted the capability to observe unique device signatures that are visible in an aggregated signal.

When PSD analysis was implemented on the power signatures of a cooking stove and vacuum cleaner, two unique signals were plotted, which can be seen in Figure 5.11. The ability to notice each device in a combined signal further proves that specific appliances can be sifted from a larger data set that pertains to an individual node. The analysis is necessary to provide accurate and efficient demand response programs that can specifically target certain devices during a day that are not in use, thus allowing frequency stability within a power grid to be maintained.

Figures 5.12-5.15 display the FFT and PSD analysis of different device combinations. The first row of each aforementioned figure displays the power signals in the time domain for the devices, the FFT for the respective power signals in row two, and the PSD analysis in row three.

From Figure 5.12 it can be determined that magnitude is a variable that can be utilized when identifying devices in a large set of power data. Because the cooking stove had a power magnitude that was ten times that of the LCD TV when plotted in the time domain, analysis from the FFT and PSD reiterated this fact, proving magnitude as tool for device identification when analyzing time dependent data in the frequency domain.

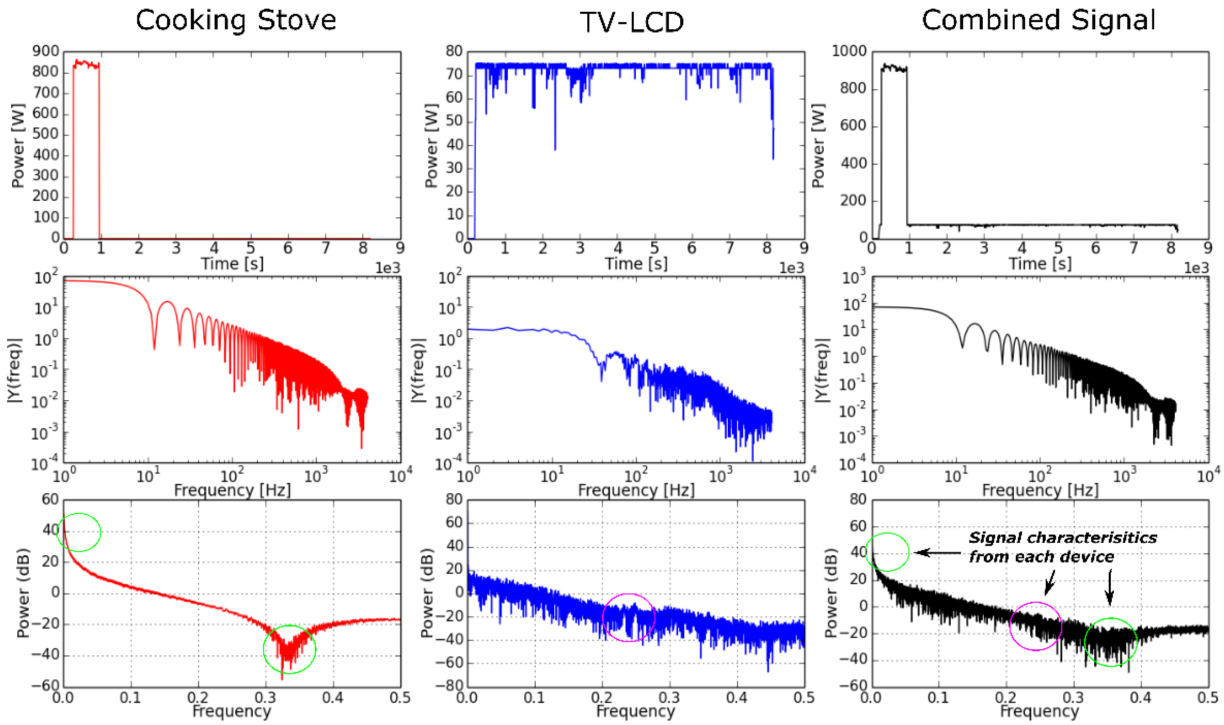


Figure 5.12: Column one displays the signal analysis for a cooking stove, column two for a LCD TV, and column three for the sum of the two signals. The green circle shows the location of a specific attribute of the cooking stove PSD signal in the aggregate, while the purple displays the attributes pertaining to the LCD TV.

Figure 5.13 again proves that magnitude is a factor that affects power signal analysis in a frequency domain, thus allowing the ability to decipher between devices that use low amounts of power, and those that use substantially higher power consumption to operate. It should also be noted that the lamp produced a usage time that was almost 25 times the magnitude of the toaster. However, it was still possible to identify the toaster using PSD analysis on the combined lamp/toaster signal. Furthermore, magnitude once again proves to be a dominate factor when time-based signals are plotted in a frequency domain as characteristics of the toaster are much more predominant in the PSD plot of the combined signal.

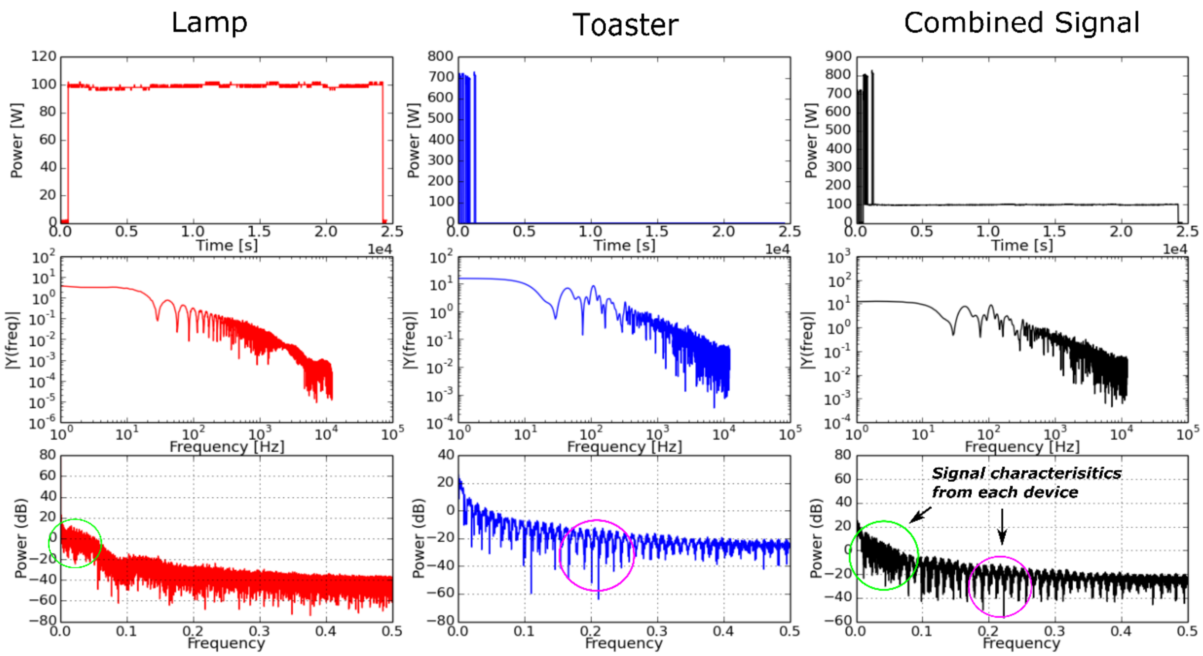


Figure 5.13: Column one displays the signal analysis for a lamp, column two for a toaster and column three for the sum of the two signals.

Figure 5.14 provided a basis of investigation into the interaction of a periodic load (printer) and a load that can be classified as constant (microwave oven). Though unique signal characteristics can be found in an aggregated PSD signal, another factor may be needed to aid in device recognition as depicted in Figure 5.15. The magnitude of the microwave oven grants the ability to locate the oven in the aggregated PSD signal. In cases such as these, when there are multiple devices with varying magnitudes, being able to identify the device with the largest magnitude allows the ability to begin a process of elimination where devices can be located based on magnitude as well as signal shape.

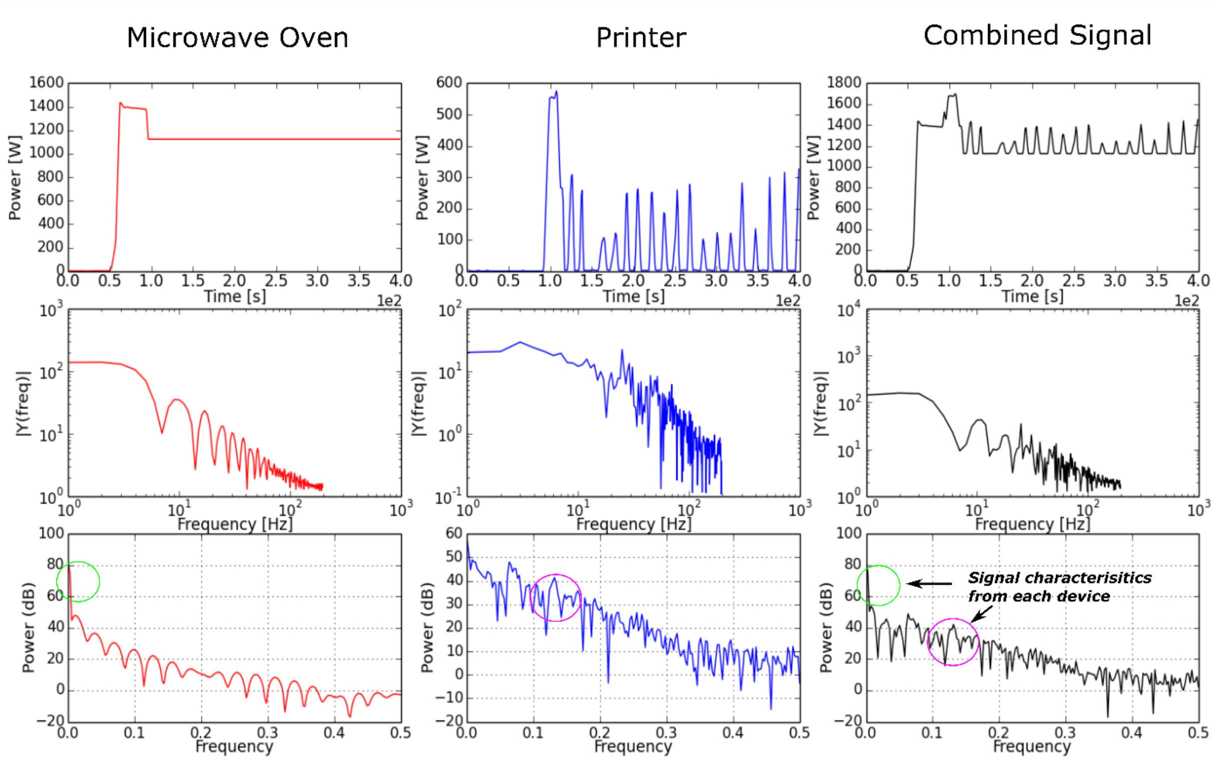


Figure 5.14: Column one displays the signal analysis for a microwave oven, column two for a printer, and column three for the sum of the two signals.

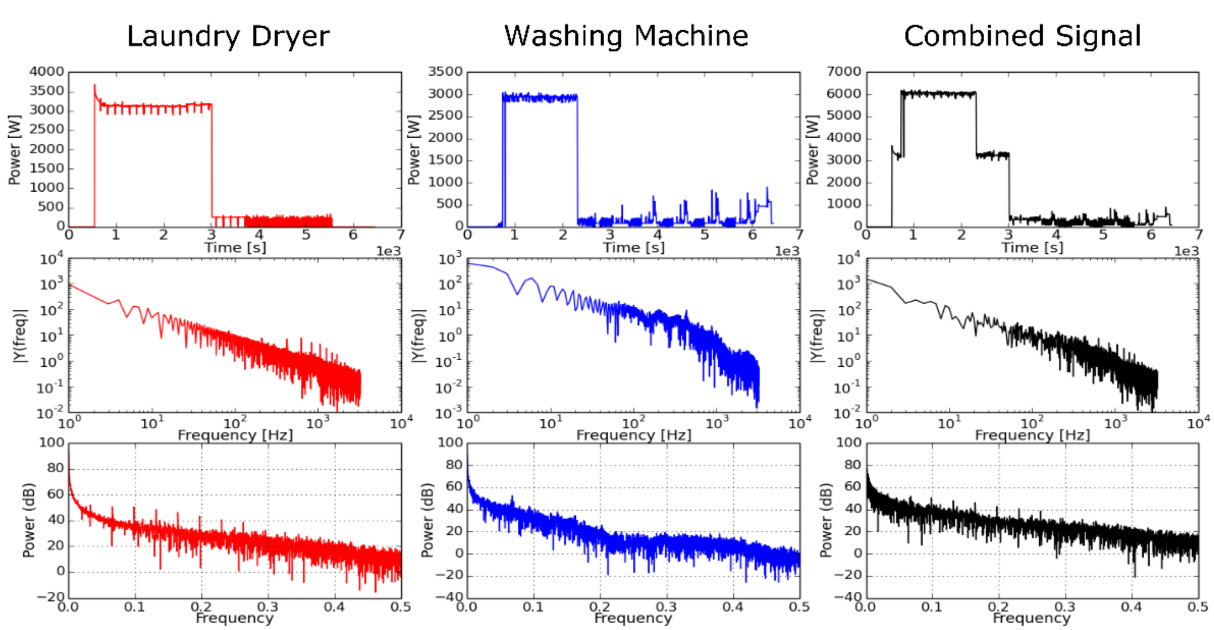


Figure 5.15: It can be seen in row three column three that it is not clear which devices make up the signal, so it is necessary to find an alternative method to identify device signatures.

5.2 Alternative to FFT Based Methods

Even with FFT and PSD analysis performed on the respective device signals in Figure 5.15 it is still difficult to distinguish unique characteristics in the aggregate plots, unless magnitude is used as a sole determining factor, however, if two separate devices have similar power draws then relying solely on magnitude alone would not suffice. So an investigation into an alternative technique to determine the viability of identifying device signals was needed.

Another PSD method was chosen, however, the alternative PSD method did not rely on Fourier analysis, but rather an autoregressive (AR) model that produce outputs based on previous terms. AR parameters are calculated using a least squares linear method. Spectral analysis in least squares relies on fitting sinusoids to the data being analyzed, and can be used on data that may be missing points, or be unequally spaced. This can be advantageous because unlike FFTs, ARs do not require equally spaced data sets to be optimal [22].

Figure 5.16 presents AR based PSD analysis on the time domain power signals of the laundry dryer and washing machine from Figure 5.15.

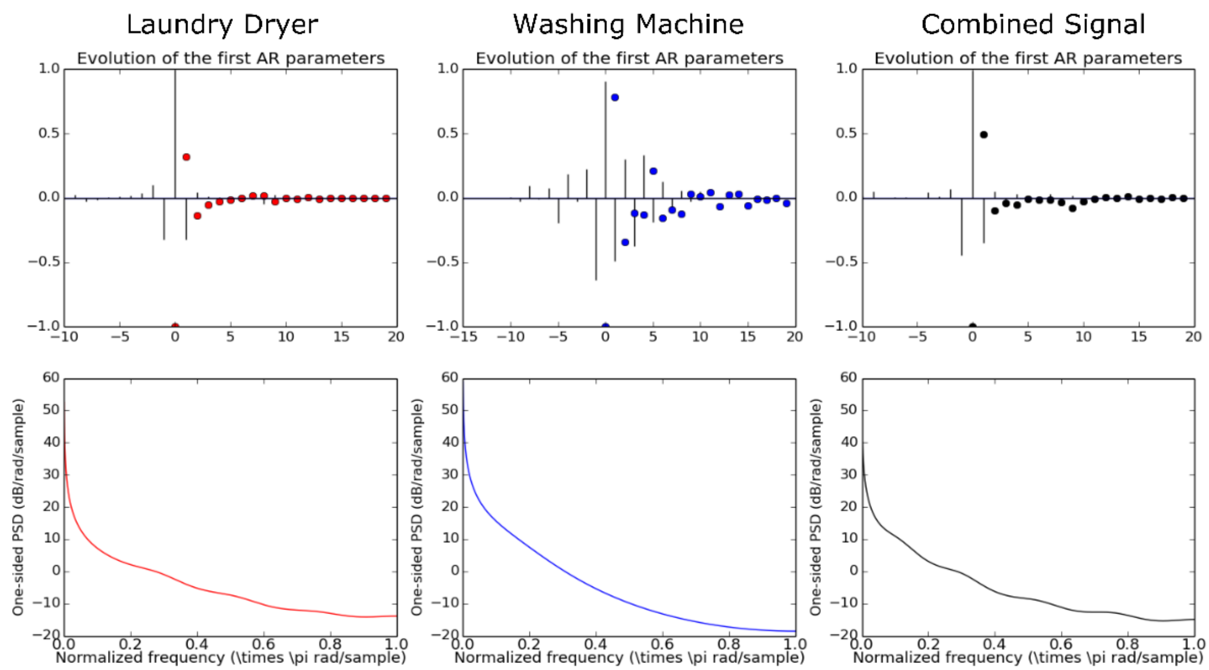


Figure 5.16: The AR parameters are plotted in the first row to show to what order they are significant for the respective devices. Defining the order of AR parameters is a necessary step in calculating the correlating PSD plot, which is shown in row two of the figure.

The first row of Figure 5.16 displays the number of significant AR parameters pertaining to the power signature of each device. The further a point from the horizontal axis, the more significant a point is to the calculation of the one-sided PSD. Row two then displays the correlating AR PSD plots. The PSD plot for the laundry dryer exhibits slight gradients throughout the signal, however, both signals do not display easily identifiable characteristics.

So the first, second, and third derivatives of the respective devices from Figure 5.16 were plotted in Figure 5.17 to determine the ability of locating characteristics in a signal that pertain to a specific device.

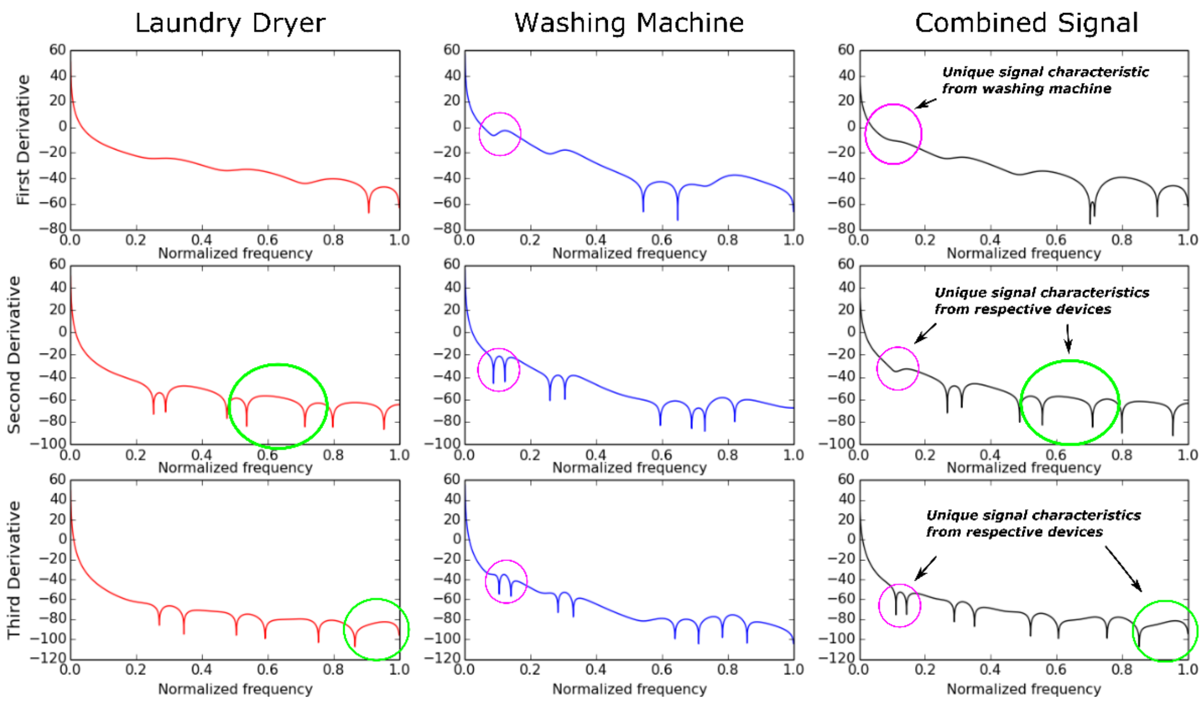


Figure 5.17: The first derivative of the washing machine AR PSD shows the influence on the aggregated signal. The second and third derivatives of the device PSDs display even greater influence on the aggregated signals, proving that devices with similar power magnitudes can be distinguished in an aggregated signal.

Taking the first three derivatives of the respective AR PSD signals allows the ability to observe unique gradients in the aggregated PSD signals that may be too small to observe otherwise. Even though both devices have similar magnitudes and signals using FFT based analysis, as shown in Figure 5.15, AR PSD methods grant the ability to decipher unique signal patterns for a device, which can be located in an aggregated signal. Knowing when and what device is in use is essential when studying power data from a node as it relates to demand response programs and future load scheduling because consumer behavior will be a driving factor in load prediction analysis.

5.3 Initial Analysis Feasibility

Initial results prove the viability of locating specific devices in an aggregated signal with magnitude being a highly influential factor when time based power data is plotted in a frequency domain. There are cases where Fourier based methods cannot produce signals with obvious characteristics, if this is the case, an AR based PSD method is an option to produce signals that provide unique characteristics when derived up to the third order.

5.4 The need to analyze EVSE

It has been shown that the SPMs can collect data, and that data can be analyzed to find specific device signals within the respective power profiles. It will now be necessary to add nodes to the study, which contain an EV with and EVSE, so that the power signatures of EVs can be studied as well as the habits of consumers that own them. In addition to individual consumers, there will need to be the ability to study large charging stations, as well as charging stations installed in public places such as parking structures and shopping centers to understand how these stations influence the larger power grid as a whole.

6.0 Impacts/Benefits, Conclusions, Future Work, Related Reports

6.1 Impacts/Benefits

This real-time data and analysis presents a critical methodology for transportation planners, policy implementers and engineers on the siting of EVSEs. Presented in this document as the final project report is this EVSE data, analysis and the process.

The research results presented in this paper can also provide a basis to better test theoretical solutions against real life results when it comes to predicting factors that affect EVs and EVSEs. As an example this system can monitor the volume and vehicles that frequent a specific EVSE, which can then allow integrators to understand EV usage within a certain part of a city at specific times, and adjust power loads accordingly to avoid potential blackouts during times of peak usage. Smart grids of the future will asset to better integrate these new components into the current power grid infrastructure.

6.2 Conclusions

The contribution of the research presented in this report was two-fold. The first was the development and implementation of a pilot system on Oahu; the system has been collecting data since August 2015. Second, was the initial investigation into the feasibility of using a bottom-up approach to analyze power data from a node. Aggregated power signals from multiple devices were analyzed using Fourier and power spectral (PSD) methods to prove the initial feasibility of disaggregation as tool for load analysis.

In order to provide the proper demand response program to a power grid, it is first necessary to collect large amounts of data in order to understand consumer behaviors and patterns. A pilot system was created with a smart metering device that can collect and transmit data at high frequencies (1Hz or less) through a SSH tunnel to a server. A robust collection of data allows for the patterns and behaviors of a dense urban population to be analyzed. Results have shown that devices produce specific power signatures and can be detected in aggregate power plots. The small scale pilot system has proven the feasibility of data collection related to large-scale demand response, and a potential for scalability. However, challenges will be present when scaling the pilot system to include more nodes, topics to be addressed will include protecting sensitive consumer information, server infrastructure, security, and the management of big data. The feasibility of using a bottom-up approach to analyze power data from a node was investigated and shows practical application in demand and frequency response programs. It will be necessary to create an algorithm to automate the ability for a power utility, or client installed within the home, to cycle devices in real time in combination with load prediction and forecasting.

A library of unique power signatures will need to be placed in a database, so the ability to categorize power signatures can be done quickly and efficiently. The database of signals could be stored in the current server architecture of the pilot system. The addition of more nodes to the current pilot system will allow for increased consumer behavior research, which will be necessary as it allows for detailed load prediction and scheduling. However, it will be necessary to mitigate security risks to protect sensitive consumer data. An algorithm must be developed to automate the process of signal recognition, so that demand response decisions can be implemented in a rapid and optimal matter. The use of ANNs in combination with the aforementioned bottom-up approach is also worth investigating.

The results show that there are cases where it is possible to determine which devices are consuming power at a given time. It is also clear that large quantities of data from a node permit the observation of consumer patterns as they relate to power usage. Combining the historical and real-time power data from multiple nodes within a section of the grid allows a power producer to understand the needs of the consumer while providing efficient load management.

The aforementioned results were a study into the viability of recognizing power signatures in aggregated power data. It will be necessary in future research to record the power draw of more devices to better understand signal characteristics pertaining to specific devices. The creation of a database of signatures will allow the ability to locate respective devices in an aggregate data set much faster. It will also be necessary to aggregate the power signatures of more than two devices to test the limits of both FFT and PSD analysis on time based power data.

6.3 Future Work

Demand response was a main motivating factor in the research that has been presented in this paper, but future work will also look to also investigate the use of the pilot system as it relates to frequency response methods as well as adding nodes to the system that use EVs.

Slight changes to the current SPM architecture can allow the ability for the metering device to partake in grid frequency monitoring. A Schmitt trigger can be implemented into the current

SPM architecture, which would allow the ability for a measured sinusoidal voltage waveform to be transformed into a digital square wave form, allowing the SPM microprocessor to measure zero crossing voltage.

Implementing a program in the SPM microprocessor will allow it to use the zero crossing measurements from the Schmitt trigger to track grid system frequency at its respective location. For example, it could be determined how long it takes for 100 samples to be recorded by the SPM microprocessor. If it takes one second to record 100 samples, and 200 samples were recorded, then two seconds have passed. Implementing the zero crossing method allows the ability to monitor the number of times the AC voltage crosses the zero threshold. So, 240 crossings in two seconds would equate to 120 cycles, or a frequency of 60Hz.

Implementing this ability into the current SPM would allow a power utility to monitor frequency at any point in the grid where a SPM is located in real-time, as well as the ability to see how cycling a device within a node affects the node, and an area as a whole, almost instantaneously. Thus allowing for a utility, or client installed within a node, to cycle off devices that are not in use, which would allow for load shedding and grid stability.

A UK-based utility company, National Grid, has been implementing frequency control programs that will serve as initial guidelines for which the pilot system can be tested in order to prove the feasibility of the SPM to partake in frequency control methods. The three response programs of National Grid are listed below [27]:

Primary Response *- Ramping up, or down, of active power within ten seconds of a grid event, with the potential to provide 20 additional seconds of active power.*

Secondary Response *- Ramping up, or down, of active power within thirty seconds of a grid event, with the potential to provide 30 additional minutes of active power.*

High Frequency Response *– Decrease in in active power within 10 seconds of a grid event and the option of continuing the high frequency response program until grid stability returns.*

The aforementioned response programs can create a criteria for which the SPM can be evaluated as it relates to the analysis of frequency control. National Grid found that in the UK, millions of kettles are used around 5pm, because of this, a decrease in grid frequency can be observed around this time [34]. This decrease can be mitigated by understanding which devices within homes are not needed while the kettles are in use, and cycling them off. These programs are especially important during times where energy usage is high, such as winter months in colder climates where a majority of energy usage goes to heating. In the UK, percentage of spare electricity during the winter dropped from over 15% in 2011 to just under 5% in 2014, which shows that energy usage is increasing, making demand response and frequency response that much more important in providing grid stability [27]. The current data collection and analysis by the pilot program can allow for the studying of consumer behaviors such as these, so that demand response programs can be used in combination with frequency response applications and load forecasting, which will be a large part of future research.

6.4 Related Reports

A report titled *"Current State-of-the-Art of EV Chargers (HNEI-01-15),"* [37] presented EV charging technologies that have potential to mitigate transient over-voltages (TOV) related to the introduction of renewable energy sources into the current power grid infrastructure. The report discussed current technologies related to EV charging that included, but were not limited to; EV battery charging modes, international charging standards, and signal and safety measurements.

Building on the aforementioned report, a second report titled, *"Transient Over-Voltage Mitigation and its Prevention in Secondary Distribution Networks with High PV-to-Load Ratio (HNEI-02-15),"* [38] briefly discussed the use of secondary network distribution systems and various techniques used to prevent TOVs within these networks. Some of the presented TOV mitigation techniques presented are listed below:

1. Inverter controlled switch-off solutions:
    a. PV inverters that switch off when a TOV is detected
    b. Supplying automatic transfer switches (ATS) to current PV inverters without a switch off capability
2. Regulating distributed generation (DG) based on parameters such as, Minimum Load to Generation Ratio (MLGR), DG Stiffness Factor, and Fault Ratio Factor
3. Using EV chargers to act as additional load in the case of a TOV detection

The presented techniques can be used with existing grid infrastructure to help monitor power grids and aid in distribution stability.

As was mentioned in the report titled, *"Transient Over-Voltage Mitigation and its Prevention in Secondary Distribution Networks with High PV-to-Load Ratio,"* TOVs have been associated with DG, this is especially the case when DG continues to energize a section of the grid that has been islanded (isolated from the electric utility). Using the IEEE 802.15.4 standard, a topology was presented using a personal area network (PAN) coordinator in conjunction with clients that connected to actuators and sensors, this work was presented in a report titled, *"Islanding Detection and Over Voltage Mitigation using Wireless Sensor Networks and Electric Vehicle Charging Stations (HNEI-08-15)"* [39]. The report presented a PAN coordinator within an EV charger and used in connection with ZigBee sensors assigned to PV panels, which would be used to detect islanding. Two methods were presented to mitigate voltage, the first being to instantly turn off the PV inverters, while the second solution involved using an EV charging station to add additional loads to the network. Power sim simulations showed that the proposed method was able to mitigate TOVs and islanding within a power grid.

This report, *"Real-Time Power Signal Disaggregation for use in Analyzing Electric Vehicle Supply Equipment (HNEI-15-16),"* has shown that certain devices used in a home can emit a specific "power fingerprint" when monitored. Currently datasets are being taken and are not yet large enough be used in conjunction with TOV mitigation simulations presented in HNEI-08-15, with time and additional resources the current research can be furthered under another funding effort.

7.0 Acknowledgements

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