Characterisation of Household Water Use Events Using a Non-Intrusive Sensor

by

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Thesis presented in fulfilment of the requirements for the degree of Master of Engineering in Civil Engineering in the Faculty of Engineering at Stellenbosch University

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December 2019

Declaration

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December 2019

Abstract

The reduction of indoor water usage is an important aspect of water conservation, especially in a water scarce country such as South Africa. Therefore, monitoring indoor water usage could help in finding techniques to reduce water consumption. A non-intrusive and relatively cheap method would help to characterise household water usage under certain constraints. A vibration device was developed as part of this study to characterise household water usage by detecting the vibrations caused by water flowing through a pipe. Various tests were conducted to ensure the accuracy and precision of the device which is IOT compatible. The device had an accuracy of about 80% in distinguishing between events and non-events and a precision of over 90% in recording event duration. The vibration device was tested in two houses in South Africa and the results were similar to that of previous studies. The vibration devices were also complemented by flow data, which was simultaneously recorded at the two houses. Several end points were analysed such as showers, taps, toilets, dishwashers and washing machines. In total 2 195 events were recorded at the two houses by the vibration devices over a combined study period of 25 days. Recommendations were given to improve the device and how to obtain more accurate results with the flow data complementing the data from the vibration device.

Acknowledgements

I would like to thank:

- Prof. H.E Jacobs for his knowledge, guidance and assistance with my thesis.
- Carl Taljaard for his assistance with data collection.
- My family for their love and support and my father for his valuable insights.
- God for my abilities.

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1 Introduction

1.1 Background

It has been estimated that 58% of the global population has piped water to their premises (UNICEF & WHO, 2015). In Sub-Saharan Africa the figure stands at 16% (UNICEF & WHO, 2015). In South Africa 92% of the urban population has a piped connection to the premises; in the rural area the figure is 38% (UNICEF & WHO, 2015). South Africa is a water scarce country and with current climate change predictions, water scarcity is expected to become more pronounced (Thorn, 2010); therefore, a better understanding of piped water usage could help combat water scarcity. Residential water consumption makes up a large proportion of water usage in many cities. Urban piped supply to the premises globally is 79% (UNICEF & WHO, 2015). South Africans consume about 233 litres of water per day per person, on average (Wegelin, 2017). According to Wegelin (2017) the water consumption per person per day on average is as follows for the following provinces; the Gauteng province consumes the most at 305 litres of water per day per person, the Limpopo province consumes the least at 182 litres of water per day per person and the Western Cape province consumes 201 litres of water per day per person. In the City of Cape Town, 68.9% of water supplied to the city in 2017 was used for domestic use, 58.2% was used by houses, 9.2% by flats and complexes, 4% by informal settlements and 2% domestic other (City of Cape Town, 2018). Studies have been completed in South Africa comparing theoretical estimates and actual measured data (Jacobs, 2007). A better understanding of residential water use holds various advantages, including for example, infrastructure planning and asset management, improved planning of water conservation programmes and consumer awareness. Disaggregation of water use events to household end-use level provides added value and is particularly useful in view of reducing indoor water consumption.

1.2 Terminology

1.2.1 End Point

The end point is defined as the points around the home at which water is extracted from the distribution system. End points could include for example a shower, dishwasher, washing machine or tap.

1.2.2 Event and Non-Event

An event is defined as the start of water flowing out from an end point continuously until the time when the water stops flowing from the end point. A non-event is a recording by a logger of an apparent event that did not occur, such as when there is interference and the interference is logged as an event.

1.2.3 Smart Water Meter

A smart water meter is a water meter that is able to measure and also subsequently record the amount of water, or the velocity of the water flowing through the meter itself. A smart water meter has logging capabilities and the data can be downloaded or transmitted to a computer.

1.2.4 Non-Intrusive Water Meters or Sensors

A non-intrusive water meter is a water meter that requires no plumbing to be fitted. The meter attaches to the outside of the pipe. A non-intrusive water meter detects the amount of water passing through the pipe, or any other attribute which is to be recorded. A non-intrusive water sensor is similar to a non-intrusive water meter; however, the sensor only detects when water is flowing, not the quantity.

1.2.5 Vibration Device

A vibration device is defined as a device that has a vibration sensor to detect the vibrations caused by water flowing through a pipe. A vibration device is IOT compatible and has logging capabilities.

1.2.6 Arduino

Arduino is a company that designs, builds, distributes and supports electronic development boards. The company has developed a language that is used to program the development boards, which is also known as Arduino. The language, however, can also be used to programme any compatible micro-controller unit (MCU) with the aid of additional software. The programming for the devices in the research was done in the Arduino IDE and the language is based on C++ (Arduino, 2008).

1.3 Problem Statement

It is relatively difficult to evaluate individual water use events in a home. Water use studies may involve a comprehensive analysis of end-use events in a home, suggesting that water usage must be recorded at the point of use, but installing water meters at each usage point is relatively expensive and requires a lot of plumbing. The presence of intrusive water meters at each usage point may also introduce study bias, because consumers are faced with the meter each time water is used and may reduce consumption artificially. This research addresses the problem of extracting useful information regarding household water uses at the point of use, without additional water meters and without any plumbing changes.

1.4 Aim and Objectives

The aim of the research project was to find, develop and employ a non-intrusive water sensing device to identify and extract the timing and duration of household water use events.

The objectives of this research study were as follows:

- Develop an Internet of Things (IOT) water sensing device for household end-uses which costs less than R1 000, is non-intrusive, easy to install and battery powered (minimum battery life of 1 month).
- Identify water use event start times and durations from case study data, collected in the Western Cape province of South Africa.
- Evaluate the feasibility of full-scale application of the non-intrusive event detection technique by conducting limited field tests.
- Analyse the data and draw conclusions regarding household water usage.

1.5 Motivation

Seldom are water metering or sensing devices placed inside the home, the most common water metering practice in South Africa involves a single flow meter per household that is plumbed into the main water line leading to the property. Additional knowledge would be gained if a non-intrusive sensor were placed at each water use point in order to complement the flow data. Investigating the flow data from the main consumer meter at high temporal resolution would show certain events, but characterisation of these events into separate end-uses (by analysing the recorded water use time series signal) can be difficult. A non-intrusive sensor placed at each water use point in and around a home can be used in combination with a smart water meter to identify specific events that are hard to detect with only a flow meter.

1.6 Methodology

A quantitative research method was used to characterize household water use events with a non-intrusive water sensor. The research dealt with a large amount of numerical data that was analysed. The process of how the research was conducted is as follows. A literature review was performed to understand the characterisation of household water use events in other studies with different devices used to collect the data. A selection process was used to determine the best type of non-intrusive device for application in the case study area. After the selection process, tests were conducted to ensure the selected sensing device was accurate in determining the time and duration of a household water use event. The next step was to construct about 10 non-intrusive water sensing devices and perform a pilot study. The pilot study was conducted in a high water use area, to ensure the devices could handle collecting large amounts of data and were able to transmit this data over the internet. Any faults that were discovered with the devices during the pilot study were rectified. The research in household water use events was then conducted, the devices were placed around a household and a flow logger was placed on the existing consumer water meter outside the household.

Once the tests had been conducted for approximately 2 weeks, the data was then analysed. The data was analysed with Microsoft Excel. The data was analysed for the frequency of a water use event, the time of day and the duration of each event. The flow logger's information was used to compared to the vibration sensor signals and was used to identify events, non-events and also related event volumes. Conclusions were drawn regarding the findings and a comparison was made with other research of the characterisation of household water use events.

1.7 Scope and Limitations

The research focused solely on household water use events and not industrial or commercial water use events. The event volume was not quantified by the vibration sensors. Therefore, to determine the amount of water used an average of 10 L per minute per household (City of Cape Town, 2011) was used to estimate the event volumes, in cases where flow data was not available.

The data was captured during the summer months in the Southern Hemisphere and therefore the consumption of household water use may be different to that of the annual average. Collection of data lasted 2 weeks. The data collected from the household is not representative of the usual usage for the household and results pertaining to water use reported in this thesis are representative of the study sample only.

1.8 Chapter Overview

The thesis comprises eight chapters, starting with an introduction. Chapter two is the literature review where a comprehensive review on water usage, devices used in each study, factors that influence water usage and tap water temperature was discussed. The literature review was used to compare the results captured in this research. Chapter three discusses the development of the device, how the device was selected and the testing of the device. The chapter comprehensively covers the performance of the device and how accurately the device captures events. Chapter four is the pilot study that was conducted in the high use area. The focus of this chapter in on how effective the devices were at capturing a high volume of events and any faults that were identified with the devices and how these faults were rectified. Chapter five contains the data collection for the main research of the topic. The chapter discusses where and how the data was captured and covers a brief overview of the data collected. Chapter six refers to the comprehensive analyses of the data captured in chapter five and compares the captured data to the literature review in chapter two. Chapter seven is the conclusion and final discussion of the research paper, while recommendations were also given to help improve further studies. Chapter eight contains all the references used in the research paper.

2 Literature Review

2.1 Overview

The literature review is organised into the following main themes: factors that influence water use, water end-use in the household, methods for identifying and measuring water use and the internet of things (IOT). The review investigated the different devices used to capture water use events such as smart water meters, ultrasonic flow meters, temperature sensors, sound recorders and vibration water sensing devices.

2.2 Household Water End-Use

Several studies into the characterization of household water usage have been performed around the world. Table 1 shows a summary of some selected studies. The per capita water use is presented in Table 1, with the percentage contribution by each end-use also shown. All values in the table represent the average of the homes in each study. All the studies show that the shower and outdoor water use are the two biggest consumers of water, while the washing machine, taps and toilet also make a sizable contribution. However, the dishwasher, bathtub and leakage have a minimal contribution to the water usage.

In South Africa a large proportion of water is lost due to leaks. According to Wegelin (2017), 35.9% of the water supplied during 2015/2016 was lost due to leakage. The Limpopo province had the highest percentage of water lost due to leakage at 55.1% of supplied water and the Western Cape had the lowest percentage of water lost due to leakage at 16.7% of supplied water. According to Couvelis & Van Zyl (2015), out of the 402 properties that were investigated in Cape Town, 17.1% of the properties had on-site water leakages. The leakage had an average rate of 3.6 L/h. The same study investigated 166 properties in Bloemfontein and found that 28.3% of the properties experienced on-site water leakages with an average rate of 11 L/h. The properties investigated in Cape Town and Bloemfontein were middle to high income domestic properties.

A similar study was conducted by Lobanga et al. (2012) in Johannesburg on 182 properties. Of the 182 properties, 128 were classified as residential and 54 classified as other. Of the 128 well established residential properties studied, 86 properties (or 67% of the total properties) were found to have leakages on the premises. The average flow rate of the leakage from residential properties was calculated to be 16.5 L/h and that accounts for 24.9% of the demand of the residential properties. For the properties classified as other, 31 properties (or 57% of the total properties) were found to have leakages on the premises.

The average flow rate of leakage from properties classified as other was 40 L/h and that accounts for 26.1% of total demand to properties classified as other. The figures obtained in both studies are significantly higher compared with the selected global studies in Table 1.

Table 1 Characterisation of household water usage from different studies

Source	**Shower (%)**	**Tap (%)**	**Toilet (%)**	**Bathtub (%)**	**Dish-washer (%)**	**Washing Machine (%)**	**Out-door (%)**	**Leak (%)**	**Total (L/p/d)**
(Willis et al., 2013)	33.0	17.0	13.0	4.0	1.0	19.0	12.0	1.0	157.2
(Loh & Coghlan, 2003)	15.0	7.0	10.0	-	-	13.0	54.0	1.0	335.0
(Roberts, 2005)	22.0	12.0	13.0	2.0	1.0	19.0	25.0	6.0	226.2
(Heinrich, 2007)	27.0	14.0	19.0	3.0	1.0	24.0	8.0	4.0	168.1
(Mayer & DeOreo, 1999)	6.8	6.3	10.8	0.7	0.6	8.7	58.7	5.5	650.3
(Willis et al., 2011)	31.0	17.0	14.0	4.0	1.0	20.0	12.0	1.0	152.3
(Beal et al., 2013)	29.5	19.0	16.5	1.0	2.0	21.0	5.0	6.0	145.3
(Gurung et al., 2015)	35.4	16.6	18.3	1.5	1.7	22.1	-	4.4	160.0
(Carragher et al., 2012)	29.5	19.3	17.2	1.1	1.6	21.6	4.2	5.6	132.6
Average	**25.1**	**13.8**	**14.3**	**1.8**	**1.1**	**18.3**	**22.1**	**3.5**	**236.3**
Average (L/p/d)	**59.3**	**32.6**	**33.8**	**4.3**	**2.6**	**43.2**	**52.2**	**8.3**	**236.3**

Table 1 indicates that the highest water consumption comes from the shower. Therefore, a focus on shower activity should be made in terms of communal showers and individual showers. Botha et al. (2017) determined the duration of shower events at two university residences at Stellenbosch University. A total of 759 shower events were recorded over a one-week period at selected showers. The experiment used iButton temperature loggers to determine the duration of the shower events, and it was determined that the average duration of the showers was 9min 30sec. Makki et al. (2013) investigated the determinants of shower water consumption, where 200 households were fitted with a smart water meter device in Queensland, Australia. The determinants that were found were; the household size, showerhead efficiency and the socio-demographics of the household. Over the two-week period the total indoor water use on average in the 200 households was 335.9 L per household per day with an average of 2.6 people per household.

The study found that 33% of total indoor water went to shower consumption, which was the highest consumption category. The two determinants that had a significant contribution to the water consumption were household makeup and showerhead efficiency. In terms of household makeup, the age of the occupants were important with the number of teenagers in the household contributing the most. Also, females tended to consume less water than males. In terms of shower head efficiency, the study found that the more efficient the shower heads, the less water was consumed.

In general, the factors influencing the water consumption mentioned by Makki et al. (2013) apply to all other household water activities. Willis et al. (2013) determined the impact of demographic factors and water efficient devices on household water consumption on the Gold Coast of Australia. The study monitored 151 households with smart water meters during the winter period in Australia. The study found that water consumption is different across the demographics. The study found that high income, older people and those who live in large new homes consume more water. The study also found a potential water savings, using water efficient devices.

Some residents have access to ground water. In the City of Cape Town area, a survey was conducted by Colvin & Saayman (2017) about how residents who have access to ground water use their ground water. It was established that residents used the ground water mainly for outdoor use. Irrigation was found to be the largest water consuming activity for groundwater use; however, some of the water is used for indoor use in the form of the washing machine. The main reason for using ground water according to residents was to reduce their water bill from the city and the second reason was to continue to use water for outdoor use without infringing on water restrictions imposed by the City of Cape Town. Meyer & Jacobs (2019), conducted a study on ground water use for garden irrigation at 10 houses with ground water access in Cape Town. The study found that over the 11-day test period, gardens at the 10 houses were irrigated on average for 2 hours and 16 minutes at a time and consumed 1.39 m^3 of ground water per irrigating event.

2.3 Factors Influencing Water Usage

The environmental attitudes of people, especially towards water conservation, have a major influence on water consumption. In general, if people have high concerns for the environment, they would use less water than those who have low concern for the environment. A study conducted on the Gold Coast of Australia (Willis et al., 2011) was aimed at quantifying the influence that environmental and water conservation attitudes had on water consumption in the household. A total of 132 households were monitored with Actaris CTS-5 smart water meters. The water meter’s resolution was 14 mL per pulse.

Willis et al. (2011) found that households with a positive attitude towards environmental and water conservation consumed significantly less water than those who were only moderately concerned with the environment and water conservation. Therefore, this would imply that if people are made more aware of water concerns, then water consumption should decrease.

A study conducted by Beal et al. (2013) aimed to reconcile the difference between perceived and actual household water consumption. A sample of 222 Households located in Queensland, Australia were fitted with Actaris CTS-5 smart water meters. The members of the household were also asked to keep a water diary to log all water use activities for 7 days. The study found that the perceived water usage differed from actual usage with an interesting pattern that those who claimed they are high consumers of water, use less water than they reported and those who claimed they are low consumers of water, use more water than they reported.

A solution to reduce water consumption would be to make people aware of the amount of water they are using during the water use event. The aim of a study conducted by Stewart et al. (2013) was to show behavioural responses to visual display monitors in 151 households on the Gold Coast of Australia. The visual alarm monitor would indicate how long the user had been in the shower, which would encourage the user to use less water when showering. The study showed that, at the beginning of the test period there was a 27% reduction in water use. However, the study also showed over time that water consumptions returned to normal levels after 4 months. However, after the 4 months the participants still believed they were conserving water, which shows the disparity between perceived and actual water usage. The experiment used a high-resolution smart water meter, the Actaris CTS-5, to measure water consumption.

Another water conservation effort made by consumers in water scarce countries is greywater reuse. Some water scarce countries use greywater for water activities that do not require the water quality of potable water, such as outdoor usage or toilet flushing. The aim of a study conducted in the Sultanate of Oman by Jamrah et al. (2008) was to determine the potential of greywater availability and to determine public acceptance of greywater reuse. The study was conducted in 169 households with a total of 1 365 people in Muscat Governorate in the Sultanate of Oman. The greywater was collected from showers, laundries and kitchens sinks. The study showed that 151 L of greywater was produced per person per day, which accounted for about 80% to 83% of total fresh water consumed. Most of the greywater that was generated came from the shower. The survey that was conducted as part of the experiment found that 76% of participants would be willing to use greywater for gardening, 53% for washing the car and 66% for toilet flushing.

Another study conducted in Bangladesh by Salauddin (2016) aimed to determine the possibility of reusing a household's greywater for non-potable uses to ease the demand for fresh water. The study stated that on average 187 L of water was used per household per day. The study found, though, that households with piped water generally consumed more water as well because of readily availability of water. The study found that 90% of the water that was being used was for bathing, washing and cooking, and the study suggests that the grey water collected from these activities should be used for non-potable purposes where fresh water was being used, to ease the demand for fresh water. However, Greywater can be a threat to human health, according to Maimon & Gross (2018), typical greywater quality does not meet the standards set by the developed world. Risks can range from microorganisms to pollutants. There are methods to treat greywater from low-cost methods to high-cost methods for an industrial scale.

Booysen et al. (2018) concluded from a case study in Cape Town, during serious water restrictions, that the fear of "Day Zero" (the pre-empted date when the Cape Town water resources would be depleted) and further monitoring and penalties from the City of Cape Town, were the main factors explaining the reduced water consumption.

Water pressure has an effect on water consumption, in the sense that if the water pressure is reduced, then water consumption will also reduce. The aim of a study conducted by Meyer et al. (2018) on 44 households in Pretoria, South Africa, was to observe the effects of water pressure on water consumption in residential areas. The study period lasted for 25 weeks with 11 pressure changes occurring, lasting 2 weeks each. The study found a nearly linear correlation between the water pressure and water consumption. A study conducted by Xu et al (2014) in Beijing, China also found similar results. Three different pressures were used for several days to determine the effects of pressure on water consumption and leakage. For the first period, which lasted 45 days, the pressure was set at 38.8 m with a standard deviation of 0.41 m. The mean flow for the first period was 31.2 L/s with a standard deviation of 9.37 L/s. The minimal night flow (MNF) was used as an estimate of the leakage occurring. The MNF in period one was recorded to be 14.5 L/s with a standard deviation of 1.37 L/s. In period two, which lasted for 38 days, the pressure was reduced to 35.1 m with a standard deviation of 1.75 m. The mean flow rate for the second period reduced to 23.1 L/s with a standard deviation of 7.97 L/s, which is a 26% reduction in mean flow rate compared to period one. The MNF was reduced by almost a half to 7.2 L/s with a standard deviation of 1.05 L/s. In the final period, period three, which lasted 98 days the pressure was reduced to 33.2 m with a standard deviation of 1.58 m. The mean flow rate was reduced to 16.9 L/s with a standard deviation of 8.32 L/s, which is a 46% reduction in the mean flow rate compared to period one.

The MNF was also reduced to 2.4 L/s with a standard deviation of 1.67 L/s. Therefore, the study shows that pressure reduction not only reduces water consumption by users, but also reduces leakage.

The size of the household not only has an influence on the household average water consumption, but also on the per capita consumption. According to Memon & Butler (2006) the per person water usage in a household decreases with the increase in the size of the household. An example is a single person household will use 40% more water per person then a 2-person household water consumption per person. However, the total water consumption of the household will increase with the size of the household.

In a study in Pietermaritzburg, South Africa by Smith (2010) it was also found that the size of the household influenced household water consumption and individual consumption. Table 2 shows the six different household sizes and the water consumption of each household and the water consumption per person. The table shows that the household water consumption increases with the size of the household, but the individual water consumption per person decreases as household size increases.

Table 2 Household size and water consumption (Smith, 2010)

Household Size	**Number of Households**	**Consumption per household**		**Consumption per person**	
		Per month (kL)	Per day (L)	Per month (kL)	Per day (L)
1	8	4.4	147	4.4	147
2	17	8.8	283	4.4	148
3	63	12.5	417	4.2	139
4	59	15.3	512	3.8	128
5	35	17.9	596	3.6	119
6	12	18.5	617	3.1	103
Total	194	14.1	467	3.9	131

Memom & Butler (2016) also found that the type of property Influenced household water consumption. The study found that water consumption was the highest in detached houses and consumption was lowest in flats. The reason for the difference was because of the outdoor use in detached houses and the absence of garden areas in flats. Renwick & Green (2000) modelled that a 10% increase in the property size will mean a 2.7% increase in water consumption for that property.

The seasons also influence water consumption. In the summer months more water is consumed than in the winter months. Howe & Linaweaver (1967) found that water demand increased in the summer months due to outdoor usage; however, they found that the outdoor usage was affected by pricing of water. A study in Seoul, Korea by Praskievicz & Chang (2013) found that higher maximum temperatures would result in higher household water demand.

The study also found that daylight length and wind speed had significant influence on household water consumption. The longer the daylight period was, the higher the household water consumption was, and the higher the wind speed was, less water was consumed. A study by Xenochristou et al. (2018) in the Netherlands showed that temperature had the most significant impact on household water consumption, with a higher temperature leading to higher water consumption. The study found relative humidity also had a significant impact on water consumption, after temperature. However, the study found that precipitation amount and duration did not have a significant impact on household water consumption.

Pricing of water for indoor household use does not have a major influence on the consumption of water at a domestic level. A study conducted by Jasen & Schulz (2006) on 275 households in the City of Cape Town across different areas with different demographics, found that on average demand for water is price inelastic. The study found that the low income areas did not change their water consumption due to pricing, but the high income areas were more likely to change their water consumption. The research found that a 10% increase in water prices will result in a 9.7% decrease in water consumption for high income areas. The study also concluded that, for low income areas, the relative cheapness of water does not mean a wastage of water. In the low income areas only 29% of households had a meter reading of above 6 kL of water used for a month (first 6 kL was free of charge). However, in some low income areas there are illegal water connections which will skew the results seen (Massey, 2014).

Showering is one of the most demanding water consuming activities on a domestic level, as seen in Table 1. A study in Barcelona, Spain by Domene & Sauri (2006) found variations in shower activity between demographics. The study found that low income people would have 2 showers less per week than high income people. The age, gender and time spent at home also influenced water consumption in general. Older people tended to use less water, women tended to use more water for personal hygiene and people who stay at home for longer, tended to use more water than average. However, the study found in the aspects of age, gender and time spent at home, showering was the least influenced in these factors.

In the same study by Domene & Sauri (2006), the property type was also evaluated. Property types were divided into three categories namely: high-density housing, mid-density housing and low-density housing. High-density housing occupants consumed the least amount of water at 120.1 L per person per day, mid-density housing occupants consumed 156.7 L of water per person per day and low-density housing occupants consumed the most water at 203.3 L of water per person per day.

Figure 1 illustrates the characterisation of the water end use between the different housing groups. The figure shows that the reason why low density housing occupants use more water than the other two housing groups was because of garden usage. In all other activities excluding outdoor usage low density households use less water than the other two housing groups.

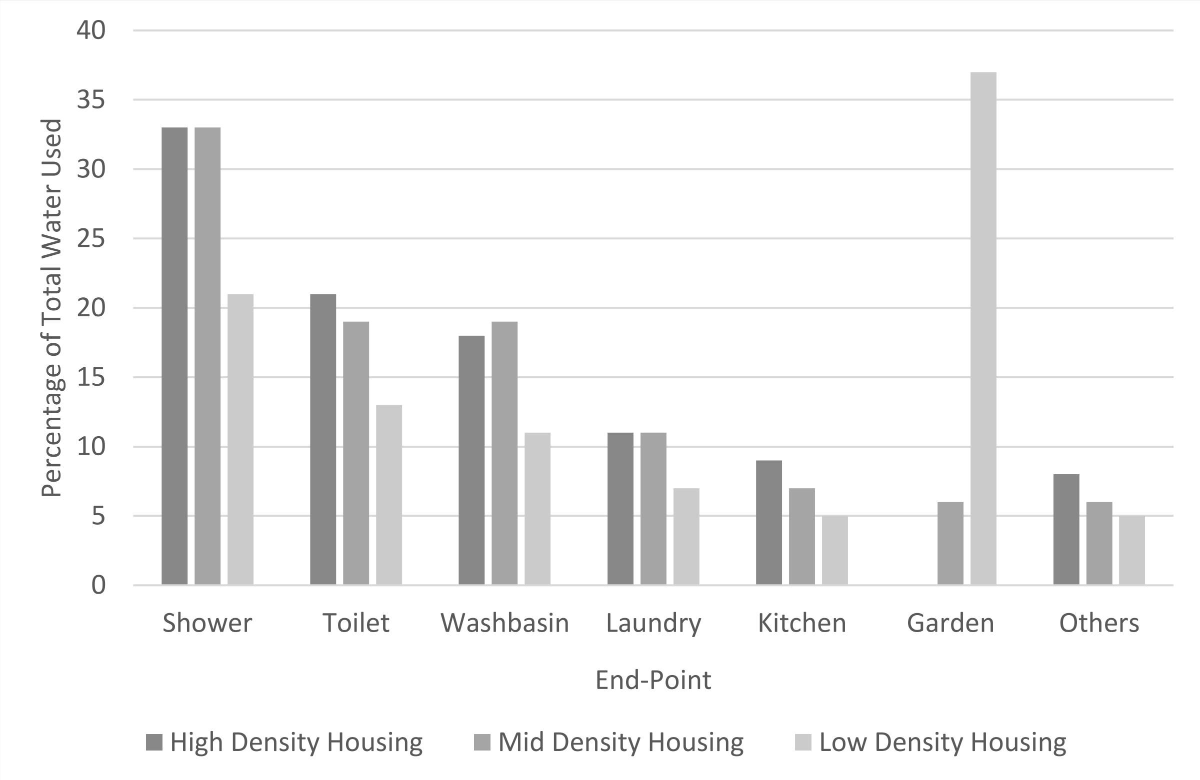

Figure 1 Distribution of water uses across housing types (Domene & Sauri, 2006)

The income group where consumers find themselves in, influences the amount of water occupants use. The higher the income group consumers are in, the higher amount of water they use. A study by Hussien et al. (2016) in Duhok city, Iraq, found that low income households used 241 L of water per person per day, medium income households used 272 L of water per person per day and high-income households used 290 L of water per person per day. The study was conducted on 92 low income households, 176 medium income households and 139 high income households. Table 3 highlights the characterisation of the household water usage for each of the three income groups. Table 3 shows that, for all three of the income groups, the tap usage was the highest water consuming activity for all three groups. Showering, dishwashing, laundry and toilet flushing were all relatively high water-consuming activities for all three income groups. Outdoor usage increased significantly with the higher income groups. The tap water usage found in the Iraq study is significantly higher than that reported in previous studies. According to Hussien et al. (2016), in Islamic culture, there are cleansing customs, which explain the higher tap usage. The same study also mentions that water consumption for the household increases with the number of adult females in the household.

Table 3 End-uses of water for different income levels in Duhok, Iraq (Hussien et al., 2016)

End-Point	**Per Capita Water Use (L/c/d)**		
	Low Income	**Medium Income**	**High Income**
Swimming Pool	0.0	0.0	0.2
Bath	0.0	0.0	1.4
Vehicle Washing	1.4	1.7	0.5
Garden Watering	10.4	20.1	23.3
House Washing	11.2	14.2	15.4
Cooking and Drinking	13.2	14.9	18.3
Toilet Flushing	33.0	25.5	22.5
Laundry	30.9	34.0	37.1
Dishwashing	33.0	38.0	36.7
Shower	28.7	36.7	42.3
Taps	79.4	87.3	92.6

2.4 Methods for Identifying and Measuring Water Use

2.4.1 Smart Water Meters

Most of the studies referred to in Table 1 involved smart water meters to capture events. One type of smart water meter that was used in various household water studies in Australia (Willis et al., 2011; Beal et al., 2013; Stewart et al., 2013) is the Actaris CTS-5 volumetric meter. The water meter has an accuracy of 14 mL per pulse. The Actaris CTS-5 can detect flow rates from 0.02 kL/h to 4.0 kL/h. (Department of Industry, Innovation and Science, Australia, 2018). However, there are limitations to the device. The meter itself needs to be connected to a data logger to record the events, and depending on the functionality of the logger, this will increase costs. The meter also needs to replace the old water meter, which requires a plumber to fit the smart water meter. External software is also needed to extract and interpret the data acquired. The software used with smart water meters characterizes the water events from the logger (Willis et al., 2011). The addition of the characterisation software will also increase the cost.

2.4.2 Temperature Sensors

Temperature sensors in iButton data loggers could be used to record the temperature of pipe walls, which gives an indication of the water temperature inside the pipe. Botha & Jacobs (2016) used changes in the recorded temperature to identify whether water was flowing, or not. The iButtons themselves are relatively cheap at R500 per logger.

However, external software to programme and extract the data is required at an additional price. The iButton temperature loggers are only able to record the temperature every 1 minute, but require no plumbing as the logger will simply be taped to the pipe. For hot water events this technique is very reliable, because when the temperature increases rapidly, the event starts and as soon as the temperature decreases, the event ends. For cold water events this technique is not reliable as the ambient temperature and water temperature could be very similar and therefore a sudden change in temperature will not be detected.

2.4.3 Ultrasonic Flow Meters

Ultrasonic flow meters can be used to capture tap water events. The ultrasonic sensors detect water flowing through a pipe and log the event and, like smart water meters, uses external software to characterise the events through artificial intelligence. Ultrasonic flow meters use high frequency ultrasonic transducers to accurately measure the velocity of the water flowing through pipes. There are two variants and several installation methods that are used with ultrasonic transducers. The variants of ultrasonic flow meters are “time of flight”, which measures the time the signal takes to go from the upstream transducer to the downstream transducer and from the downstream transducer to the upstream transducer. The distance between the two transducers is known and, therefore, the velocity of the water can be calculated. The other variant of ultrasonic flow meters is the “doppler shift”, which measures the reflection of the signal produced from a single ultrasonic transducer to calculate the velocity of the water. However, for the “doppler shift” technique the water must have small particles or air bubbles for the signal to reflect to the transducer (Yuen et al., 2012). Both these variants are non-intrusive, so no plumbing is required; however ultrasonic flow meters are relatively expensive, and an ultrasonic flow meter can cost R12 900 excluding the data logger, which is an additional R1 100.

2.4.4 Sound Sensors

Capturing sound to determine tap water events by placing microphones on water pipes to “listen” for the flow of water can also be used and has been used to determine outdoor events as well as shower activities. Makwiza & Jacobs (2017) used sound recording devices, which are non-intrusive devices, to record outdoor tap water use. The sound sensors and related algorithms were able to characterize tap water use events with an accuracy of at least 80%. The devices used were relatively cheap as well, only costing R500 per device. Kuznetsov & Paulos (2010) presented low-cost water meter devices to encourage shorter shower events. The device used a microphone to capture water use of the shower. The device used an onboard microcontroller to analyse the sound in real-time, so no audio files were created. The microcontroller used Fast Fourier Transformation to identify tap events at a sample frequency of 10 kHz, which eliminated noise from the recordings.

The microcontroller was used to analyse the amplitude to determine how much water was flowing through the tap. The higher the amplitude, the more water was flowing through the tap. The device could capture how much water was being used at a resolution of 0.76 litres per shower event.

2.4.5 Vibration Sensors

However, sound captured on sound recording devices is essentially vibrations caused by the water flowing through a pipe (Young et al., 2012). Therefore, a device that can capture vibrations instead of sound could capture tap water events. Using vibration sensors to capture household water use events is achievable by detecting the small vibrations when water flows through the pipe. Pirow (2018) developed a water meter to detect and determine the amount of water entering a geyser. The device used the LSM303 accelerometer and a temperature sensor to detect the vibration caused by water flowing through a pipe. The sensor was able to record events with a 90% accuracy with events occurring 2 minutes apart. Ismail et al. (2015) compared two different accelerometers for water leakage in a non-metal pipe, and the researchers found that the MPU6050 worked the best in detecting water leaks at household pressures. The MPU6050 was able to detect a water leak from 0.5 m to 1.5 m away from the sensor with holes of 1 mm to 3 mm in diameter. Using vibration sensors is a viable way of detecting water flowing through a pipe, as the sensors are relatively inexpensive and are easy to install, being non-intrusive devices (Pirow, 2018). Vibration sensors, unlike sound sensors can detect water in non-metal pipes for domestic use (Ismail et al., 2015). However, with vibration sensors, the flow cannot be determined without calibrating the devices to work with each specific setup and, therefore, vibration sensors can only accurately determine when a water event occurs and the duration of such an event (Pirow, 2018).

2.5 Internet of Things

The internet of things (IOT) are devices or sensors that are connected to the internet and communicate with other machines and or users. IOT devices are used in a wide range of applications in a wide range of fields, including engineering. Lee & Lee (2015), estimated that there would be around 23 billion IOT devices active in 2019.

IOT devices are able to send data to the user in real-time without the user being physically in contact with the devices. Therefore, data can be collected remotely in real-time, that the analyst can evaluate the sensor performance and analyse the data during the test period. IOT devices also have a number of ways to connect to the internet. There is a wired connection to the internet through the local area network (LAN) and the more popular route is a wireless connection to the internet.

According to Kos et al. (2018), there are several different wireless connection types to the internet, such as Wi-Fi, Low Power Wide Area Network (LPWAN), Radio Communication and Global System for Mobile Communication (GSM).

A Wi-Fi connection is similar to a LAN connection in that the connection to the internet is via a local connection. Therefore, the internet source for Wi-Fi must be close (100 m) however, Wi-Fi has a fast data transfer speed at 300 mbps but the upload speed is limited by the broadband speed and, therefore, Wi-Fi can only be used in applications where the device is personal as the device will require the owner’s Service Set Identifier (SSID) and password (Arefin et al., 2017).

For large data collection projects where the device is not personal and Wi-Fi range is a problem, LPWAN or Radio Communication must be considered. The most popular connection for large data collection devices is LPWAN.

Although LPWAN has a wide range of up to 10 km, the speed of data transfer is slow at 50 kbps and, therefore, only small amounts of data can be transferred, which means post-analysis cannot be done by the IOT device and must be done on a local device. LPWAN does require reception towers that are owned by a third party; therefore, a subscription to a third-party company is required to use LPWAN. Aernouts et al. (2018), used LPWAN for their research in large urban and rural areas.

Radio Communication can also be used for large scale data and works in a similar way to LPWAN. Unlike LPWAN the receiver does not require a subscription as the receiver is part of the IOT setup. Radio Communication range depends on the speed of the data transfer and the power output. However, with radio communication all the IOT devices used must be in the same area so the receiver can connect to all the devices (Jia & Xu, 2013).

GSM is a popular method in transferring large amounts of data long range for IOT devices. The data is transferred to the internet via the same towers used by mobile phones. A subscription with a GSM operator is required. The main disadvantage of GSM is the high-power consumption of the GSM module. Therefore, a large power supply is required to operate a GSM-enabled IOT device, which will increase the cost or decrease the run time of the IOT device (Booysen et al., 2013).

In a study by Muller & Booysen (2014) an IOT device was created to monitor electricity and water consumption. The IOT device was developed on the Arduino development board and programmed with Arduino. The communication type was wireless, and the data was transferred via a GSM network. The data was sent to a server and a web page displayed the information received by the IOT device. The information that the device would send to the server was a live reading of the water and electricity consumption.

An IOT device was developed by Brown & Booysen (2015) which connects wirelessly to the internet via Wi-Fi. The device monitors the water consumption and temperature of the geyser and has the ability to control the temperature and water supply of the geyser. The IOT device displays a webpage over the Wi-Fi where the information from the device is displayed and the temperature and water supply are also controlled from the webpage. The Beagle-Bone Black, a single board computer, was chosen as the control and processing unit. The board ran a version of Linux called Debian and programming language for the control system was JavaScript and the webpage in HTML 5.

The review of earlier work underlines the value of using IOT enabled devices in data collection. Wi-Fi enabled devices are a good choice for network capabilities because of the ease to connect to an already existing Wi-Fi network and without needing a subscription from a 3rd party. Wi-Fi also allows for large amounts of data to be transferred at a relatively fast upload speed.

3 Identification and Development of Measuring Device

3.1 Device Selection

Non-intrusive water meters or sensors were considered for this research study. Four different types of non-intrusive water meters or sensors were considered, namely ultrasonic flow meters, temperature loggers, sound sensors and vibration sensors.

Ultrasonic flow meters determine the rate of the water flowing through a pipe. The accuracy of the flow meter is high and can capture the time and duration of each event as well. However, ultrasonic flow meters are relatively expensive compared to other devices, and for a household application the cost is not justifiable. To develop an ultrasonic device for the research would take a considerable amount of time and the electronics involved to make such a device are highly complex.

Temperature loggers are relatively cheap compared to ultrasonic devices and the price can be reduced further by developing a device for the research, as the electronics are much simpler. However, with temperature loggers the device only works when there is a detectable difference in the change of temperature between two timestamps. There could be a delay when the event actually starts or ends and when there is a detectable change in temperature. The accuracy of the device in terms of time is low. Temperature loggers will also have different accuracies with cold and hot water events. For hot water events the temperature loggers will work as expected and give good accuracy in terms of the duration and frequency. However, with cold water events, since there will not be a great change in temperature from when the tap is turned on, the device will struggle to determine the frequency of events and duration.

Sound sensors could accurately determine when a water use event occurs from any activity by listening to when water is running through a tap. The device would be able to accurately determine when an event occurs, the duration and the frequency at which the events takes place. The sound recorders are relatively cheap to purchase and have simple electronics to develop a device for the research. However, with sound sensors, the device could be triggered by any sound that corresponds to what the device thinks running water sounds like. Therefore, some false events could be recorded; however, advanced computer programming could help to reduce false events. Nevertheless, the biggest problem with sound sensors is an ethical problem, where it could take a while before being allowed to install microphones in a household and there could be restrictions as to where the devices will be allowed to be installed.

Vibration sensors work similarly to sound sensors, but instead of listening to water flowing through a pipe, a vibration sensor detects the vibration of the pipe due to water flowing through the pipe.

Vibration sensors can accurately determine when the start of an event occurs, the duration and the frequency of the events. These devices could easily be installed in any part of the household without the ethical problems of the sound sensors. The vibration sensors also have simple electronics, making them ideal to use for the research. There was, however, no such device on the market at the time of the research, only concepts were developed in published research. Therefore, a vibration sensing device would need to be developed for the research.

After comparing the advantages and disadvantages of each alternative, it was decided to develop a vibration sensor to be used to characterise household water use events. A temperature sensor was included with the device used in this study to record the temperature of each event. The vibration sensor was selected because of the relatively less-complicated electronics needed to develop the device, the lack of ethical problems that would be encountered (with recording sound) and the high accuracy of the device in terms of frequency and duration. Table 4 highlights the comparison between all the devices considered for the research.

Table 4 Device comparison

Device	Advantages	Disadvantages
Smart water meter	• Flow data is recorded • Accurate	• Expensive to buy and install • Requires Plumbing
Ultra-sonic flow meter	• Accurate • Flow data is recorded • Non-invasive device	• Expensive
Temperature sensors	• Device itself inexpensive • Accurate with hot water events	• Inaccurate with cold water events • Only measures every minute • Software is expensive • No flow data is recorded
Sound sensor	• Inexpensive • Records duration accurately for all types of events	• No flow data is recorded • Raises ethical questions when recording inside a household
Vibration device	• Operates and performs similarly to sound sensor • Requires no ethical clearance	• No flow data is recorded • Requires development first

3.2 Components

An explanation of the technical aspects of the vibration device, such as the components used and how the micro-controller reads analog signals, is given below.

3.2.1 Micro-Controller

An MCU is the electronic component that controls the actions of the electronic device. The MCU is responsible for data collection, data transmission and determining when the water is flowing. The MCU used in the research is the ATMEL ATmega 1284P-PU, which is a 40-pin MCU and has enough capabilities for the experiment. The 16 384 Bytes of Random-Access Memory (RAM) was the reason for the choice to use the MCU.

3.2.2 Temperature Sensor

A temperature sensor is an electronic component that produces a voltage depending on the current temperature. The temperature sensor used in the research is the MCP9700, which emits a voltage between 0 V, when the temperature is -40 ^{o}C, and 3.3 V when the temperature is 125 ^{o}C. The temperature sensor recorded only the temperature at the end of the event and was ultimately not used with the vibration sensor in determining event activity.

3.2.3 Vibration Sensor

A vibration sensor is an electronic component that detects movement in the object the sensor is attached to. The two used in the research were the piezoelectric sensor and the accelerometer. The piezoelectric sensor is relatively simple compared to the accelerometer and converts mechanical waves into an electrical signal. The accelerometer used was the MPU6050, which measures the acceleration caused by water flowing in all three axes.

3.2.4 Analog Digital Conversion

The analog digital conversion (ADC) value is used by the MCU to interpret the signals sent from the vibration sensor and the temperature sensor. The ADC value is dimensionless. The ADC value ranges between 0 and 1 024. An ADC value of 0 relates to a voltage of 0 and 1 024 relates to the maximum voltage, in this case 3.3 V. The ADC value is used in all the calculations performed by the MCU.

3.3 Device Development

There are two ways to detect vibrations of a water pipeline, either an accelerometer, which was described in the literature review, or a piezoelectric sensor, which converts a mechanical signal into an electrical signal. A comparison was made of the two methods by using a 27 mm piezoelectric disk element and the MPU6050 accelerometer. All three axes of the MPU6050 were recorded and then used to determine the magnitude of the vibration detected. Both sensors were attached to the same microcontroller and also on the same pipeline. The tests were also conducted simultaneously to eliminate unnecessary variables.

The test was conducted on a kitchen tap and three types of water flows were used, namely full water flow from the tap, half flow from the tap and low flow from the tap. Each state was conducted three times. The results are presented in Figure 2. The results show that the piezoelectric disk and the accelerometer were able to detect full and half flow from the tap, however the accelerometer did not detect the low flow case, while the piezoelectric disk did. The piezoelectric disk also detects the events much more clearly. Therefore, from the results, it was decided that the piezoelectric element would be used in the research.

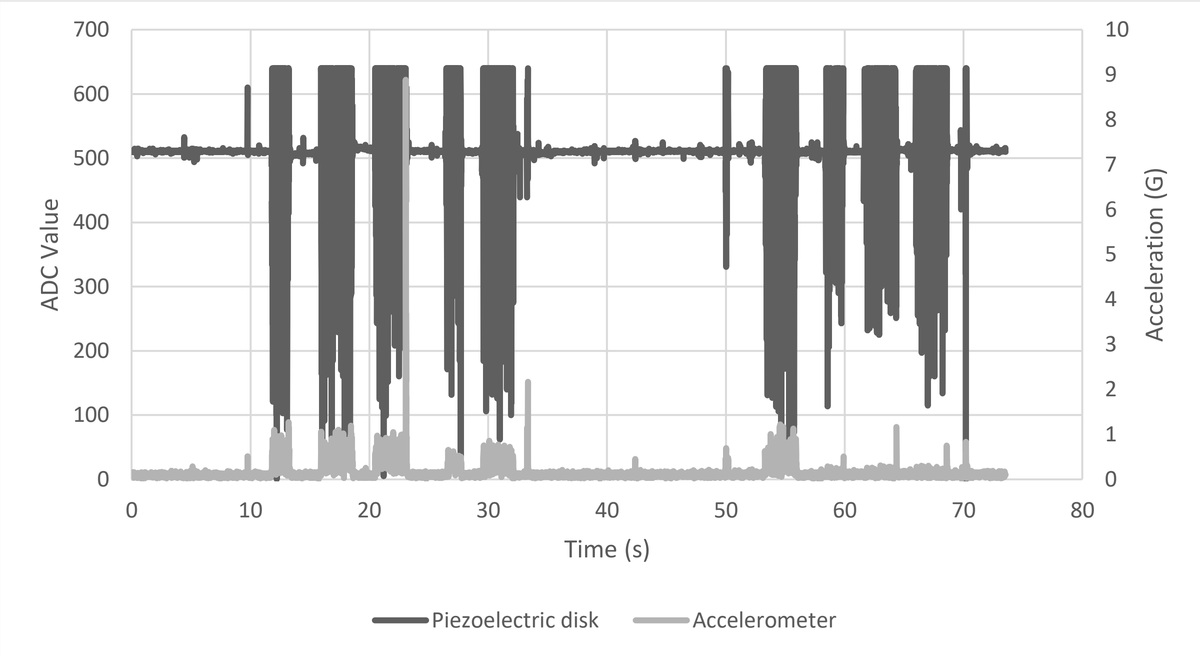

Figure 2 Comparison between piezoelectric disk and MPU6050

The design of the vibration device was inspired by Kuznetsov & Paulos (2008) at the Living Environments Lab at Carnegie Mellon University Human Computer Interaction Institute. The device works by detecting vibrations in the water pipe, caused by water flowing through the pipe. The device also has a temperature sensor attached and has built-in logging capabilities. There are three main components to the device, namely; the piezoelectric element that detects the vibrations, the temperature sensor that records the temperature at the end of the event and the MCU which processes the information.

The piezoelectric element detects the vibrations in the water pipe caused by water flowing through the pipe. The disk element is 27 mm in diameter and is cheap and readily available, as the component is found in all types of buzzers. The disk element detects vibrations by converting the mechanical signal into an electrical signal, and the signal is boosted before being received by the MCU.

The temperature sensor used in the developed vibration device is the MCP9700, which is a small and relatively cheap component that is easily interfaced to the MCU. The device measures the temperature by measuring the voltage. The voltage read by the temperature sensor is then compared to the reference voltage by the MCU and a temperature can then be determined with a simple formula. Testing was done to determine how accurate the temperature sensor is, compared to the highly accurate Center 306 Data Logger Thermometer. The test was performed by attaching both temperature sensors to a metal bowl and recording the temperature every second for approximately three and a half hours. Boiling water was poured into the bowl shortly after the experiment began to determine the accuracy of the MCP9700 over the different temperature ranges. Figure 3 shows the results of the test, comparing the MCP9700 to the Center 306 Data Logger Thermometer. The results show that the MCP9700 temperature sensor stays within 1 °C to the Center 306 Data Logger Thermometer. However, the response time of the MCP9700 is not as quick as the Center 306 Data Logger Thermometer, but since the temperature of an event is recorded at the end of the event, the response time of the temperature sensor can be ignored.

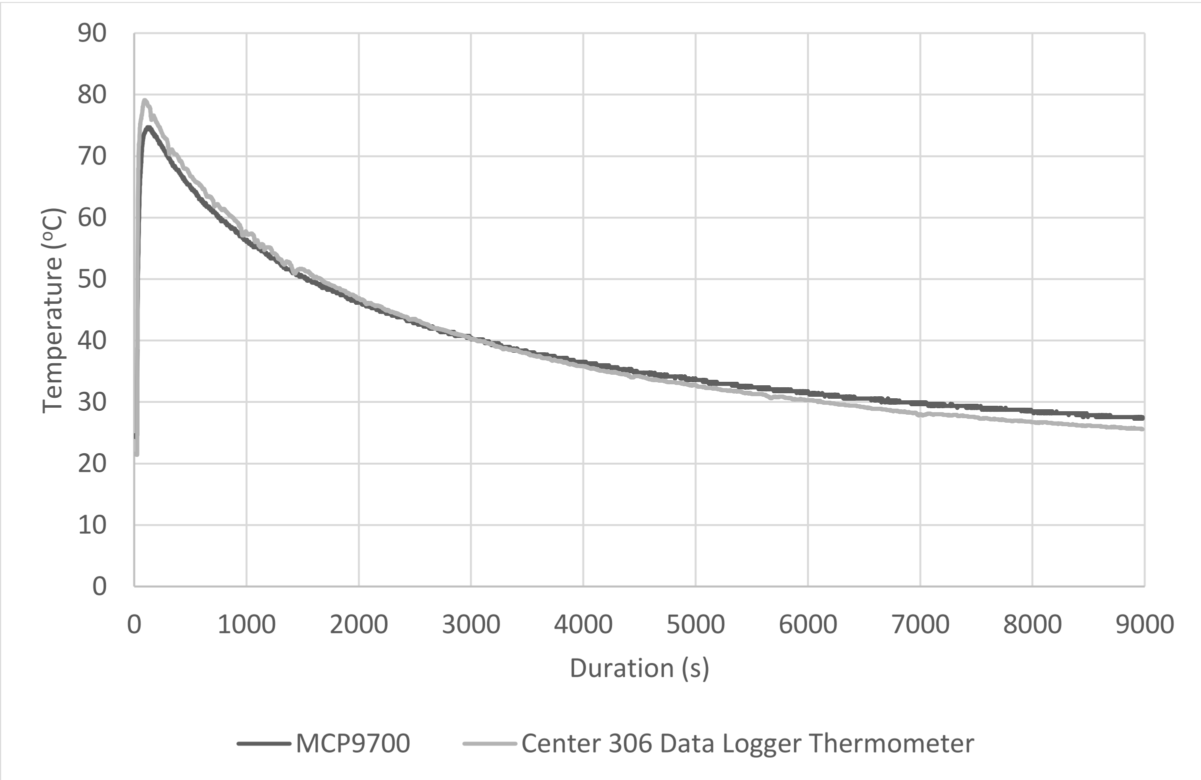

Figure 3 Comparison between MCP9700 and Center 306 Data Logger Thermometer

The MCU that was chosen to process the data was the Atmel Atmega1284P-PU. This MCU was chosen because of the relative low cost and the chip is also supported by the Arduino IDE. The Arduino IDE has a large community of developers, therefore, assistance with programming the chip was easily found.

There are many useful libraries found on the internet to assist with the programming of the MCU. The Arduino IDE uses its own programming language which is based on C++. The language was written with the Atmel Micro Controllers as the supported chip; therefore, programming the MCU with the Arduino IDE is the obvious choice (Arduino, 2008).

The Atmeag1284P-PU is a 40-pin MCU that has several inputs and outputs. The piezoelectric element and temperature sensor are connected to the MCU's analog inputs; therefore, the MCU reads all readings from the piezoelectric element and temperature sensor as an ADC value, which ranges from 0 to 1 024. The ADC value directly relates to the voltage being read by the input. The ADC value of 0 relates to 0 V and an ADC value of 1 024 relates to reference voltage of the MCU. The ADC value is a linear relationship to the voltage. The MCU processes the data received by the two sensors to determine if a tap event has occurred, the duration of the event and the temperature at the end of the event. There is an external Real-time Clock (RTC) and SD card reader attached to the MCU to give the chip logging capabilities. The device is also equipped with a Wi-Fi module to give the device IOT capabilities. The device uploads the entire recorded data to a webpage at about 00:15h every day. The user can access the website anytime and copy the data uploaded to Microsoft Excel for further analyses. The device is powered by two 3.7 V Lithium-Polymer batteries in parallel, with 2 900 mA each, allowing for 50 days continuous operation.

The vibration sensor was linked to the internet via Wi-Fi, reporting all recorded values to a webpage. The webpage is programmed in HTML 5 and is made secure with a login page coded with a PHP script. Once the user has logged in, the website displays a selection of all 10 devices that were built during this research. The user has to click on one of the devices to see the entire data that was recorded by the vibration device in a comma separated variable (CSV) format.

3.4 Device Verification

The vibration and temperature sensing device was tested on three main water use activities to verify that the device is capable of recording water use events. The three water use activities the device was tested on is the shower, a kitchen tap and a toilet. The kitchen tap, toilet and some of the shower events were tested in a 3rd floor apartment in the centre of Stellenbosch, the rest of the shower events were tested on a two-storey house in a suburb of Cape Town. The test was conducted by recording the ADC value from the piezoelectric element and the temperature from temperature sensor about every 50 ms. A stopwatch was used to record the actual duration of the event and the Center 306 Data Logger Thermometer was used to record the actual temperature of the pipe. The vibration device and temperature sensor was setup by taping the piezoelectric element firmly onto the outlet pipe for each of the end points used.

In cases where the pipe leading to the end point was not accessible, the piezoelectric element and temperature sensor were attached to the spout of the end point. The vibration device is setup as described for all subsequent tests in the research.

3.4.1 Vibration Testing

Figure 4 shows the vibration of the shower head pipe in terms of the ADC value compared to the duration of the event measured on a stopwatch. The figure shows that when the tap is turned on there is a notable spike in the ADC value and this spike continues until the tap is turned off. Therefore, the test proves that the device is capable of detecting and recording the number of shower events and the duration of each shower event.

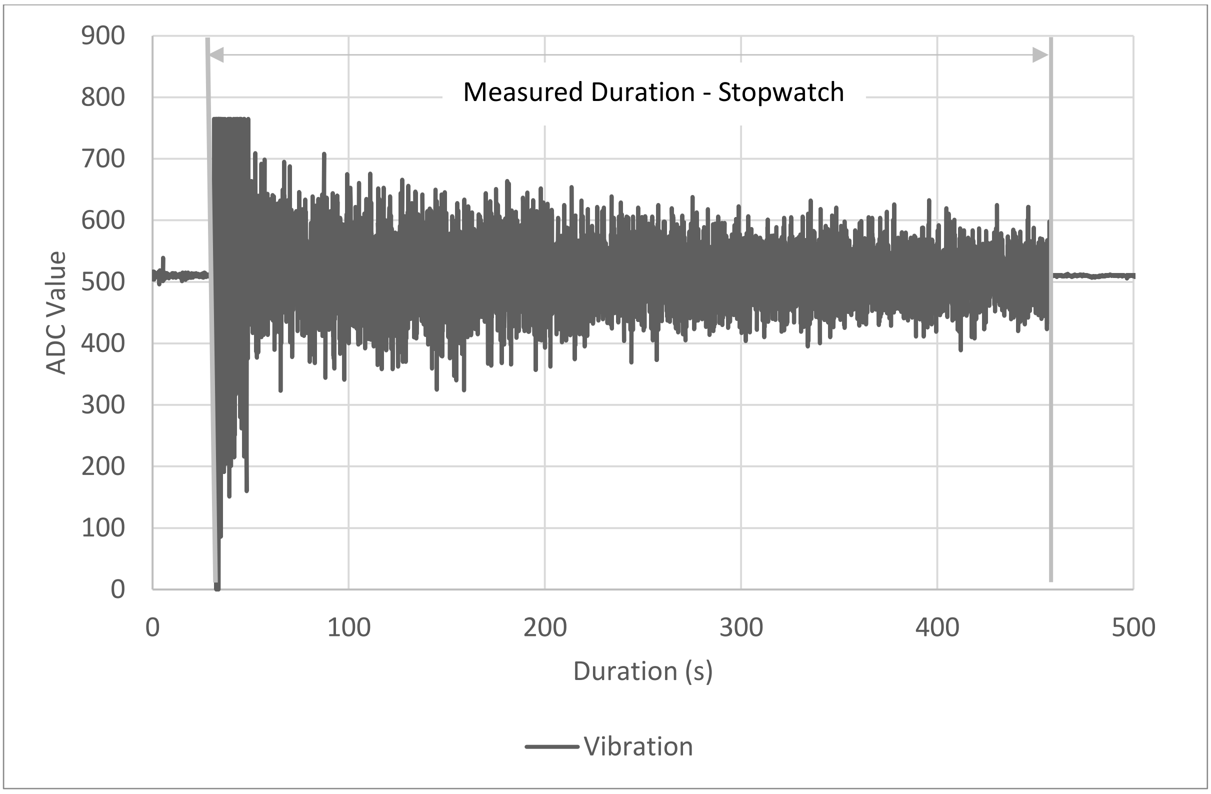

Figure 4 Shower vibration test

Figure 5 shows similar results; the figure shows the vibration of the kitchen tap spout in terms of the ADC value compared to the actual duration of the event measured by a stopwatch. Again, the device quite clearly detects when the tap is turned on and when the tap is turned off. Therefore, the device is capable of detecting and recording the number of kitchen-tap events and the duration of each kitchen-tap event.

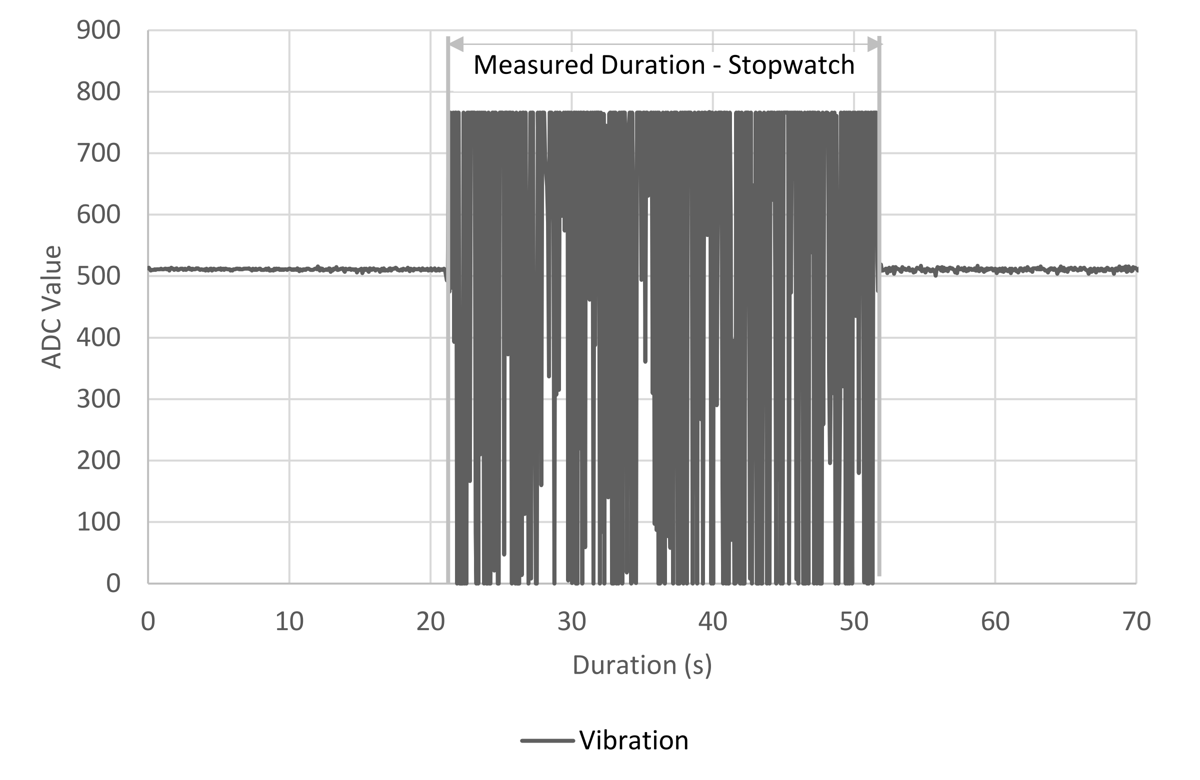

Figure 5 Kitchen tap vibration test

Figure 6 shows the vibration of the inlet pipe to the toilet in terms of the ADC value compared to the actual duration of the event. The toilet filling event is not as clear as the shower or tap event because the rate at which the toilet fills slows down as the cistern fills. Since the toilet takes a considerable amount of time to fill completely a decision was taken to say that the toilet filling event ends when the cistern is 95% full. Hence the stopwatch stops timing once this mark has been reached in the cistern. There is also a clear drop in the spike of the ADC value at this point as well. Therefore, the device is capable of detecting and recording the number of toilet events up to a 95% cistern capacity and the duration of each toilet filling event.

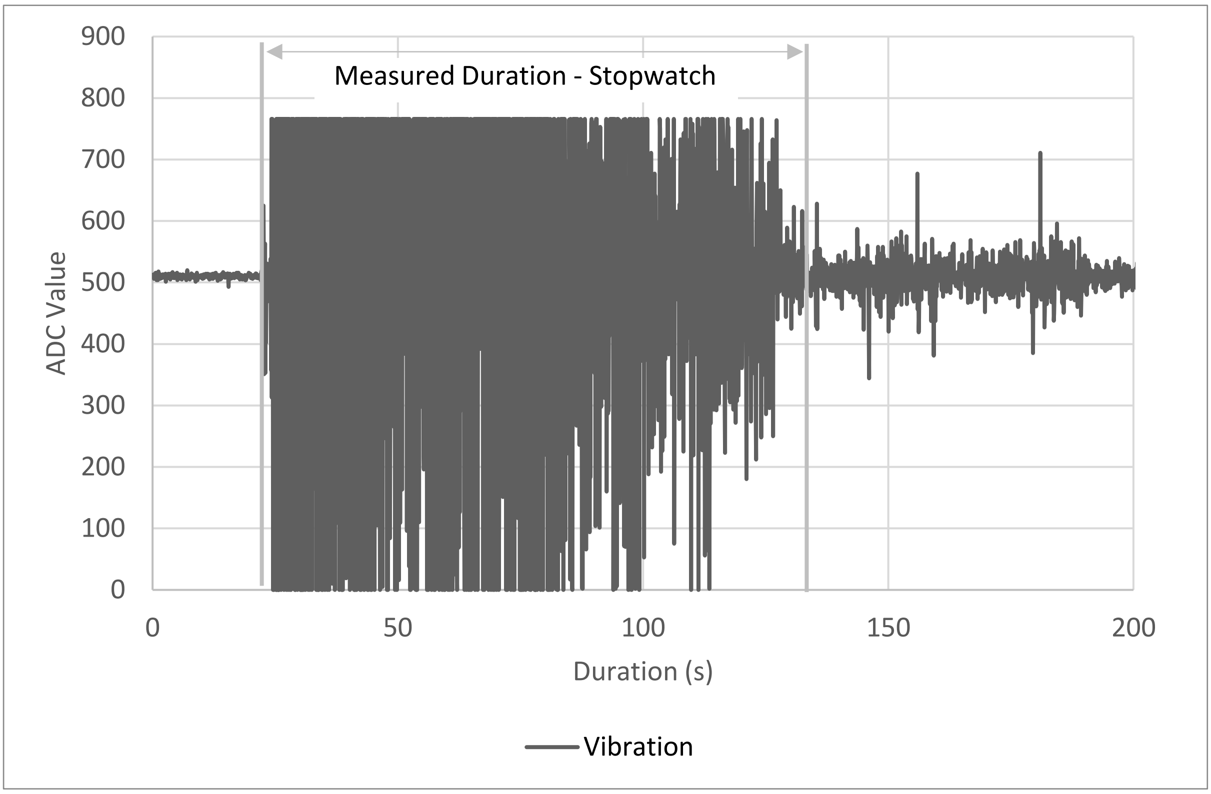

Figure 6 Toilet vibration test

3.4.2 Temperature Testing

Figure 7 shows the temperature of the shower event over the whole duration of the shower event in terms of both the MCP9700 temperature sensor used by the device and the accurate Center 306 Data Logger Thermometer. Both temperature sensors show that there is a clear spike in the temperature when there is a shower event, with the temperature at the end of the shower event according to the stopwatch, is 41.0 °C according to the MCP9700 and 42.3 °C according to the Center 306 Data Logger Thermometer. The difference between the two sensors was about 1.0 °C, which is what was expected. Again, the response time of the MCP9700 is slower than the Center 306 Data Logger Thermometer but this did not influence the final temperature. Therefore, the temperature could be used to determine if an event is occurring, but determining if an event is occurring by detecting vibrations is more reliable and accurate, however, both temperature and vibrations are recorded in this study.

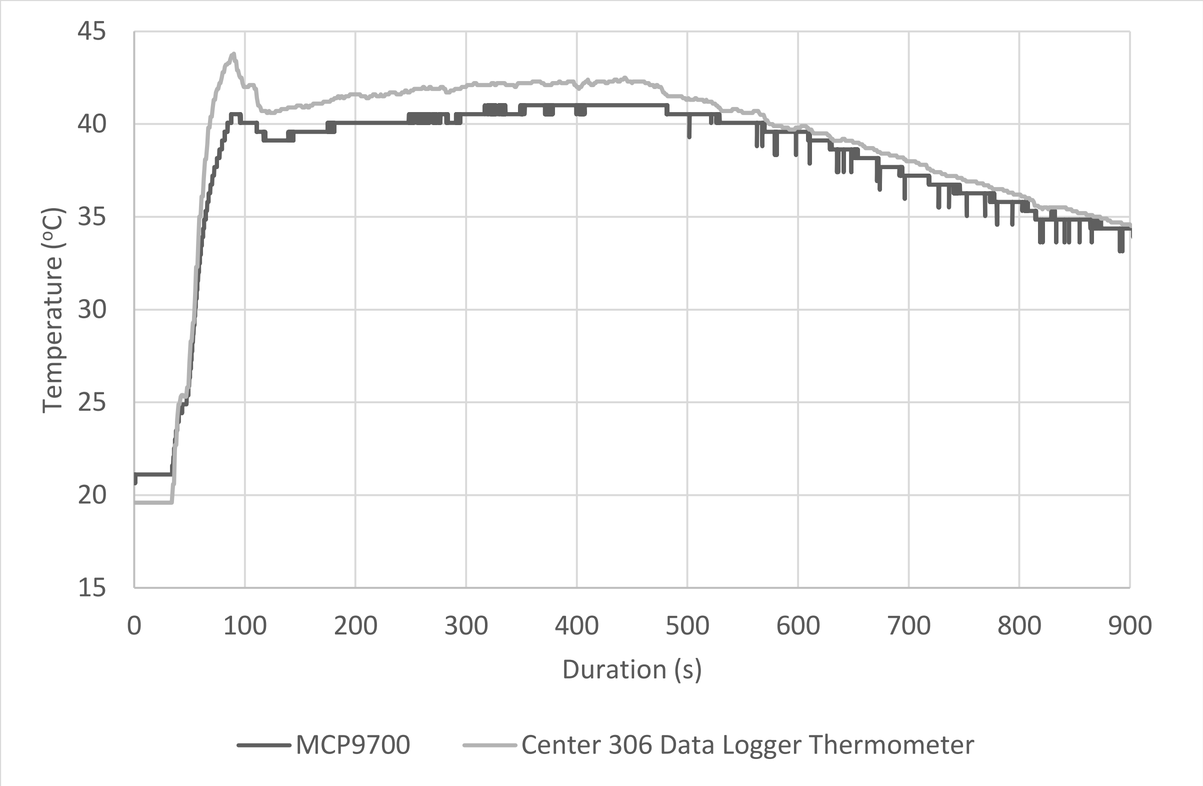

Figure 7 Shower temperature test

Figure 8 shows the temperature of the kitchen tap event over the whole duration of the kitchen tap event in terms of both the MCP9700 temperature sensor used by the device and the accurate Center 306 Data Logger Thermometer. Both sensors show that the temperature did not change dramatically as compared to the shower event temperature but there was a slight drop in the temperature of the pipe. However, this decrease is too small to be used to consider if a kitchen tap event is occurring. The temperature measured by the MCP9700 was 21.1 °C and the temperature measured by the Center 306 Data Logger Thermometer was 19.7 °C, again, the difference between the two was considered to be acceptable in view of other inherent errors in the data.

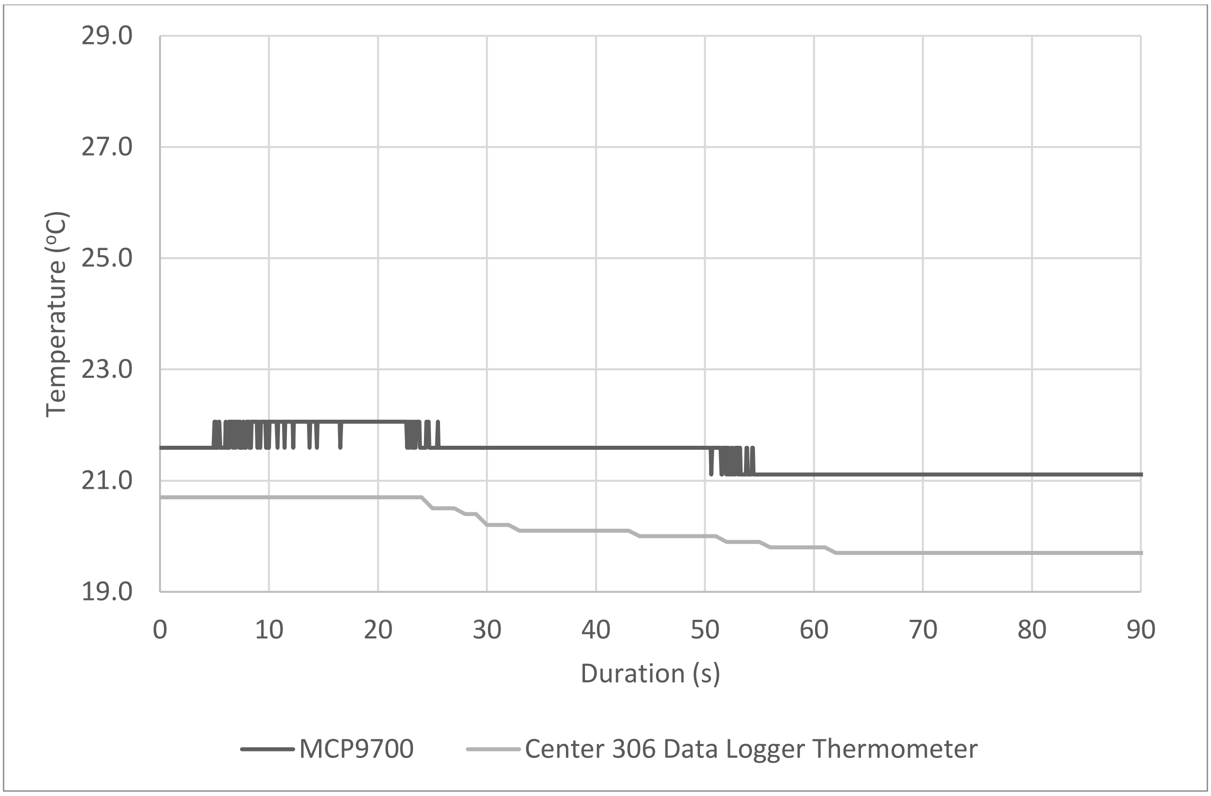

Figure 8 Kitchen tap temperature test

Figure 9 shows the temperature of the toilet filling event over the whole duration of the toilet filling event in terms of both the MCP9700 temperature sensor used by the device and the accurate Center 306 Data Logger Thermometer. The results are similar to the results found for the temperature of the kitchen tap. There was a slight decrease in the temperature of the pipe, but decrease was not as notable as for the shower temperature. Therefore, like with the kitchen-tap temperature, the temperature of the toilet filling cannot be used to determine if an event is occurring. The temperature measured by the MCP9700 was 21.1 °C and the temperature measured by the Center 306 Data Logger Thermometer was 19.6 °C; again, the difference between the two was considered to be acceptable in view of other inherent errors in the data.

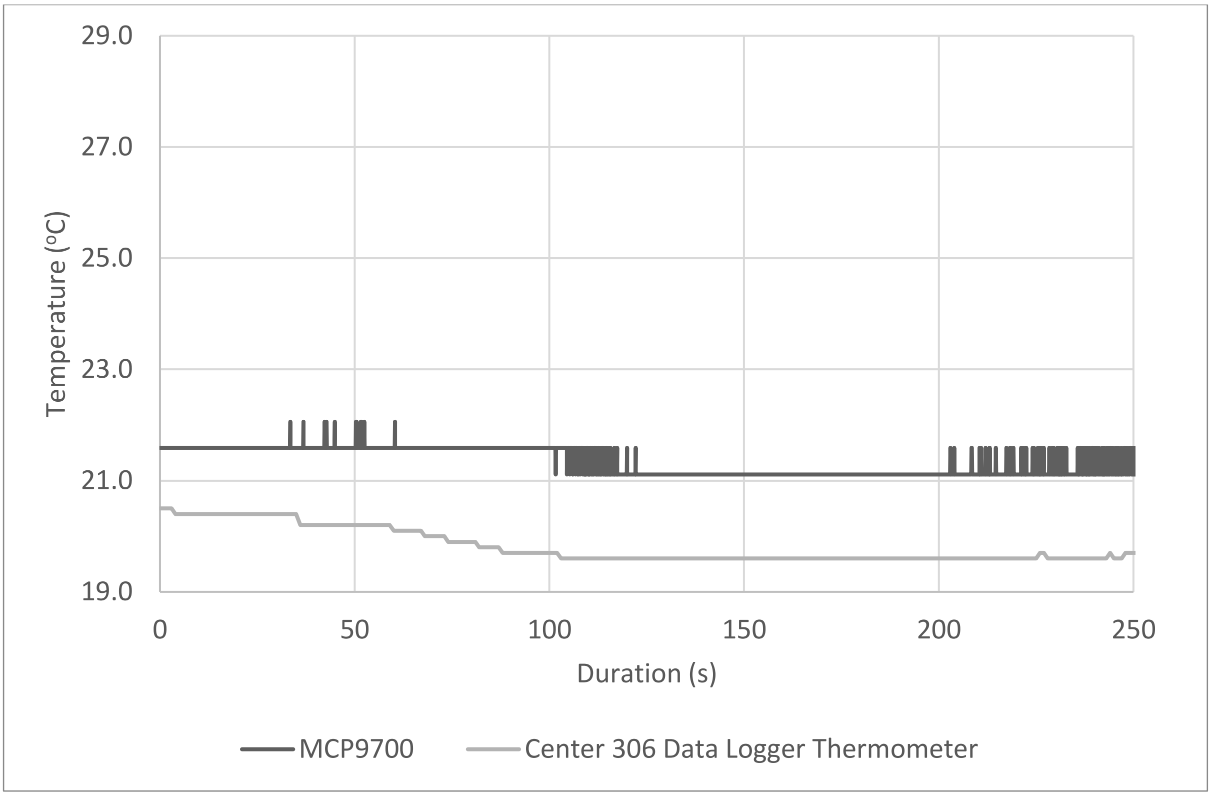

Figure 9 Toilet temperature test

3.5 Programme Specifications

Based on results gathered from the vibration and temperature tests, the MCU was programmed to determine when an event occurs and the duration of the event. The MCU also had to discard any non-events. The MCU was programmed to consider an event occurring if the ADC value spike from the midpoint value of 510 was greater than 100, therefore any values detected above an ADC value of 610 or below 410 would trigger the vibration device in starting the timer. The ADC value of 100 was chosen through trial and error and was found to be the best value in terms of blocking out noise and detecting a water event. If two spikes were within 2 seconds of each other, the MCU considered them the same event and if two spikes were greater than 2 seconds apart, the MCU considered them two separate events. The device would then stop the clock on the first event and write the date, time, duration and temperature of that event to the SD card and start the clock on the next event. If an event had a duration of less than 4 seconds, this event was considered a non-event and the MCU would discard that event. Figure 10 illustrates the developed and tested vibration device.

Figure 10 Developed vibration device

The vibration sensing and temperature device was installed on a shower head pipe, toilet and kitchen tap with the parameters specified to determine if the device accurately records the number of events and the duration of each event.

In terms of the verification of shower events, the device recorded 76 shower events. Each shower that was taken was also recorded with a stopwatch to determine the actual duration of the shower, the date and time was also noted. Of the 76 shower events that were recorded by the device, 20 of the events were non-events, which gives the vibration device an accuracy of 73.7%. However, these non-events are easily recognisable as the duration is noticeably short at around 5 seconds and the temperature that was recorded is much lower compared to the temperature of actual shower events. The total amount of seconds of shower time recorded, according to the device, is 8 139.0 seconds which include the non-events that were recorded. Therefore, excluding the non-events, the total amount of recorded time was 7 973.4 seconds. The total amount of shower time recorded with the stopwatch was 8 106.0 seconds. Therefore, even if the non-events are included the precision of the device is still high. However, the consistency of expecting non-events in the recordings is low as the experiment was conducted again in the same location for 7 days and no non-events was recorded, and all shower events were recorded accurately. Figure 11 shows the correlation between the actual duration of shower events and the duration of shower events recorded by the device. A line of best fit was added to the data and the coefficient of determination was found to be 0.9949. There are some short events around 15 seconds, which indicates that the shower was turned on and off during the shower event.

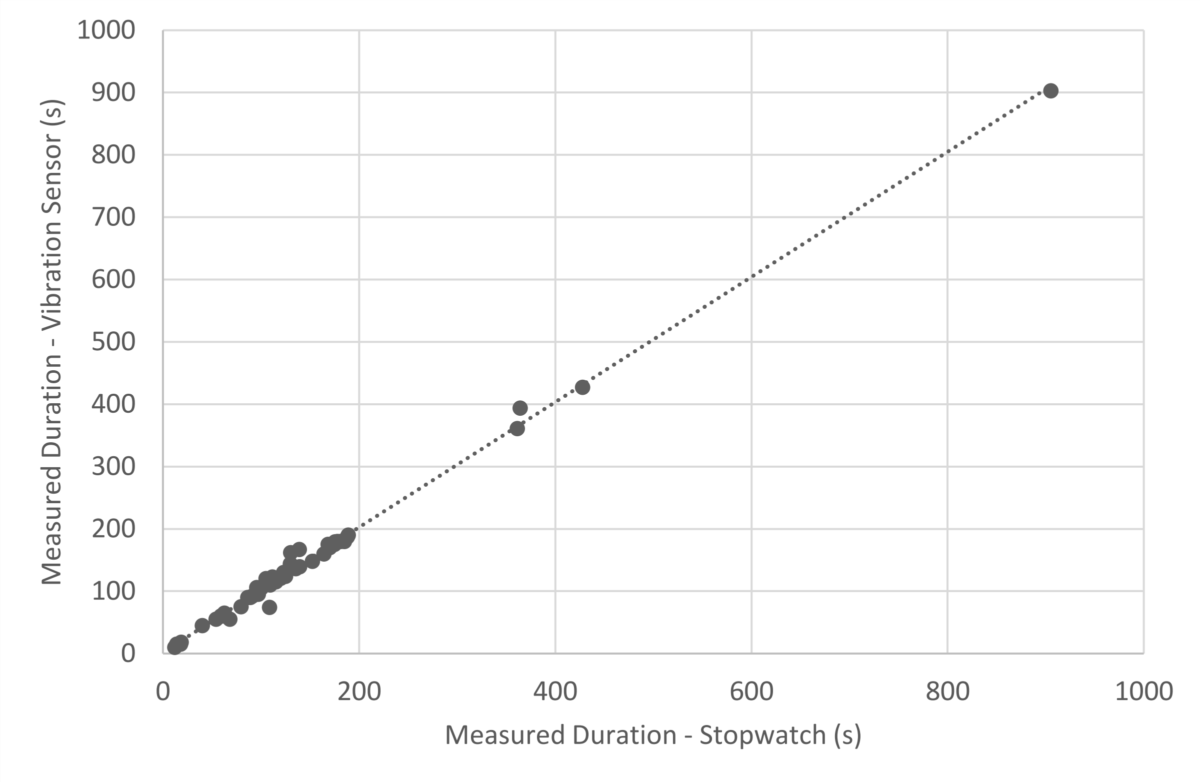

Figure 11 Correlation between actual and measured duration of shower events

In terms of the verification of kitchen tap events, 164 kitchen-tap events were recorded by the device. During the testing there were three states in which water could be flowing from the tap namely; cold water was flowing out; hot water was flowing out or the filter system was attached, and the cold tap was turned on. All three states were detected by the device. The duration of all the events was recorded with a stopwatch and the time and date of each event was noted. Of the 164 events recorded by the device, 139 were actual events and 25 were non-events, which gives the vibration device an accuracy of 84.8%. The total recorded time of the events according to the device was 2 376 seconds and the total recorded time with the stopwatch was 2 306 seconds. Some of the non-events were caused by activities in the apartment. The shower triggered the device in the kitchen on two occasions. Again, experiments which were run multiple times, recorded no non-events, but like the shower events all tap events were recorded at a high precision. Therefore, like the shower events, the consistency of expecting non-events being recorded, is low. Figure 12 shows the correlation between the actual duration of the kitchen-tap events recorded by the stopwatch and the duration of the kitchen-tap events recorded by the device. A line of best fit was added, and the coefficient of determination was found to be 0.9129.

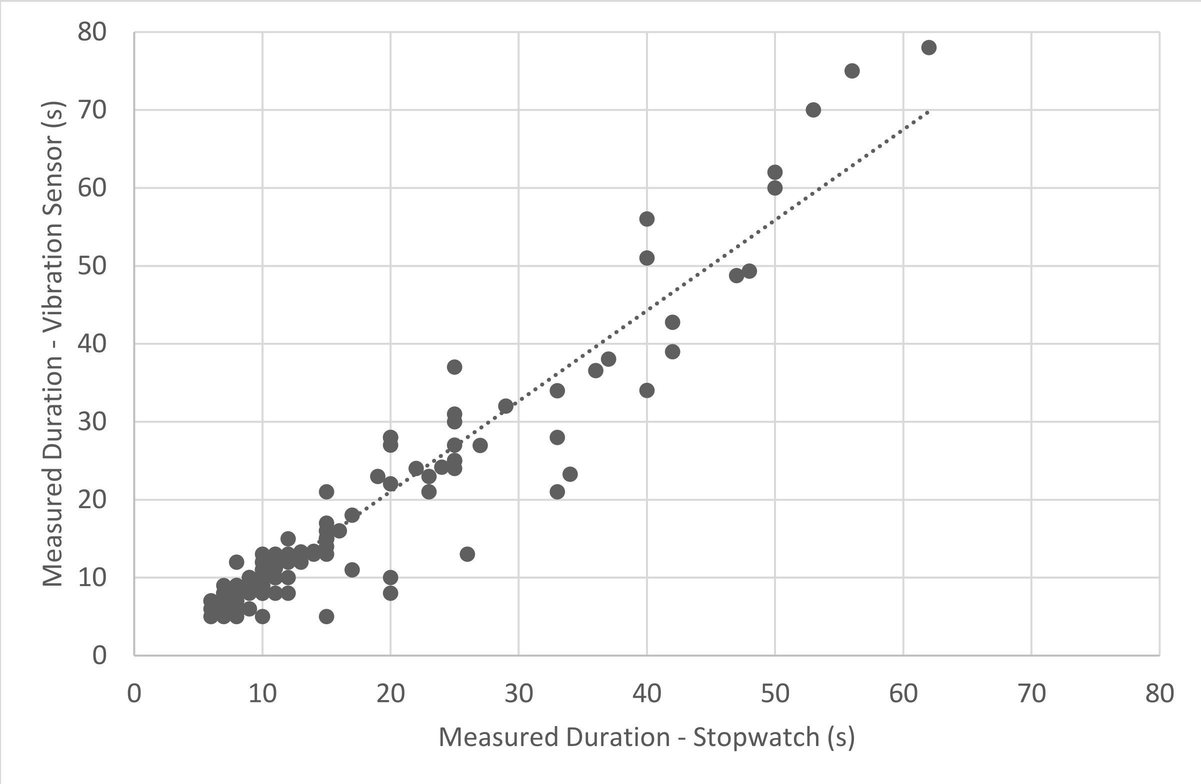

Figure 12 Correlation of actual duration and measured duration of kitchen tap events

In terms of the verification of toilet filling events, 20 events were recorded by the device. For toilet filling events the toilet's cistern had to be marked to a point where the device stops detecting the vibration of the filling. This mark was when the cistern was about 95% full. All 20 events recorded were actual toilet events, with no non-events being recorded. A stopwatch was used to determine the actual duration, and was stopped when the cistern reached 95% capacity. Also, the toilet was flushed in four different ways, namely; a full flush, three quarters flush, half flush and one quarter flush. The total duration of all the toilet filling events by the device was 1 517 seconds and the total duration of all the toilet filling events recorded by the stopwatch was 1 519 seconds. Therefore, the precision of the device for toilet filling events is high. Figure 13 shows the correlation between the actual duration and the measured duration of toilet filling events. A line of best fit was added, and the coefficient of determination was 0.9964.

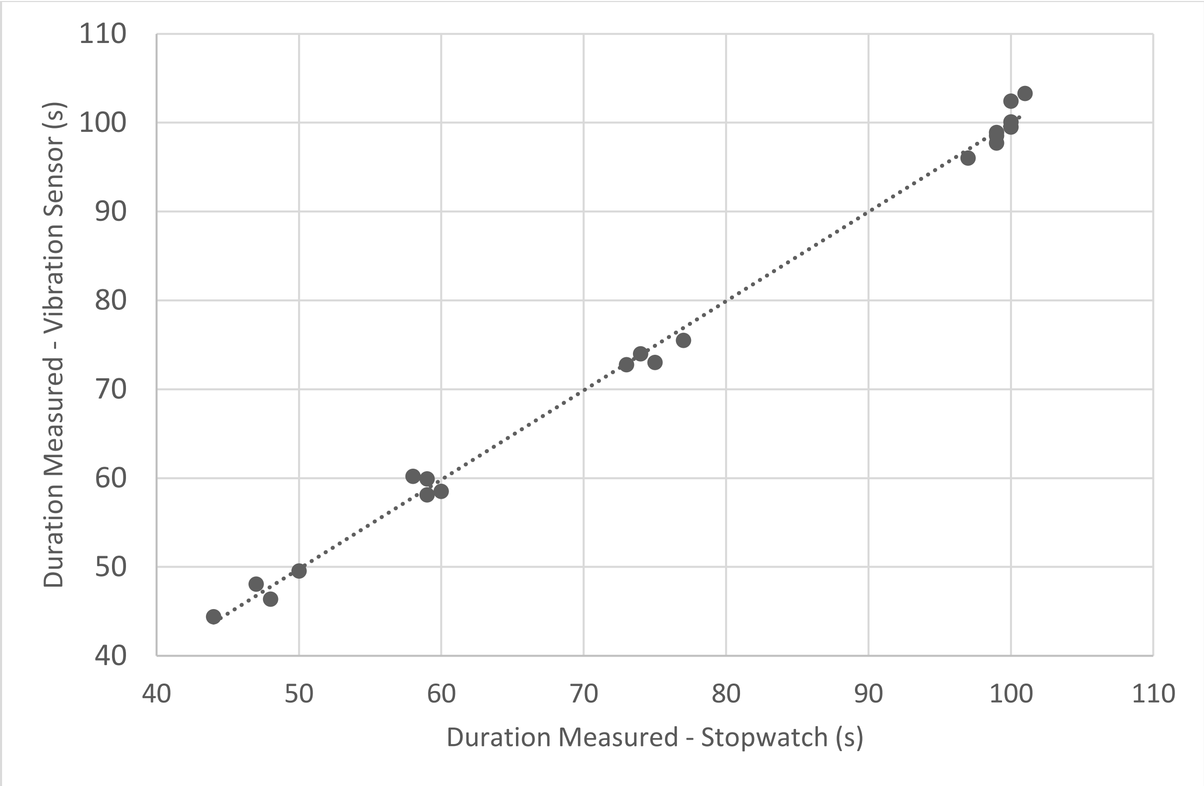

Figure 13 Correlation between the actual and measured duration of toilet filling events

4 Pilot Study

4.1 Data Collection

A pilot study was conducted to ensure all 10 of the vibration and temperature sensing devices worked as expected and to eliminate any bugs that occurred in the software. The study was conducted in a public bathroom in the engineering building of Stellenbosch University for a period of 23 days from 5th November 2018 to 28th November 2018. The devices were connected to the 4 toilets and 4 basins that were in the men's toilets. Rotation of the devices occurred to ensure all 10 devices were tested. Although software bugs relating to the network were detected during the test, the bugs were fixed, and the devices ran as expected. To obtain the amount of water used, a flow rate of 10 L/min was used in all calculations. During the pilot study 12 176 events were recorded from all 10 devices, 8 865 events were recorded from the toilet events and 3 311 events were recorded from basin events. In total an estimate of 144.7 kL of water was used during the pilot study. Figure 14 shows the number of events captured at each end point in the public bathroom. The figure shows that nearly three-quarters of all the events recorded were from toilet use. The figure also shows that between all the basins in the bathroom "Tap 2" was the preferred basin to use during the study.

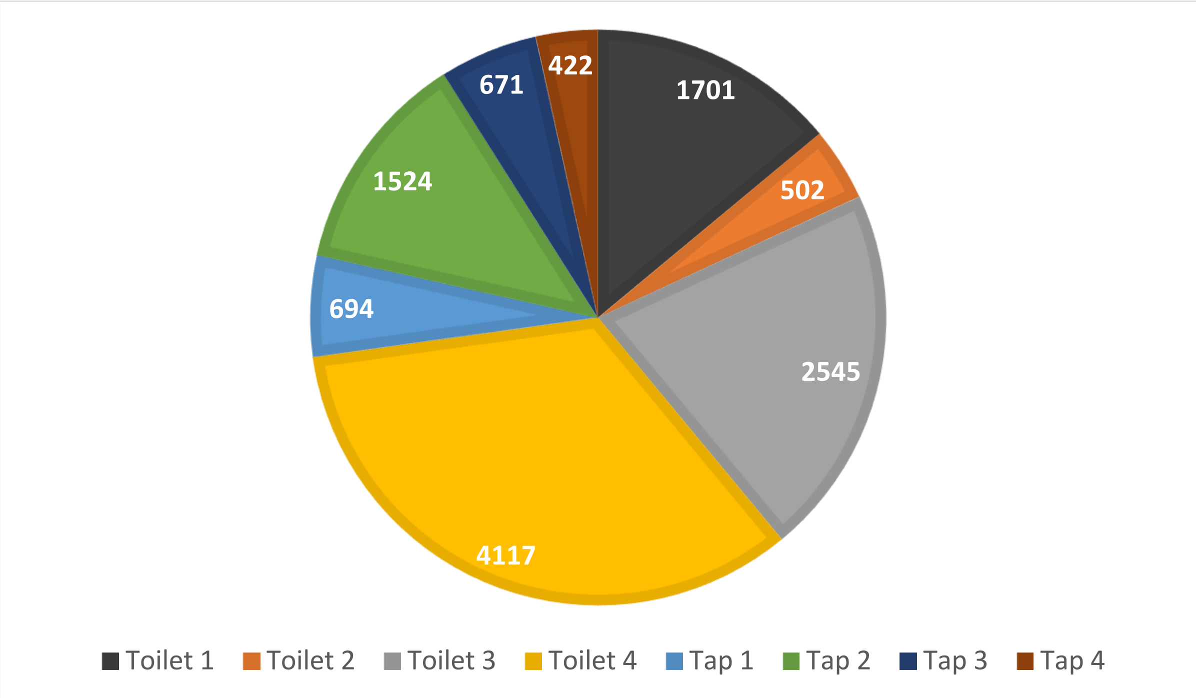

Figure 14 Number of events recorded by each end point in pilot study

4.2 Bathroom Layout

The toilets and basins were numbered as follows; when entering the bathroom, with the toilet cubicles facing the entrance, the toilets were numbered 1-4 from left to right. The basins are located in front of the cubicles and were number 1-4 from left to right in reference to the cubicles looking at the basins. Figure 15 illustrates the layout of the bathroom in the engineering building at Stellenbosch University used in the pilot study.

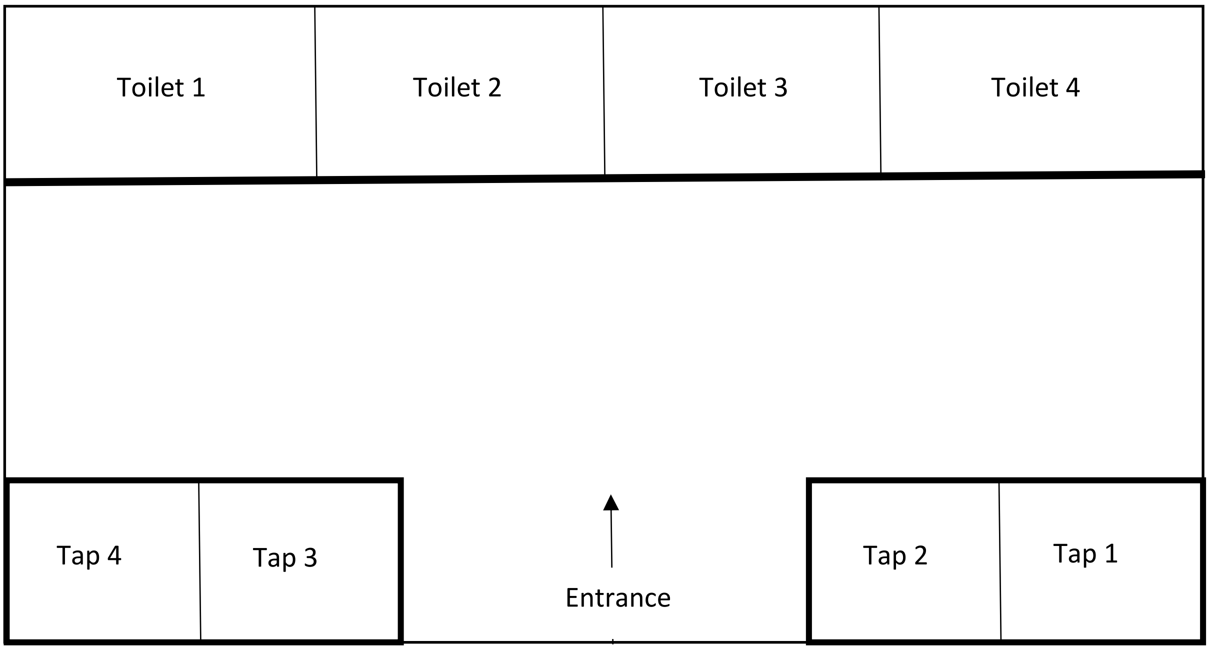

Figure 15 Public bathroom layout

4.3 Results and Analysis

The results of the pilot study can be found in Table 5. The standard deviation of the duration for both the toilet and basin events shows that there is a large range of how long an event can take place. In the case of the toilet events, the “spitting effect” was evident, where the flow of water is inconsistent near the end of the toilet cistern filling, which results in a number of smaller events succeeding after a long event, and consequently resulted in the large standard deviation. In the case of the basin events, each person’s hygiene practice influences the duration the user washes their hands. According to the literature in Table 1, the average number of litres of water used for the toilet per person per day is 33.7 L. If the assumption is that each event represents a different person, then the results obtained from the pilot study, which range from 10.1 L per event to 18.0 L per event, compare well to that found in literature. The longest event recorded for toilets was 2 798.9 seconds at Toilet 4 at 12:32 on the 8th November 2018 and the longest recorded event for basins was 109.9 seconds at 15:00 on the 22nd November 2018 at Tap 2. The minimum duration for all events was set at 4 seconds, such that the minimum number of seconds for an event not to be considered as a noise event.

Table 5 Results of pilot study

Location	Toilet 1	Toilet 2	Toilet 3	Toilet 4	Tap 1	Tap 2	Tap 3	Tap 4
Days operating	23	19	23	23	14	23	23	23
Average number of events per day	74.0	26.4	110.7	179.0	49.6	66.3	29.2	18.4
Average duration of events (s)	60.5	107.9	105.2	100.3	10.1	9.7	8.6	7.9
Standard deviation of duration (s)	106.6	111.4	177.8	203.2	6.8	7.6	5.3	4.8
Maximum duration (s)	912.1	924.3	1553.2	2799.0	55.8	109.9	62.5	39.8
Minimum duration (s)	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0
Average litres of water used per event (L)	10.1	18.0	17.5	16.7	1.7	1.6	1.4	1.3
Standard Deviation of litres of water used per event (L)	17.8	18.6	29.6	33.9	1.1	1.3	0.9	0.8

The temperature of the pipe, just as each event ends, was also recorded. These recorded temperatures give an idea of what the ambient temperature was during each event. The average temperature across all locations is shown in Table 6. The results show that the temperature had an average of 25.0 °C with a standard deviation of 1.4 °C. The results show that the temperature remained consistent for the 23 days and did not vary too much between the locations. The maximum temperature recorded was 30.9 °C at Toilet 1 at 16:28 on the 20th November 2018 and the minimum temperature recorded was 15.9 °C at Toilet 3 at 02:49 on 6th November 2018. November is one of South Africa's summer months, hence the high temperatures that were recorded.

Table 6 Temperature results of pilot study

Location	Toilet 1	Toilet 2	Toilet 3	Toilet 4	Tap 1	Tap 2	Tap 3	Tap 4
Average temperature (°C)	26.8	23.3	26.3	24.0	22.8	25.7	26.5	24.8
Standard deviation of temperature (°C)	1.4	1.3	1.3	1.8	1.4	1.2	1.3	1.6
Maximum temperature (°C)	30.9	26.4	29.8	28.8	28.8	28.5	29.7	28.8
Minimum temperature (°C)	20.4	18.9	15.9	18.0	20.1	21.6	22.2	21.6

The diurnal frequency of the events logged by all the devices during the study period is illustrated in Figure 16. The figure shows that there is minimal activity in the bathroom between 00:00h and 07:00h, which is to be expected, as there are few people in the engineering building at night. During the night-time of the pilot study, there were a sizeable number of events that were recorded. The reason for this was that the pilot study was scheduled during the exam period of the university, which necessitated some people to stay late at night, studying, and therefore bathroom events were recorded. The figure shows that there is an increase in activity from 07:00h onwards, during which time the majority of students and staff members were arriving at the Engineering Building. From 16:00h events start to decrease as staff members and some students leave the building. Again, a slight increase in events occurred at 20:00h, a possible reason being that between 18:00 and 19:30 dinner is served at the university residences and, therefore, the increase could be attributed to the students arriving back at the Engineering Building to study, after having had dinner at their residence.

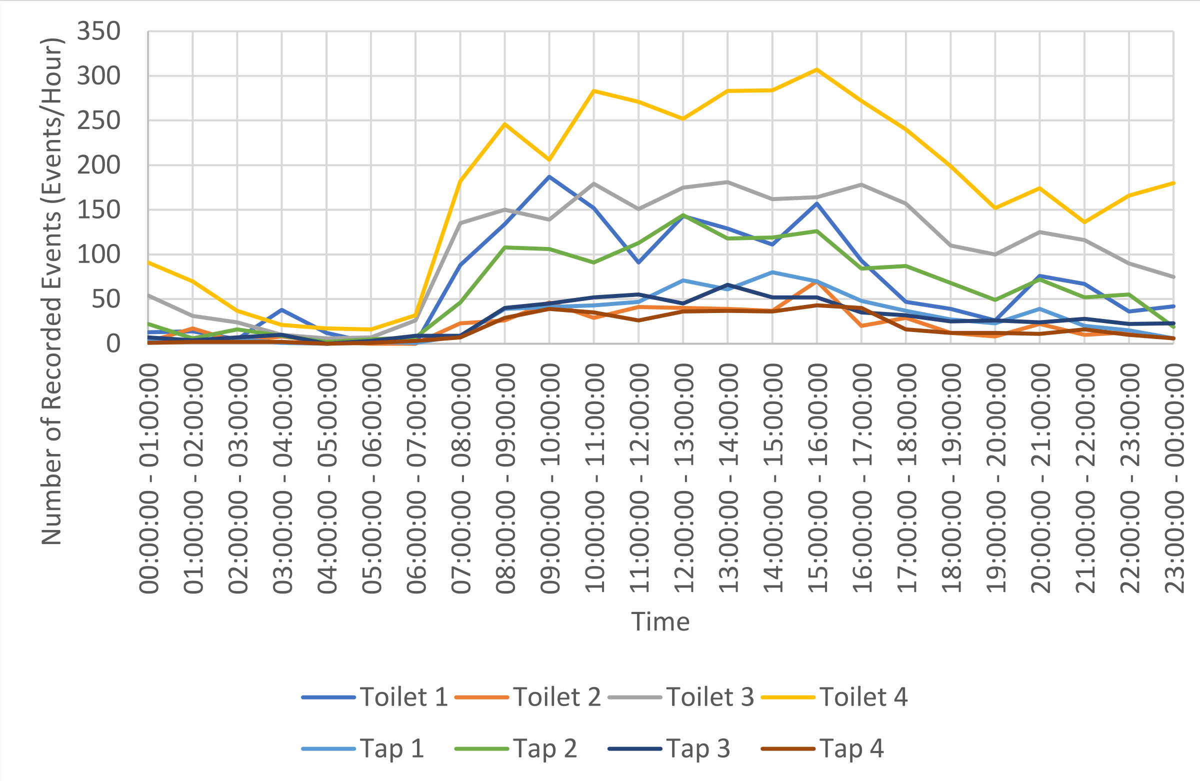

Figure 16 Frequency of events for pilot study

A number of the events were observed physically to make sure the devices detected the events and recorded the durations accurately. All the spot observations were detected and recorded accurately by the devices. “Tap 3 and Tap 4” had relatively low number of events because some people believed that the taps were not working correctly; however, the taps were merely choked and consequently fewer people used those taps.

"Toilet 4" has abnormally high number of events compared to the other toilets, and the reason for the anomaly is "Toilet 4" is located close to the main water line and, therefore, interference was detected.

4.4 Remarks

The pilot study proved that all 10 devices that were used in the research, functioned as expected. The study showed that the devices could capture large amounts of data and be able to transmit the data over the internet. There were occasions where transmitting of the data failed; however, the next day the transmitting of the data was successful. Although the reliability of the network connections could be improved, due to time constraints and the complexities around network connections, it was decided to store the data locally on each device, and consequently no improvements were made to network reliability.

5 Data Collection

5.1 Identification of Data Collection Sites

Data that was analysed for the research study was gathered from two houses that are located in a suburb on the outskirts of Cape Town, South Africa and were labelled House 1 and House 2. The two houses were each fitted with a highly accurate water flow meter, that gives the timestamp and the flow rate each time 500 mL passes through the meter. Several of the vibration devices were placed in the two houses to record different water use activities. The data gathered from the vibration device and the water flow meter was analysed together.

5.2 Data Collection and Transmission

The water end-use events were captured by the vibration device placed at various end points and a smart water meter was placed at the municipal meter to record the amount of water entering the property. Table 7 highlights the end points to which the vibration devices were attached.

Table 7 Location of vibration devices around House 1 and House 2

Vibration Device Number	House 1	House 2
Device 1	Dishwasher	Dishwasher
Device 2	Washing Machine	Washing Machine
Device 3	N/A	Kitchen Tap 1
Device 4	N/A	N/A
Device 5	Toilet 1	Kitchen Tap 2
Device 6	Shower 2	N/A
Device 7	Toilet 2	N/A
Device 8	Shower 1	Shower
Device 9	Outside Tap	Bathroom Tap
Device 10	Water Meter	Water Meter

The reason why some vibration devices were not in operation was because there were hardware issues with some of the devices which prevented the devices from recording. The vibration devices were attached to the inflow pipe or spout of each of the end points mentioned in Table 7. Both the piezoelectric element and temperature sensor were attached to the pipe with insolation tape. The logger was placed on the wall with pliant adhesive. If the pipe was not accessible, the piezoelectric element and temperature sensor were then attached to the spout of the end point.

Figure 17 illustrates how the vibration device is attached to a spout of an end point, when the pipe leading to the end point is not accessible. Figure 18 illustrates how the vibration device is attached to the pipe leading to an end point when the pipe is accessible.

Figure 17 Attachment of vibration device to spout

Figure 18 Attachment of vibration device to pipe

The vibration devices are connected to the Wi-Fi of the households for the duration of the respective experiments. Once a day at about 00:15 the vibration devices would upload the data recorded on the SD card to a secure website. The data from the vibration devices could then be accessed remotely to ensure the device was still operating and to further analyse the data. The data was imported from the website to Microsoft Excel for further analysis. The flow data collected by the smart water meter stored the data physically and was only accessed once the test period had finished. Figure 19 illustrates how the vibration devices and smart water meter communicate with the user to analyse the data.

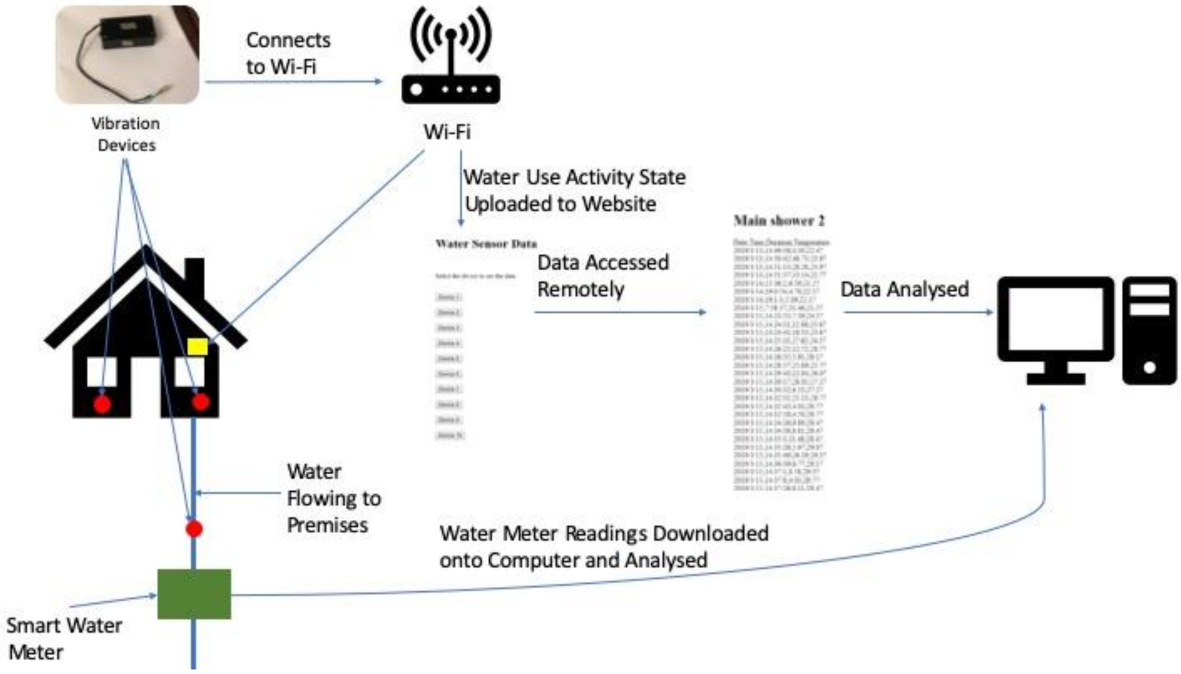

Figure 19 Schematic showing communication between devices

5.3 Extraction and Identification of Events

Several processes were involved to extract events from the smart water meter and match the data to the data from the vibration devices. The process of extraction and identification of events is described below.

5.3.1 Identification of Events from Smart Water Meter

To transform the smart water meter data from a flow rate for each 500 mL passed to the amount of water used for each event, a program was written in Java to perform the transformation. The program works by combining all measurements that are within one minute of each other together as one event. The time between the two measurements in the event was multiplied by the flow rate of the first of the two measurements to obtain the amount of water used in that instance. Once all measurements had been transformed from flow rates to water used per event, the individual water use between two measurements in the event were added together to obtain the total water used for a specific event. Table 8 illustrates how the java program transforms the flow rate data from the smart water meter to water consumed per event.

Table 8 Mechanics of Java water consumption program

Date	Time	Flow rate (L/s)	ΔTime to previous recording (s)	Within 1 Minute of Previous recording	ΔWater Used (L)
16/06/2018	06:26:55	0.0			
16/06/2018	06:56:04	0.2	1749	No	
16/06/2018	06:56:13	0.2	3	Yes	0.5
16/06/2018	06:56:16	0.2	3	Yes	0.5
16/06/2018	06:56:19	0.2	3	Yes	0.5
16/06/2018	06:56:22	0.2	3	Yes	0.5
16/06/2018	06:56:25	0.2	3	Yes	0.5
16/06/2018	06:56:28	0.2	3	Yes	0.5
16/06/2018	06:56:31	0.2	3	Yes	0.5
16/06/2018	06:56:34	0.2	3	Yes	0.5
16/06/2018	06:56:37	0.2	3	Yes	0.5
16/06/2018	06:56:42	0.2	3	Yes	0.5
16/06/2018	06:56:45	0.2	3	Yes	0.5
16/06/2018	06:56:48	0.2	3	Yes	0.5
16/06/2018	07:16:14	0.2	1166	No	
	Total	0.2	36		6.0

5.3.2 Verification Step One

The data from the vibration device was scrutinised by two verification steps. The first verification step was to combine recorded events. If two recordings were within 1 minute of each other then the events were combined together. The start time of the event was recorded by the vibration device, the end time needed to be calculated by adding the duration of the event to the start time. If the start time was less than 1 minute from the end time of the previous event, the current event was considered to be within 1 minute of the previous event and the two events were package together. The package process continued if the current event was within 1 minute of the previous event in the log. If the current event was not within one minute of the previous event in the log, then the package process stopped, and a new package was created. The process continued until all events in the log were packaged. To create the new event from the package, the event duration was the sum of all the durations in the package, the timestamp was that of the first event in the package and the temperature was that of the last event in the package. The first verification step was done in order to accommodate the smart water meter which considered pulses one minute within each other as the same event. Figure 20 illustrates how the first verification step was carried out.

	Date	Star Time	End Time	Duration	Temperature	Within 1 Minute of Previous Event
Package 1	06/04/2019	14:35:43	14:35:52	9.0	24.0	
Package 2	06/04/2019	14:48:27	14:48:34	6.9	23.1	No
	06/04/2019	14:48:41	14:48:45	4.1	24.9	Yes
	06/04/2019	14:49:20	14:49:25	5.5	25.5	Yes
Package 3	07/04/2019	09:58:39	09:58:44	4.6	24.3	No

	New Date	New Start Time	New Duration	New Temperature
From Package 1	06/04/2019	14:35:43	9.0	24.0
From Package 2	06/04/2019	14:48:27	16.5	25.5
From Package 3	07/04/2019	09:58:39	4.6	24.3

Figure 20 Illustration of verification step one

5.3.3 Verification Step Two

The second verification step was to combine the data recorded by the vibration devices from the first verification step to the smart water meter data that was categorised into events by the Java program. Another Java program was used to combine the two data sets. The two data sets were combined by matching the timestamp between the two sets. To ensure a high accuracy of a matched event and to accommodate the two clocks not being synchronised, a 10-minute leeway between the two events was used, the event duration was recorded by the vibration device and the smart water meter was used as a confirmation of the match. If there were events recorded by the vibration device that were not matched with events recorded by the flow meter, then the vibration device events that were not matched were considered noise events and deleted. Figure 21 illustrates how the data from verification step one is combined with the flow data after the event identification to create a new combined data set. The new combined data set is used in all further analyses. Note that the time stamp used for the combined data was that of the vibration device.

Vibration Device Data After Verification Step One

Date	Time	Duration	Temperature	Match
23/03/2019	22:34:13	7.8	25.2	No
23/03/2019	22:32:36	7.7	25.2	No
23/03/2019	22:30:58	7.8	25.5	No
23/03/2019	22:59:21	184.9	25.2	Yes
24/03/2019	00:18:38	66.0	28.2	Yes
24/03/2019	00:24:56	67.6	27.0	Yes

Smart Water Meter Flow Data After Event Identification

Date	Time	Water Used	Duration	Flow Rate	Match
23/03/2019	22:00:34	4.5	22	0.20	No
23/03/2019	22:06:07	0.0	1	0.00	No
23/03/2019	22:55:44	0.5	6	0.10	No
23/03/2019	22:57:48	7.5	208	0.04	Yes
23/03/2019	23:07:50	1.0	10	0.10	No
23/03/2019	23:26:15	4.5	23	0.20	No
24/03/2019	00:15:56	4.0	60	0.07	Yes
24/03/2019	00:22:13	4.0	60	0.07	Yes

Combined Event Log

Date	Time	Duration (s)	Temperature (°C)	Meter Duration (s)	Water Used (L)	Rate (L/s)
23/03/2019	22:59:21	184.9	25.2	208	7.5	0.04
24/03/2019	00:18:38	66.0	28.2	60	4.0	0.07
24/03/2019	00:23:48	67.6	27.0	60	4.0	0.07

Figure 21 Illustration of verification step two

5.3.4 Rectification Process

After both verification steps, in some instances, a rectification of the water used for each event was needed. The water consumption for an event could be exaggerated by the smart water meter. The exaggeration could be caused by the smart water meter combining events from other water end points into one event. In order to rectify the water consumed, the average flow rate of the event in question would be multiplied by the event duration according to the vibration device. The rectification process was used in instances where the water consumption was extremely higher than the consumption seen in Table 1.

5.4 Field Experiments

5.4.1 House 1

The testing at House 1 was conducted for 14 days, and the test started on 16/03/2019 at 00:00 and ended on 31/03/2019 at 00:00. The house had 2 occupants for most of the study period, with some movement of people that was not accounted for, including a domestic worker, gardener, and two children who were absent from the home for most of the time. In total, 8 vibration devices were fitted in House 1 at various locations, namely; the dishwasher, washing machine, Toilet 1, Toilet 2, Shower 1, Shower 2, the outside tap and one at the flow meter. The events recorded by the vibration device at the flow meter did not go through the same processes as the data recorded by the other devices. The vibration device at the flow meter was used to see if the flow meter and the vibration device recorded the same events. Table 9 shows the number of recorded events by each of the vibration devices, excluding the one at the flow meter, and the number of events of each of the verification phases. The most significant verification phase was the first verification phase as the total number of events decreased from 1 623 to 827. The second verification phase revealed how many events were noise events, and the total number of noise events were 194. The accuracy of the vibration device was determined by calculating the percentage of events remaining from the second verification phase compared to the first verification phase.

Table 9 Events recorded with vibration device and verification phases for House 1

Location	**Recorded Events**	**Events after first verification phase**	**Events after second verification phase**	**Accuracy (%)**
Dishwasher	32	24	19	79.2
Washing Machine	677	240	165	68.8
Toilet 1	477	341	267	78.3
Toilet 2	364	159	121	76.1
Shower 1	61	56	55	98.2
Shower 2	5	4	4	100.0
Outside Tap	7	3	2	66.7
Total	1623	827	633	76.5

On further inspection of the data captured, there were some events that were identical on both the devices situated in Toilet 2 and the device situated at the washing machine. The room where the washing machine was situated and the Toilet 2 bathroom were adjacent and, according to the occupants of the house, the pipes for the washing machine and the toilet run close to each other. Therefore, interference was recorded from both devices when either the toilet or the washing machine was in use. However, according to the occupants of the house Toilet 2 recharges relatively quickly at around 40 seconds.

Therefore, to eliminate all the duplicates, if a duplicate event was over 100 seconds, then the event would be deleted from Toilet 2's record, and if the event was less than 100 seconds then the duplicate event would be deleted from the washing machine's record. Table 10 shows the final number of events that was analysed from House 1 after all the verification phases and after all duplicates had been eliminated. In total there were 117 duplicates identified. The performance of the vibration device is similar to that seen in the development stages of the device, indicating that the devices were performing as expected.

Table 10 Final number of events for House 1

Location	Number of Events
Dishwasher	19
Washing Machine	104
Toilet 1	267
Toilet 2	65
Shower 1	55
Shower 2	4
Outside Tap	2
Total	516

Table 11 shows the number of events at the flow meter recorded by the smart water meter and the vibration device. The data from the vibration device was subjected to only the first verification step. The difference between the two devices is considerable, with the vibration device recording 306 events fewer than the smart water meter. Figure 22 illustrates the fraction of events from both the vibration device at the water meter and the events recorded by the water meter over 24 hours. There are differences in values between the two; however, the pattern of usage between the two are similar, indicating that the vibration device at the water meter was recording actual water use events and performed relatively well.

Table 11 Number of events recorded at flow meter for House 1

Device	Number of Events at Flow Meter
Flow Meter	935
Vibration device	629

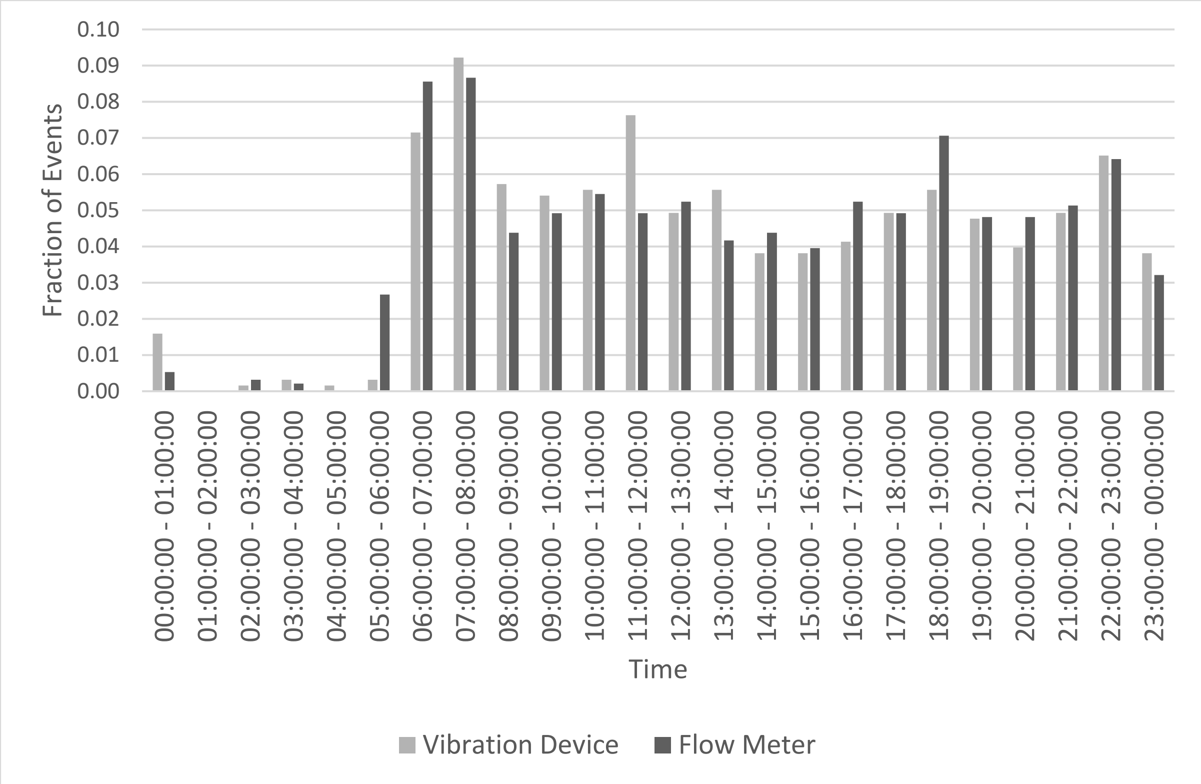

Figure 22 Fraction of events of vibration device and water meter for House 1

Inspecting the water meter flow data, the data for most of the events were untouched. However, for the events recorded for Toilet 1 and Toilet 2, the water usage seemed too high. The durations recorded by the flow meter were much greater than the duration recorded by the vibration device. The reason for the discrepancy could be that the flow meter was combining other events all into one. For example, the toilet event, a tap event and a shower event could all be captured into one event if they all occurred within one minute of each other, and that one event could be assigned to the toilet. Therefore, to rectify this discrepancy, the average flow rate for all Toilet 1 and Toilet 2 events was multiplied by the duration of the event according to the vibration device. Table 12 shows the total water used by each of the monitored end points in House 1 before and after the rectification process.

Table 12 Total water used before and after rectification for House 1

Location	**Total Water Used Before Rectification (L)**	**Total Water Used After Rectification (L)**
Dishwasher	91.7	91.7
Washing Machine	1412.4	1412.4
Toilet 1	2580.4	1422.5
Toilet 2	589.0	498.9
Shower 1	1992.8	1992.8
Shower 2	45.0	45.0
Outside Tap	152.1	152.1
Total	6863.3	5615.4

5.4.2 House 2

The testing at House 2 was conducted for 11 days from 06/04/2019 at 00:00 to 17/04/2019 at 18:00. The house had four occupants, 2 adults and 2 children for most of the study period, with some movement of people that was not accounted for, including a domestic worker, and a gardener. In total 7 devices were installed on the premises at various locations, such as the dishwasher, washing machine, two kitchen taps, the shower, a bathroom tap and at the flow meter. However, due to a suspected installation issue, the devices at the washing machine and dishwasher did not record any meaningful events. The vibration device at the flow meter was subjected to only the first verification phases as described before. Table 13 shows the number of recorded events at the flow meter by the flow meter itself and the vibration device. The data shows that the vibration device completely underperformed at the flow meter compared to the smart water meter. Figure 23 illustrates there was no correlation between the vibration device and the smart water meter at the flow meter.

Table 13 Number of recorded events at flow meter for House 2

Device	**Number of Events at Flow Meter**
Flow Meter	595
Vibration device	45

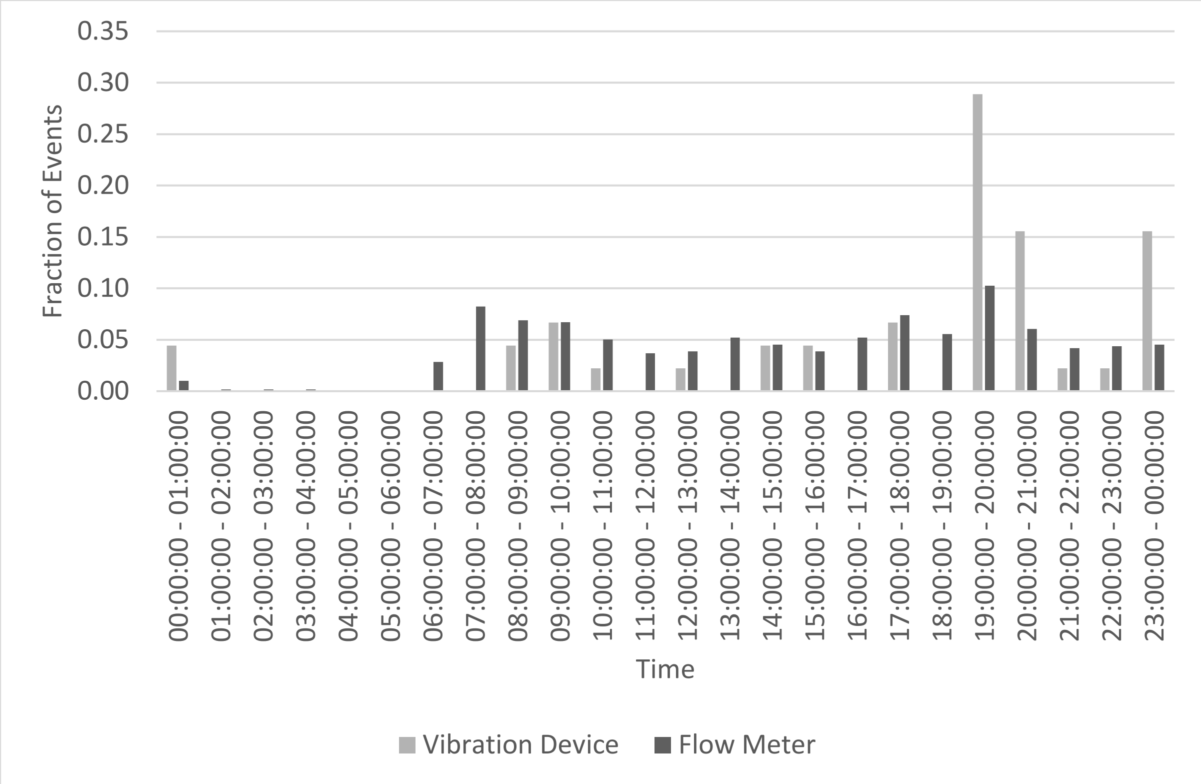

Figure 23 Fraction of events of vibration device and water meter for House 2

For the remaining four vibration devices, the two verification steps were applied. In total, from the vibration devices located at the two kitchen taps, the shower and the bathroom tap, 572 events were recorded over the 11-day period. After the first verification process which combines events that are within 1 minute of each other, the number of events decreased to 398 events and once the second verification process was completed, which matches the events recorded by the vibration device to the flow meter, the number of events decreased to 352 events. From the two verification processes an average accuracy of 88% was achieved by the vibration device. However, during the test there were spot events performed at the kitchen tap. While the vibration device did record these spot events, the flow meter, however, did not record some of the spot events. The reason for this is because the flow meter is a volumetric meter which only records an event after 500 mL has passed through the meter, so for small events the flow meter will not record these events. Therefore, in reality the accuracy of the vibration device is higher than 88%. Table 14 shows a summary of the number of events that were recorded by each vibration device, the number of events remaining after each verification process and the accuracy of the device at each location. The data shows that the vibration device works best at the shower.

Table 14 Events recorded with vibration device and verification phases for House 2

Location	Recorded Events	Events after first verification phase	Events after second verification phase	Accuracy (%)
Kitchen Tap 1	124	109	92	84.4
Kitchen Tap 2	261	148	140	94.6
Shower	14	4	4	100.0
Bathroom Tap	173	137	116	84.7
Total	572	398	352	88.4

During the 11-day period the flow meter recorded a total water usage of 4 388 L. Of the 4 388 L used, 719.2 L were characterised between the two kitchen taps, the shower and the bathroom tap; therefore, 3 669 L were not characterised. A rectification was performed on the water used for both kitchen taps and the bathroom tap. The reason for the rectification was the water consumption allocated to the events seemed high and was possibly combined with other events by other end points that were not monitored by a vibration device. There were no duplicate events recorded by any of the devices. Table 15 shows a summary of the total amount of water used at each location. The most water was used at the bathroom tap and the least amount of water used was at the shower.

Table 15 Total water used before and after rectification for House 2

Location	Total Water Used Before Rectification (L)	Total Water Used After Rectification (L)
Kitchen Tap 1	176.1	64.8
Kitchen Tap 2	400.1	289.1
Shower	153.0	153.0
Bathroom Tap	1273.8	212.3
Total	1896.5	719.2

6 Results and Discussion

The data collected from House 1 and House 2 over the test period was analysed in order to characterise water usage in both houses. An analysis was conducted on the data collected from the smart water meter and a more detailed analysis was done with the data captured by the smart water meter in combination with the vibration devices connected to specific end points.

6.1 House 1 Analysis

Over the 14-day test period House 1 used a total of 6 161 L of water. Of the total usage, 5 615 L were characterised, and 546 L were from end points unmonitored by the vibration device. On average the household used 440 L of water per day. The unit consumption was 220 L per capita per day. Table 16 highlights the water characterisation of House 1 with the percentage of total usage of each monitored end point. Comparing the percentages of total water use in Table 16 with the percentages of total water use in Table 1, the figures are relatively close in value, suggesting the vibration device worked well in capturing events around the house. Of the uncharacterised water usage, which makes up 8.86% of total water usage, the uncharacterised water is most likely from tap usage, and again, compared to Table 1, the uncharacterised percentage of total water use is relatively close to the tap usage percentage of total water use. Figure 24 illustrates the diurnal frequency of events from the end points monitored by the vibration device. Figure 24 shows that there was a significant increase in usage of Toilet 1 and Shower 1 during the morning between 05:00h and 08:00h and in the evening between 21:00h and 23:00h. There is also little to no usage during the early hours of the morning between 00:00h and 05:00h.

Table 16 House 1 water characterisation with percentages

Location	Total water used over 14 days (L)	Percentage of total household consumption (%)	Percentage of total household consumption according to Table 1 (%)
Dishwasher	91.7	1.5	1.1
Washing Machine	1412.4	22.9	18.3
Toilet 1	1422.5	23.1	7.2
Toilet 2	498.9	8.1	7.2
Shower 1	1992.8	32.3	12.6
Shower 2	45.0	0.7	12.6
Outside Tap	152.1	2.5	22.1
Total	5615.4	91.1	

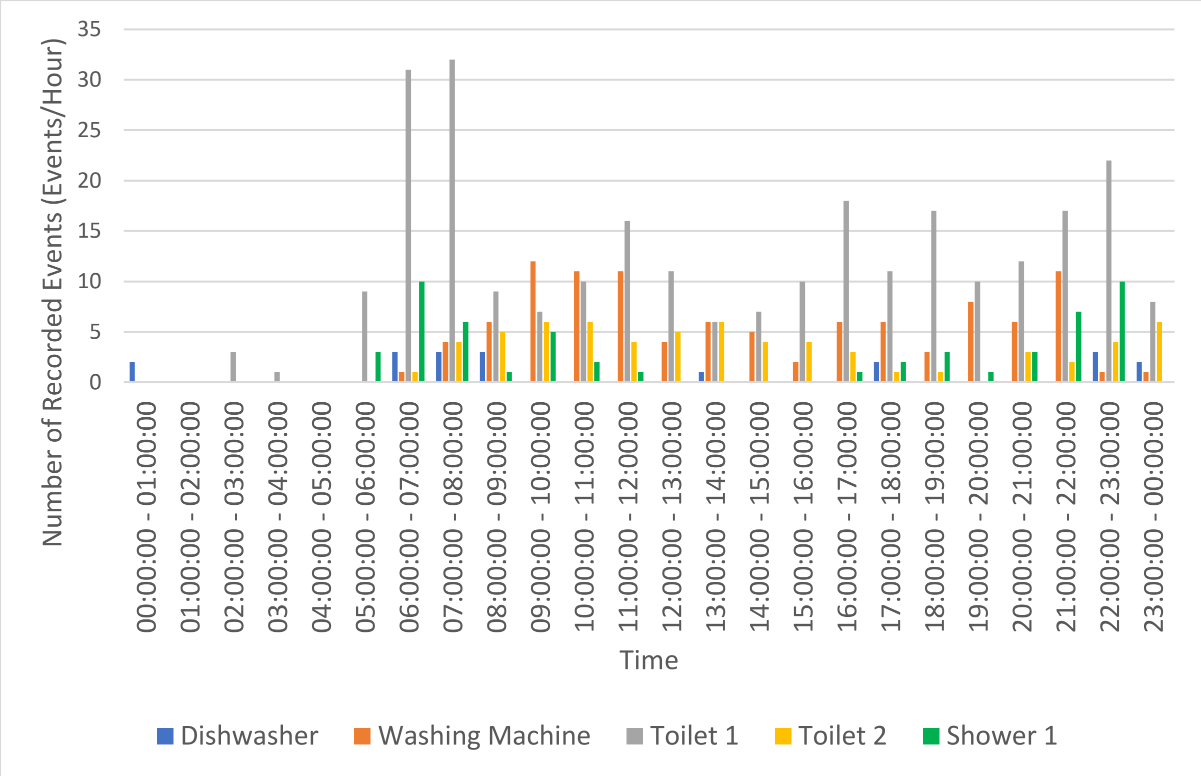

Figure 24 Diurnal frequency of monitored end points for House 1

The average water used and duration per event for each of the end points monitored by the vibration device were calculated and the results are tabulated in Table 17. The results show that the outside tap usage was the longest recorded event and used the most water; but was used the least amount with only being used twice during the 14-day test period. The dishwasher used the least amount of water per recorded event.

Table 17 Average water used and duration per event of House 1

Location	Average Water Used (L)	Standard Deviation of Water Used (L)	Average Duration (s)	Standard Deviation of Duration (s)
Dishwasher	4.8	1.5	77.4	26.1
Washing Machine	13.6	6.4	132.5	83.8
Toilet 1	5.3	7.1	35.6	48.9
Toilet 2	7.7	2.8	52.7	19.7
Shower 1	36.2	17.8	304.9	120.5
Shower 2	11.2	1.0	202.2	20.5
Outside Tap	76.0	72.0	685.7	603.9

The dishwasher and washing machine performed slightly differently to the other end points in that the dishwasher and washing machine operate by filling up with water at different points in the cycle of the machine. From the data recorded by the vibration device the different cycles are easily identified.

To identify the recorded events in the cycle of the two machines, events that were relatively close to each other were considered of the same cycle. The analysis shows that the dishwasher has on average 3 recorded events per cycle, while the washing machine has a wide range of recorded events per cycle, from 2 to 17 recorded events. By combining all the recorded events into their respective cycles, the average volume of water used by the dishwasher, per cycle, is 13.1 L and the average water used by the washing machine is 83.1 L per cycle. According to a report by Beal & Stewart (2011), a dishwasher will use between 4.1 L and 6.9 L per cycle with a standard deviation of between 5.3 L and 9.6 L. A washing machine according to the same report will use between 99.5 L and 113.8 L per cycle with a standard deviation of between 64.4 L and 77.5 L. Therefore, the results gathered by the vibration device were confirmed to be accurate. Re-analysing the data, including the number of events per cycle, the dishwasher was operating on average once per day, with some days being skipped, and a total of 7 cycles were recorded. The dishwasher's cycles last for, on average, 1 hour and 20 minutes with the events in the cycle lasting between 80 and 66 seconds. The washing machine was operating about twice a day on certain days and not at all on other days; a total of 17 cycles were recorded. The washing machine's cycle lasts for a wide range of times from about 30 minutes to about 3 hours and 30 minutes. The durations measured by the vibration device and the smart water meter do not differ significantly for both the dish washer and washing machine. For the washing machine the sum of the duration of all the events analysed was 13 778 seconds from the vibration device and 10 892 seconds from the smart water meter. The reason for the difference could be that the vibrations of the washing machine operating could influence the duration of the event according to the vibration device. For the dishwasher the sum of the duration of all the events analysed was 1 470 seconds according to the vibration device and 1 704 seconds according to the smart water meter. The reason for the difference was that, during one of the cycles a shower event was taking place at the same time the dishwasher was operating, which increased the duration for the dishwasher event according to the smart water meter.

Shower 1 consumed the most water during the 14-day study period. The data shows that the occupants were showering on average twice a day, once in the morning and once in the evening, with an average duration of 304 seconds. The longest shower recorded was 605 seconds and the shortest shower recorded was 144 seconds. The average flow rate for Shower 1 was 6.4 L/min with a standard deviation of 1.4 L/min. The average temperature that the shower was taken at was 32.1 ^{o}C with a standard deviation of 1.0 ^{o}C. The average duration of a shower in the morning was 306.5 seconds and the average duration of a shower in the evening was 303.3 seconds. Therefore, from the recorded data, there is no variation between the showers taken in the morning or the evening.

During the 14-day test period, Shower 2 was used four times which occurred twice a night for two nights. Shower 2 has a low flow nozzle attached and so the average flow rate was 3.4 L/min with a standard deviation of 0.5 L/min. The user also showered for a shorter period compared to the showers taken in Shower 1, at an average of 202.2 seconds per shower, with a standard deviation of 20.5 seconds. The longest shower recorded was 226 seconds and the shortest shower recorded was 176 seconds. The users of Shower 2 seemed to shower at colder temperatures compared to events at Shower 1 with an average temperature of 25.8 ^{o}C, with a standard deviation of 1.0 ^{o}C. The effect of the low flow nozzle on water usage can have a considerable impact. If Shower 1 had the low flow nozzle fitted, the total water used would decrease from 1 993 L to 959 L, which is a reduction of 52%.

Toilet 1 was flushed on average 19 times a day during the 14-day study period, which equates to 9.5 flushes per person per day, with the average amount of water used per flush being 5.3 L with a standard deviation of 7.1 L. According to a report by Beal & Stewart (2011), a person flushes the toilet about 8 to 10 times a day and the number of litres per flush is between 3.9 to 8.9 L with a standard deviation of between 1.1 L to 2.1 L. The average duration of a toilet filling event was 35 seconds with a standard deviation of 49 seconds. The longest filling event recorded was 427 seconds and the shortest was 4 seconds.

Toilet 2 was flushed on average 4.6 times a day. A flush on average would require 7.7 L with a standard deviation of 2.8 L. The water usage and the frequency of flushing for both Toilet 1 and Toilet 2 seems to be accurate. The average filling event for Toilet 2 was 52 seconds with a standard deviation of 20 seconds. The longest filling event was 142 seconds and the shortest filling event was 27 seconds.

The outside tap was the least used end point in the house for the 14-day test period, while the longest duration and most water used for a single event was recorded at the outside tap. The duration of the longest event was 21 minutes and the water consumed in the event was 148 L. The only other event recorded at the outside tap was relatively short at 81 seconds and consuming 4 L of water.

The vibration device worked well in House 1 with the percentage of total water used for each monitored end point matching closely with the studies involved in Table 1. The vibration device also complemented the flow data from the smart water meter well. Therefore, a large-scale study could be undertaken using the vibration device with the aid of a smart water meter.

6.2 House 2 Analysis

House 2, over the 11-day test period, consumed 4 388 L of water. Of the 4 388 L of water used 719 L were characterised between the two kitchen taps, the bathroom tap and the shower, 3 669 L of water was uncharacterised. The household on average consumed 398.9 L of water per day which equates to 99.7 L per capita per day of water. Table 18 shows the total amount of water used at each location and the percentage of the total water used at each location compared to the total water consumption. The shower event percentage does not compare well with Table 1, but the reason for the discrepancy is that the shower is not used by every member of the household consistently. However, summing the kitchen taps and bathroom tap percentages gives a percentage of 12.9% which is consistent with the tap usage in previous studies found in Table 1.

Table 18 House 2 water characterisation with percentages

Location	**Total water used over 11 days (L)**	**Percentage of Total household consumption (%)**	**Percentage of total household consumption according to Table 1 (%)**
Kitchen Tap 1	64.8	1.5	4.6
Kitchen Tap 2	289.1	6.6	4.6
Shower	153.0	3.5	25.1
Bathroom Tap	212.3	4.8	4.6
Total	719.2	16.4	

Figure 25 illustrates the diurnal frequency of events at each of the monitored end points. There are two main peak times in the data, namely in the morning between 07:00 and 10:00 and in the late afternoon between 16:00 and 20:00, there is little to no activity between 00:00 and 06:00. However, after 23:00 only the bathroom tap is used. All other end points use stops at 23:00.

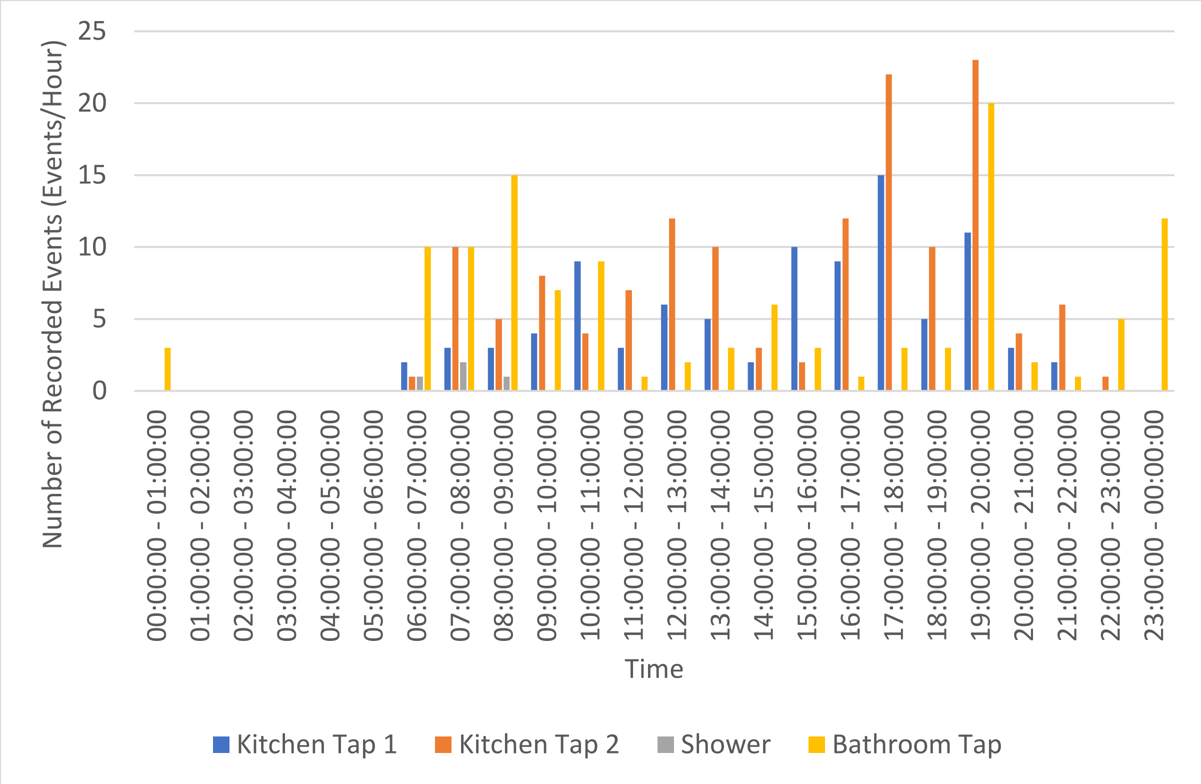

Figure 25 Diurnal frequency of monitored end points for House 2

Table 19 summarises the average water used and average duration of each event at each of the different end points. Kitchen Tap 1 used the least amount of water per event and also the shortest duration on average per event. The shower used the most water and was the longest per event. Notable variation was evident in the water used and the duration of all the events.

Table 19 Average water used and duration per event of House 2

Location	Average Water Used (L)	Standard Deviation of Water Used (L)	Average Duration (s)	Standard Deviation of Duration (s)
Kitchen Tap 1	0.7	1.1	11.5	12.3
Kitchen Tap 2	2.1	4.0	38.6	63.2
Shower	38.2	11.2	297.4	71.8
Bathroom Tap	1.8	1.7	19.2	13.9

The kitchen taps were the most used end points during the 11-day test period, with 232 events recorded between both taps. At kitchen Tap 1 the average amount of water used per event was 0.7 L with a standard deviation of 1.1 L. The tap was used on average 8 times a day with an average duration of 11.5 seconds with a standard deviation of 12.3 seconds per event. At kitchen Tap 2 the average amount of water used per event was 2.1 L with a standard deviation of 4.0 L. The tap was on average used 13 times a day with an average duration of 38.1 seconds, and with a standard deviation of 63.2 seconds per event.

At kitchen Tap 2 there were also hot water events according to the temperature sensor. A hot water event at a tap is a temperature reading of over 27.0 ^{o}C. In total there were 27 hot water events and 106 cold water events. Of the 27 hot water events a total of 191 L of water was used, with an average of 3.0 L of water per event, and with a standard deviation of 4.9 L. The average temperature of a hot water event was 29.0 ^{o}C with a standard deviation of 0.7 ^{o}C. The maximum temperature of a hot water event was 30.3 ^{o}C.

The shower was used a total of 4 times over the 11-day period. All 4 shower events took place in the morning but on varying days. The average duration of a shower was 297.4 seconds with a standard deviation of 71.8 seconds. The longest shower event was 420 seconds and the shortest was 239 seconds. A shower event on average used 38.3 L of water with a standard deviation of 11.2 L of water. The average temperature of a shower event was 30.1 ^{o}C with a standard deviation of 0.2 ^{o}C. The average flow rate for a shower event was 7.4 L/min with a standard deviation of 0.1 L/min. Therefore, there was little variation in the type of shower in terms of temperature and flow rate.

The bathroom tap used the most water in total over the 11-day test period. On average 1.8 L of water was used per event with a standard deviation of 1.7 L of water. The average duration of a bathroom tap event was 19.2 seconds with a standard deviation of 13.9 seconds. The longest event was 64.0 seconds and the shortest event was 4.0 seconds. There were hot water events that were detected by the temperature sensor. The number of events that were over 27 ^{o}C was 24 events. Of the 24 events the average temperature was 31.0 ^{o}C with a standard deviation of 2.8 ^{o}C. The average duration of a hot water event was 29.4 seconds with a standard deviation of 16.7 seconds. The average amount of water used per hot water event was 3.6 L of water with a standard deviation of 2.5 L of water.

The vibration device worked well in House 2. There were some suspected installation issues which prevented the recording of events at the dishwasher and washing machine; however, with the devices that did record properly the results were logical. For long events the vibration device and flow meter complemented each other; however, for short events the smart water meter did not record well.

6.3 Remarks

The vibration device performed well in both tests at House 1 and House 2. The addition of flow data complemented the vibration device well in both occasions; however, for short events at taps the flow meter did not record the event well. Therefore, a smart water meter with a higher resolution should be used in future tests to accurately record low volume events. The vibration device could also function without the assistance of a flow meter in those cases, where only event activity state needs to be assessed.

In terms of the general performance of the vibration device, the IOT capabilities of the device worked as expected. The devices were able to reliably connect to the internet. There were some instances where, for a particular day, the device failed to connect, but the next day was able to connect and upload data (including the missing day). The connection behaviour was expected as seen in the pilot study. The website where all the data was uploaded performed well and data was easily accessible through the website and used in Microsoft Excel. In terms of battery performance, the voltages of all the vibration devices was checked after the test and the discharge was consistent with a 50-day battery life.

7 Conclusion

7.1 Summary of Findings

The characterisation of household water use with a non-intrusive sensor was completed successfully, with pilot tests and subsequent field experiments performed at two homes. A non-intrusive sensor was developed to record the vibrations in a pipe caused by water flowing. The vibration device was IOT compatible and could identify start times, durations and temperatures of water use events. In the two tests that were conducted the vibration device had an accuracy of 88% to 76% in recording actual events.

In terms of identifying start time and duration, the vibration device, provided acceptable precision. The device's temperature sensor compared well with a calibrated, independent temperature probe. The durations of a series of test-events recorded by the vibration device were almost exactly the same as that recorded on a stopwatch. The device was IOT compatible and uploaded the data recorded on the SD card to an online platform, using the Wi-Fi on the premises. The website was secured with a username and password for login, so information was secure and could only be accessed by those involved with the project.

The vibration device was created with electronic components that were readily available in South Africa. The vibration device cost approximately R1 000 per device. The vibration device could remain active for 50 days with a fully charged battery pack and could last indefinitely with the solar panel attached if placed in direct sunlight. The cost of the vibration device could be reduced to approximately R700 by using only one battery and no solar panel.

Two homes were involved as part of a case study. The research undertaken at House 1 included all water use end points, besides taps. The characterisation of all the end points monitored correlated well with data found in previous studies, with the remaining uncharacterised amount matching closely to what could be expected from tap usage. The results from House 1 showed usage of 220 L per person per day. The vibration device performed well in characterising household water use events in House 1. The research undertaken at House 2 focused mainly on tap events. There were some installation issues, which meant that data recorded from washing machine and dishwasher use was not available. Tap usage activities were a complex issue as the volumetric flow meter did not record an event at the exact time if less than 500 mL was used (the pulse volume of the water meter was 500 mL). Therefore, the vibration device would have recorded events that were not recorded by the flow meter hence, for tap use events, the flow meter did not complement the data recorded by the vibration devices. The results compared well to previous studies. Water use at House 2 was 99 L per person per day.

The results suggest that a large-scale study could be done with vibration devices to characterise household water usage, provided that data would be handled automatically and would be analysed by an AI agent, because manual procedures would be cumbersome for many homes. Refinement of the installation process should be performed in order to prevent issues of the vibration device not recording events because of an error at installation.

7.2 Future Research Needs

The Atmega Atmel 1284P-PU MCU used in this research does not provide native support for Wi-Fi operations; therefore, a separate Wi-Fi module needed to be added for the project. Also, to achieve the 50-day battery life, components were needed to turn the Wi-Fi module on and off when needed, these components add to the cost of the vibration device. A solution would be to use an MCU that is Wi-Fi enabled (e.g. ESP8266-12F). The Atmega Atmel 1284P-PU needed to be clocked at 8 Mhz to increase battery life, while the ESP8266-12F can be clocked at 80 Mhz and can still consume the same amount of power as the Atmega Atmel 1284P-PU MCU. The reduced part count should also reduce the cost of the device and eliminate some complexities in the circuit which will improve reliability and power consumption. Therefore, the ESP8266-12F should reduce the cost of the device, improve reliability and solve the network issues that were encountered.

A swop of the SD card module and SD card should also be considered. In the current vibration device, the old standard size SD card is used. A swop to the micro SD card and SD card module should be done to remain with current technology standards and to reduce the footprint inside the vibration device.

The temperature sensor attached to the vibration device could be used to add value. The hardware is already present; therefore, only software implementation is needed to achieve added value extracted from temperature recordings, especially in view of the water-energy nexus. Hot water requires more energy and saving hot water translates directly to energy savings as well.

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