PER CAPITA WATER AND FIXTURE USE IN RURAL ALASKA

By

Cameron W. Wilson, B.S.

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of

MASTER OF SCIENCE

in

Civil Engineering

University of Alaska Anchorage

August 2020

APPROVED:

Aaron Dotson, Ph.D., Committee Chair
Martin Cenek, Ph.D., Committee Member
Matthew Calhoun, Ph.D., Committee Member
Scott Hamel, Ph.D., Chair
Department of Civil Engineering
Jennifer Brock, Ph.D., Associate Dean for Academics
College of Engineering
John Stalvey, Ph.D., Interim Provost and Acting Dean
Graduate School

Abstract

An accurate picture of exactly how and when water is used within the home is valuable to both consumers and producers for many reasons; including, but not limited to water conservation efforts and monitoring water usage behavioral patterns. Developing that picture is often difficult within the confines of current residential infrastructure and although multiple methodologies have been tested, there have been varying degrees of success and further improvement is warranted. Most of the previous systems have been proven on a smaller scale such as either on a lab bench or in one to two homes for a short period of time. We have designed and developed a system utilizing a non-intrusive, non-invasive, ground-truth approach with vibrational sensors and a flowmeter. Performance of the system was analyzed for effectiveness, longevity, and accuracy. Data produced by the setup provided water volume information with up to 94% accuracy and exceeded reliability expectations. Water volumes at each fixture and water usage events were identified over a 90-day period for four homes in rural Alaska. Compiling the data gathered from each of these events offered insights on hygiene habits such as handwashing after toilet use, showering frequency, and shower duration. The study also identified examples of excessive water use and targeted those areas for conservation efforts within the home with as little impact on the individual as possible. The regions where this study takes place are subject to potable water scarcity and more aggressive measures such as switching to a dry toilet and reusing graywater were examined as options to conserve as much water as possible. These strategies were considered while simultaneously identifying shortcomings in hygiene behavior and providing enough water to maintain a low risk to health for those within the home. Utilizing engineering controls and modifying behavior, homes in this study showed opportunities to improve hygiene and reduce water usage by up to 60%.

Table of Contents

List of Figures

List of Tables

Acknowledgements

I would to first thank my advisor, Dr. Aaron Dotson, for making this project possible through the Alaska Department of Environmental Conservation and the United States Environmental Protection Agency. I would also like to thank my advisory committee, including Dr. Martin Cenek and Dr. Matthew Calhoun, for providing feedback and guidance throughout the process. Thanks to Alan Mitchell for offering advice on system communication, Kacy Grundhauser for feedback and ideas, and to Chris Cronick at the Alaska Native Tribal Health Consortium for setting up and helping to complete installation. The water operators in the villages were absolutely invaluable and the project would not have happened without them. Finally, I would like to thank my wife for offering words of encouragement and endless patience from the moment all of this started.

General Introduction

Water production and distribution in rural Alaska is uniquely challenging for several reasons. The first is simply the distance between villages and the lack of roads between them. Many of the locations are only accessible by either plane or boat depending on weather conditions and the transportation logistics for equipment and supplies make it both difficult and expensive to build and maintain water systems. Arctic environments produce obstacles like permafrost creating the need for increased system complexity like compounded recirculation loops and above-ground utilidors. The added complexity adds to the ever-present chance for leaks making it difficult to know how much water is actually consumed on a per capita basis. This data point is important to the design of water systems and in rural Alaska, and the current source of information in the Cold Region Utilities Monograph (CRUM) published in 1996.

There are several limitations to this information; first being the length of time since publication. Besides the likelihood of outdated information, the data gathered probably does not reflect any improvements implemented after the Energy Act of 1992. Second, the methodology for calculating the water used per person per day is to take the total water produced and divide by the population served. As mentioned before, leaks need to be accounted for and the current information may be an overestimation. Finally, there is no information on what is occurring within the home and the variation between individual households. There is a significant number of households in rural Alaska that do not have adequate access to water meaning they have to haul their own water year-round and use 5-gallon buckets for sewage waste. The Alaska Water and Sewer Challenge was created by the Alaska Department of Environmental Conservation to improve this situation in remote areas (Hickel et al., 2018). The University of Alaska Anchorage Department Civil of Engineering team designed a graywater reuse system to maximize the utility of any water hauled to the home. Moving the treatment closer to the home means that there is a need for higher granularity data on water usage.

Water usage data is either limited to a general estimation based on the whole community or in some more urban areas, flowmeters placed before each home. The main purpose of water is for the maintenance of health and there needs to be an adequate supply to achieve that goal. Areas where potable water is scarce, such as some parts of rural Alaska, conservation is absolutely necessary. The key to simultaneously achieving both of these goals is water usage data with high granularity. Knowing where and when water is used within the home, on a per fixture basis, can lead to targeted conservation efforts and help utilize both engineering controls and behavior modification. The purpose of this project is to first, explore how to gather information on when and where water is used within the home in rural Alaska. And second, what insights does the information offer and how can it be utilized. Approval for this research was provided by the Alaska Area Institutional Review Board on March 19, 2018. The letter of approval is shown in the appendix.

Chapter 1 – Monitoring Water and Fixture Use Within the Home

Abstract

An accurate picture of exactly how and when water is used within the home is valuable to both consumers and producers for many reasons; including, but not limited to water conservation efforts and monitoring water usage behavioral patterns. Developing that picture is often difficult within the confines of current residential infrastructure and although multiple methodologies have been tested, there have been varying degrees of success and further improvement is warranted. Most of the previous systems have been proven on a smaller scale such as either on a lab bench or in one to two homes for a short period of time. We have designed and developed a system utilizing a non-intrusive, non-invasive, ground-truth approach with vibrational sensors and a flowmeter. The system was tested in a remote area with minimal installation time and little to no intervention or maintenance over a long period of time. Performance of the system was analyzed for effectiveness, longevity, and accuracy. Data produced by the setup provided water volume information with up to 94% accuracy in the form of daily diurnal curves for each fixture within the home.

1.1 Introduction

Knowledge of when and where water is used within a residential household is valuable to a host of different stakeholders ranging from the utilities that provide the water to the individuals using that water (Carboni et al., 2016). The information can be used to improve water conservation efforts (DeOreo et al., 1996) and give insights on behavioral patterns that may need to change in order to achieve these efforts (Anda et al., 2013). Yet obtaining data with granularity suitable to support these efforts remains challenging in real world situations. Both the technical difficulties of adapting to existing infrastructure and the privacy concerns of consumers, inhibit the widespread adoption of water monitoring systems within the home. Fortunately, both of these concerns can be addressed with the technology arising with smart homes, smart meters, and the internet of things (IoT) (Di Mauro et al., 2019). This paper provides a field-tested methodology for acquiring water usage data over an extended period of time even in remote locations.

Any method presented to achieve these goals needs to meet several basic criteria in order to be both practical and effective. The first requirement is the system must be non-invasive, referring to privacy issues that can be created when employing sensors such as microphones or cameras (Tapia et al., 2004). Secondly, any installed sensors need to be non-intrusive. Any sort of interference in monitoring water usage may affect user practices stemming from either physical inconvenience or the Hawthorne effect where participants change their habits based on the conscious knowledge of being studied (DeOreo et al., 1996). To obtain high levels of user acceptance, the system must be easy to use, have low cost, be easy to install, and have minimal maintenance. This user acceptance contributes to higher implementation rates (Carboni et al., 2016). Finally, there may be disaggregation challenges related to the data gathered depending on how the data was gathered. For example, differentiating flow based on characteristic signatures from two different toilets in different bathrooms may be difficult because of high similarity, while a single fixture such as a kitchen sink can exhibit different signatures based on how it is used (e.g. how far open the valve is when used). Adding to this complexity, events are not mutually exclusive and overlap must be considered for simultaneous usage (Carboni et al., 2016).

Multiple techniques have been presented and tested for proof of concept in literature including both multiple point and single point sensing. Simply put, multiple point sensing takes advantage of more that one type sensor input, often spread out to disaggregate the volume information. Single point sensing only uses one sensor to accomplish this task.

Often the least invasive approach possible is single-point sensing combined with learned data processing algorithms because data will ultimately come from a single source typically hidden away. The basis of this technique is to use recorded data from an installed water flowmeter and correlate with either surveys (DeOreo et al., 1996), or flow switches (Fontdecaba and Sánchez-espigares, 2013) to establish a training dataset. After the initial period of learning flow signatures, the training dataset is removed and the stand alone flowmeter data is disaggregated with varying success (Carboni et al., 2016). Single-point sensing has also been demonstrated using a pressure sensor in lieu of a flowmeter to both estimate flow and fixture events under idealized research conditions and known fixture inputs (Froehlich et al., 2009).

Multi-point sensing using varying types of sensors within the home is an alternative methodology to determining flow volumes. Examples include combining a permanent flowmeter with permanent sensors such as motion detectors placed on the walls of each room containing a water fixture (Srinivasan et al., 2011), or accelerometers placed on the pipes within the walls leading to these fixtures (Kim et al., 2008). The fixture use is determined by the timing of either motion sensor activation or vibrations in the distribution pipes. The drawback of using motion detectors is difficulty identifying a fixture when multiple sensors are triggered by multiple people for a single flow event. In addition to this, sensors cannot be hidden to avoid observation effects. Accelerometers installed on the water distribution system within the walls of the home detect water flow through each pipe in the home and may be well hidden, but would be very difficult and intrusive to install in existing households within a reasonable timeframe.

Unique from these other methods, a system developed by Fogarty *et al.*, where acoustic sensors are placed throughout the home as a practical field application that is both non-invasive and nonintrusive. In this technique, an acoustic sensor is placed on both cold and hot water pipes feeding the home to detect water usage events. The same type of sensor is placed on the fixture itself to confirm the fixture is actually activated, assisting the system in identifying the fixture being used (Fogarty et al., 2008). Vibration within fixtures themselves caused by cavitation (Schantz et al., 2014), and/or aeration can be detected and used as the ground truth for a system of disaggregation. Combined with flowmeter data, a labeled dataset is then created with timestamps for each event.

The methodology presented in this paper is adapted from insights learned from these previous studies. Single point sensing requires more supervision than is practical outside of a laboratory setting for this particular application. Therefore, multiple sensors were utilized to establish the labeled dataset starting with a flowmeter to capture volume information. We chose to sense vibration at the fixtures to indicate where the volumes were being used primarily because of adaptability. There is no plumbing or modifications necessary at the fixture to indicate activity. Using a single home as a case study, this paper will describe a new system's viability in a real-world application and potential insights that can be gained through data analysis.

1.2 Materials and Methods

The overarching design of the system, as seen in Figure 1.1, relies on a flowmeter placed in the supply line directly after entering the home coupled with wireless vibration sensors attached to each fixture within the home that activate when a fixture is being used. A base station, connected to the home's electrical power, records and processes data from the flowmeter and wireless sensors placed on each fixture. The basic principle is to apply a timestamp to both the pulses received from the flowmeter and to the signals received from the fixture sensors. We then use the timestamps applied to each to correlate water usage within the home. The following sections will describe details of how the system was designed, constructed, installed, and used.

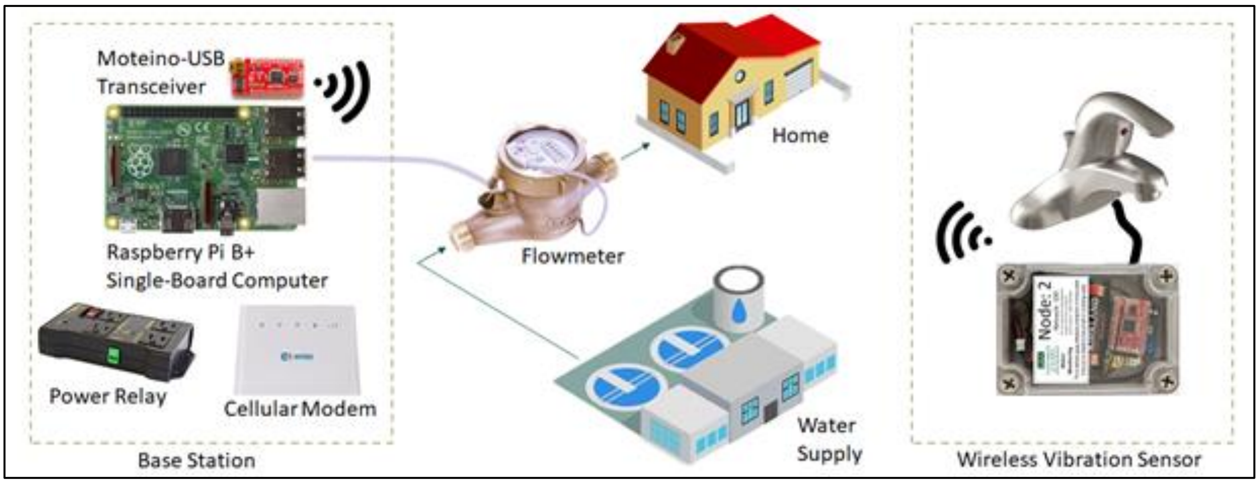

Figure 1.1 System Overview Including Flowmeter, Base Station and Vibration Sensor

1.2.1 Design Considerations

Previous studies listed by Carboni et al. show success in the main objective of determining where water is used in the home, but lack practical considerations such as portability, easy installation, durability, and longevity. Each of these attributes make the system more field deployable and must be included. Portability, regarding both dimensions and materials, has a significant impact on the usability from the standpoint of both end user and researcher. Lithium batteries have high energy density, but travel restrictions listed by the Federal Aviation Administration make it difficult to transport this battery type to remote locations (FAA, 2020). Alkaline batteries were used as the power source for the wireless sensors in this study for this reason. Manufacturability and cost were both guiding principles of design in order to produce enough of these sensors. To ensure convenience for the participants in this study, who did not have any prior association with the research team, time to install and calibrate the system was minimized. Finally, due to the remote location and the need to perform for no less than one year from the beginning of the study, dependability was of paramount importance for successful completion of the project.

1.2.2 Equipment

The flowmeter installed in the home was a Seametrics MJNR-075-20P. This meter type utilizes a multi-jet impeller with a brass body and is NSF/ANSI-61 certified for drinking water at a maximum temperature of 105°F and a maximum pressure of 150 psi. The fittings are 0.75-inches and as shown in Figure 1.2, the pre-installed wired sensor is dual reed switch placed on opposite sides of the 0.01-gallon pinwheel. Every rotation of this dial will close each reed switch once resulting in 20 pulses for each gallon that flows through the meter. A Raspberry Pi computer supplies constant 3.3V power to the reed switches and receives that voltage as a digital pulse at a sensor pin with a built-in pull-down resistor when either switch is closed. To avoid unnecessary wear on the bearings and to receive the most accurate readings possible, the manufacturer recommended that the meter is installed in a horizontal orientation. The total length of the meter when coupled with SharkBite Push-to-Connect adapters was approximately 14.5-

inches. Installation of the meter was not permanent and to expedite removal at the end of the project the meter would be replaced with a blank section of appropriate pipe material and any other plumbing modifications to install the meter would remain in place. The installation procedure ensured that no airlock occurred and allowed the plumbing system in the home to be drained if needed, a common practice in homes in cold climates when household heating is not maintained.

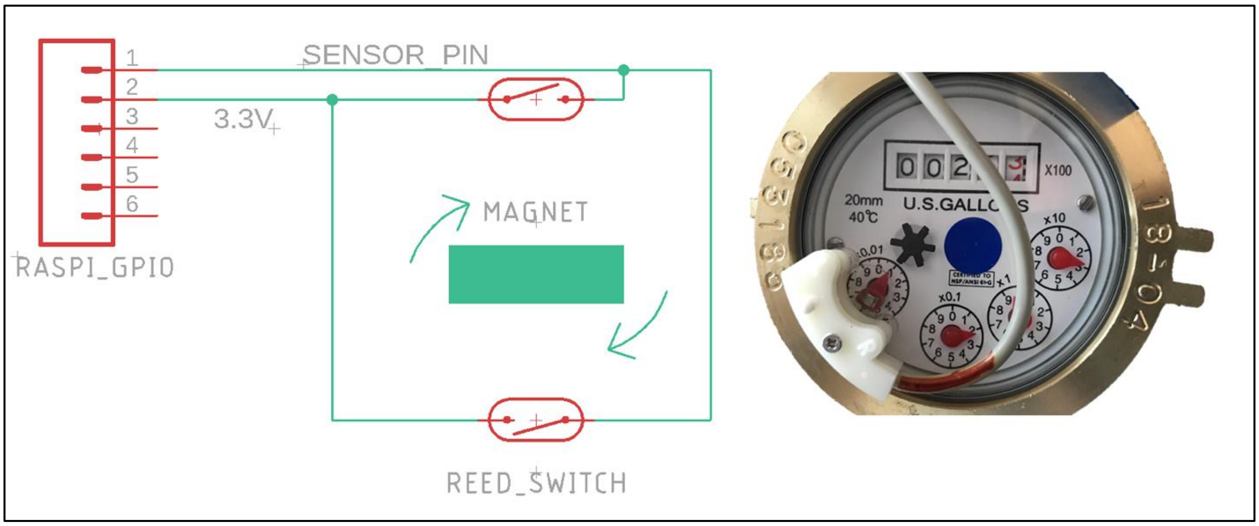

Figure 1.2 Flowmeter Pulse Sensor

The vibration sensors are based around a Moteino, an Arduino clone that has a transceiver built onto the chip. Combined with an accompanying power supply circuit board, 6 AA batteries, and a custom amplifier circuit connected to a piezoelectric element on a 14.5-inch extension wire, the sensor fits in an 80mm x 110mm x 45mm weatherproof enclosure. This form factor allows for easy mounting in a variety of locations and flexibility during installation. The total material retail cost for each wireless sensor came to approximately $65 per unit. Almost 70% of this cost is because each sensor was a prototype. Circuit boards like the Moteino were built generically and have capability beyond the scope of work. Additionally, and the enclosure was more durable than necessary. Circuit headers and plugs were used in the design to facilitate easy replacement in the field and we used through-hole soldering for easy prototyping.

When a water fixture (e.g. sink, toilet, shower, etc.) is turned on, vibrations occur within that fixture as water flows through the pipe and appurtenances (e.g. valve, aerator, etc.) and can be converted to an AC voltage using a piezo element. In this study, a 30mm enclosed piezo was either attached to the locknut of the faucet supply line under a sink, on the locknut entering the tank of a toilet, or directly behind the showerhead using a cable tie and tensioning tool. The hole built into the piezo enclosure was covered with electrical tape to reduce the amount of ambient noise reaching the element and to ensure a sufficient physical connection to the plumbing. The elasticity of the tape also helped prevent slippage after the piezo is installed. To aid in installation, the piezo element is connected to the sensor housing using a 5.5mm waterproof barrel plug. This connection point allows the piezo to be attached before mounting the sensor and allowed the unit to be swapped out if the piezo element or sensor was found to be faulty.

The signal and ground wire of the piezo element were passed through a hole in the sensor housing later sealed with hot glue and connected to the custom amplifier circuit board with a 3.5mm screw terminal block. The schematic and printed circuit board (PCB) are shown in Figure 1.3. Current coming from the piezo is pulled to ground with a 1M ohm resistor providing input impedance to the signal. The signal is then coupled to the circuit using a 0.1μF capacitor to block direct current from reaching the operational-amplifier and is again pulled to ground using a 100k ohm resistor. These components protect the circuit and condition the signal for non-inverting amplification. The op-amp component used in the circuit has two amplifiers built in with a single power input. The first amplifier receives the conditioned signal on the positive pin and produces a gain of 1001x using a 1M and 1k ohm resistor combination. The amplified signal is passed to the positive pin of the second amplifier which acts as a comparator. The threshold for the comparator is determined by a manual field adjustable 10k ohm potentiometer. The output of the comparator is saturated to the input voltage, acting as a readable digital pulse, once the amplified signal exceeds the adjusted threshold. The basic circuit design (Houlding, 2014) was prototyped using a breadboard for proof of concept, CNC milling for board sizing, and finally was manufactured on a silkscreened PCB.

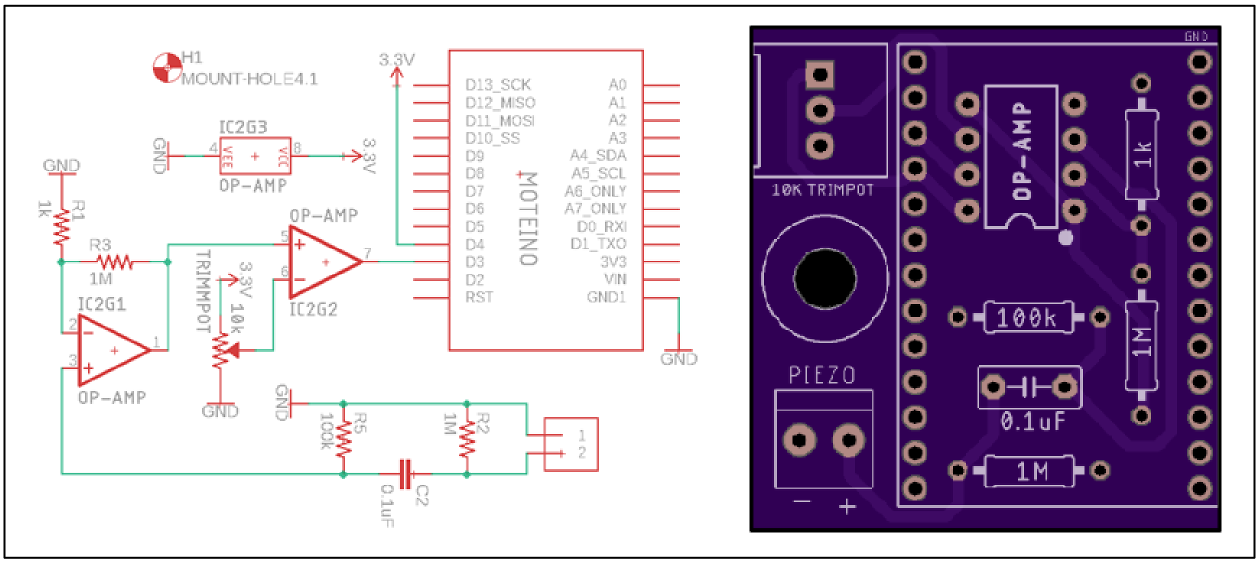

Figure 1.3 Amplifier Circuit Schematic and PCB

Each digital pulse is sent to the Moteino through digital input pin 3. The Moteino also powers the amplifier circuit from digital pin 4 to read-in the vibration in the software layer. With the permanent high gain of the first amplifier, sensitivity must be field adjustable to avoid interference from external sources including ambient noise and movement in the household. The first possible adjustment is modifying the amplitude threshold of the piezo element signal using the potentiometer on the amplifier board. The second option is to adjust the frequency of digital pulses related to actual fixture activation using the Arduino software layer. Frequency adjustment can be achieved in two manners. First by varying the read period when counting pulses. This value was typically defined as 5-milliseconds. Secondly, it could be adjusted by changing the number of pulses within that read period that indicate fixture activation. With a typical value of 10 pulses per 5-milliseconds the digital frequency threshold was typically 2,000 Hz. Transient, short duration vibrations can occur around the fixture from general activity not related to fixture usage. To reduce the number of false positives when these transient vibrations occur, the vibration readings must be sequentially above threshold twice; the initial reading and a second one 120-milliseconds afterwards. In the case of varying flow and therefore varying vibration from the fixture, there must also be two sequential readings within a 1-second window that are below threshold to indicate the fixture is no longer being used. When the fixture is determined to be active after the first two positive readings, the vibration is checked every 750-milliseconds and a wireless serial data packet is transmitted over the 915 Hz radio frequency to the base station containing the number of digital pulses read during that event. Each sensor node has a unique numerical identifier and specifies the network matching the receiver. Once two negative readings occur, the power supply voltage is read and transmitted after a 1-second delay. Finally, after another 1-second delay a serial null value of "0000" is sent to indicate the fixture is no longer being used. Any time the sensor is not sending power to the amplifier circuit to check for vibration or transmitting data, it is put into a low-power sleep mode to conserve battery power over long time periods. To further conserve power, a feature where the radio listens for a reply from the receiver to indicates how much power the radio needs to use to reach the receiver was used. It will also attempt to send the data for a predetermined number of tries before ceasing transmission. The power usage of the circuit will be described in the results.

Power for the sensor node was provided by two sets of 3 AA alkaline batteries. Within each set the batteries were connected in series to achieve a nominal 4.5 volts. The two sets were then connected in parallel to double the capacity. A Power Shield with a boost/buck voltage converter was used to interface the battery with the Moteino and amplifier circuit. This board, manufactured for the Moteino, produces a consistent 5-volt power supply even as the batteries are depleted down to 0.85-volts (Linear Technology Datasheet, 2005). Another advantage of utilizing this board is the simple battery voltage reading derived from one of the analog pins. This information provides both indication that the batteries need to be replaced and a depletion curve for analysis.

A Raspberry Pi single-board computer placed in a central base station within the home receives all of the information transmitted from the sensor nodes and flowmeter. The Raspberry Pi is connected to multiple peripherals including a matching 915 Hz MoteinoUSB to receive radio signals from the sensor nodes, an ethernet-connected cellular modem and a custom General-Purpose Input/Output (GPIO) interface circuit seen in Figure 1.5. Enclosed in an 8-inch x 8-inch x 4-inch PVC junction box, the total material cost of each station was approximately $205.

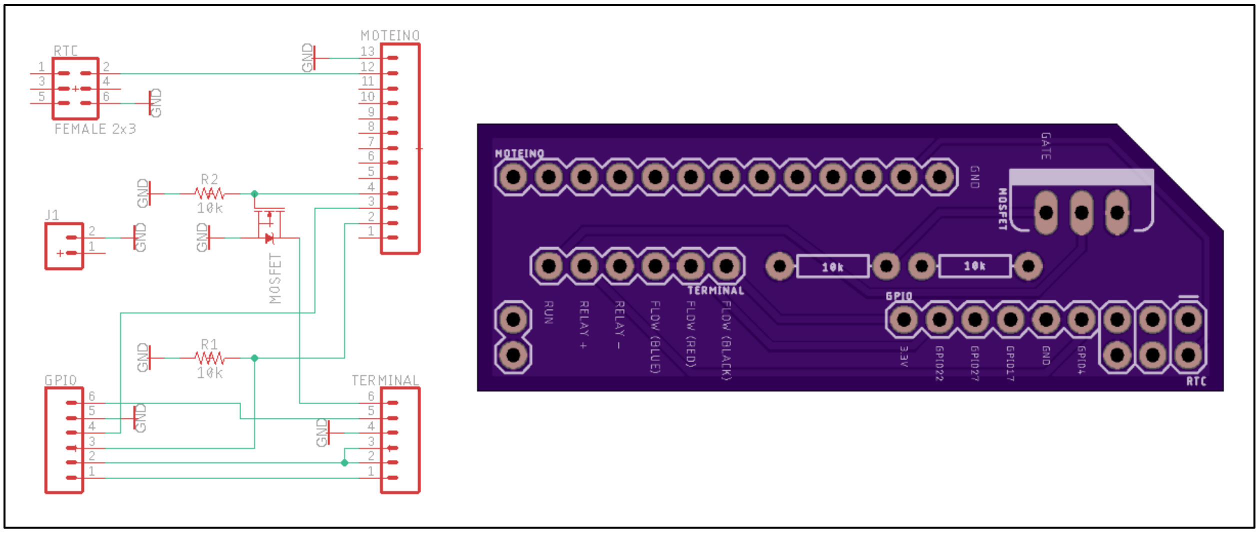

Figure 1.4 GPIO Interface Circuit

The enclosure also contained an AC power supply with a built-in relay for IoT projects. The Raspberry Pi was connected to an outlet on the power supply that always provides power and the modem was connected to an outlet that would turn off if the relay was powered. The GPIO interface circuit served four separate functions. The first was to allow the flowmeter to be connected to the Raspberry Pi in the field using a simple screw terminal. Second, using a Python program, the Raspberry Pi could send a voltage to the IoT power relay and disrupt power to the modem to force a hard reboot. The third function was to connect a real-time clock (RTC) to the Raspberry Pi for a consistent timestamp that did not rely on an active internet connection. Finally, the circuit integrated an additional Moteino as a type of hardware-based watchdog to perform a hard reboot of the Raspberry Pi if necessary. Unlike the sensor nodes that used a built-in Enhanced Watchdog Timer (WDT), the Raspberry Pi needed an independent method to force a reboot if the Raspberry Pi either froze or was shutdown remotely for any reason. The implementation of this function runs continuously after startup in the background using the rc.local file configuration. Every 60 seconds, a voltage would be sent from the shore powered

Moteino to the Raspberry Pi and would wait 50-milliseconds for a response before turning off. If no response was received after 5 tries the Moteino would send a 500-millisecond signal to the gate pin of a N-channel MOSFET that would in turn ground the connected power pin on the Raspberry Pi rebooting the device. Since the Moteino does not have an available software enabled pull-down resistor for pin inputs, a physical pull-down resistor was also included in the circuit for both the Moteino pin receiving a signal from the Raspberry Pi and the MOSFET gate pin. To prevent a device system crash, the modem was scheduled to reboot twice per day and the Raspberry Pi would reboot every 24 hours at 4 am using built-in crontab functionality.

1.2.3 Data Processing

Multiple levels of local data processing are used on the Raspberry Pi between the raw serial data coming in and final packaging. Information received from the sensor nodes and flowmeter are recorded continuously in separate daily CSV files using Python scripts and rc.local initialization. Files are processed and transmitted daily over email to a central account. Starting with the flowmeter pulses, a Python script that utilizes the RPi.GPIO library to detect the rising edge of a digital pulse counts how many of these events occur during a one second period. Since the pulses are produced by the flowmeter which is an analog device, they are not a perfect square wave. To account for any signal bounce, the program will not count any more than one event that occurs within 100-milliseconds. This parameter limits the detectable flowrate to 30 gallons per minute with a 20 pulse per gallon flowmeter. However, the limitation was considered reasonable for the interior of a residential household. The script pulls the current time from the RTC as a timestamp with hour, minute and second whenever the pulse count is nonzero. The timestamp is combined with the pulse count as a single string separated by a comma. The line of data is then appended to a CSV file. To create this file on a daily basis, the script only records to the file while the day is the same as what was noted at start up. When the while loop is broken by the next day, a new daily file is created with the header, taken from a central Python script called “location”, printed to the first line. The previous day’s file is kept separate and never altered after proceeding to the next day to ensure data redundancy. The header of the file is “Time, Flow”, with the flow value shown in gallons derived from the number of pulses read by the counter and how many pulses per gallon are shown by a bucket test performed during installation.

Similar to the flowmeter, data received from the sensor nodes are saved to another separate CSV file on a daily basis and is also unaltered after proceeding to the next day. However, since the data is received from more than one sensor, additional work must be done to include information from all reporting devices on a single line. The MoteinoUSB connected to the Raspberry Pi’s USB port constantly listens for data from all of the nodes on its network and uses a buffer system to update the information reported from each node before transferring data. Each node has its own unique buffer and is overwritten as data is received from that node during a 1-second window. If any of the node buffers do not equal a null “0000”, indicating there is data to print, a single line of serial data is printed/sent from the MoteinoUSB to the Raspberry Pi over the wired connection. Contained within this line of data is either the information received from the node such as pulse count, battery voltage, or in the case of a null value, a comma placeholder for that node. The order of these comma-separated values indicates the identity of the associated nodes. The null values are used because in the event of two nodes reporting at the same time, one node can stop reporting while the other continues. To accommodate this event, the node decides to stop printing information on its buffer, not the receiver. One drawback to this technique is in the event that the null value sent is not successfully received, it will continue to print indefinitely.

The Arduino script will assign a null value to all node buffers if no information has been received from any node after 10-seconds and at least one of the buffers still indicate the need to print. The reset will be recorded as a communication failure in the node serial data file.

The Raspberry Pi receives the serial line data from the wired Moteino receiver in 1-second increments and processes that information with a Python script and the pyserial-3.4 library. Similar to the flowmeter algorithm, a timestamp is assigned to each line in as it is received, placed in the first column, and appended to a daily CSV file. A header is created showing which column is associated with which node. The nodes are on a 1-second sleep cycle that may miss the exact moment a fixture is activated. To compensate, if no data has been received from the MoteinoUSB in the last 3-seconds, meaning no sensors have been reporting, the script would duplicate the first line of data received, and assign a "backdated" timestamp. This procedure would print three lines of data labeled one second apart simultaneously using the information from the initial reporting node. Delaying the node's transmission of a null value accomplishes this extrapolation after the fixture is deactivated.

At the end of each day, two CSV files are ready to be processed. One contains the flow information and associated timestamp and the other contains the node information and their associated timestamp. Merging these two files based on the timestamp in the first column of each file creates a labeled dataset. Since the merge function relies on the header of each file, if it is incorrect in either file the merge will fail. During CSV file creation at midnight, if data is received at the same time the script is creating a new file for the next day, the incoming data will misplace the header in terms of row order. The processing script checks for this phenomenon before attempting to merge and will skip to the next line in the data frame if the header is not correct within the first 5 lines. If the header is not present in the first five lines, the merge will fail. However, since the original separated data files are not altered or destroyed, they are added unmodified to a ZIP file so that the header can be adjusted manually in the individual files at a later time. If successful, the script merges the two files into a new data frame with time as the first column, flow as the second, and then each node following with their own column. The data frame is then written to a new CSV file and zipped for data transmission.

Monitoring water usage in a remote location for an extended period of time can make it difficult to access data physically for early processing/troubleshooting and using cellular internet in a remote location can be somewhat unreliable throughout the day from signal fluctuations. Most of the Raspberry Pi's scheduled events occur at night during low traffic periods but not having internet access during a scheduled data transmission can be problematic. An algorithm, seen in Figure 1.7, will attempt to send the merged data file over email multiple times a day. Each time the day's two data files were successfully merged by the previous processing script; the file name was appended to a "merged" CSV file. Another Python script would run after this processing to email the file and upon success would append the file name to a "sent" CSV file. Before attempting to send the file, the script would first check for an internet connection and if connected would determine if there was a file that needed to be sent. It did this by comparing the "merged" and "sent" lists. If there was a discrepancy, it would attempt to send the file produced by that comparison. The email script was scheduled to run every 5 hours throughout the day. This would improve the probability that an internet connection was present at run time and if the internet was down for an extended period of time, the multiple attempts would allow the backlog of unsent files to be processed automatically. In the case of any unforeseen problems, the data and programming could also be accessed by the third party remote terminal service Dataplicity.

This service also offered port duplication so that files could be transferred over cellular networks if necessary.

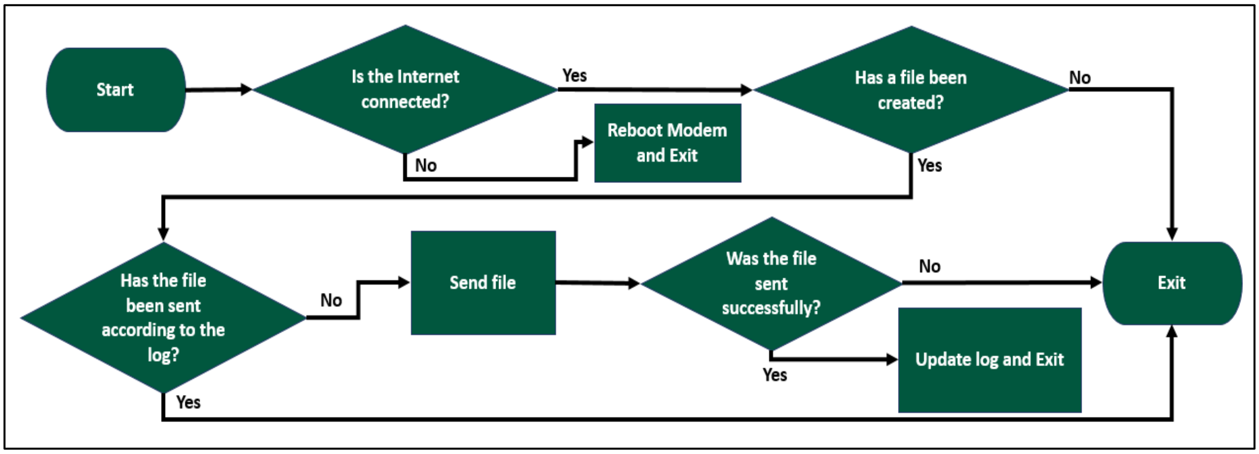

Figure 1.5 Data File Transmission Process

1.2.4 Methodology

The setup for this case study involves a single-family home in a remote area not accessible by roads. The home has 3 bedrooms, 1 bath, and 4 household members using a total of 5 fixtures; including a shower, bathroom sink, toilet, kitchen sink, and washing machine. No additional or outdoor water fixtures were present. Installation involved the labor of two researchers over a 2-hour timeframe. After the plumbing into the home was deemed accessible and the participant provided consent, one researcher completed plumbing for the flowmeter while the other attached and mounted the sensor nodes. Once the flowmeter was installed and the water supply into the home was turned back on, testing and calibration began using the local modem WIFI network and a smartphone terminal application. The first task was to make sure that each sensor would activate when the fixture was used. If not successful, the sensitivity was increased using the manual amplitude adjustment or if needed, frequency tuning via reprogramming. If there was any detectable vibrational communication between the fixtures through the plumbing, the sensitivity was adjusted accordingly to avoid cross-detection. Once all of the sensors reported as designed, flowmeter calibration began.

A bucket test was performed in the kitchen sink with a pulse counting Python script, with the same parameters as the flow recording script, and a 0.5-gallon pitcher. With no other water being used in the house, the pitcher was filled four times totaling 2-gallons. After noting the pulse count, the process was repeated for another 2-gallon test proceeded with a 1-gallon and 0.5-gallon test. The “location” script was then updated with the now known pulses per gallon. The flow recording script utilized this information and reported gallons instead of pulses each second.

Once all of the sensors have been adjusted and the flowmeter calibrated with the bucket test, the Raspberry Pi’s SD card was copied using a stand-alone USB duplicator. The duplicate SD card was a complete image including the operating system and all associated location calibration information. In the rare case of a corrupted primary SD card in the Raspberry Pi, the backup card could serve as a field replacement. The information transmitted via email before this possible corruption would not be lost in this event.

1.3 Results

The system sensors produce digital pulses from both vibration at the fixtures and the water moving through the flowmeter. Looking at how these data points are produced in response to physical input both before and after field deployment demonstrates the system’s feasibility.

1.3.1 Pre-Deployment Testing

Before field deployment, to get a better picture of the vibration occurring in the fixtures and how that would be translated to sensor readings, multiple representative fixtures were separately recorded at a 0.5-second sampling rate. The results of these tests can be found in Figure 1.6. Each fixture had its own frequency signature. The shower and toilet were constant at a constant flow rate and the sink was shown to be variable due to the range of valve opening. Overlaps between the sink vibration and the loud artificial background noise, shown for demonstrative purposes, were separated by sampling rate sensitivity adjustment described previously. Vibration is inherently present in an appliance such as a washing machine even when water is not being used. As shown in Figure 1.7, there is a frequency differential between water usage portions of the washing machine cycle and non-usage portions. Adjustment in the frequency activation threshold can help to distinguish these differences for reporting water usage activity.

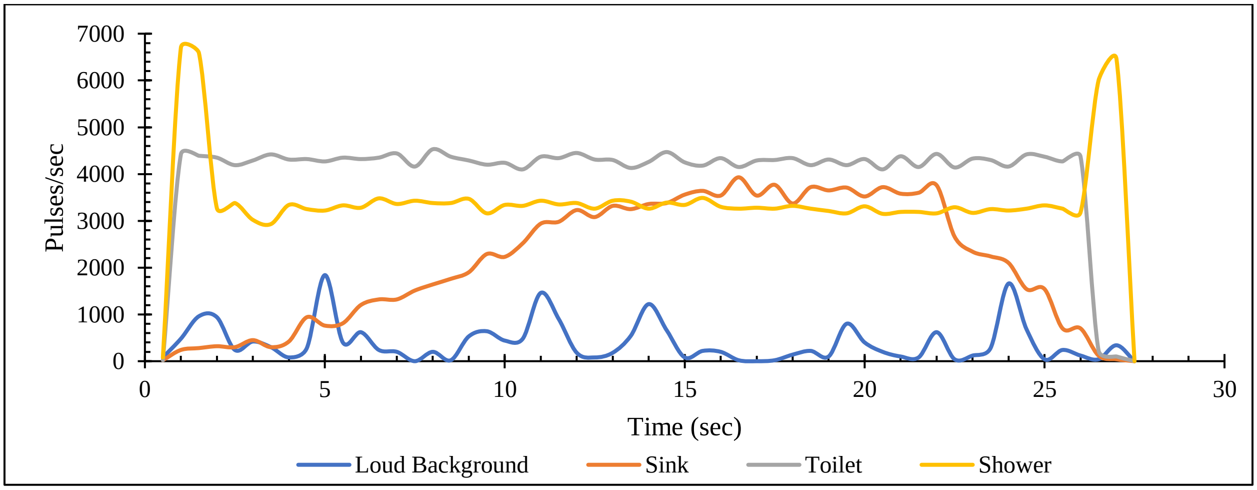

Figure 1.6 Pre-Deployment Fixture Vibration Frequency Test

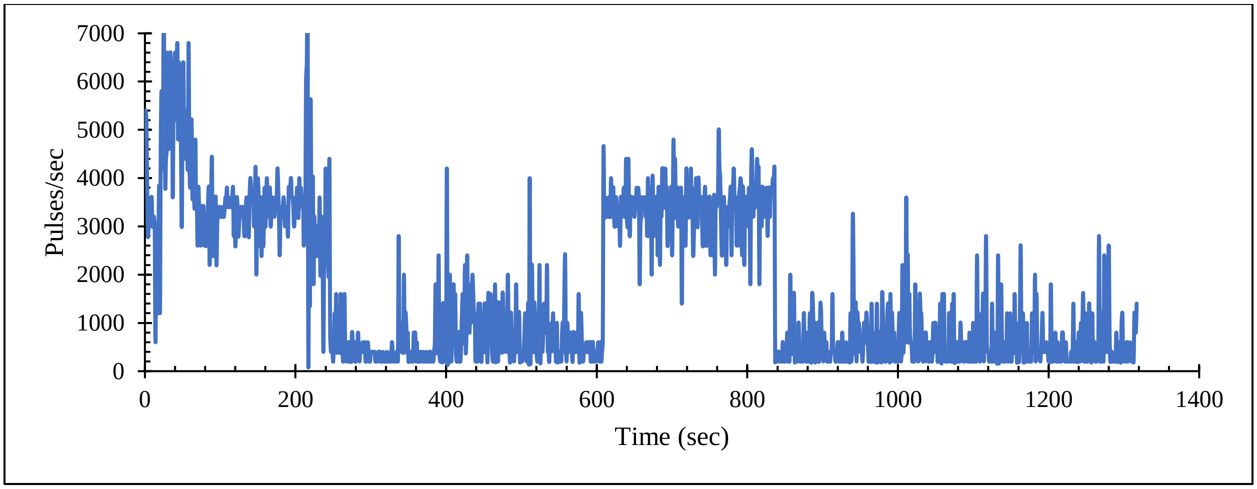

Figure 1.7 Washing Machine Vibration Test

The wireless sensors depend on the batteries to operate and the discharge analysis of that source can help estimate the maintenance interval required. Before testing in the field, to estimate the amount of capacity used, a sensor was connected to the battery through an ammeter and the amperage was recorded every 0.03366 seconds for 3.33234 seconds. We recorded various power cycles as shown in Figure 1.8. The sensor uses approximately 10 mA to power the amplifier circuity to check for vibration and alternates between 0.025 mA and 0.044 mA in sleep only mode due to the Moteino's minimal power drain and the power board boosting to 5 volts. When sending serial data, the sensor uses up to 35 mA. If the data is not confirmed as received, the sensor tries consecutively higher power levels on the radio until the data is either successfully transmitted or the number of tries is reached. Using this information, the power usage was estimated to be an average of 1.924×10^{-5} mAh every second of sleep and 4.99×10^{-4} mAh per second when sending data.

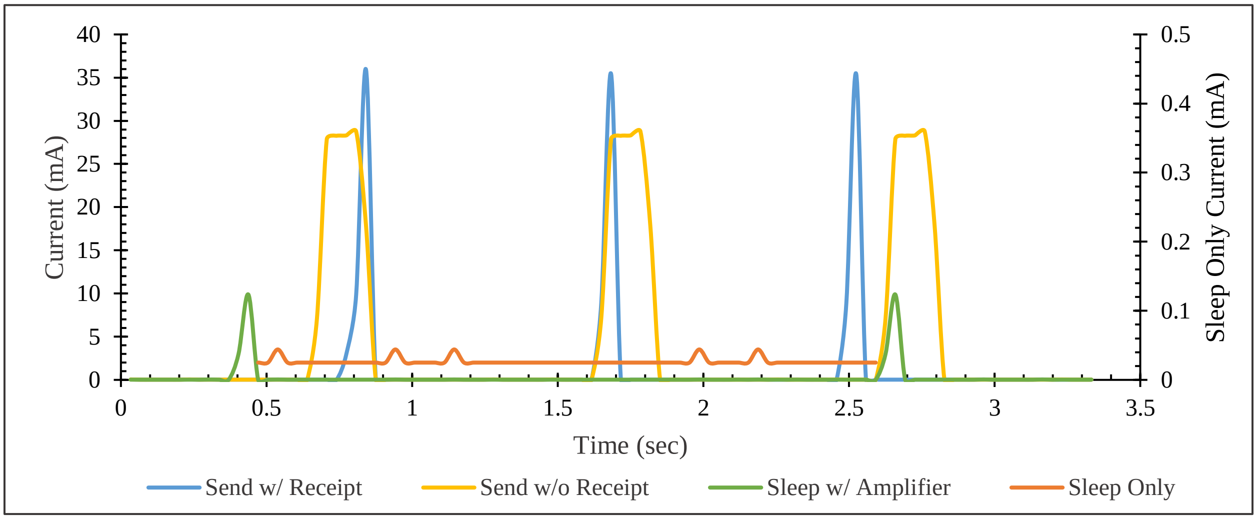

Figure 1.8 Recorded Sensor Power Cycles

1.3.2 Post-Deployment Performance

When employing an automated measurement system in the field, there are multiple modes of failure that can occur ranging from software crashes to hardware failure. Once deployed, the first goal is to avoid these failures, and then look to see how well the system performed gathering data. The justification for this type of analysis is during the design phase, the first goal of the system is high quality data collection. After overcoming this hurdle, enhancements are made to ensure that quality is consistent and lasting. Over the six months, or 184 days of testing, there were zero gaps in data collection. The Raspberry Pi either lost shore power or rebooted via the watchdog circuit a total of nine times. The modem was rebooted a total of 17 times due to a lack in internet connectivity stemming from either local cellular network signal loss or modem software crash. In both reboot cases, identifying whether complications were internal or external was not able to be accomplished. However, they were successfully resolved using the automatic processes in each case. Communication failures between the nodes and base station, meaning the null value was not successfully transmitted, occurred a total of six times. Each instance was isolated and did not indicate an actual sensor failure because data was transmitted and received from that sensor immediately after the recorded failure. Zero flow occurred during each 10-second window of false reporting.

Sensor battery performance can be demonstrated using a discharge curve, shown in Figure 1.9. It was developed using the reported voltage and by counting how many times the sensors are in each state over the six-month period. Since the mAh were previously measured for each of these cycles, a total discharge could be calculated from these counts.

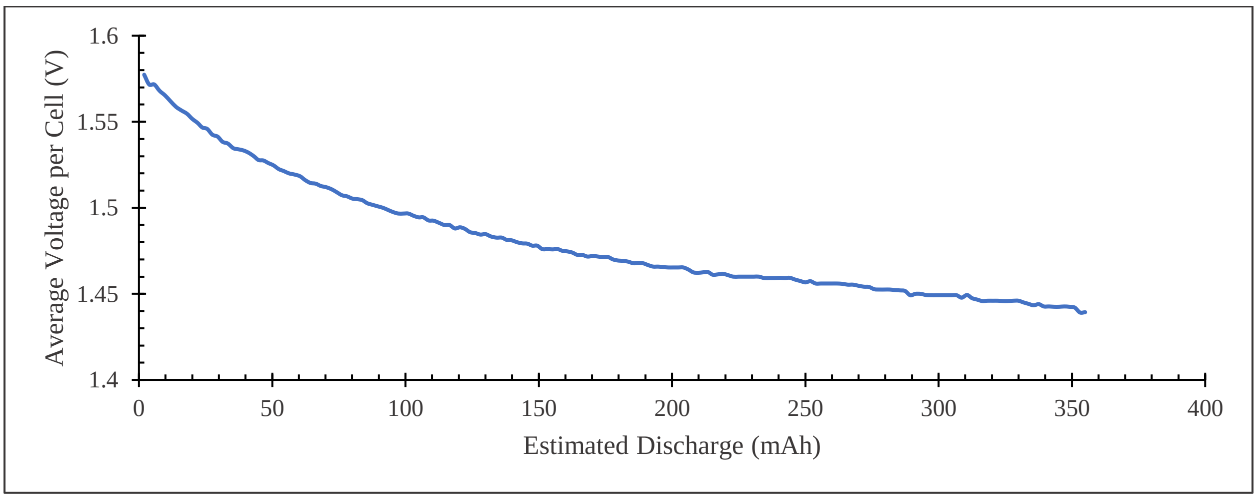

Figure 1.9 Average Battery Discharge for Wireless Sensor Batteries

As for the data quality, the files received on a daily basis through email were downloaded, decompressed, and then processed to condense the information. An example of the raw merged data can be seen in Table 1.1. In this sample, three event types can be seen. The first is flow without any vibration sensors reporting, which will be referred to as unmonitored. Second is a single sensor reporting and third is multiple sensors reporting. The first event is the least desirable and the fraction of unmonitored flow to total flow can be seen in Figure 1.10. There is a significant increase in this fraction on day 77. Before this day, the unmonitored fraction averaged 5.73%, indicating over 94% of the data was captured by the sensors. After this day, the unmonitored portion made up an average of 17.13%. The reasoning for the increase of unmonitored flow is demonstrated by comparing a day that had a low fraction of 5.11% before the change, Figure 1.11, to a day with a high fraction of 50.93% after the change, Figure 1.12. The distribution of the third data type, multiple sensors reporting, can be seen in Figure 1.13. Here the single-sensor water volume for each day is compared to both two sensors reporting simultaneously and three-or-more reporting simultaneously. On average, the dual reporting sensors made up 6.25% of the total volume and the three-or-more portion only made up 0.14%. Data processing captures the water volume total for each possible permutation of reporting sensors and identifies when it occurs during the day. The average total for each hour over the six-month period can be seen in Figure 1.14.

Table 1.1 Example Reported Data of Toilet Flush and Bathroom Sink Usage

Time	Gal	SHWR	B_SINK	TOIL	K_SINK	WASH
12:37:13	0.026316					
12:37:26	0.026316					
12:39:42	0.052632			29		
12:39:43	0.078947			29		
12:39:44	0.078947			29		
12:39:45	0.078947			26		
12:39:46	0.052632			33		
12:39:47	0.078947			31		
12:39:48	0.078947			25		
12:39:49	0.052632			35		
12:39:50	0.052632			29		
12:39:51	0.105263			27		
12:39:52	0.052632			28		
12:39:53	0.078947			28		
12:39:54	0.078947		14	26		
12:39:55	0.105263		20	27		
12:39:56	0.078947		20	30		
12:39:57	0.078947		19	27		
12:39:58	0.078947		19	30		
12:39:59	0.105263		22	26		
12:40:00	0.078947		25	32		
12:40:01	0.105263		21	23		
12:40:02	0.078947		26	25		
12:40:03	0.105263		16	25		
12:40:04	0.078947		18	27		
12:40:05	0.105263		14	28		
12:40:05	0.105263		20	27		
12:40:07	0.078947		24	28		
12:40:08	0.105263		24	32		
12:40:09	0.078947		20	26		
12:40:10	0.078947		28	28		
12:40:11	0.105263		24	28		
12:40:12	0.078947		28	24		
12:40:13	0.078947		27	4.31		
12:40:14	0.026316		22			
12:40:15	0.026316		4.32			

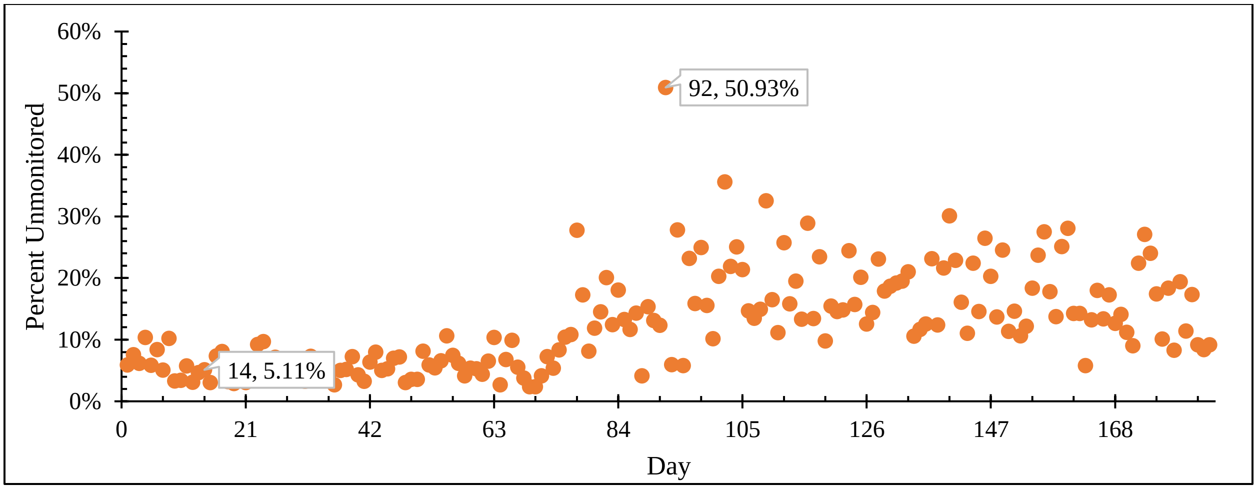

Figure 1.10 Fraction of Unmonitored Flow Each Day

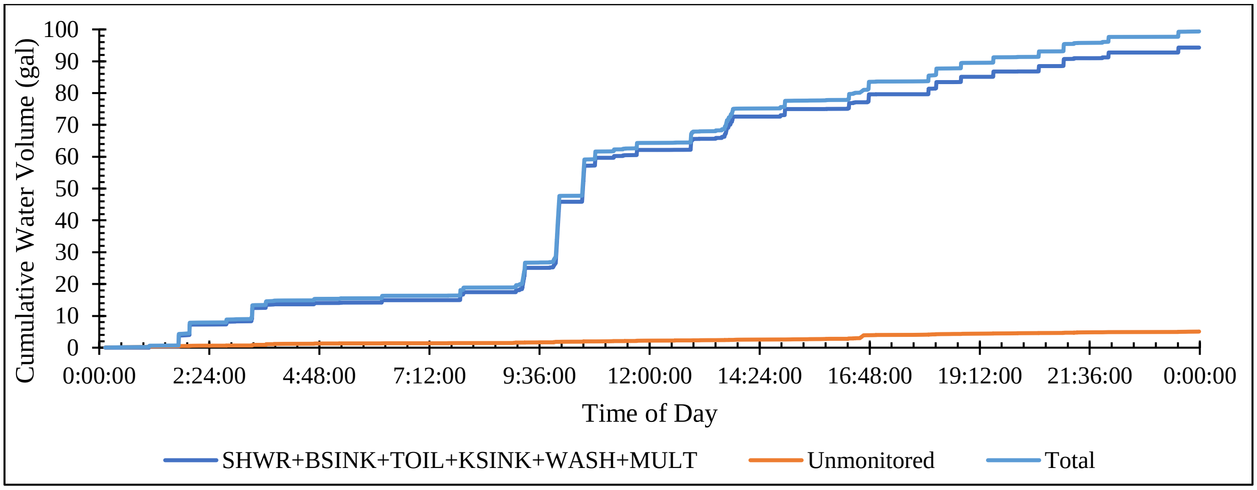

Figure 1.11 Low Unmonitored Fraction Example on Day 14

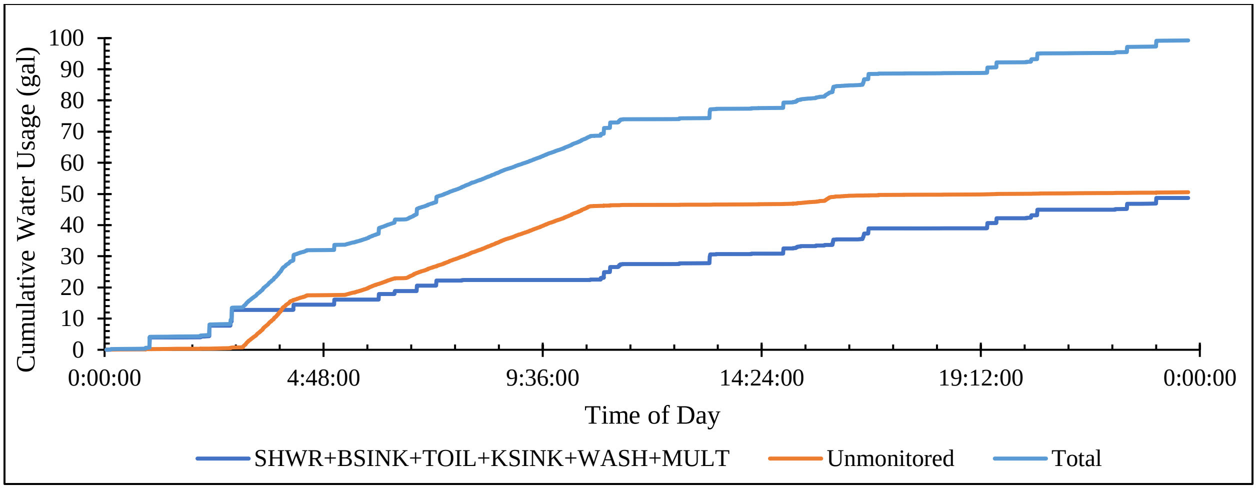

Figure 1.12 High Unmonitored Fraction Example on Day 92

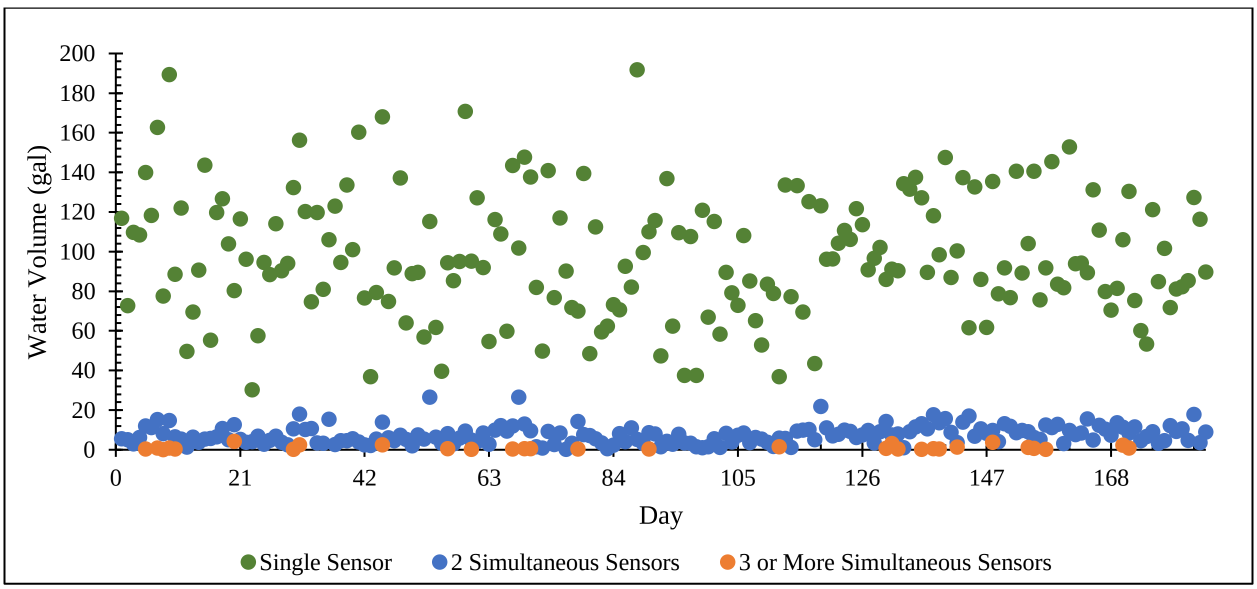

Figure 1.13 Total Volume of Each Fixture Combination Type

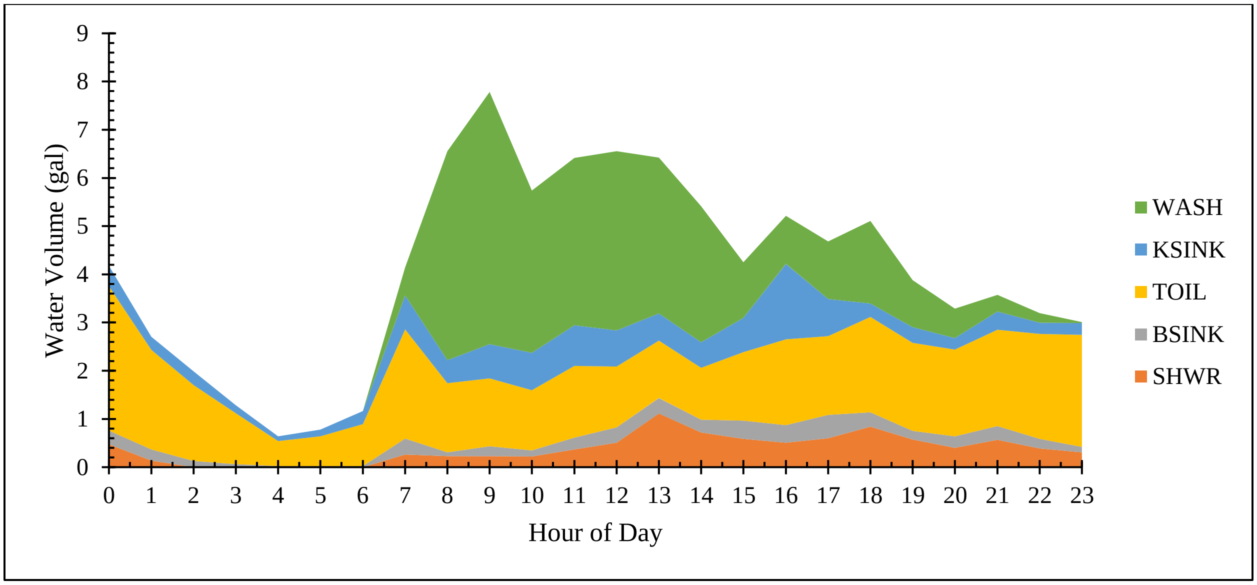

Figure 1.14 6-Month Average Water Use per Hour for Each Fixture

1.4 Discussion

The case study for this sensor system takes advantage of a small number of fixtures within the home simplifying installation and analysis. Implementing vibration sensors physically attached to the fixtures themselves offers increased accuracy in pinpointing the activation of a particular fixture; especially in a home with non-copper plumbing and adequate space between fixtures. There is a risk of communication between the fixtures based on the architecture of the existing plumbing and the noise level of individual fixtures. Balancing the sensitivity of each sensor can be a challenge in these layouts that are conducive to increased communication. Plumbing supports that attach the plumbing to the frame of the home can attenuate mixed signaling, but these infrastructure specifications do limit the number and type of homes where the current sensor system can be easily implemented.

The total capacity for a AA alkaline cell using a test cycle of 100mA for 1 minute and 100µA for 110 minutes is approximately 2750 mAh with a 0.8 volt cutoff point (Floyd, 2011).

Given the battery setup in the wireless sensors the capacity can be considered to be approximately 4675 mAh with a 15% safety margin. Using the mAh per cycle calculation previously described and an average of 12 minutes of use per fixture per day, the expected service life is expected to exceed 6 years. Slightly more than 350 mAh of drainage was calculated over the six-month period. The fixture sensors report a final average of 1.44 volts per cell which correlates with only 150 mAh cell drainage on the discharge curve reported by Floyd. Even though the discharge rates are not identical, the disparity likely indicates an overestimation in battery discharge using the cycle count methodology. The sensors are likely to exceed 6 years of battery life in the current test setup signifying excessive capacity in the design. Combining the cells in series to supply a nominal 4.5 volts to the circuit also likely decreased demand on the batteries contributing to the redundant capacity.

Successful disaggregation using this methodology is highly impacted by flow volumes that do not have a corresponding fixture. Though the disaggregation can be done indirectly using flow rates and event indicators, direct comparison is the most accurate and reliable procedure. The increase in unmonitored flow seen in Figure 1.12 is directly attributed to very low flow rates over an extended period of time. This event type is likely a faucet left on or a faulty toilet valve. In either case, the indication is that there is an issue that need to be investigated in order to conserve that water. Knowledge that this event is occurring is more important than the location of the flow because it is unlikely that the water is being actively used by a person in the household. All flow detection devices have a flow threshold including the vibration sensors deployed in this study. However, instead of an actual water flow minimum, additional factors such as piezo placement and fixture type impact the effectiveness of the sensor.

Similar to having zero sensors reporting during flow, multiple sensors reporting simultaneously also complicates the disaggregation process. When only two sensors are reporting, the average rates can be used to estimate the proportion each fixture is using. This is especially true when one of the reporting fixtures has a constant flow such as a shower. Two sinks running at the same time is much more difficult to dissociate due to variable flow in each. More than two reporting sensors is also more difficult to disaggregate. Fortunately, this case is rare as shown in Figure 1.13. The low occurrence of more than two fixtures reporting at the same time is also indicative there is little to no vibrational interference between fixtures.

Information was reported on a per-second basis. To facilitate the presentation of this information it was condensed to a volume per hour of the day for each fixture combination. Averaging this usage over the six-month period gives an accurate representation of when and where water is used within the home throughout the day. Portrayed in Figure 1.14, this type of information is just a single example of useful data seen by both water producers and consumers. Data processing is an important part of finding meaning in the very large datasets produced by this methodology. Much of the previous work done in this sector involves figuring out how to determine where the water is flowing only using a single data source such as flowmeter. A large dataset with highly correlated flow values could prove useful in developing algorithms that no longer need vibration sensors in place for ground truth.

Besides more efficient data processing, improvements can be made to the sensors themselves. For instance, battery usage was overestimated unnecessarily increasing the size and weight of the sensor package. Lower powered radios are available and lithium batteries could be used if the entire package was smaller and more portable. The best way to achieve this goal would be to integrate all of the components onto a single circuit board possibly including a built-in accelerometer in place of an amplified piezo. Additionally, instead of making adjustments to sensitivity once upon installation, which is unlikely to capture all of the possible flow rates from a fixture, remote programming could be implemented via the wireless data connection. As built, reprogramming will only adjust the sampling time and threshold frequency. But, if a digital potentiometer was used in place of a manual one, the amplitude threshold could be adjusted with programming as well. These changes would give more flexibility and make it easier to make the adjustments necessary.

In conclusion, this methodology is an improvement on the current state of the art in terms of field testing both reliability and usability. Vibration varies between fixtures but remains consistent for most individual fixtures. The sensors used in this study are easy to install and are likely to operate over six years while generating little observation bias. There are some limitations, including not identifying the location of very low flowrates, and requiring simultaneous fixture usage to be processed after the data is emailed each day. However, when the leaks are not occurring the water usage can be identified almost 94% of the time. The sensors have room for improvement and as technology advances, especially in the IoT field and advanced machine learning in more connected households, costs will go down and implementation will be easier with this methodology. Future research can include making these improvements and further exploring the insights to be ascertained from this type of information.

1.5 References

Anda, M., Le Gay Brereton, F., Brennan, J., Paskett, E., 2013. Smart Metering Infrastructure for Residential Water Efficiency: Results of a Trial in a Behavioural Change Program in Perth, Western Australia. Proc. First Int. Conf. Inf. Commun. Technol. Sustain. ETH Zurich, Febr. 14-16, 2013 175–182. https://doi.org/10.3929/ethz-a-007337628

Carboni, D., Gluhak, A., McCann, J.A., Beach, T.H., 2016. Contextualising water use in residential settings: A survey of non-intrusive techniques and approaches. Sensors (Switzerland) 16. https://doi.org/10.3390/s16050738

DeOreo, W.B., Heaney, J.P., Mayer, P.W., 1996. Flow trace analysis to access water use. J. Am. Water Works Assoc. 88, 79–90. https://doi.org/10.1002/j.1551-8833.1996.tb06487.x

Di Mauro, A., Di Nardo, A., Santonastaso, G.F., Venticinque, S., 2019. An IoT system for monitoring and data collection of residential water end-use consumption. Proc. - Int. Conf. Comput. Commun. Networks, ICCCN 2019-July, 1–6. https://doi.org/10.1109/ICCCN.2019.8847120

FAA, 2020. PackSafe for Passengers [WWW Document]. URL https://www.faa.gov/hazmat/packsafe/ (accessed 5.7.20).

Floyd, A., 2011. Measurement and analysis of alkaline battery performance for low power wireless applications. University of Manchester.

Fogarty, J., Au, C., Hudson, S.E., 2008. Sensing from the basement: A feasibility study of unobtrusive and low-cost home activity recognition. UIST 2006 Proc. 19th Annu. ACM Symp. User Interface Softw. Technol. 91–100. https://doi.org/10.1145/1166253.1166269

Fontdecaba, S., Sánchez-espigares, J.A., 2013. An Approach to Disaggregating Total Household Water Consumption into Major End-Uses 2155–2177. https://doi.org/10.1007/s11269-013-

0281-8

Froehlich, J., Larson, E., Campbell, T., Haggerty, C., Fogarty, J., Patel, S.N., 2009. HydroSense: Infrastructure-mediated single-point sensing of whole-home water activity. ACM Int. Conf. Proceeding Ser. 235–244. https://doi.org/10.1145/1620545.1620581

Houlding, D., 2014. High Sensitivity Vibration Sensor Using Arduino [WWW Document]. Blogspot. URL http://davidhoulding.blogspot.com/2014/02/high-sensitivity-vibration-sensor-using.html (accessed 5.7.20).

Kim, Y., Schmid, T., Charbiwala, Z.M., Friedman, J., Srivastava, M.B., 2008. NAWMS: Nonintrusive autonomous water monitoring system. SenSys'08 - Proc. 6th ACM Conf. Embed. Networked Sens. Syst. 309–321. https://doi.org/10.1145/1460412.1460443

Linear Technology Datasheet, 2005. LTC3525 - 400mA Micropower Synchronous Step-Up DC/DC Converter with Output Disconnect 1–16.

Schantz, C., Sennett, B., Donnal, J., Gillman, M., Leeb, S., 2014. Non-intrusive load monitoring for water (WaterNILM). WIT Trans. Built Environ. 139, 103–114. https://doi.org/10.2495/UW140091

Srinivasan, V., Stankovic, J., Whitehouse, K., 2011. WaterSense: Water flow disaggregation using motion sensors. BuildSys 2011 - Proc. 3rd ACM Work. Embed. Sens. Syst. Energy-Efficiency Build. Held Conjunction with ACM SenSys 2011 19–24. https://doi.org/10.1145/2434020.2434026

Tapia, E.M., Intille, S.S., Larson, K., 2004. Activity Recognition in Home Using Simple and Ubiquitous Sensors. Pervasive Comput. 3001, 158–175. https://doi.org/10.1007/b96922

Chapter 2 – Hygiene and Water Conservation

Abstract

Monitoring the water usage in the home on a per fixture basis produces both water volume and usage event datasets over a period of time. Volume information from this type of investigation has a higher specificity than what is typically gathered for water usage because it includes both how much total water was used at each fixture and when that fixture was utilized throughout the day. Water usage events in this study of four homes in rural Alaska were identified from the recorded information. Compiling the data gathered from each of these events offered insights on hygiene habits such as handwashing after toilet use, showering frequency, and shower duration. The study also identified examples of excessive water use and targeted those areas for conservation efforts within the home with as little impact on the individual as possible. The regions where this study takes place are subject to potable water scarcity and more aggressive measures such as switching to a dry toilet and reusing graywater were examined as options to conserve as much water as possible. These strategies were considered for conservation measures while simultaneously identifying shortcomings in hygiene behavior and providing enough water to maintain a low risk to health for those within the home. Utilizing engineering controls and modifying behavior, homes in this study showed opportunities to improve hygiene and reduce water usage by up to 60%.

2.1 Introduction

Fresh, potable water is an irreplaceable resource valuable to every person on earth. Increased scarcity makes users appreciate this resource and entities responsible for its distribution demand more detail on how it is used. The most prevalent metric for water monitoring is simply the aggregated quantity consumed by a customer within a time period for the purpose of billing (Srinivasan et al., 2011). Typically, this quantity is measured by a flowmeter connected to the home. There is however increasing interest in water usage data with higher granularity than basic total volumes (Carboni et al., 2016). Knowledge of how, when, and where water is utilized within the home can reveal if and how individuals are meeting basic needs for health and hygiene and also help identify excessive use patterns to target for better conservation efforts. In addition to behavior modification, these patterns also help develop systems that process graywater for reuse within the home further increasing the effective utility of one gallon of water. Monitoring behavior within the home opens the doors to a multitude of other insights, even including the health status of an aging individual living alone (Tapia et al., 2004).

The minimum clean water supply recommendation for consumption and hygiene is approximately 4 gallons per person per day in emergency situations (Sphere Project, 2018). In order to maintain a low level of health concern over a sustained period, 13.2 gallons per person per day should be supplied without any substantial roadblocks to access such as distance to source or wait times (Howard and Bartram, 2003). The most efficient method for delivery addressing these concerns is piped water directly into the user's home. This system may be taken for granted in most developed nations, but it stands in contrast to areas that rely on a central water source and self-haul like East Africa (Thomson et al., 2001). Increasing water usage through access to piped water over a self-haul system can significantly decrease the amount of 'water-washed' infectious diseases in a population because once an individual's water supply is not inhibited by labor or cost, the frequency of handwashing and bathing can increase (Thomas et al., 2016).

Federal regulation, starting with the Energy Policy Act of 1992, has shaped new construction and water delivery standards with efficiency at the forefront of design. When these requirements are combined with educational efforts on conservation it has been shown that future residential water demand will likely continue to decrease over time (DeOreo and Mayer, 2012). If an individual knows how much water they are using throughout the day, they can add to these improvements by means of behavior self-modification (Anda et al., 2013). It is important to note that in arid locations where water is physically scarce or remote areas that require energy intensive treatment and distribution, conservation is actually needed to ensure reliable access. Water conservation not only affects the demand for supply, but also the quantity of waste. In some areas the transportation and treatment of sewage is cost prohibitive and can have a negative impact on health (Eichelberger, 2010). Reducing the production of waste from excessive water usage while simultaneously ensuring enough water is provided and used for basic hygiene is a societal and engineering paradox for regions without easy access to water. Once again, reuse systems can help to alleviate these problems.

Th broader goal is to design engineered water systems that best serve all communities, not just urban centers and their water infrastructure. There is ongoing development in smart-home monitoring for water similar to that used for energy (Sønderlund et al., 2014), but new smart-meters that have the ability to determine usage patterns are expensive (Fogarty et al., 2008). Because of this, any data gathered from that methodology is likely to only be from areas where individuals can afford the technology and may not apply well to poorer rural areas. The aim of this paper is to evaluate any insights gained by water usage patterns within the home. The paradox of simultaneously providing enough water to sustain health while also conserving enough water to ensure reliable access will be a primary focus and we will present a case study of four residential homes in three different remote areas of rural Alaska. Rural areas have a need for alternative water delivery systems including, but not limited to, graywater reuse (Hickel et al., 2018). Systems like these can take advantage of the water more readily available and traditionally sourced from either ice, snow, or rainwater (Mattos et al., 2019), and the data from this project will likely influence their design and implementation. Some examples of specific questions to be answered in this project include: Is there a significant amount of water used at night? Will installing a new appliance like a dishwasher help to conserve water? Can we tell if people are washing their hands? If so, is it consistent?

2.2 Materials and Methods

Homes for this study were selected based on social and physical parameters. The number of people in the home needed to represent a typical household in the area and since the homes in the regions studied were not previously monitored, the infrastructure within the home had to easily accept measurement equipment. Three sets of linked information were required to analyze the locational and temporal flow patterns within these homes. First is the volume of water consumed. A flowmeter placed between the supply line entering the home and the fixtures where the water is used provided quantitative volumes as flow occurred. Second, vibration within the fixture activated sensors placed on the usage points subsequent to the flowmeter. These sensors provide location data labeling each unit of water spatially. Finally, a digital clock provided a timestamp for each of the previous sets of information linking them together. This approach is demonstrated in Chapter 1 and the methodology was used to record data from the four separate households over a period of 90 days. Each home, with the exception of Home-2, had five fixtures including a shower, bathroom sink, toilet, kitchen sink, and washing machine. Home-2 did not have a washing machine and it is important to note that the sensor placed on the showerhead in all homes is activated when a bath is run or the shower is used.

The system collects and records data in 24-hour time periods. Two separate data files, one containing timestamped flow volumes and other containing timestamped location sensor activations, were merged in Python using the pandas DataFrame merge function and sent over email to a central account. The reporting sensors have their own dedicated column and the presence or absence of data was translated into a digital permutation. For instance, the third sensor column contains vibrational data from the toilet. If the toilet sensor is reporting during a specific timestamp and no other sensors are reporting, the information is translated to '00100', indicating 5 possible sensors and only one currently reporting. When multiple sensors report simultaneously, such as the shower running while the toilet is flushed, the translated data line becomes '10100'. Each line of data is translated into a permutation, the volume reported, and which hour that permutation occurred during the day. These volumes are then summed using a pivot table. An excerpt of one of these tables can be found in Figure 2.1 for demonstration purposes with column labels listed as hour of the day and rows labels listing the particular permutation. The data from each table is appended to a single file containing the date, home identifier, permutation and volume of water used each hour. The process is repeated for each day for each home to condense the information into a dataset where trends can be identified more easily.

Table 2.1 Permutation, Hour of Day, and Water Volume Pivot Table Excerpt

	Hour of Day								
Permutation	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
00000					0.053	0.026		0.395	0.158
00010								0.289	0.684
00100						1.237		4.632	
01000									1.289
01100								0.211	
10100								0.237	
11000									0.053
Grand Total (gal)					**0.053**	**1.263**		**5.763**	**2.184**

2.2.1 Initial Water Volume Allocations

The previous process condensed all of the information into a more manageable format, but we still need produce usable information. One route is a summary of results. Each permutation and the associated water volume was summed to get a picture of where the water was used within the household. A large majority of the water volumes were associated with a single fixture. However, there were other combinations of multiple fixtures and instances of unallocated volumes. Home-1 is used as an example in the following sections for demonstration purposes. The initial percent allocations over the 90-day period for this first home are shown in Table 2.2. Each single fixture is listed along with the top three combinations based on its percent allocation for the household. All of the other permutations are combined into a single data point listed as multiple fixtures. The data values in this table are colored based on their value with red as the highest value and green as the lowest value. The unallocated percentage is close to 10% and will be evaluated further.

Table 2.2 Unmodified Percent Allocation of Each Flow Category for Home-1

		Percent Allocation
Home		1
Total		100.00%
Shower	(10000)	9.40%
Bathroom Sink	(01000)	3.61%
Toilet	(00100)	26.55%
Kitchen Sink	(00010)	16.50%
Wash	(00001)	23.43%
Wash & Shower	(10001)	1.09%
Toilet & Kitchen Sink	(00110)	1.32%
Bathroom Sink & Toilet	(01100)	5.43%
Unallocated	(00000)	9.82%
Multiple		2.84%

2.2.2 Unallocated Volumes

The most undesirable data permutation is unallocated, listed as the '00000' permutation, or flow reported without a sensor being activated. This instance is undesirable because there is less information available to identify where the water consumption is taking place. But, time of use and volume consumed is shown to be effective in identifying the most likely flow location or type. An example of this type of indirect disaggregation is seen by comparing two days in Figures 2.2 and 2.3. In Figure 2.2, Home-1 is shown to have around 5.2% of the total volume of water unallocated by the end of the day. The volume is displayed as a line on the chart and is also demonstrated by the disparity between the cumulative total water volume and summed allocated volumes of the shower, bathroom sink, toilet, kitchen sink, and multiple simultaneous fixtures. The wash is listed separately to indicate there was no vibration indicated at the washing machine that particular day. In Figure 2.3, the unallocated volume steadily increases throughout the day likely due to instances of low sink flow rate and therefore low vibration demonstrated in Chapter 1. The percentage of unallocated volume in this case is low and no visual indications of unallocated events are present so this particular day does not need to be addressed. However, in Figure 2.2, 31.2% of the volume is unallocated. This result is unacceptable and is addressed by identifying the most likely event occurring and adding the unallocated volume to that particular fixture.

There are two instances of laundry indicated on this particular day. Each load consists of a major wash and a major rinse cycle shown by the four large increases in total water usage. Part of each of these cycles were allocated to the wash using the vibration sensor indicating that the unallocated portions were in fact wash cycles. The likely reason only part of the cycle was allocated to the wash is the sensor placement only picking up the hot water and missing cold water usage or vice versa. To allocate the volume to the wash category, the 5-second averaged water flow rate during the unallocated events was used and is shown in Figure 2.3. There are consistently two categories of flow rate that end up unallocated. First, are the low flowrates that do not provide enough vibration to trigger the sensors at either sink. The second category is the high flowrates that align with washing machine cycles. These flowrates, which are consistently above 1.9 gallons per minute shown on the chart, are assumed to be associated with wash cycles. In the case of Home-1, if the flow rate is above the threshold, we allocated any flow volumes that have not been previously allocated somewhere else to the washing machine. All values with a flow rate below the threshold remain unallocated. The new allocation percentages are shown in Table 2.3.

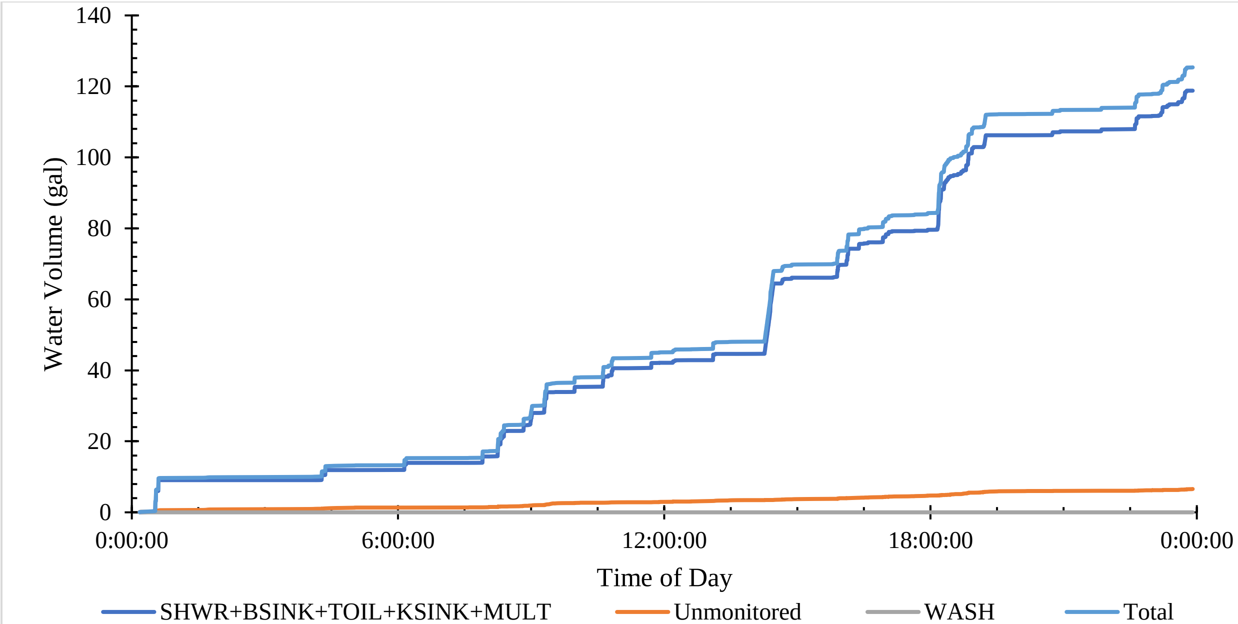

Figure 2.1 Day with Zero Loads of Laundry in Home-1

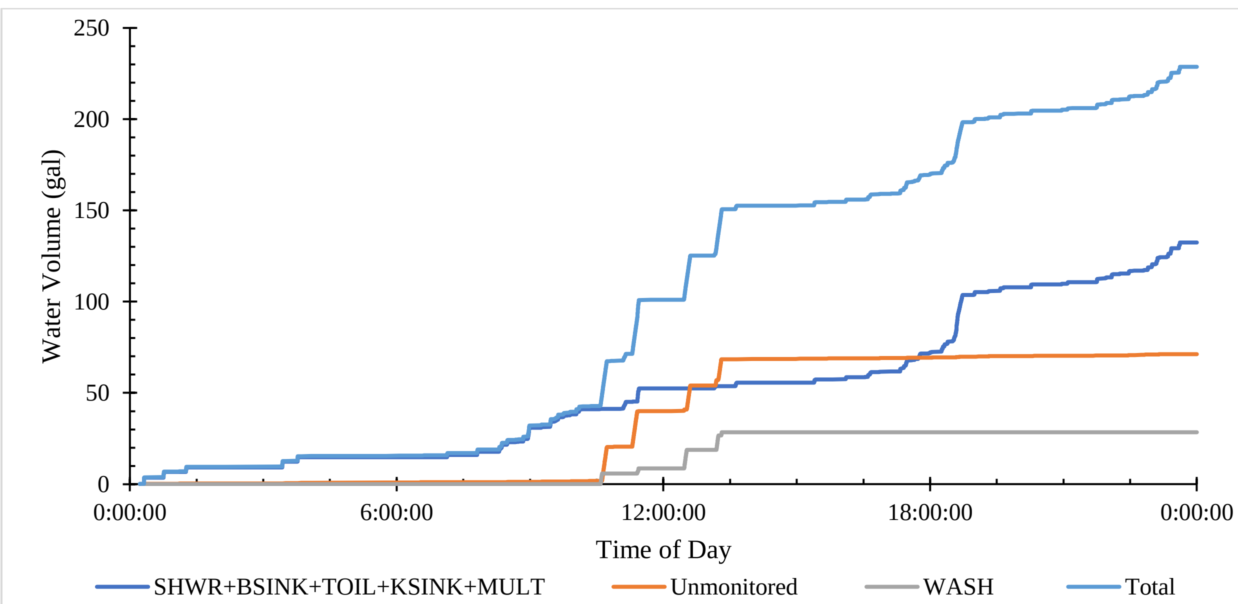

Figure 2.2 Day with Two Loads of Laundry in Home-1

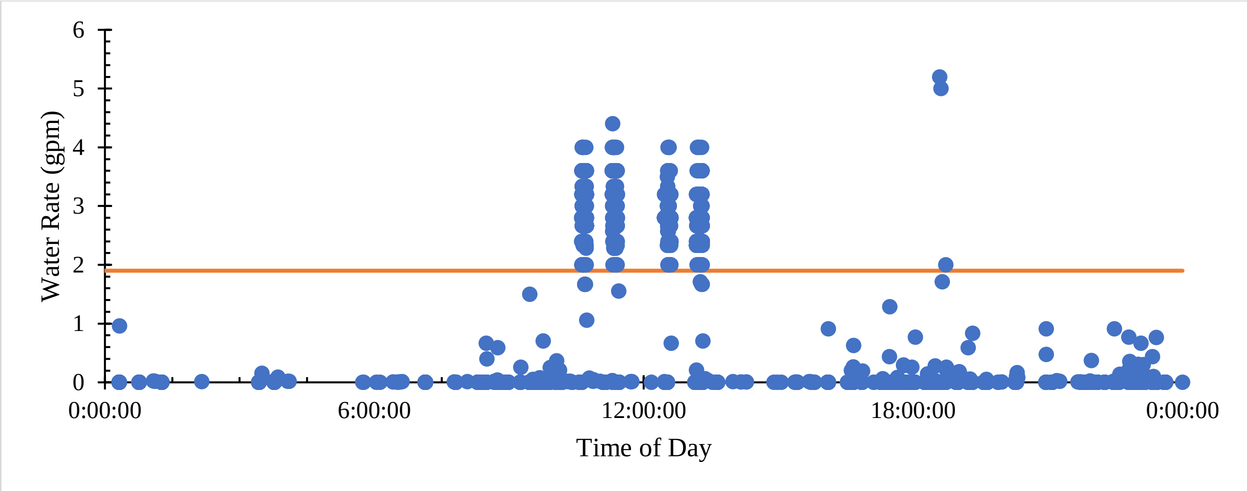

Figure 2.3 Unallocated Water Usage Rate with Two Loads of Laundry in Home-1

Table 2.3 Percent Allocation of Each Flow Category with Distributed Wash for Home-1

		Percent Allocation
Home		1
Total		100.00%
Shower	(10000)	9.40%
Bathroom Sink	(01000)	3.61%
Toilet	(00100)	26.55%
Kitchen Sink	(00010)	16.50%
Wash	(00001)	29.75%
Wash & Shower	(10001)	1.09%
Toilet & Kitchen Sink	(00110)	1.32%
Bathroom Sink & Toilet	(01100)	5.43%
Unallocated	(00000)	3.50%
Multiple		2.84%

2.2.3 Multiple Fixtures

The next step in allocation is instances where multiple fixtures report simultaneously. Shown in Table 2.2, the portion of the total volume allocated is separated into several categories. First is each fixture, then the top three combinations of multiple fixtures reporting at the same time, the remaining unallocated percentage, and finally any other permutation that does not fit the preceding categories. The top three fixture combinations can be divided into individual fixture volumes using their respective rates in each home. For instance, in Home-1, the average bathroom sink rate was 1.1 GPM and the average toilet rate was 4.4 GPM. Converting to a fraction of flow, which assumes an equal reduction in flow for both fixtures during simultaneous use from the corresponding pressure drop, approximately 80% of the '01100' permutation in Table 2.3 should be allocated to the toilet in that particular home. This methodology was applied to the top three permutations for all four homes and the final percent allocation for Home-1 using this methodology is shown in Table 2.4.

Table 2.4 Final Percent Allocation of Each Flow Category for Home-1

		Percent Allocation
Home		1
Total		100.00%
Shower	(10000)	9.40%
Bathroom Sink	(01000)	4.72%
Toilet	(00100)	31.87%
Kitchen Sink	(00010)	17.17%
Wash	(00001)	30.50%
Unallocated	(00000)	3.50%
Multiple		2.84%

2.2.4 Event Identification

Using vibration sensors placed on the fixtures to determine activation allows for a second by second account of when each fixture is used throughout the day regardless of the flow rate in most situations. For instance, if a sink was used at a lower flow rate than one pulse per second, which would otherwise establish event continuity in the one line per second flow dataset, the vibration data alone provides the continuity for that event. Therefore, in the event identification portion of data processing, we used vibration sensor data exclusively. Hygiene events such as toilet flushes, likely handwashing after a toilet flush, and showers were identified and recorded. The first step in the process was to distribute the reported data into an 86400-row array, based on the timestamp of each report. This step converts the temporal data into a pseudo-spatial configuration because there are 86400 seconds in a day. Here we can see if two reported values are connected based on their location in that array. We would then check each line of the array and count the number of sequential data points that met criteria for an event. For a shower event, there would need to be 60-seconds of continuous shower sensor reporting to identify as a shower event. In order to account for any interruptions after this 60-seconds, the sensor would have to cease reporting for 120-seconds to indicate the event has ended. This data processing logic is similar to what was used in the vibration sensor program to determine if the fixture itself was active. The steps to identify a toilet flush are identical except for the use of a 7-second initiation and a 30-second deactivation. Finally, the steps to identify a wash event were a 30-second initiation and a 30-second deactivation. Each of these processes also looked in the water volume column to add up how much water was used during the event and the count of sequential data points indicated the number of seconds the event lasted.

Determining when a likely hand washing event took place followed a similar process but involved some extra steps to also capture time of use. The '01100' permutation occurs when the toilet has been flushed and was still running while the bathroom sink was being used indicating that the individual was likely washing their hands. It was possible that the toilet can stop running before the bathroom sink event was concluded. Measuring the length of this event cannot solely depend on the '01100' permutation. To address this problem, the program used starts counting the number of ‘01100’ permutations with a threshold of two and when a blank value is found it starts counting the data in the ‘01000’ column as the bathroom sink continues after the toilet has stopped running. Once one row shows no data in this column the count was concluded and the total handwashing time was recorded for that event. The total time for handwashing that day is also tabulated and used along with the average sink rate to calculate an average volume per handwash. While rates for the shower and toilet were found using the time and volume information gathered by the program, handwashing at the bathroom sink relied on simultaneous toilet and sink use and would be artificially higher if automatically tabulated. Rates for the sinks and washing machine were found by manually evaluating at least three events of independent usage and calculating an average for that fixture.

2.2.5 Diurnal Curves

Summarized event and volume data give a good picture of what happens in a day, but there is no information on when events occur. Data copied from the pivot table of each datafile contains the total volume of water used for each permutation as well as what hour of the day that volume was used. After processing this information to distribute unallocated wash volumes from the top three fixture combinations to individual fixtures, the fixture water volumes from the 90-day period are averaged to produce a diurnal curve representing where and how much water is used throughout the day. Combined with the number of individuals within the home, per capita water usage volumes create the graphical and numerical insights desired for designing water reuse systems, conserving water, and even modifying behavior.

2.3 Results

The daily files for each home over the 90-day period were processed to condense the volume data and evaluate the water usage events for each day. Modifications mentioned previously were made as necessary and the resulting data is presented as graphs and tables.

2.3.1 Water Volumes

A summary of the unmodified data for each home is shown in Table 2.5 and Table 2.6. As used previously, the percent allocated to each category is colored based on its value. The top three combinations are shown for each home and all blank values are zero. The only home where unallocated volumes will be distributed is Home-1. After processing, the final summary is shown in Table 2.7 and Table 2.8. The average volume used by each person in gallons per capita day (gpcd) is shown in Table 2.9.

Table 2.5 Unmodified 90-day Water Fixture Allocation Summary for Each Home

		Percent Allocation			
Home		1	2	3	4
Total		100.00%	100.00%	100.00%	100.00%
Shower	(10000)	9.40%		4.64%	23.16%
Bathroom Sink	(01000)	3.61%	1.49%	5.20%	4.14%
Toilet	(00100)	26.55%	46.40%	29.95%	23.57%
Kitchen Sink	(00010)	16.50%	33.42%	16.72%	7.65%
Wash	(00001)	23.43%	N/A	31.12%	26.74%
Kitchen Sink & Shower	(00011)	1.09%		1.32%	
Toilet & Kitchen Sink	(00110)	1.32%	1.04%		
Bathroom Sink & Toilet	(01100)	5.43%	12.10%	2.04%	3.13%
Shower & Wash	(10001)		N/A		2.62%
Shower & Toilet	(10100)			2.70%	1.72%
Unallocated	(00000)	9.82%	5.16%	3.52%	2.83%
Multiple		2.84%	0.39%	2.80%	4.44%

Table 2.6 Unmodified 90-day Water Fixture Allocation Summary for Each Home

		Total 3-Month Volume (gal)			
Home		1	2	3	4
Total		20858.2	5506.7	7733.6	12262.7
Shower	(10000)	1960.5	0.0	358.9	2840.4
Bathroom Sink	(01000)	752.8	82.1	401.9	508.2
Toilet	(00100)	5538.4	2555.0	2315.9	2890.6
Kitchen Sink	(00010)	3442.3	1840.2	1293.3	938.5
Wash	(00001)	4887.6	N/A	2406.6	3278.6
Kitchen Sink & Shower	(00011)	228.1		102.1	
Toilet & Kitchen Sink	(00110)	275.4	57.4		
Bathroom Sink & Toilet	(01100)	1132.3	666.4	157.4	383.7
Shower & Wash	(10001)				320.8
Shower & Toilet	(10100)			208.6	210.4
Unallocated	(00000)	2048.4	284.3	272.4	347.4
Multiple		592.4	21.4	216.5	544.2

Table 2.7 Modified 90-day Water Fixture Allocation Summary for Each Home

		Percent Allocation			
Home		1	2	3	4
Total		100.00%	100.00%	100.00%	100.00%
Shower	(10000)	9.40%	0.00%	5.52%	25.62%
Bathroom Sink	(01000)	4.72%	2.76%	5.68%	5.93%
Toilet	(00100)	31.87%	58.06%	33.32%	25.47%
Kitchen Sink	(00010)	17.17%	33.63%	17.09%	7.65%
Wash	(00001)	30.50%	N/A	32.07%	28.06%
Unallocated	(00000)	3.50%	5.16%	3.52%	2.83%
Multiple		2.84%	0.39%	2.80%	4.44%

Table 2.8 Modified 90-day Water Fixture Volume Summary for Each Home

		Total 3-Month Volume (gal)			
Home		1	2	3	4
Total		20858.2	5506.7	7733.6	12262.7
Shower	(10000)	1960.5	0.0	427.0	3142.2
Bathroom Sink	(01000)	984.9	152.2	439.1	727.1
Toilet	(00100)	6647.2	3197.1	2576.6	3122.7
Kitchen Sink	(00010)	3580.9	1851.6	1321.7	938.5
Wash	(00001)	6362.3	0.0	2480.3	3440.5
Unallocated	(00000)	729.9	284.3	272.4	347.4
Multiple		592.4	21.4	216.5	544.2

Table 2.9 90-Day Average Water Volume Used Per Person Per Day

		Volume (gpcd)			
Home		1	2	3	4
Total		57.9	20.4	12.3	34.1
Shower	(10000)	5.4	0.0	0.7	8.7
Bathroom Sink	(01000)	2.7	0.6	0.7	2.0
Toilet	(00100)	18.5	11.8	4.1	8.7
Kitchen Sink	(00010)	9.9	6.9	2.1	2.6
Wash	(00001)	17.7	N/A	3.9	9.6
Unallocated	(00000)	2.0	1.1	0.4	1.0
Multiple Fixtures		1.6	0.1	0.3	1.5
Number of People		4	3	7	4

2.3.2 Water Usage Events

The event processing results can be seen in Figures 2.4 through 2.7 showing how many total toilet, handwashing, shower, and manual dishwashing events occurred each day. The charts demonstrate the variability of the number of events each day as well as the relative consistency in related events like toilet use and handwashing in each home.

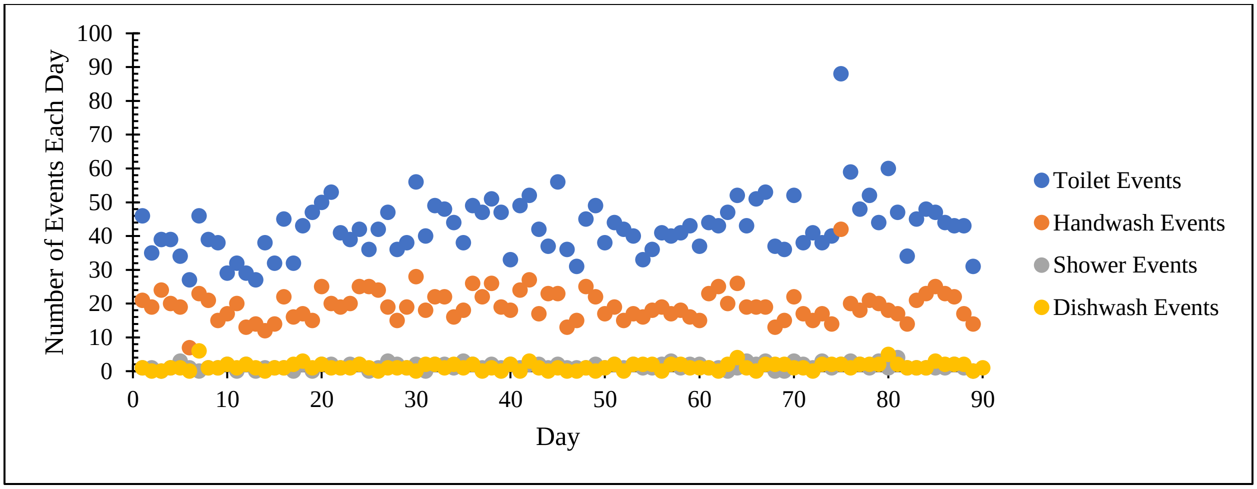

Figure 2.4 Toilet, Handwashing, and Shower Events Each Day in Home-1

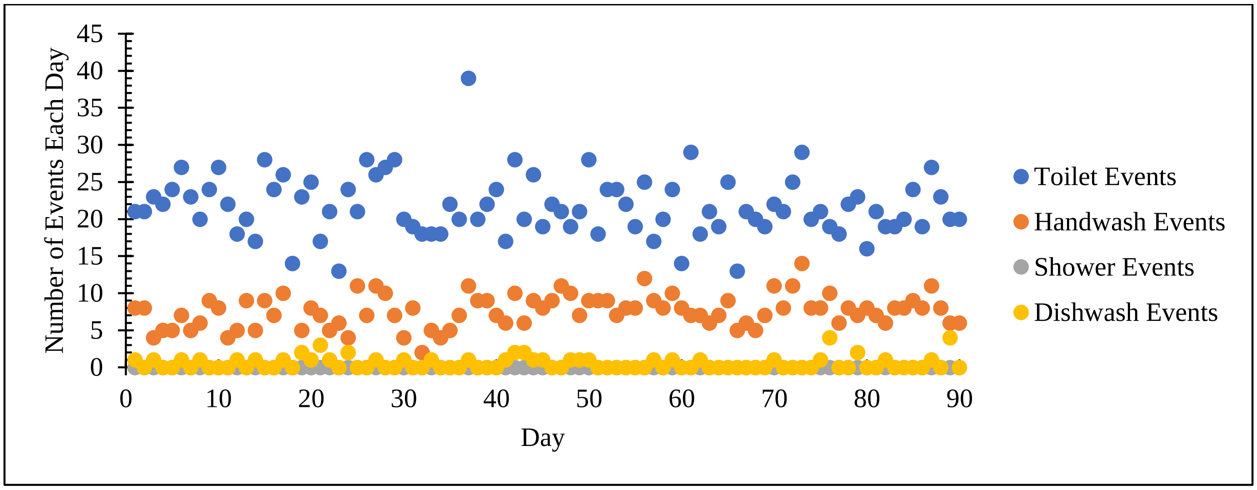

Figure 2.5 Toilet, Handwashing, and Shower Events Each Day in Home-2

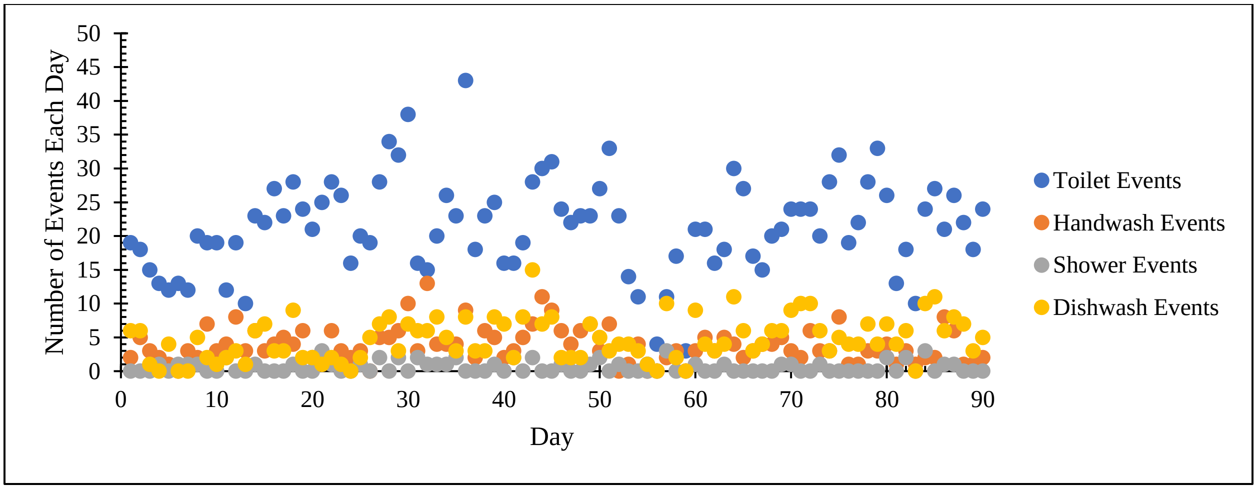

Figure 2.6 Toilet, Handwashing, and Shower Events Each Day in Home-3

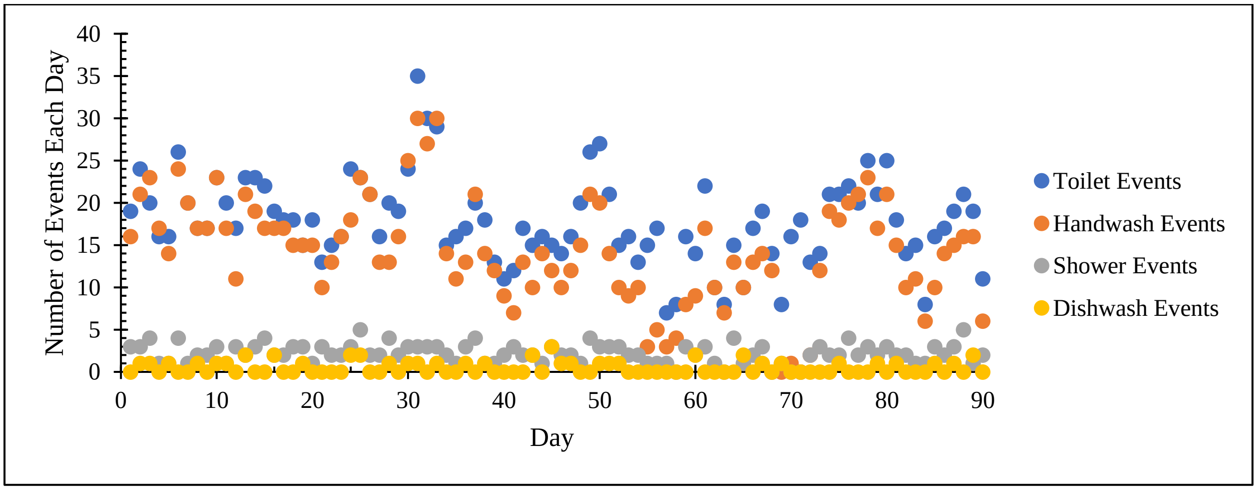

Figure 2.7 Toilet, Handwashing, and Shower Events Each Day in Home-4

The events shown above with their respective volumes are shown in Table 2.10 through Table 2.14. The volume per wash is a best estimate found by manually inspecting the data because water is added in short burst in a typical modern machine and the cycle varies based on load size and wash selection. The average number of each event like handwashing, toilet flushes, showers, washing machine cycles, and dishwashing events are supported by their associated volumes and time of use.

Table 2.10 Average Handwashing Events and Volumes Used Per Day

Home	Average Handwashing Events Per Day	Average Handwashing Time (sec)	Bathroom Sink Rate (gpm)	Average Volume per Handwash (gal)	Average Handwashing Volume (gpcd)
1	19.4	13.1	1.1	0.3	1.2
2	7.5	19.5	0.4	0.1	0.3
3	3.9	9.0	1.2	0.2	0.1
4	14.2	12.9	1.0	0.2	0.8

Table 2.11 Toilet Events, Volumes, and Associated Handwashing Targets

Home	Average Toilet Events Per Day	Average Volume Per Flush (gal)	20-Sec Volume per Handwash (gal)	Target Handwashing Volume (gpcd)	Handwashing Volume Deficit per Person w/ Same Sink (gal)	Handwashing Volume Deficit per Person w/0.5 GPM Sink (gal)
1	42.8	1.8	0.4	4.1	2.9	0.6
2	21.0	1.7	0.1	1.0	0.6	N/A
3	21.2	1.4	0.4	1.2	1.1	0.4
4	17.8	1.7	0.3	1.5	0.7	-0.04

Table 2.12 Average Shower Events and Volumes Used Per Day

Home	Average Shower Events Per Person Per Week	Average Shower Time (min)	Average Shower Rate (gpm)	Average Volume Per Shower (gal)	Average Shower Volume (gpcd)
1	2.5	8.6	2.0	16.9	6.1
2	N/A	N/A	N/A	N/A	N/A
3	0.6	3.0	1.9	5.7	0.5
4	3.9	9.5	1.7	16.1	8.9

Table 2.13 Average Wash Events and Volumes Used Per Day

Home	Average Wash Events Per Person Per Week	Average Volume Per Wash (gal)	Average Wash Volume (gpcd)	Average Wash Volume w/12 gal per load (gpcd)	1.5 Wash Loads Per Person Per Week (gpcd)
1	4.9	25	17.7	8.5	2.6
2	N/A	N/A	0.0	N/A	N/A
3	1.0	29	3.9	1.6	N/A
4	2.4	28	9.6	4.1	2.6

Table 2.14 Average Dishwashing Events and Volumes Used Per Day

Home	Average Dishwash Events Per Person Per Week	Average Volume Per Dishwash (gal)	Average Dishwash Volume (gpcd)	1 Dishwasher Load Per Person Per Week
1	2.3	5.3	0.4	0.4
2	1.2	4.0	0.3	0.4
3	0.1	3.2	0.0	0.4
4	0.9	4.8	0.2	0.4

2.3.3 Diurnal Water Usage Curves

The diurnal water usage per fixture curves are presented in Figure 2.8 through Figure 2.11. Only the individual fixtures are shown excluding any fixture combinations and unallocated volumes. The areas of each fixture are cumulative on the chart and do not overlap. Note that the curves for Home-2 in Figure 2.9 are unusual and will be discussed. Other indications are present including expected low water use late at night and spikes in the morning and evening.

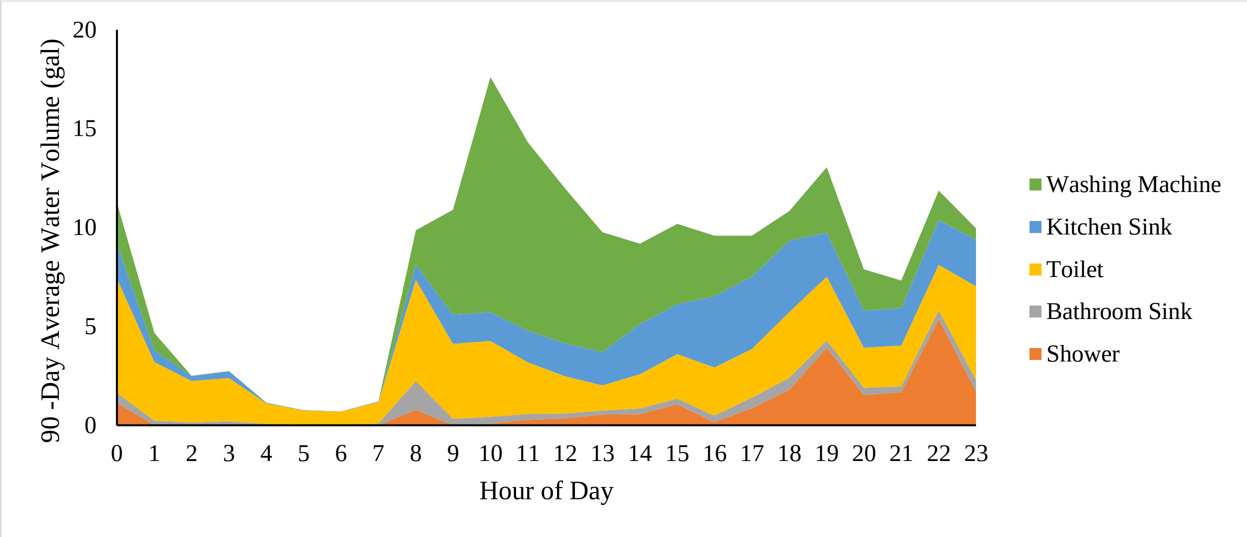

Figure 2.8 Diurnal Water Volume Per Fixture Use in Home-1

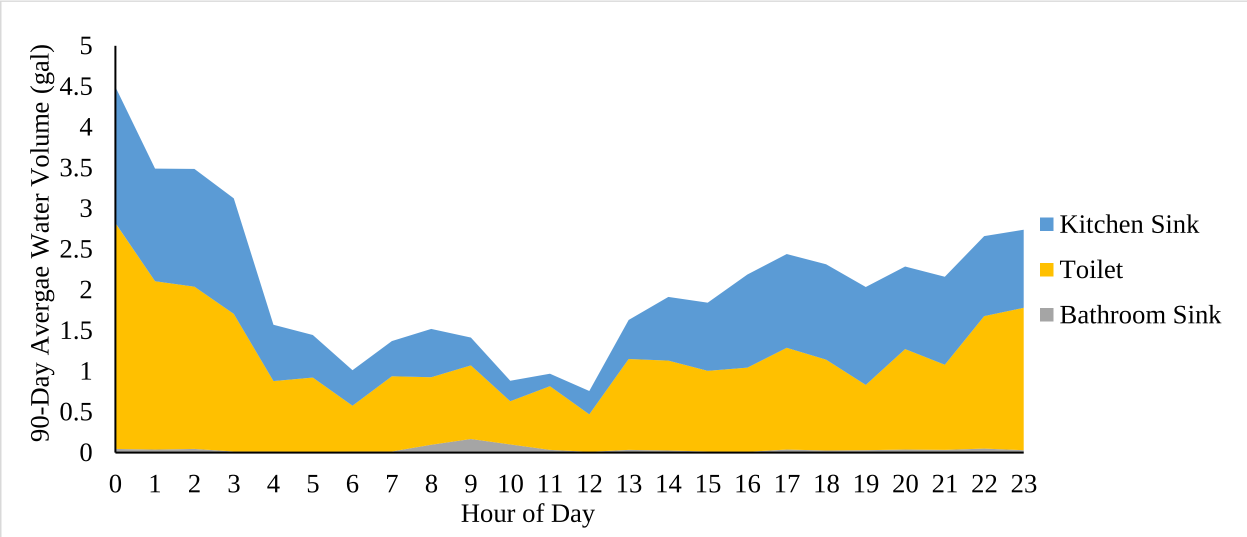

Figure 2.9 Diurnal Water Volume Per Fixture Use in Home-2

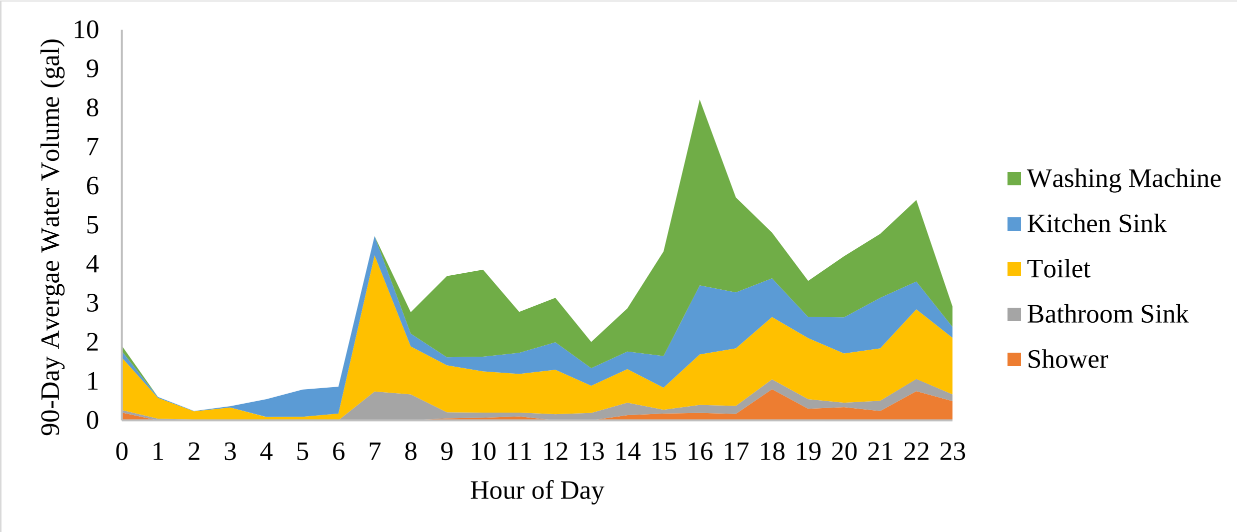

Figure 2.10 Diurnal Water Volume Per Fixture Use in Home-3

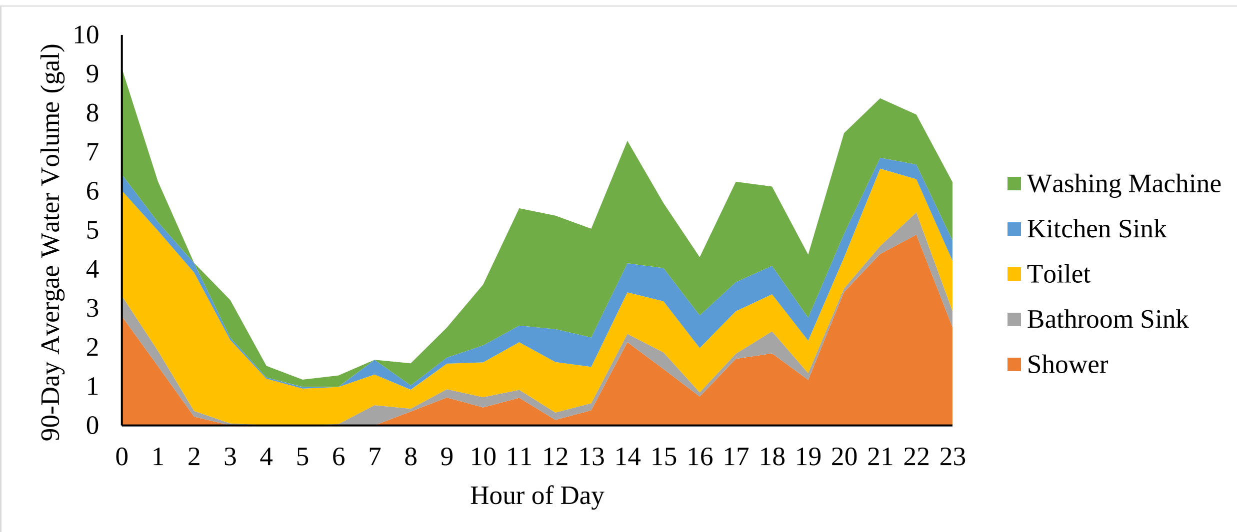

Figure 2.11 Diurnal Water Volume Per Fixture Use in Home-4

2.4 Discussion

Each home presents a unique water usage pattern that needs to be analyzed individually. The first goal of the analysis is to identify any behavioral changes where water usage needs to be increased to improve hygiene. Per capita volume increases will then be balanced by investigating where water is used the most and implement conservation efforts by systematically targeting fixtures by their percent allocation.

The overall result of this process is shown in Table 2.15. Improved fixture technology and efficiency developed after the 1992 Energy Act can be leveraged for the purpose of conservation. One example of an increase in water use for the purpose of hygiene is the target volume of water dedicated to handwashing. The minimum handwashing volume per person is calculated using the average number of toilet flushes per day as the baseline for the minimum number of handwashes per day, and increasing the duration to the Centers for Disease Control and Prevention's recommended 20-seconds (CDC, 2020). This data, presented in Table 2.11, will be used for the increased water allotment for hygiene purposes in each home. The bathing and laundry frequency will not be artificially increased, because although higher frequencies are generally indicative of better hygiene practices, a recommended minimum for these events was not found. Balancing the water usage within the home and using the data to develop reuse systems will make it possible to achieve the recommended 13.2 gallons per person per day even in areas where water is scarce.

Results produced using the methodology was validated both in person while installing the sensors and with manual spot checks of data during processing. It is important to make sure the information is accurate and reasonable because even though this is pilot data collection, it is in preparation for longer term and wider spread monitoring and analysis.

Table 2.15 Summary of Water Usage Modifications for Each Home

Home 1	Average gpcd	Increase Handwash Volume with Low-Flow Sink	Switch to Dry Toilet	Reduce Wash Volume per Load	Reduce Wash Frequency to 1.5 Loads per Person per Week	Reduce Shower Time (50%)
	57.9	58.5	40.0	30.9	24.9	21.9

Home 2	Average gpcd	Increase Handwash Volume with Low-Flow Sink	Switch to Dry Toilet
	20.4	21.0	9.2

Home 3	Average gpcd	Increase Handwash Volume with Low-Flow Sink
	12.3	12.7

Home 4	Average gpcd	Decrease Handwash Volume with Low-Flow Sink	Reduce Wash Volume Per Load	Reduce Wash Frequency to 1.5 Loads per Person per Week	Reduce Shower Time (50%)	Switch to Dry Toilet
	34.1	34.0	28.6	27.0	22.6	13.9

2.4.1 Home-1

The first home in the study has the largest per capita water usage per day with an average of 57.9 gallons. Looking at the handwashing frequency first, there is a 2.9 gallon deficit between the average of 1.2 gallons actually used per person per day for handwashing and the recommended 4.1 gallons. The deficit comes from both a consistent handwashing frequency of about half the number of toilet flushes shown in Figure 2.4, and an average handwashing time less than the suggested 20-seconds. If a new, low flow sink is used instead, the deficit only comes to 0.6 gallons and adding it to the average total results in a recommended average of 58.5 gallons per person per day. When targeting conservation, we will first look at the toilet making up almost 32% of the water used in the home. Since there is not a significant amount of room for improvement in the toilet efficiency at 1.8 gallons per flush, switching to a dry toilet is a reasonable option for the region. This change will reduce the daily per capita water usage to 40.0 gpcd. Next, the washing machine average volume per cycle was estimated to be approximately 25 gallons. Replacing the washing machine with a higher efficiency model that uses as little as 12 gallons per wash will reduce water usage in the home to 30.9 gpcd. The frequency of wash, if reduced to an assumptive 1.5 loads per person per week, will reduce usage further to 24.9 gpcd. The kitchen sink uses a significant amount of water and according to Figure 2.14, the likely reason is manual dishwashing. Unfortunately, even utilizing a high efficiency dishwasher, the volume used per person is unlikely to come down unless there is a behavior modification. Finally, the shower time averaged 8.6 minutes. If shower time was reduced by 50%, it would lead to a final daily per capita water usage of 21.9 gallons.

The unedited diurnal curve for Home-1 reveals not only where and how much water is used at each fixture, but just as importantly, when it is used and what type of waste is being produced. For instance, there is a total of 74 gallons of blackwater produced per day, but with the curve we know it stays somewhat constant throughout the day neglecting a significant increase in the morning. This volume is not particularly consistent on a daily basis shown by the variability in number of toilet flushes in Figure 2.4 and needs to be considered for system sizing and operation. The washing machine dominates the midday water usage and the shower/bath is mostly used in the evening. Knowing these habits can influence the programming of a reuse system. Additionally, the average 158 gallons of greywater per day is a significant volume and any holding tank needs to have an adequate capacity to handle it.

2.4.2 Home-2

The water usage in Home-2 is unique compared to the other homes and what would be expected in any typical home. There are only 3 people in the home and do not appear to follow a schedule that involves leaving the home during the day, likely due their advancing age. There was not a washing machine present so that task was likely completed outside the home. Because of this, the per capita water usage for that particular fixture cannot be estimated using this methodology. There was also a lack of shower use during the period monitored. Again, this could occur outside of the home or the data does in fact accurately reflect a lack of usage. The reasoning for a lack of bathing could simply just be a broken fixture. Data input such an interview with the homeowner would be needed to answer these types of question. The unique usage pattern in this home help to support the need for activity monitoring for aging individuals.

The event analysis in Figure 2.5 shows consistent toilet use and handwashing and the handwashing volume deficit in the home is only 0.6 gpcd bringing the recommended total up to 21.0 gcpd from 20.4 gpcd. Conservation in this case is very simple because over 58% of the water use occurs at the toilet. Keeping with the strategy of targeting the highest percentage of water allocated in the home, switching to a dry toilet would bring the daily per capita water usage down to 9.2 gallons, well below the 13.4-gallon target. Ideally, in a home with an initial water usage already somewhat close to the target consumption value, a dramatic change such as switching to a dry toilet would be avoided. However, the only other fixture that uses a significant amount of water each day is the kitchen sink and switching to a dishwasher would not save any water in the home.

2.4.3 Home-3

Contrasting Home-2, the water usage patterns in Home-3 are much more typical with minimal volumes after midnight and fixture spikes illustrating daily routines. There are over twice as many individuals in the home at a total of 7 so the per capita usage is actually the lowest of the four homes only reaching 12.3 gallons per day. With a large variability in the number toilet events each day, very little handwashing seems to have occurred. The handwashing deficit actually brings the daily usage up to the target 12.7 gallons per person. Conserving water past this point looking at washing both clothes and dishes would not be effective since there was only 1 washing machine cycle per person per week and 0.1 dishwashing events per person per week. The only available conservation method would be switching to a dry toilet because the toilet installed only uses 1.4 gallons per flush. Considering the existing low water usage in the home, this would only need to be done if a reuse or waste system could not accept any blackwater for treatment or transport.

2.4.4 Home-4

The handwashing habits in Home-4 is on average the highest percentage compared to the other homes in the study, regardless of the high variability in toilet events each day. Even though the average handwashing time was less than recommended, there is only a 0.7-gallon deficit to reach the target handwashing volume if the same sink is used. Switching to a low-flow faucet actually reverses the deficit and reduces water usage to 34.0 gpcd. The washing machine in the home consumes over 28% of the water used and by replacing the unit with a higher efficiency model the daily water usage in the home would be reduced from 34.0 gpcd to 28.6 gpcd. There is an average of 2.4 wash cycles per person per week and if the frequency is reduced to 1.5 cycles per person per week with a new machine the total water usage will decrease to 27.0 gpcd. Moving on to the next highest consumption point in the home at almost 26%, the shower, which had an average rate of 1.7 GPM, an average time of around 9.5 minutes, and an average frequency of almost 4 per person per week. Since it is not feasible to lower the rate by a significant amount, the only option is to reduce the time by 50%. That habit change would drop the total water usage down to 22.6 gpcd. Eliminating water usage at the toilet, consuming over 25% of the water in the household, would reduce the total water usage to a final 13.9 gpcd.

Looking at the unedited diurnal curve for this home, there is, on average, only a lull in usage between 0500 and 0600 each day. There appears to be activity late into the night especially toilet usage and it appears that most of the laundry is done midday. The greatest source of variability is the shower later in the day. The shower also dominates the water usage at the end of the day. The curve therefore indicates that any reuse system will need to be able to handle large spikes in greywater production from both the shower and wash in the later half of the day. Blackwater production is high in the middle of the night right before the typical processing window in the early morning and will need to be considered for treatment design.

2.5 Conclusion

We have demonstrated that we can determine water volumes at each fixture and identify water usage events occurring throughout the day using the data gathered in this project. While it does answer the questions of how much and when, there are many other insights valuable to the individuals using the water. One example is a day in one of the homes where the water was left running at the kitchen sink after a toilet use in the middle of the night. Over 180 gallons of water was wasted at 1 gpm before someone noticed and turned it off. This event demonstrates that real-time monitoring can be valuable and development of commercial products marketing a solution to that problem is picking up (Dahmen et al., 2017). The Seametrics MJNR-075-20P flowmeter used in this study is rated from a minimum of 0.25 gpm to a maximum of 20 gpm. Extremely slow leaks may either be completely missed, or indicated by a slow and steady pulse occurring throughout the day. Since the leak rate is below the published minimal flow rate, the volume needed to generate one pulse may be different than the volume recorded by the flowmeter. Therefore, the water leak indication will likely be more qualitative than quantitative. Another good reason for involving the homeowner more in the study is that there are some questions that cannot be answered by a third party only looking at data. Thanks to the information we have, we do know that some events are happening, some are not, and we now can inquire why.

People's lives depend on water and each home utilizes it in their own unique way. On a large scale the differences even out and can be ignored by larger water utilities. When the water treatment is changed from community wide to a reuse system custom made for a home needing to provide an adequate supply of safe water to each person every single day, the differences are much more important and cannot be ignored. Ideally the habits would be studied beforehand to make sure the system would be capable to suppling enough water and since the data collection system was designed to be retrofitted onto existing infrastructure, it would work hand-in-hand with a reuse system being added to a home. Overall, the data driven approach presented for this scenario is superior to a one-size-fits-all solution.

2.6 References

Anda, M., Le Gay Brereton, F., Brennan, J., Paskett, E., 2013. Smart Metering Infrastructure for Residential Water Efficiency: Results of a Trial in a Behavioural Change Program in Perth, Western Australia. Proc. First Int. Conf. Inf. Commun. Technol. Sustain. ETH Zurich, Febr. 14-16, 2013 175–182. https://doi.org/10.3929/ethz-a-007337628

Carboni, D., Gluhak, A., McCann, J.A., Beach, T.H., 2016. Contextualising water use in residential settings: A survey of non-intrusive techniques and approaches. Sensors (Switzerland) 16. https://doi.org/10.3390/s16050738

CDC, 2020. Show Me the Science - How to Wash Your Hands [WWW Document]. Centers Dis. Control Prev. URL https://www.cdc.gov/handwashing/show-me-the-science-handwashing.html (accessed 5.7.20).

Dahmen, J., Cook, D.J., Wang, X., Honglei, W., 2017. Smart Secure Homes: A Survey of Smart Home Technologies that Sense, Assess, and Respond to Security Threats. J. Reliab. Intell. Environ. 3, 83–98. https://doi.org/10.1007/s40860-017-0035-0

DeOreo, W.B., Mayer, P.W., 2012. Insights into declining single-family residential water demands. J. Am. Water Works Assoc. 104, E383--E394.

Eichelberger, L.P., 2010. Living in utility scarcity: Energy and water insecurity in Northwest Alaska. Am. J. Public Health 100, 1010–1018. https://doi.org/10.2105/AJPH.2009.160846

Fogarty, J., Au, C., Hudson, S.E., 2008. Sensing from the basement: A feasibility study of unobtrusive and low-cost home activity recognition. UIST 2006 Proc. 19th Annu. ACM Symp. User Interface Softw. Technol. 91–100. https://doi.org/10.1145/1166253.1166269

Hickel, K.A., Dotson, A., Thomas, T.K., Heavener, M., Hébert, J., Warren, J.A., 2018. The search for an alternative to piped water and sewer systems in the Alaskan Arctic 32873–

32880. https://doi.org/10.1007/s11356-017-8815-x

Howard, G., Bartram, J., 2003. Domestic Water Quantity , Service Level and Health. World Heal. Organ. 39. https://doi.org/10.1128/JB.187.23.8156

Mattos, K., King, E., Lucas, C., Snyder, E.H., Dotson, A., Linden, K., 2019. Rainwater catchments in rural Alaska have the potential to produce high-quality water and high quantities of water for household use 788–800. https://doi.org/10.2166/wh.2019.238

Sønderlund, A.L., Smith, J.R., Hutton, C., Kapelan, Z., 2014. Using smart meters for household water consumption feedback: Knowns and unknowns. Procedia Eng. 89, 990–997. https://doi.org/10.1016/j.proeng.2014.11.216

Sphere Association, 2018. The Sphere Handbook: Humanitarian Charter and Minimum Standards in Humanitarian Response, fourth. ed. Geneva, Switzerland.

Srinivasan, V., Stankovic, J., Whitehouse, K., 2011. WaterSense: Water flow disaggregation using motion sensors. BuildSys 2011 - Proc. 3rd ACM Work. Embed. Sens. Syst. Energy-Efficiency Build. Held Conjunction with ACM SenSys 2011 19–24. https://doi.org/10.1145/2434020.2434026

Tapia, E.M., Intille, S.S., Larson, K., 2004. Activity Recognition in Home Using Simple and Ubiquitous Sensors. Pervasive Comput. 3001, 158–175. https://doi.org/10.1007/b96922

Thomas, T.K., Ritter, T., Bruden, D., Bruce, M., Byrd, K., Goldberger, R., Dobson, J., Hickel, K., Smith, J., Hennessy, T., 2016. Impact of providing in-home water service on the rates of infectious diseases: Results from four communities in Western Alaska. J. Water Health 14, 132–141. https://doi.org/10.2166/wh.2015.110

Thomson, J., Porras, I., Tumwine, J., Mujwahuzi, M., Katui-Katua, M., Johnstone, N., Wood, L., 2001. Drawers of Water II. 30 years of change in domestic water use and environmental healt in East Africa. Bull. World Health Organ. 80, 63–73. https://doi.org/10.3362/0262-8104.2003.039

General Conclusions

Gathering per capita water usage information in rural Alaska on a per fixture basis has proved to be challenging, but feasible. The focus of the project was to keep high levels of user acceptance for the participants involved and high reliability in system performance. Data quality was variable mostly due the irregular infrastructure within the different homes. The use of vibration as the primary disaggregation methodology works very well for modern homes with plastic piping and significant distance between fixtures, but a few of the smaller homes with copper piping proved to be difficult. Vibrational communication between sensors was a challenge to overcome in the field during sensitivity adjustments and more advanced post-processing was necessary.

Once the event data and volume information were processed and condensed, it proved to be valuable in hypothetically achieving the goals of sustained hygiene and water conservation. Fortunately, most of the conservation efforts were engineering controls such as swapping out a sink fixture or purchasing an appliance with higher efficiency. These hypothetical controls did require some behavior modification. For instance, switching a dry toilet is a major change within a household. Reducing shower times proved to be necessary for some homes but not effective in others. This difference highlights that each home is different and knowing how they are different is invaluable for water treatment and distribution.

While the data presented only includes 4 homes for demonstration purposes, the system was placed in 19 homes in three different regions for the period of a year. It has shown a lot of promise during this extensive field trial. Seasonal changes still need to be analyzed for the Alaska Water and Sewer Challenge and to conclude the project, the systems will still need to be uninstalled. Ideally a follow up bucket test will be conducted at this time to confirm the initial one done at installation. Follow up interviews would also give the opportunity to answer some of the questions raised by the data. Finally, technical improvements in the design have been offered. Especially customized circuitry to reduce weight, size, and cost of the vibration sensors. Interactive programming, machine learning, and even flowrate measurement combined with water pressure monitoring can help to both increase efficiency and effectiveness of the system. Overall, the prototype design was effective in disaggregating volume information on a per fixture basis and the data produced proved to be valuable.

References

Hickel, K.A., Dotson, A., Thomas, T.K., Heavener, M., Hébert, J., Warren, J.A., 2018. The search for an alternative to piped water and sewer systems in the Alaskan Arctic 32873–32880. https://doi.org/10.1007/s11356-017-8815-x

Appendix

Alaska Area Institutional Review Board | 4315 Diplomacy Drive - IRB
Anchorage, AK 99508

DATE:	March 19, 2019
TO:	Aaron Dotson, PhD Principal Investigator University of Alaska Anchorage 3211 Providence Drive Anchorage, AK 99508
FROM:	Alaska Area Institutional Review Board (IHS IRB #2)
STUDY TITLE:	[1353021-3] Alaska Water and Sewer Challenge: Per Capita Water and Fixture Use in Rural Alaska
IRB REFERENCE #:	2018-12-052
SUBMISSION TYPE:	New Project
ACTION:	APPROVED
APPROVAL DATE:	March 19, 2019
EXPIRATION DATE:	March 28, 2020
REVIEW TYPE:	Expedited Review
REVIEW CATEGORY:	45 CFR 46.110

Dear Dr. Dotson:

The Alaska Area Institutional Review Board (AAIRB) has given approval through Expedited Review to the protocol 2018-12-052 Alaska Water and Sewer Challenge: Per Capita Water and Fixture Use in Rural Alaska. Tribal approval is required in addition to IRB approval. The protocol was approved on March 19, 2019 and has and expiration date of March 28 2020.

As a reminder, the protocol and all accompanying documents **may not have modifications** for this decision to remain valid. It is your responsibility as Principal Investigator (PI) to maintain the status of your project by tracking and monitoring all activities related to the protocol. All research approved by the AAIRB is subject to 45 CFR 46 "Protection of Human Subjects" regulations, the US Food and Drug Administration regulations and the principles of the Belmont Report. Investigators are expected to be familiar with these provisions and adhere strictly to all requirements. You are required to have all personnel involved in the research complete the training at www.citiprogram.org, once every 36 months, and retain your completion certificates from the Collaborative Institutional Training Initiative (CITI).

Prior to making any changes to the protocol you must receive approval from the AAIRB. The IRB does not accept modifications and the Status Report and Renewal Application at the same time. Please ensure that project information is complete and submitted to the IRB using the electronic submission process at IRBNet at least four weeks prior to the expiration date of the project. In addition remember that the IRB agenda is closed on the first day of each month; all complete submissions received after the first day of each month will be placed in the IRB queue for the next IRB meeting.

The AAIRB has moved to an electronic submission process using IRBNet. To submit to the IRB proceed to IRBNet (www.irbnet.org) and log in to your existing project. The continuing review information must include but not be limited to the Alaska Area IRB Status Report and Renewal Application forms, the current IRB approved protocol, a short abstract of the protocol, a current copy of the consent/assent forms, and a cover letter to the IRB signed by the principal investigator. Submit to the Alaska Area

Institutional Review Board (I.H.S. IRB #2) by uploading into IRBNet and add each item to the project. Send a single paper copy of all items submitted in IRBNet to the IRB Office for the official protocol file, and inform the IRB by letter when the protocol is complete/closed.

As a reminder, the IRB must review and approve all human subjects' research protocols at intervals appropriate to the degree of risk, but not less than once per year. Per 45 CFR 46.109(e), there is no grace period beyond one year from the last IRB approval date unless the protocol approval period is shorter than one year.

It is your responsibility as Principal Investigator (PI) to maintain approval status for your project by tracking, renewing and obtaining IRB approval for all modifications to the protocol and the consent form. Keep this approval in your protocol file as proof of IRB approval and as a reminder of the expiration date. To avoid lapses in approval of your research which will result in suspension of participant enrollment and/or termination of the protocol submit the protocol continuation request at least 4 weeks prior to the expiration **date of March 28, 2020**.

All research involving staff, patients, or resources at the Alaska Native Medical Center (ANMC) must be reviewed and approved by ANMC's parent organizations after the Alaska Area Institutional Review Board approval is obtained. The parent organizations of ANMC are the Alaska Native Tribal Health Consortium (ANTHC) and the Southcentral Foundation (SCF). Tribal review and approval is required for all research protocols prior to initiation. Any manuscripts or abstracts for publication or presentations involving ANMC staff, patients, or resources must also be reviewed and receive tribal approval prior to submission. To initiate tribal review please contact rampreview@anthc.org, this is a shared SCF and ANTHC email group. Please allow at least 8 weeks for tribal review and approval.

If you have further questions for the Alaska Area IRB you may contact us at akaalaskaareaIRB@anthc.org or call (907) 729-3917.

Sincerely,

Terry J. M. Powell
Alaska Area Institutional Review Board
IRB Administrator