Utilization of the Internet of Things for Real-time Data Collection and Storage of Big Data as it Relates to Improved Demand Response

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Abstract: Demand response programs are viewed as a solution to counter the increasing demand in energy consumption, as well as a way to combat the stochastic nature of renewable sources within the current grid infrastructure. In order to apply an efficient demand response program, it is first necessary to understand the power consumption behaviours within a power grid system. Obtaining large quantities of consumer power consumption data will al-low the ability to tailor a demand response program to efficiently implement control decisions in real-time. The programs are a cost effective alternative to high priced spinning reserves and energy storage. The focus of data collection will be on dense urban environments, which provide a number of factors that can be evaluated as they relate to an efficient demand response program. The island of Oahu was the location of a pilot program to test the feasibility of large data collection and storage. A smart metering device collected high resolution data, which was transmitted to a server where load forecasting and peak shaving decisions could be calculated. The design of the pilot system and initial results of the large data collection are discussed.

1 INTRODUCTION

American utility companies are currently trying to meet increased energy demand with an aging, and sometimes overloaded, power infrastructure. The *American Society of Civil Engineers* (ASCE) estimates that the current power grid would need a \$107 billion investment to remain operational (Halsey, 2012). A main concern for utilities is the need to meet the expected increase in energy demand after 2020. A suggested option to alleviate this pressure is to integrate more renewable energy sources into the consumer sector of the grid system. However, the stochastic nature of renewable sources combined with the use of an aging infrastructure creates logistical issues that must be solved before efficient renewable energy penetration can be accomplished. The ASCE has suggested using real time forecasting and smart grid implementation to better manage power loads to create a more reliable and efficient power delivery system (ASCE, 2013).

Distributed generation (DG) can be a reliable and cost efficient solution for customers in dense urban centres. Installing renewable energy sources at DG sites allows for a more environmentally friendly alternative to fossil fuels (IRENA, 2013). Hybrid renewable systems being used as *distributed generation* (DG) provide a way for utility companies to move peak loads and deliver reliable power transmission (Salameh and Davis, 2003).

However, with more DG generation becoming interconnected into 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. Advances in technology will only reduce the cost of renewable energy infrastructure, allowing for increased renewable energy penetration and interconnection into the existing grid. It will be necessary to collect large amounts of data that can be processed and analysed, which will grant the capability to analyse real time grid states and predict future occurrences. Processing the large amounts of data related to power consumption will lead to the creation of efficient demand response algorithms that can better manage and shift loads based on consumer activity.

Utilities companies must become power brokers with the ability to manage energy production on both the supply and demand side of the power grid. In the following sections, this paper will discuss the

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implementation of a pilot system with devices (smart meters) that can collect large amounts of data for large scale computational processing. System analysis of the grid states can create energy management strategies through demand response programs, thus creating a cost effective and reliable environment as it relates to the power grid.

1.1 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 renew-able energy sources (NREL 2012, Wesoff 2013, IRENA 2013). 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 (IRENA 2013, Barai et al., 2015). Even though there has been research into the feasibility of renewables into the current grid infrastructure, utilities and policymakers find themselves still requiring ways to understand the benefits and drawbacks of demand response programs (Lew et al., 2013, FERC, 2008).

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 (NAERC, 2007). Many current grid infrastructures have a utility generating energy at a plant, and sending it through a network to the consumer (Energy.gov 2015). 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 be-forehand. In exchange, a consumer will receive discounts and/or credits towards their energy bills.

Because demand response is relatively new solution to controlling peak loads, large data collection with high sampling rates will be necessary to provide as much detailed data as possible. The necessity for large amounts of data comes from the fact that there is still a lack of experience with long term demand response programs (O’Connell et al., 2014).

Demand response for a large urban area is hard to model as it is complex and multi-layered, so data is needed to properly simulate demand response in a densely populated area (O’Connell et al., 2014). To better understand the factors that affect demand response programs, data relating to consumer behaviours, as well as external factors such as weather, price sensitivity, and the changing of seasons must be obtained, and researched. An outline of the demand response logic as it pertains to the pilot system is displayed in Figure 1.

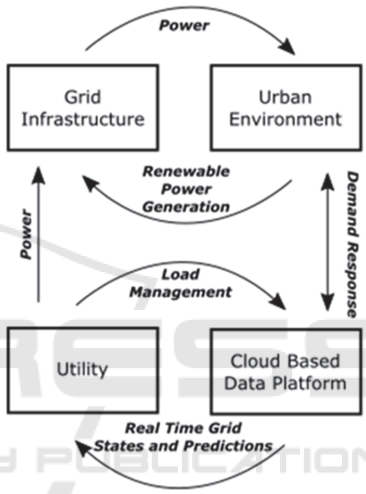


Figure 1: The system demand structure for a data collection system is presented. A cloud based platform will store and analyze data collected from a home, or business, in real-time, allowing for quick control decisions in demand response programs.

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. Current research on the pilot system collects and analyses 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. Results from the pilot system have shown that different devices such as a stove top, or a water heater, create 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 analyse 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 home, or business, and understand which devices can be cycled during peak loads to relieve grid pressure, especially in high energy consumption areas like urban centres where large percentages of a population tend to live. In order to accomplish this, a device is needed to record a consumer’s power usage. A pilot program has been created at the University of Hawai’i that currently involves monitoring aggregate power usage from 20 homes on the island of Oahu using a *smart power meter* (SPM). The components, challenges and scalability of the pilot system will be discussed, as well as future work pertaining to demand response programs, which will be discussed in the following sections.

1.2 Related Research

The study and feasibility of demand response as it relates to power grids is ongoing, and the pilot program looks to contribute to that research in the areas of large data collection, storage and analysis (FERC 2008, NAERC 2007).

Demand response programs allow for increased peak load reduction as well as the ability to balance supply and demand of energy in power grids (FERC, 2008). Stability and load shifting are two factors that are important in maintaining grid stability, which can be accomplished through demand response programs. Cost efficiency is another benefit of demand response because there is no need to maintain spinning reserves and large power storage infrastructure (NREL 2012).

Similar research is being done on smart meters to collect and analyse data. A group from the University of Bath investigated the use of smart metering devices in combination with voltage control techniques. Their re-search focused on analysing the consumer side of demand response as a way to create cost efficiency for a consumer as well as a tool to restore grid system faults and maintain transmission stability. The Lon Local Operating System (LonWorks) and ZigBee Wireless Network Standard were two suggestions for creating a system of communication between smart meters and controllers to handle real-time data (Gao and Redfern, 2011).

A research group in Europe proposed the use of local area networks (LAN) and wireless local area networks (WLAN) in combination with KNX communication standards as an option to set up communication between smart metering devices. The use of ZigBee and KNX components were deemed feasible to monitor load consumption of devices in order to create a timetable of shiftable loads. The load shifts refer to the rescheduling of device usage from peak hours to times that do not provide large strains on the grid. Real-time analysis and visualization would allow consumers to make the proper choices in energy consumption that are related to cost efficiency. An algorithm based on tariffs was the basis for the load timetables (Kunold et al., 2011).

Researchers in Canada proposed a smart metering system based on load disaggregation where a power signal is analysed into the various device components that produce it. Their research focused on the factors that affect load disaggregation such as noisy signals, simultaneous loading, computational costs and privacy issues. They noticed that devices produced different power signals when cycled, for example, constant vs. periodic loads. To train algorithms in detecting a device, the research group suggested algorithm training based on probabilities and the clustering of individual devices. The research group deemed the definition of deferrable actions as necessary in their proposed system. Deferrable actions are those relating to devices whose utilization is not a priority and cycling can instead be scheduled at an alternative time, which would allow for load shedding. These devices include washer/dryers, ovens and dishwashers (Makonin, 2013).

A UK-based power utility, National Grid, looked into the affect the power usage of certain devices had on the grid. They 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. National Grid uses the aforementioned knowledge to maintain grid frequency. Aggregating these cycling patterns with the loads of other houses in a neighbourhood, or region, allow for the ability to maintain grid stability throughout sections of a power grid (National Grid, 2015).

2 SPM PILOT SYSTEM

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 (Press Release 2015, Namata 2015). 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. Because most buildings have circuit breaker boxes, a common interface is already in place to install the SPMs. The device collects data at one-second intervals and sends it through a local WiFi network to a remote cloud server using a SSH tunnel. Data storage, analysis, forecasting and control can all occur within the cloud. The server will have the ability to send 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. Figure 2 illustrates the overall pilot system.

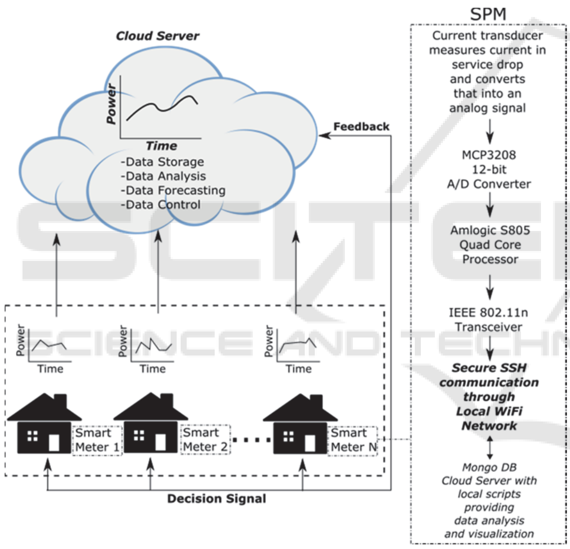


Figure 2: The setup of the proposed system implements a SPM to monitor and transmit data from a circuit box. Data is then transmitted to a server for analysis. The current server can be scaled to cloud storage, so that more nodes can participate in the pilot program and provide more data for load forecasting analysis.

2.1 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 pre-processing 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, which are transformed into analog voltage signals, and sent to a MCP3208 12 bit analog digital converter (ADC), which collects data at 80kSps. Images of an installed device are shown in Figure 3.

Figure 3: A SPM meter 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 voltage. The median power pertaining to one second of collected data is obtained for each phase, and sent to the cloud server for storage and analysing. Figure 4 describes data collection and transmission on the consumer level.

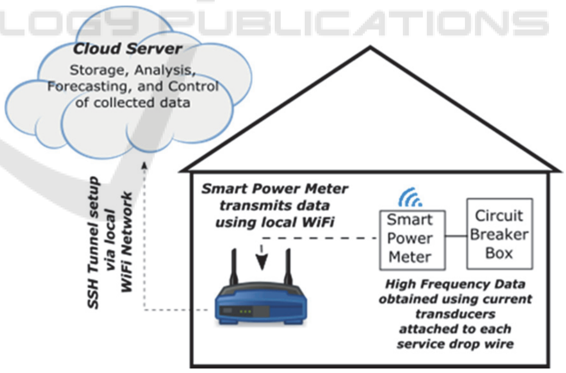


Figure 4: Utilizing pre-existing WiFi connections within a home allow for a cost effective solution for data transmission. Circuit breaker boxes are usually located in a remote area of a building, so it is necessary to utilize a wireless connection to allow for a robust system to monitor and transmit data from a node. A secure SSH connection allows for safe and reliable transmission of data to a server in real-time.

2.2 Communication

After the power data is collected and pre-processed by the SPM, the data is then transmitted to a remote server using a secure SSH tunnel via a local WiFi network. 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 pre-existing 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 hosted on a cloud server. 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 re-established to minimize data-loss. Despite the 1Hz transmission rate of the SPM, bandwidth and storage requirements are kept minimal. Each database query consists of just three integers, which total 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 950,000, assuming 200,000 households, 400 GB of power data would be sent to the servers each day at a rate of 4.63MB/s.

2.3 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 is quintessential for power analysis of large complex urban centres. 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 analyse data in real-time, thus allowing for fast and efficient conclusions and decisions. 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 con-trolled using a client. Thus granting the ability to create forecasts that enable efficient demand response pro-grams to be implemented, which will reduce peak loads and ensure reliable power transmission within the grid infrastructure.

2.4 Control

Future work revolves around enabling the cloud server to analyse 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.

3 DATA ANALYSIS

Data collection is currently in progress using a total of 20 nodes and has been ongoing since August 2015. Participants volunteered (not compensated) to participate in the study and the household sizes range from two to six members. The backgrounds of the various participants are varied, however, specific details are kept confidential for privacy reasons. There was no criteria for selecting participants, the only requirement was that they had an accessible circuit breaker box within their home.

Each phase in the circuit breaker box is measured, and the power for each phase is plotted. Figure 5 gives an example of data from a node for one day. Phase one and two are plotted in red and black, respectively.

It can be seen that there are unique device signatures throughout the day, which correspond to a combination of specific devices within the node. In the displayed example, from midnight to 7 am, 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 mid-day. 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 6 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 dinner-related 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.

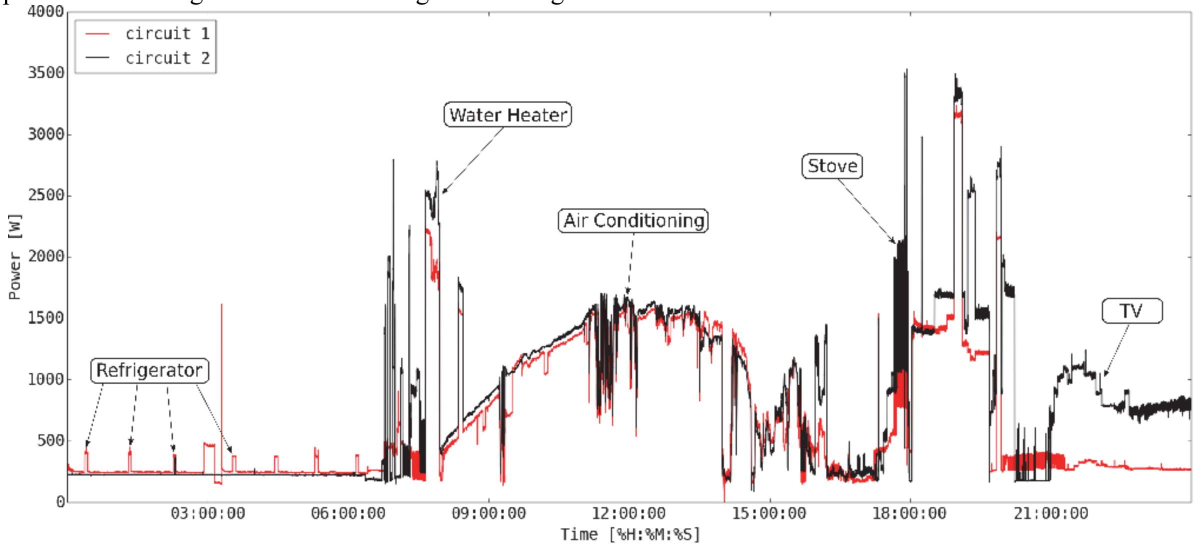


Figure 5: Devices produce specific power signatures when in use. It can be observed when certain devices are cycled. The cycling of loads within a node displays the behaviour and patterns of a consumer that can be used to predict and schedule power generation.

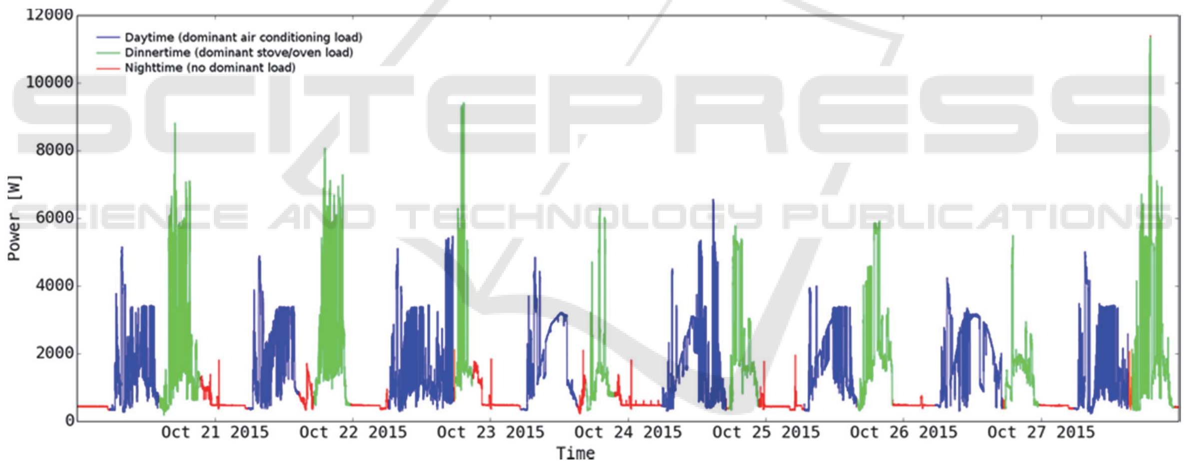


Figure 6: One week of total power consumption is plotted for one family home. Consumer pattern behaviour is evident from the increases in power consumption.

are repeated daily throughout the week. Nighttime loads are reduced to a bare minimum because of inactivity at night.

Devices show different patterns of power draw when plotted in the time domain, as shown in Figure 7.

Aiding in the study of demand response it the fact that each device produces a specific power signature, or fingerprint, when Fourier analysis is performed on the plotted time dependent power signal obtained by the SPM, which was shown in Figure 7. Fourier analysis can be applied to the time dependent power draws like those from Figure 7, which produce signals with distinct characteristics as shown in Figure 8.

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.

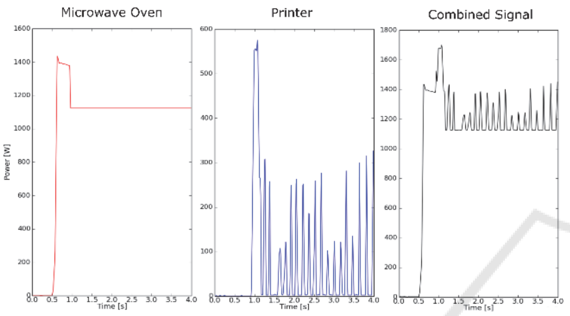


Figure 7: Two devices can be combined to create a time dependent plot that features both signals, in this case a microwave oven and a printer, however it can be seen that the devices were recorded at different times, so it is necessary to combine the signals into one aggregated signature.

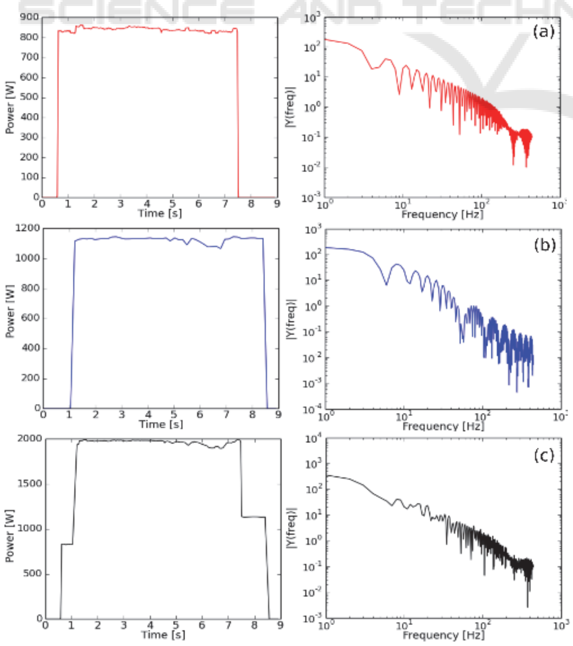


Figure 8: Once two device signals ([a]cooking stove, [b]vacuum cleaner [c]combined signal) are combined they can then be analysed in the frequency domain to better understand if the signals exhibit a specific characteristic pattern. The left column displays the time domain power draw while the right column shows the power draw in the frequency domain.

Using PSD, transient variabilities from the time domain can be found in a frequency domain. Figure 9 highlights these variabilities using the cooking stove and vacuum cleaner example from Figure 8.

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 9. The ability to notice each device in a combined signal further proves that specific

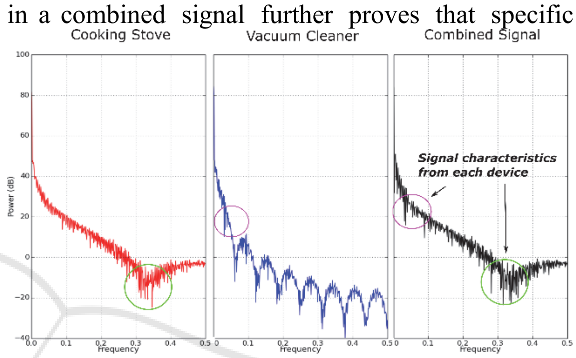


Figure 9: The implementation of PSD granted the capability to observe unique device signatures that are visible in an aggregated signal.

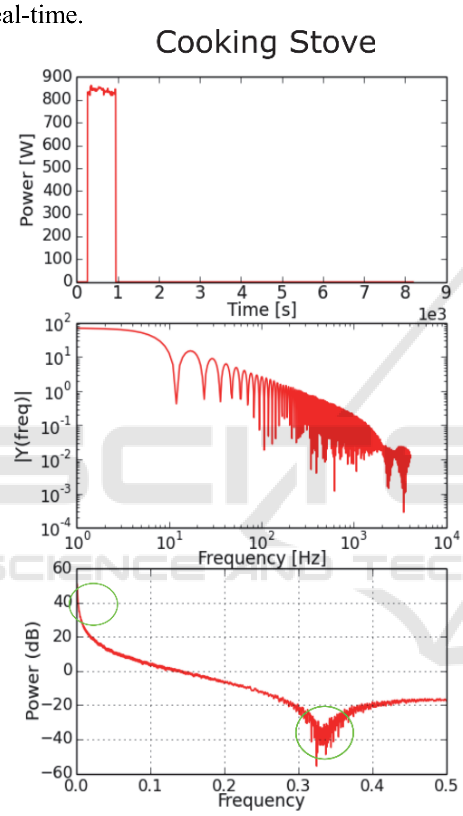
appliances can be sifted from a larger data set that pertains to an individual node. The analysis is necessary to provide accurate and efficient demand response programs that can specifically target certain devices during a day that are not in use, thus allowing frequency stability within a power grid to be maintained.

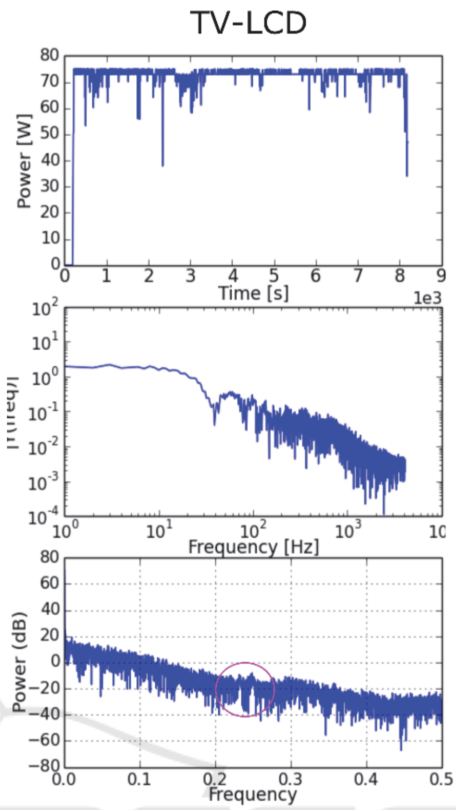
Figure 10 displays the FFT and PSD analysis of another device combination. The first row of each afore-mentioned figure displays the power signals in the time domain for the devices, the FFT for the respective power signals in row two, and the PSD analysis in row three.

From Figure 10 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 analysing time dependent data in the frequency domain.

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 and 6. 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 *and heating, ventilation, and air conditioning* (HVAC) units within a node (Ahmad et al., 2016). 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.





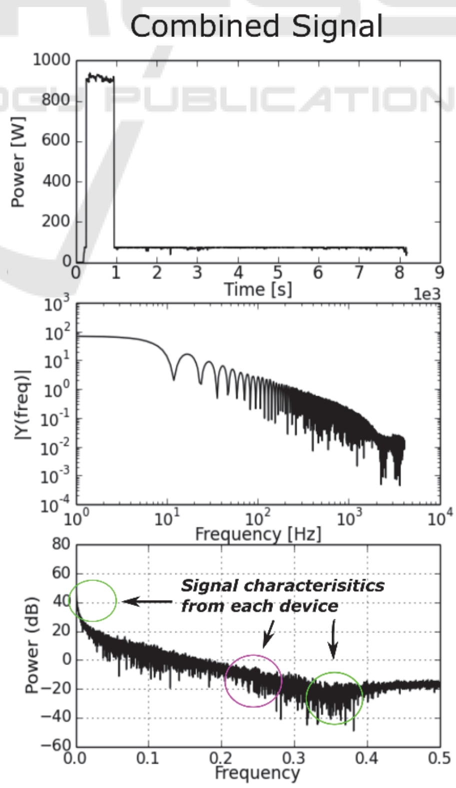


Figure 10: The first set displays the signal analysis for a cooking stove, the second for a LCD TV, and the third for the sum of the two signals. The green circle shows the location of a specific attribute of the cooking stove PSD signal in the aggregate, while the purple displays the attributes pertaining to the LCD TV.

The results show that 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. However, it should be noted that the observed data can be sensitive as it displays patterns and behaviours of consumers, which must remain confidential to protect privacy.

4 SCALABILITY

A large and flexible database is necessary for bulk amounts of data being collected from an urban centre. MongoDB is a “NoSQL” cloud database where large data collection will be stored and analysed 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 (Scalability Benchmarking 2015, Olavsrud 2015, Bhattacharjee 2014, McNulty 2014). 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 (Cattell, 2010). MongoDB utilizes a flexible data model, which allows the opportunity for easier development and scalability.

4.1 Data Security

Analysing data will grant the ability to understand the behaviour of a consumer, and as the pilot system is scaled up to include thousands of users within an urban environment, it will be necessary to protect sensitive information. The information is sensitive because it can reveal what a person, or persons, are doing at a specific time in the day. Many activities can be monitored, such as a person cooking, taking a shower, or working on the computer. It can also be determined when a person is home based on their air conditioning and heating usage. The monitoring of data can even analyse the power spectrum of a television, allowing for the TV power signal to be compared to the TV signatures of known channels, and from there determine what TV programs a person is watching. Unauthorized disclosure of this potentially sensitive information could allow an unauthorized agent to study the habits and routines of an end-user, thus creating potential threats to the privacy of the consumer.

Currently, the pilot system utilizes a single server, however, when scaling up the system to include consumers from a dense urban population, a cloud server will be used. Once the computational and storage limits of the single server are reached, the pilot system will be scaled to cloud computational storage. The use of cloud services has been increasing due to a number of factors, some of these factors include; the potential for scalability, geographic reach, cost savings and higher availability (Rightscale, 2014). With the growth of cloud service and usage comes the need to address potential for security risks.

4.2 Vulnerabilities in Cloud Security

There are many vulnerabilities that are associated with cloud server use, a few will be mentioned to provide a foundation for future security protocols.

4.2.1 Data Interception

Data interception is a key concern because a large number of consumers will be sending sensitive data to a cloud server in the range of seconds. To remedy this, a secure shell (SSH) will implemented in the transfer of data from the consumer to the cloud. A SSH provides data encryption and the ability to implement a proxy for added security (ENISA, 2009).

4.2.2 Data Leakage

There is potential for data within MongoDB to be leaked to unauthorized users, however, the developers of MongoDB look to actively recognize and address any issues relating to data leakage, which are usually related to versions of MongoDB that are outdated and unpatched. Other ways to prevent data leakage is using proper encryption methods, and recognizing when and where data is sent, so that it can be properly monitored. Physical protection of servers and personnel screening provide added security benefits (ENISA, 2009).

4.2.3 Insecure or Ineffective Deletion of Data

When deleting data from a cloud server, there is always potential that data deletion may be incomplete, or insufficient. To counteract any potential issues from data deletion, it will be necessary to follow proper deletion protocols related to the cloud server platform, and in worst case scenarios, insure that a disk containing sensitive data is destroyed. Once again, proper encryption of data will decrease the risk related to ineffective data deletion (ENISA, 2009).

5 CONCLUSION AND FUTURE WORK

Collecting, storing, and processing large amounts of data is necessary to understand the power consumption habits of consumers. A smart metering device was used to collect and transmit data at high frequencies. A SSH tunnel provided a secure channel to send the data to a server where large amounts of data could be stored and analysed. Initial data collection has shown that patterns in power consumption data can be deciphered, how-ever, because human behaviour can be complex it is necessary to continue the collection of data to see how external factors such as weather and global events affect human power consumption. A foundation to study human power consumption behaviour, and the factors affecting it, has been implemented through the Oahu pilot system. The continued addition of nodes to the system will allow a broader and more in depth look at consumer behaviour, which will lead to the creation of demand response programs to insure grid stability and efficiency. Future work will involve the scaling of the pilot system to include more nodes, research into security measures to protect sensitive data, scaling the current server to a cloud server, and development of pattern recognition software to recognize consumer power usage as it relates to demand response programs.

REFERENCES

2013 Report Card for America's Infrastructure. *ASCE, Reston*, VA, 2013.

The Potential Benefits of Distributed Generation and Rate Related Issues that may impede their Expansion. *US Department of Energy*, Washington, DC, 2007.

Z. M. Salameh and A.J. Davis (2003) Case Study of a Residential-Scale Hybrid Renewable Energy Power System in an Urban Setting. *Paper presented at the Power Engineering Society General Meeting*, Toronto, Canada, 13-17 July 2003.

Impacts of Solar Power on Operating Reserve Requirements. *NREL,* Golden, CO, 2012.

E. Wesoff (2013, September 25) What are the Impacts of High Wind and Solar Penetration on the Grid?. *http://www.greentechmedia.com*. Accessed 2 Nov 2015.

Smart Grids and Renewables: *A Guide for Effective Deployment*. IRENA, Abu Dhabi, UAE, 2013.

D. Lew et al. The Western Wind and Solar Integration Study Phase 2. *NREL*, Golden, CO, 2013.

Demand Response and Advanced Metering. *FERC,* Washington, DC, 2008.

Demand Response Discussion for the 2007 Long-Term Reliability Assessment. *NAERC*, Atlanta, GA, 2007.

Smart Grid (2015). http://energy.gov. Accessed 20 Oct 2015.

N. O'Connell et al. (2014) Benefits and challenges of electrical demand response: *A critical review*. Elsevier 39: 686-699.

Press Release: Governor Ige Signs Bill Setting 100 Percent Renewable Energy Goal in Power Sector. *http://governor.hawaii.gov.* Accessed 2 Nov 2015.

B. Namata. (2015, June 8) *New Law requires 100-percent renewable energy in Hawaii by 2045*. http://khon2.com. Accessed 21 Oct 2015.

Scalability Benchmarking: *MongoDB and NoSQL Systems.* USA, Pleasanton, CA, 2015.

R. Cattell (2010) Scalable SQL and NoSQL Data Stores. *ACM 39.4:* 12-27.

Cloud Computing Trends: 2014 *State of the Cloud Survey. RightScale*, Santa Barbara, CA, 2014.

National Grid (2015) Frequency Response Services. *http://www2.nationalgrid.com/uk/services/balancing-services/frequency-response.* Accessed 22 Nov 2015.

C. Gao and M.A. Redfern (2011) A Review of Voltage Control in Smart Grid and Smart Metering Technologies on Distribution Networks. *Paper presented at the 46th International Universities' Power*

Engineering Conference, Soest, Germany, 5-8 September 2011.

I. Kunold et al. (2011) A System Concept of an Energy Information System in Flats Using Wireless Technologies and Smart Metering Devices. Paper *presented at the 6th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems*: Technology and Applications, Prague, Czech Republic, 15-17 September 2011.

S. Makonin (2013) The Cognitive Power Meter: Looking Beyond the Smart Meter. *Paper presented at the 26th IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, Regina, Canada, 5-8 May 2013.

T. Olavsrud (2015, November 24) 9 MongoDB success stories. *http://www.cio.com/article/3008114/open-source-tools/9-mongodb-success-stories.html.* Accessed 10 Dec 2015.

A. Bhattacharjee (2014, May 8) NoSQL vs SQL – *Which is a Better Option?*. https://blog.udemy.com/nosql-vs-sql-2. Accessed 11 Dec 2015.

E. McNulty (2014, July 1) SQL VS. NOSQL- *What you Need to Know.* http://dataconomy.com/sql-vs-nosql-need-know/. Accessed 10 Dec 2015.

Cloud Computing: *Benefits, risks and recommendations for information security*. ENISA, Crete, Greece, 2009.

A. Halsey (2012, August 1) Aging power grid on overload as U.S. demands more electricity. *https:// www.washingtonpost.com/local/trafficandcommuting/ aging-power-grid-on-overload-as-us-demands- more-electricity/ 2012/ 08/ 01/ gJQAB5LDQX _story.html*. Accessed 23 Feb 2016.

G.R. Barai et al. (2015) Smart metering and functionalities of smart meters in smart grid – a review. *Paper presented at the Electrical Power and Energy Conference (EPEC)*, London, ON, Canada, 26-28 October 2015.

A. Ahmad et al. (2016) Smart cyber society: Integration of capillary devices with high usability based on Cyber-Physical System. *Future Generation Computer Systems, Volume 56*, March 2016, pp. 493-503.