Smart Plumbing Systems for Households:

Event characterisation and anomaly detection through the monitoring and analysis of transient pressure

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Executive Summary

Researchers at Deakin University conducted pressure monitoring in several residential houses in Victoria, Australia. Pressure data was collected via a dual-channel high frequency data acquisition device connected to both the cold water and heated-water pipes. Typical locations included fixtures at washing machines or underneath kitchen and bathroom sinks. Pressure data was collected at ~925Hz for each channel continuously for several weeks. Study participants also periodically recorded date and time of fixture use events to support the research.

The project's focus was to explore the usefulness of pressure data to perform event and anomaly detection in residential plumbing systems. Fixture and appliance events were detected from pressure data by using the rapid fall (event start) and rise (event finish) observed from pressures and applied to a modified cumulative sum algorithm. Detected event windows were then processed to extract relevant statistical and time and frequency domain features that were integrated into a k-means algorithm, which is an unsupervised machine learning model that is effective in detecting similar behaviours and patterns in data. Principal component analysis and the dynamic time warping algorithms were used to demonstrate the effectiveness of k-means in separating several discernible patterns in select houses. The event and anomaly detection appeared to perform better in homes with metallic pipework compared to those with plastic pipework, which presented challenges in extracting meaningful differences across detected events. Nonetheless, the research provides a strong proof of concept for pressure data to be used as an effective means for monitoring the operating conditions of residential plumbing systems.

The collected pressure data also offered valuable insights toward policy and guidance. The pressure data showed that some of the plumbing systems monitored were regularly subjected to "excessive pressures" greater than the maximum pressure allowable (500 kPa) by the Australian plumbing standard (AS/NZS 3500). The findings to date specifically highlight three critical issues:

1) systemic over-pressure: properties without boundary pressure control are influenced the main's pressure fluctuations, often exceeding the maximum pressure limit;
2) thermal expansion: water heating cycles cause significant pressure rises in systems with heated water storages; and
3) transient pressure entrapment: check-valves within modern "mini stop taps" can trap hydraulic transients (water hammer) within the braided hose between the tap and the water fixture.

While the sample size of monitored households is small, the behaviours of specific components monitored such as heated water storage units and "mini-stop" taps are

commonly used items that feature in most modern residential plumbing systems suggesting that the issue of excessive pressure and non-compliance with plumbing standards is not uncommon in Victorian houses.

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Glossary of Terms

Anomaly detection
The process of identifying unusual or unexpected behaviour in the plumbing system. In this report, anomaly detection refers to using pressure data to find events or pressure patterns that may indicate abnormal operation.

Artificial intelligence (AI)
Computer-based methods that can identify patterns, make decisions or support analysis. In this report, AI refers to the use of data analytics and machine learning to help interpret plumbing pressure data.

AS/NZS 3500
The Australian and New Zealand plumbing and drainage standard.

Backflow
The reverse movement of water through a plumbing system. Backflow can create a contamination risk if water flows in the wrong direction.

Braided hose
A flexible hose commonly used to connect fixtures and appliances to the plumbing system. The report notes that braided hoses may be affected by trapped transient pressures.

Cavitation
A process where small vapour or air pockets form and collapse within water. Cavitation can damage internal pipe surfaces over time.

Check valve
A valve designed to allow water to flow in one direction only. In this report, some check valves are discussed as potentially trapping transient pressure in parts of the plumbing system.

Creep
Slow deformation or long-term material strain caused by sustained pressure. In this report, creep is mainly relevant to plastic pipework exposed to static pressure over time.

Cumulative pressure-induced stress (CPIS)
A measure used to describe the cumulative effect of repeated pressure changes in a plumbing system. It helps compare the potential impact of transient pressure events across different houses.

Cumulative sum algorithm (CUMSUM)
A method used to detect changes in data over time. In this report, a modified CUMSUM algorithm is used to detect sudden pressure changes linked to fixture or appliance use.

Damage index
A calculated indicator used to compare the relative effect of observed pressure conditions across study houses. It is not intended to directly predict pipe failure or remaining service life.

Data acquisition device (DAQ device)
The monitoring device used to collect pressure data from household plumbing systems. In this study, each device was connected to pressure transducers on cold and heated water pipes.

Diurnal pressure profile
The average pressure pattern observed across a day. In this report, diurnal pressure profiles are used to show how pressure changes over a typical 24-hour period.

Down surge
A sudden drop in pressure. This often occurs when a fixture or appliance starts using water.

Dynamic time warping (DTW)
A method used to compare two pressure signals that may have similar shapes but occur at slightly different speeds or times. It helps determine whether two events are similar.

Event characterisation
The process of describing the features of a detected pressure event. This may include its size, duration, shape, frequency content and other measurable properties.

Event detection
The process of identifying when a pressure event has occurred in the data. In this report, event detection is used to find pressure changes linked to fixture and appliance use.

Event window
The section of pressure data that contains a detected event. This window is used for further analysis and feature extraction.

Feature
A measurable property of a pressure signal used for analysis or machine learning. Examples include peak amplitude, duration, slope, settling time, dominant frequency, skewness and kurtosis.

Frequency-domain feature
A feature that describes how a pressure signal behaves in terms of frequency. These features can help identify repeated patterns or mechanical signatures in pressure data.

Heated water service
The part of the household plumbing system that supplies heated water to fixtures and appliances.

Hoop stress
Stress that acts around the wall of a pipe due to internal pressure. It is relevant when considering how pressure may affect pipe materials.

Internet of Things (IoT)
A network of connected devices that can collect and transmit data. In this report, IoT refers to pressure monitoring devices that collect plumbing system data and send it for analysis.

k-means clustering
A machine learning method that groups similar data points together. In this report, it is used to group pressure events with similar features or signal shapes.

Kilopascal (kPa)
A unit used to measure pressure. In this report, household plumbing pressure is reported in kPa.

Machine learning (ML)
A type of data analysis where algorithms identify patterns in data. In this report, ML is used to explore whether pressure events can be grouped or recognised based on their signal features.

Mini-stop tap
A small isolation tap commonly installed near fixtures and appliances. In this report, mini-stop taps with check valves are discussed because they may trap pressure transients in some plumbing arrangements.

PEX
Cross-linked polyethylene pipe. This is a type of plastic pipe used in plumbing systems. PEX can dampen pressure transients but may be more affected by long-term static pressure and temperature.

Piecewise approximation aggregation (PAA)
A data processing method that reduces detail in a signal by averaging values over set windows. In this report, it is used to support event detection and reduce noise.

Piecewise-linear approximation (PLA)
A method that simplifies a pressure signal into straight-line segments. In this report, it is used as part of the inflexion coding process.

Pressure limiting valve (PLV)
A valve used to limit the maximum pressure entering or within a plumbing system.

Pressure reducing valve (PRV)
A valve used to reduce incoming water pressure to a lower controlled pressure.

Pressure transducer
A sensor that measures water pressure and converts it into an electrical signal that can be recorded by a data acquisition device.

Principal component analysis (PCA)
A data analysis method used to reduce complex datasets into fewer dimensions while retaining important patterns. In this report, PCA is used to help visualise how pressure event clusters separate from each other.

Rainflow counting
A method used to count repeated pressure cycles in a signal. It supports the calculation of pressure-related stress indicators.

Residual pressure
The pressure in the plumbing system while water is flowing.

Root mean square (RMS)
A statistical measure used to describe the overall size or energy of a signal.

Smart plumbing system (SPS)
A plumbing system that uses sensors, data collection and analytics to monitor performance and support better operation, maintenance or fault detection.

Static pressure
The pressure in the plumbing system when no water is being used.

Temperature and pressure relief valve (TPR valve)
A safety valve fitted to heated water storage systems. It releases water when temperature or pressure becomes too high.

Thermal expansion
The increase in water volume that occurs as water is heated. In heated water storage systems, thermal expansion can increase pressure.

Transient pressure
A short-term change in pressure caused by a change in flow conditions, such as a tap opening or closing.

Upsurge
A sudden increase in pressure. This often occurs when a fixture or appliance stops using water.

Water hammer
A layman's term used to describe a pressure surge caused when moving water is suddenly stopped or redirected (transient pressure event). It can create vibration, noise and repeated pressure stress in the plumbing system.

1 Introduction

Transient pressures are the momentary change in pressures that occur over time. Opening or closing a fixture within a plumbing system (e.g., by turning on a tap), disrupts the steady-state pressure and flow conditions, creating these temporary pressure changes.

Figure 1 presents an example of measured pressure over time during a short duration tap usage event. At point A, the tap is opened (valve opening) and a momentary pressure drop (down surge) is observed. Shortly after, the pressure settles and finds a new steady-state. Then when the tap is closed (point B), the steady state is interrupted again, but this time, the momentum of water hits a dead end instantly, resulting in a pressure spike, or up surge (point C). Because water is incompressible, it can’t "squish" to absorb the impact. Instead, the energy creates a shockwave that reverberates back and forth through the pipe, until the energy dissipates as shown by the ripples after the valve closure at point D, before returning to a steady-state once again.

The term “water hammer” is derived from the loud bang or thud noise commonly heard within walls of houses with copper (metallic) pipework immediately after a tap is turned off or when an appliance (e.g., washing machine) completes filling. The audible bang is a by-product of pressure surge that occurs when moving water is forced to stop or change direction suddenly. The resulting shockwave transmits energy through the plumbing system, and can cause pipes to vibrate, rattle, or strike against surrounding structural elements (e.g., framing).

In modern plumbing systems constructed from plastic materials, water hammer effects are still present, but the magnitude and audible impact are reduced. The inherent flexibility of plastic pipes allows them to momentarily expand under pressure, absorbing part of the transient energy and reducing the pressure spike, negating the audible noise.

As shown Figure 1, pressure transients can induce both low- and high-pressure extremes within plumbing systems. Low pressure events may result in negative pressures, which can lead to backflow (reverse flow) and cavitation within pipework. Back flow poses a risk of introducing contaminants into a house’s plumbing system, while cavitation can cause internal pipe damage as small pockets of air explode on the pipe wall. High pressure spikes are also of concern, as repeated water hammer events can lead to progressive degradation of plumbing components. This may include the development of leaks at joints due to sustained vibration, which weakens soldered and threaded connections. In more severe cases, extreme pressure spikes can cause pipe deformation or rupture. Additionally, elevated transient pressures can accelerate wear in fixtures and appliances by stressing internal valve components, shortening their lifespan.

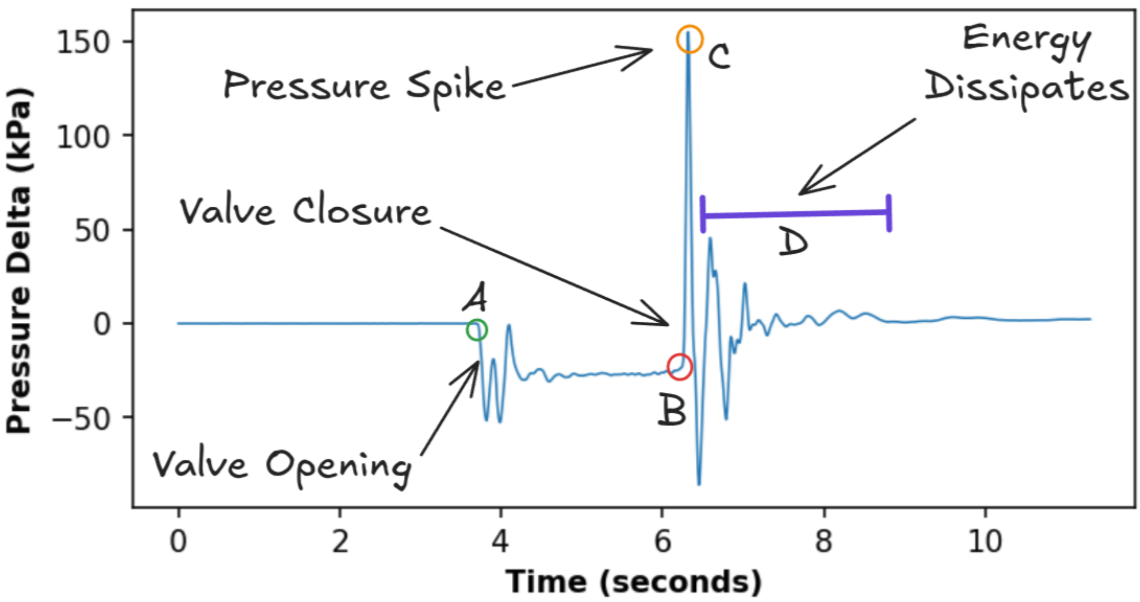

Figure 1 – Example of a transient pressure event generated by a fixture opening and closure.

Beyond their potential to cause damage, transient pressures can also serve as a powerful diagnostic tool for assessing pipe condition and detecting leaks. Pressure waves travel at a known speed determined by the pipe's material and wall thickness, and their behaviour changes predictably when encountering physical anomalies. When a transient wave travels through a distribution system, a portion of that energy is reflected toward the source whenever it hits a change in the pipe's environment. By analysing these reflected signals (or "echoes"), engineers can identify leaks, which act as damping points that dissipate energy and produce distinct reflection patterns. Additionally, the speed at which the wave travels (celerity) can provide insight into the internal state of the infrastructure; for example, a slower-than-expected wave may indicate internal corrosion or reduced pipe wall stiffness. These transient-based detection techniques are primarily used by large municipal water utilities to assess the condition of underground assets. By enabling the detection of issues without excavation, they offer a non-invasive and efficient means of evaluating system health, reducing the need for disruptive and time-consuming investigative methods.

However, the application of transient pressure analysis within a house or building-scale plumbing system remains relatively under-explored. This research project aims to undertake foundational data collection and methodological development to support the integration of “smart water” technologies at the house level, with the objective of improving understanding of pressure conditions in residential plumbing systems.

Key objectives of this project include:

1) gathering of high-resolution pressure data in household plumbing networks (10 houses);

2) a detailed analysis of steady-state and transient pressure to quantify code compliance and risk toward pipe fatigue/failure;
3) development of smart classification algorithms (ML+AI) to differentiate fixture use events and learn “normal” system behaviours; and
4) based on the results, providing recommendations on policy updates and future work.

Specifically, the project addresses the research question *“how can the Internet-of-Things (IoT)-based sensing, combined with machine learning (ML) and artificial intelligence (AI)-enabled data analytics, be leveraged to develop smart plumbing systems (SPS) and enhance the design, operation and proactive maintenance of cold and heated water services?”*

2 Methodology

2.1 Recruitment Process

To recruit study houses, the research team first obtained ethics approval in line with Deakin University’s ethics policy and guidelines. An opt-in recruitment approach was adopted, where the study was publicly advertised on LinkedIn using both the BPC and researcher profiles and interested households voluntarily registered their interest in participating.

Following ethics approval, an expression of interest platform was launched. Interested households were subsequently invited to participate in an interview to discuss the study in detail and confirm their eligibility. To qualify for participation, households and participants were required to meet the following criteria:

1) the participant is over 18 years of age
2) the study house is owner-occupied, with permission granted to temporarily modify the house’s plumbing system
3) the property is a single, detached dwelling located in Melbourne or Geelong
4) the participant is proficient in English, and
5) the participant is comfortable completing a survey using web-based applications.

The requirement for owner-occupied dwellings ensured that any modifications to the plumbing system were authorised and did not affect rental properties without appropriate consent. The focus on single or detached dwellings was intended to minimise interference from pressure events within the broader water distribution system. For example, in properties without individual water service lines, fixture usage in one dwelling may be detectable in an adjacent home, potentially impacting the study results.

Once prospective households were confirmed as eligible, participants were required to review and sign a Plain Language and Consent Form, providing written confirmation that they understood the study requirements. A copy of this form is provided in **Appendix A**.

There were no incentives in the form of cash or gifts exchanged for participating in the study. In some cases, the research team provided houses with a personalised report regarding the pressure data collected at their property.

2.2 Data Collection

2.2.1 Pressure Data

To undertake research objective 1, pressure data were collected from participating households using a high-frequency data acquisition (DAQ) device (Figure 2), each connected to two pressure transducers with a measurement range of 0-1000kPa. At each monitoring location, one transducer measured cold-water pressure and the other measured heated-water pressure (Figure 2). In total, two DAQ devices were installed at separate locations within each house, typically at washing machines or underneath kitchen and bathroom sinks. All sensing equipment was installed by licensed plumbing practitioners.

The DAQ units were developed and constructed by Deakin University researchers. Each unit comprises a Raspberry Pi 5 (small board computer) with 8Gb of ram and 64Gb SD card for internal storage, coupled with a WaveShare ADS1256 Analogue to Digital Converter (ADC) and a custom-built 240V AC to 24V DC power converter.

Pressure data were recorded at approximately 925Hz per channel, with each transducer corresponding to an individual data channel. All samples were time-stamped and chunked into 10-second intervals stored in a binary file format. These files were saved locally on the device and simultaneously pushed to a cloud-based platform for post-processing. This setup enabled near real-time access to pressure data for participating households (Figure 3).

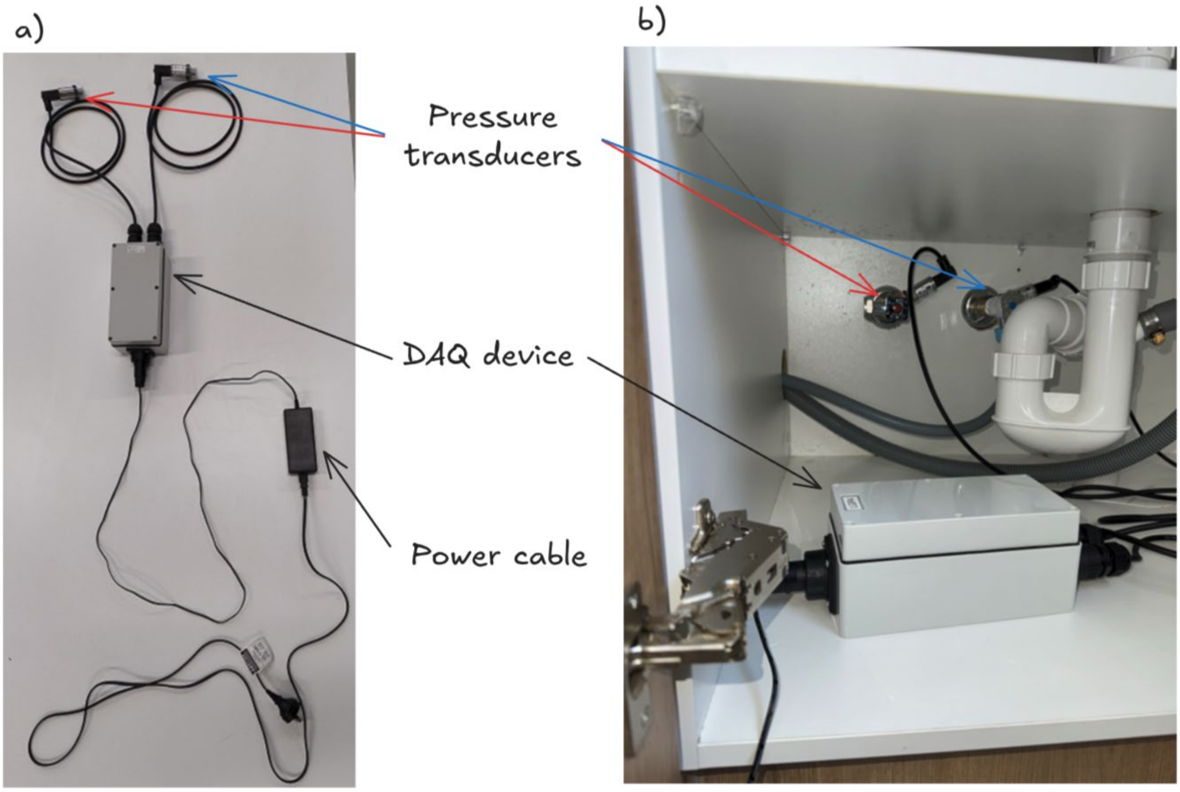

Figure 2 - a) a DAQ device connected with two pressure transducers, and b) a DAQ device installed in line with cold and heated water pipes under a sink

Figure 3 - Example of dashboard for study households to view live pressure data.

2.2.2 Household Fixture and Appliance Data

To complement the pressure data, each participating household completed a survey capturing key demographic information, including occupancy characteristics, the age of the building, and types of water-using fixture and appliances present. A copy of the household fixture and appliance survey is provided in **Appendix B**.

In addition to completing the household fixture and appliance survey, participating households were requested to periodically record the time, data and type of fixture or appliance used during the monitoring period. This was completed via a web-based application developed by the research team (see Figure 4). Household occupants were requested to provide at least five recorded instances of water use for each fixture type. The logged event data were subsequently used to support the classification of pressure signals for event recognition algorithms.

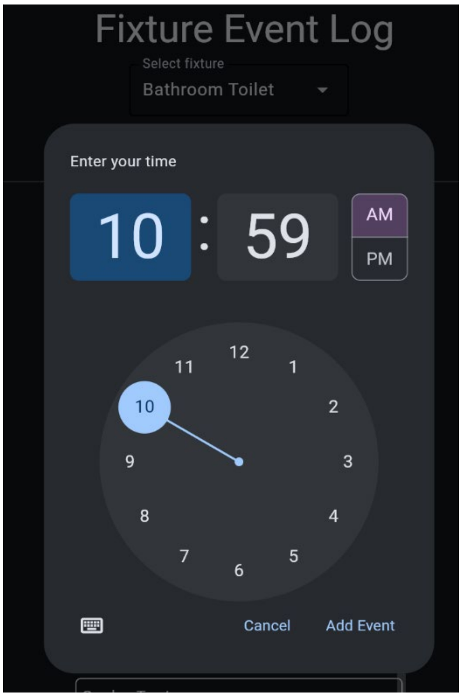

Figure 4 - Screenshot of fixture and appliance event logging application.

2.3 Data Analysis

2.3.1 Diurnal Pressure Profile

To present the diurnal (average hourly) pressure profiles for each study house, data for both cold and heated water services were aggregated into mean 10-second pressure, across each separable 10-second window across an entire day (n=8640). In instances of data loss, the study evaluated available data on a "per hour basis", where only hours that have data for 95% of the hour were included in the datasets.

A 10-second interval was selected to minimise the influence of short-duration transient events, providing a more realistic representative measure of static (no water use) and residual (water in use) pressure conditions at each monitoring location.

The resulting 10-second pressure values were subsequently grouped into hourly bins (360 10-second observations per hour for each day) to calculate the average pressure for each hour across of the day (n=24).

2.3.2 Compliance with AS/NZS 3500 Pressure Requirements

The Australian standard AS/NZS 3500 is the Deemed to Satisfy provision for plumbing and drainage systems defined in Volume 3 of the National Construction Code: Plumbing Code of Australia.

The research project assessed each house against the key pressure performance requirements specified within AS/NZS3500, which stipulate that pressure at fixture points must not exceed 500kPa and must remain above a minimum of 50kPa (Standards

Australia, 2025a, 2025b). Compliance was quantified by the percentage of time that both cold and heated water services operated within the defined range of 50-500kPa. This was calculated based on the aggregated mean pressure for each 10-second period.

2.3.3 Damage Index

To facilitate comparison of the impacts of transient and static pressures across study houses, an average hourly damage index was developed, incorporating both cumulative pressure-induced stress (CPIS) and creep stress. CPIS provides a measure of the dynamic effects associated with transient pressure events (i.e., water hammer) (Hoskins, 2015; Rezaei, 2017), while creep accounts for the influence of sustained static pressures on the system.

Modern plumbing systems may comprise of copper (metallic), plastic, or a combination of both pipe materials, each exhibiting distinct behaviours when considering fatigue and failure modes. Metallic pipework is rigid, so it tends to produce stronger water hammer spikes. These repeated pressure spikes can contribute to wear and damage over the life of the pipe. In contrast, plastic pipework is less rigid and is effective in absorbing the energy from water hammer events but more susceptible to “creep” from static pressures over time. Additionally, plastic pipes are temperature-sensitive with lower allowable pressure limits as temperature increases. In practice, metallic pipework is assumed to be immune from creep.

The damage index presented in this study is not intended to directly predict fatigue in the system or remaining service life. Rather, it serves as an indicator of the relative influence of observed pressure conditions across the system over a 24-hour period. For houses containing metallic pipework (n=7, see Table 3), damage index values were calculated for both copper (metallic) and plastic pipe conditions. This is because braided lines are still likely to exist in each house, giving an indication of damage across different materials within the same plumbing system.

2.3.3.1 Cumulative Pressure Induced Stress (CPIS)

Transient pressures include both sudden and gradual changes in pressure. Sudden high amplitude pressure variations can accelerate crack growth and lead to failure in pipework, while low amplitude and gradual pressure variations can contribute to crack initiation and propagation over time (Konstantinou et al., 2024). Cumulative pressure induced stress (CPIS), as shown in Eq. (1), is recognised as a comprehensive metric in assessing the cumulative impacts of transient pressures over time. $CPIS$ considers the mean pressure, P_{mean} and the dynamic pressure to determine a “damage index” aligned with pressures experienced for a specific section of interest within a water distribution system. P_{mean} is taken as the average “1-hour diurnal pressure” and forms the baseline pressure for each pressure amplitude collected for a specific hour. The dynamic portion of $CPIS$ evaluates each identified cyclic loading event (M) and combines the pressure amplitude, σ_a, and the number of cycles, n_a, for each pressure variation event (a).

$$CPIS = \sum_{a=1}^{M} [(\sigma_a \cdot n_a) + P_{mean}] \tag{1}$$

The inclusion of P_{mean} infers that a higher mean pressure for the same pressure amplitude, σ_a, and number of cycles, n_a, contributes a higher effective stress contribution that accumulates fatigue damage faster. In the current study's context, an assumption is that P_{mean} will likely operate near static pressure for a given hour. Elevated cycle quantities (n_a) infer a specific system that takes longer to dissipate the transient event, or greater transient activity (more water use events), exposing the system to elevated pressure variations for longer, with the potential to increase pipe stress over time. By analysing $CPIS$, the current study can demonstrate the differences between the amplitudes of transient pressure as well as the quantity (number of times) each system is subjected to specific transient pressure across study households.

To determine the $CPIS$, collected pressure data was aggregated to 100Hz, and was pre-processed via inflexion coding and cycle counting. The inflexion coding implemented a piecewise-linear approximation (PLA) that consists of quantisation, step removal, and extrema detection stages (Figure 5). For the current study, quantisation of data determines a step change for a pressure variation of 5kPa. Cycle counting implements an improved rain flow counting algorithm, where amplitudes less than 30kPa are excluded from cycle counts. Technical details on this implementation can be found in Hoskins (2015) and Rezaei (2017).

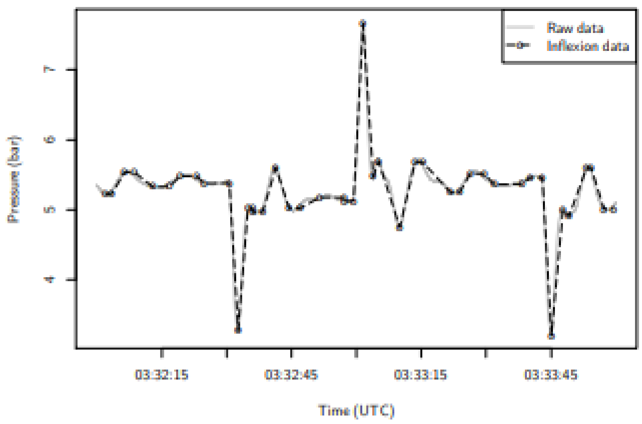

Figure 5 – Example of raw pressure signal and inflexion coding from (Hoskins, 2015)

2.3.3.2 Damage Index Formulas

A damage index is presented for both metallic (copper) and plastic (PEX) pipework. For copper pipes, the damage index focuses on the dynamic effects of transient pressures through the use of CPIS.

The copper pipe damage index employs Miner's rule, a linear cumulative damage model that compares the total number of cycles a material can withstand at a given stress (N_i) with the number of cycles (n_i) observed at that given stress amplitude, see Eq. (2). N_i is calculated using the Basquin equation [Eq. (3)], that considers the stress amplitude σ_i (hoop stress), the fatigue strength, σ_f, and the fatigue strength exponent, b. For this study the fatigue strength and fatigue exponents for copper pipework are estimated as $\sigma_f = 250MPa$ and b = -0.12 respectively. Pipe dimensions are assumed to be a DN20 Type B copper with an internal diameter (d_n) of 17.0mm and a wall thickness (e_n) 1.02mm (International Copper Association Australia, 2021).

$$D_{copper} = \sum \frac{n_i}{N_i} \tag{2}$$

$$N_i = \left(\frac{\sigma_i}{\sigma_f}\right)^{1/b} \tag{3}$$

$$\text{(hoop stress) } \sigma_i = \frac{CPIS(d_n)}{2e_n} \tag{4}$$

Plastic pipes are more effective at absorbing transient pressures spikes. Data suggest that cross-linked polyethylene pipes (PEX) vastly improves the material's resistance to slow crack growth compared to standard polyethylene pipes (PE) (Pinter et al., 2016). However, there does not currently appear to be an accepted "cyclic fatigue" model for PEX pipework. Instead, lifetime predictions are typically based on static stress and temperature conditions (Munier et al., 2002), as PEX is more susceptible to pressure creep due to the prolonged exposure to static pressure over time.

The damage index for PEX pipework is presented in equation Eq. (5). It is a ratio of the average hourly pressure P_{mean} and the allowable pressure rating PEX pipe is rated for its 50-year service life, P_{allow}. A ratio of 1.0 identifies the pressure at that current hour is aging the pipe in accordance with its expected design life. Separate P_{allow} values are used for cold and heated water pressures. For the current study, P_{allow} values for cold and heated water are 1,055kPa (23°C) and 795kPa (65°C) respectively. These values are retrieved from the REHAU PEXa Desing and Installation manual (REHAU, 2023). These design values generally have a safety factor of 2 or more.

$$D_{pex} = \sum \frac{P_{mean_i}}{P_{allow}} \tag{5}$$

2.4 Event Detection and Characterisation

To support the broader aim of developing smart plumbing systems using IoT-based sensing and data analytics, this component of the research focused on event and anomaly detection within residential plumbing systems. High-frequency pressure data collected from the data acquisition device described in Section 2.2.1 Pressure Data is analysed to determine whether plumbing fixtures and household appliances generate consistent and repeatable pressure patterns.

The identification of these patterns enables the detection of specific usage events, as well as the recognition of abnormal system behaviour.

This section outlines the methodology developed to:

1) detect the occurrence of transient pressure events; and
2) characterise the properties of the detected events using the k-means clustering algorithm.

2.4.1 Event Detection

To detect transient pressure events, 925Hz data was aggregated to 100Hz to suppress high-frequency noise and improve computational efficiency. Event detection was aimed at extracting both the down surge (associated with fixture opening) and upsurge (associated with fixture closing). The data were further pre-processed using piecewise approximation aggregation (PAA), which calculates the mean value over a defined window (w) of observations. The size of this window was adjusted between houses to improve event detection.

The core detection process is based on a modified cumulative sum (CUMSUM) algorithm, following the approach presented by Xing and Sela (2019), see Eq. (6) and Eq. (7). The algorithm incrementally calculates the cumulative change in pressure $[dp(t)]$ in both a positive (c^+) and negative directions (c^-) at each time step (t). It suppresses small pressures fluctuation set by the drift parameter (k). The c^+_{real} and c^-_{real} are used to track the true cumulative change. When the cumulative change reaches a threshold, an event is detected, the end of the event is selected when the cumulative sum reaches zero considering the absolute maximum value of c^+_{real} and c^-_{real} simultaneously (Figure 6).

$$\begin{Bmatrix} dp(t) = p(t) - p(t-1) \\ c^+(t) = c^+(t-1) + dp(t) - k \\ c^-(t) = c^-(t-1) - dp(t) - k \end{Bmatrix} \tag{6}$$

$$\begin{Bmatrix} c^+_{real}(t) = c^+_{real}(t-1) + dp(t) \\ c^-_{real}(t) = c^+_{real}(t-1) - dp(t) \end{Bmatrix} \tag{7}$$

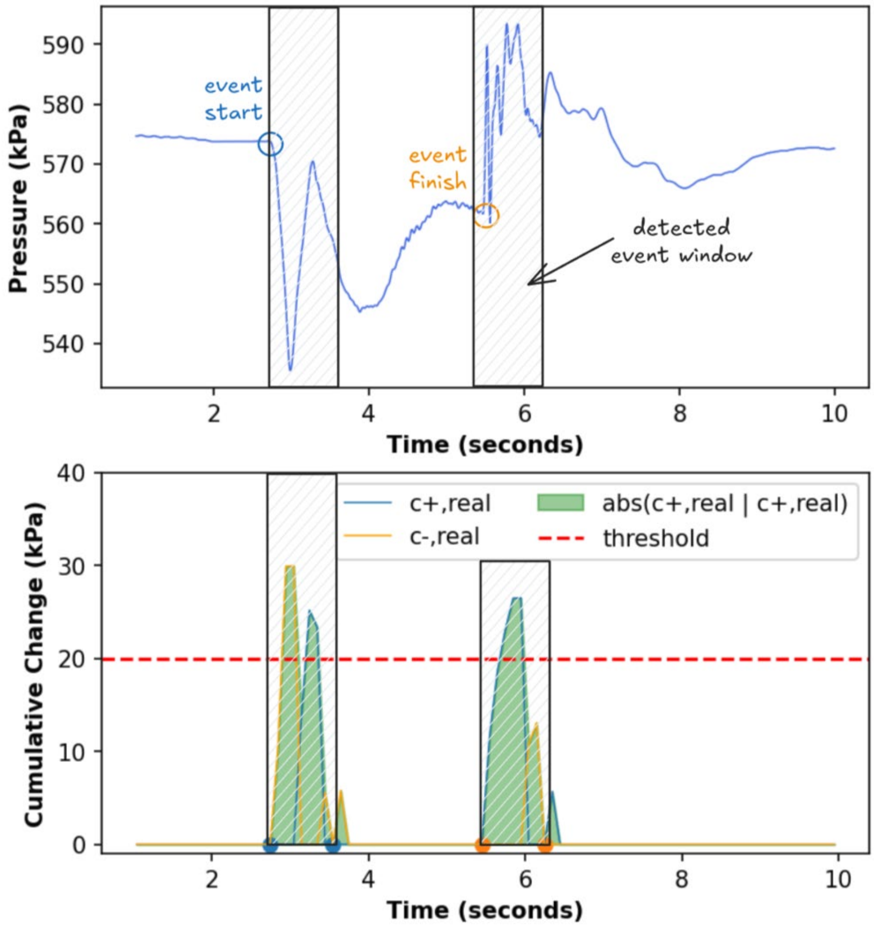

Figure 6 – Example of cumulative sum algorithm used to detect transient events.

2.4.2 Feature Selection

To understand the characteristics of transient events in residential houses within the study, a wide range of "features" was extracted from each detected event. These include general statistical descriptors such as mean, variance, and kurtosis, as well as higher-resolution metrics from both the time and frequency domains to distinguish between similar pressure profiles.

Time-domain features, including rise time and peak-to-peak amplitude, define the temporal evolution of a transient event. In parallel, frequency-domain analysis via Fast Fourier Transforms (FFT) or Power Spectral Density (PSD) reveals the harmonic characteristics unique to specific appliances, valve operations or plumbing configurations. The combination of these features enables clustering-based algorithms to identify and group similar transient events, supporting differentiation from routine water usage patterns within the dataset.

Table 1 – Overview of machine learning features used for model training.

Category	Potential Features	Purpose
Time-Domain	Peak amplitude, duration, slope, settling time.	Characterizes the "shape" and severity of the pressure wave.
Frequency-Domain	Dominant frequencies, spectral centroid, energy distribution.	Identifies mechanical signatures of specific fixtures.
Statistical	Skewness, Kurtosis, RMS, Standard Deviation.	Captures the distribution of pressure noise and variability.

2.4.3 Dynamic Time-Warping

Dynamic Time Warping (DTW) is a method used to compare two different sequences of data to determine their similarity, even if they are not perfectly aligned in time. In traditional data analysis, comparing two trends usually requires them to be the exact same length and occur at the same speed, but real-world data is rarely that consistent. This algorithm addresses that limitation by stretching or compressing sections of a time series to find the best possible match between two patterns.

The primary advantage of DTW is its ability to recognise similar shapes that are shifted or distorted in time. For example, if two sensors capture the same physical event but one signal is slightly delayed or evolves at a different rate, a standard point-to-point comparison would suggest the two signals are unrelated. DTW instead identifies the optimal alignment by matching key features, such as peaks to peaks and troughs to troughs, effectively warping the time axis until the sequences align as closely as possible.

When calculating this alignment, the algorithm builds a path that minimises the total cumulative distance between the matched points. This approach ensures that the most similar features within each dataset are paired, regardless of when they occur in the sequence. By focusing on the overall structural relationship of signals rather than rigid timestamps, DTW provides a much more robust measure of similarity for complex time-series datasets such as sensor readings, financial trends, or physiological signals.

In the context of a technical report, this method is valuable because it accounts for the inherent variability and "jitter" found in captured real-world data. It enables researchers to categorise patterns and detect anomalies with greater accuracy than simpler linear methods. Ultimately, DTW serves as a bridge between raw, messy temporal data and a clear understanding of whether two separate events within a dataset are following the same underlying behaviour.

To calculate the distance between two time series, $X = (x_1, x_2, \dots, x_n)$ and $Y = (y_1, y_2, \dots, y_n)$, Dynamic Time Warping uses a recursive formula to find the optimal alignment. The process begins by defining a local cost measure, typically the squared Euclidean distance, between any two points, see Eq. (8).

$$d(i,j) = \left(x_i - y_j\right)^2 \tag{8}$$

The algorithm then populates a cumulative cost matrix, $D(i,j)$ which represents the minimum distance required to align the sequences up to indices i and j. This is achieved using the following recurrence relation presented in Eq. (9).

$$D(i,j) = d(i,j) + min\begin{Bmatrix} D(i-1,j) & (insertion) \\ D(i,j-1) & (deletion) \\ D(i-1,j-1) & (match) \end{Bmatrix} \tag{9}$$

In this formula, $D(i,j)$ is the sum of the current point's distance and the minimum cumulative cost of the three adjacent preceding cells in the matrix. This ensures the path through the data always moves forward while choosing the "cheapest" route to align the two signals.

This process is applied pairwise for each detected event, generating a distance score for each event signal. The smaller the distance score, the more similar the signals are. Figure 7 illustrates the distances for 50 signals randomly sampled from a normal distribution. The diagonal line of low values represents each signal compared with itself, indicating a perfect match. The calculated distances and heatmap can be used as a visual aid in determining which signals are like one another (lower distance score).

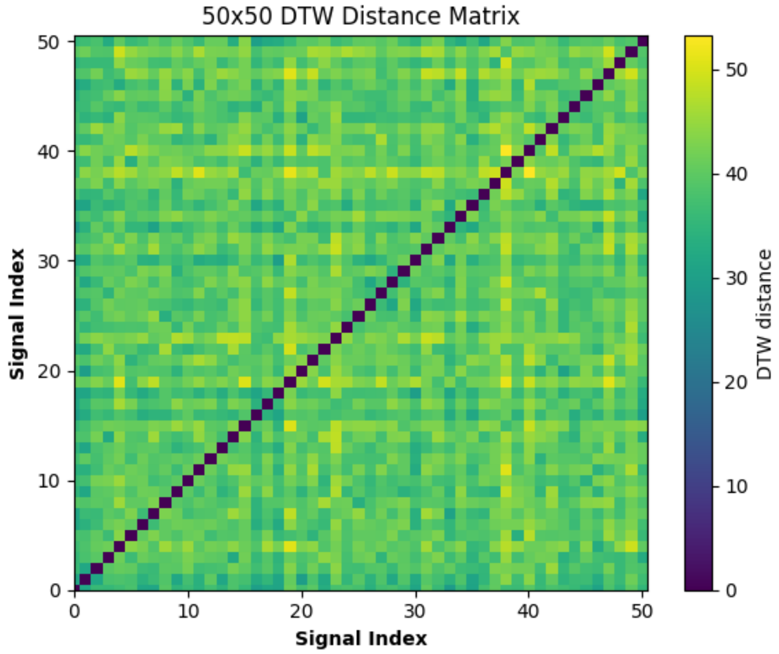

Figure 7 – Example of calculated distances for 50 signals compared pairwise and their calculated distances using dynamic time warping.

2.4.4 Clustering of Events: k-means

To support the research objective 3 in characterising transient events to determine whether there are repeatable patterns that correspond to specific fixture and appliance use, the k-means clustering algorithm, along with the extracted signal features, was applied to each house's dataset to identify any repeatable patterns (normal water use).

The k-means algorithm is a fundamental method used in data science to group a set of observations into a specific number of distinct clusters. The aim is to organise a large and unstructured dataset and partition it so that observations within the same group are as similar as possible, while observations in different groups are as distinct as possible. This is achieved by calculating the mathematical "centre" of each cluster and assigning each data point to the cluster centre that sits closest to it.

The process begins by selecting a value for k, which represents the total number of clusters to be identified. The algorithm then randomly selects k points in the data space to act as the initial starting centres, or centroids. Once these starting points are established, every other data point in the set is measured against them and assigned to the nearest one. This creates the first rough version of the groups, though they are rarely perfect on the first attempt.

After this initial assignment, the algorithm enters an iterative refinement phase. In each iteration, it recalculates the position of each centroid by taking the average of all the points currently assigned to that group, effectively moving the centre to the true middle of its members. Because the centres have moved, some data points may become closer to a different group than before. The algorithm reassigns these points and repeats the calculation until the centres no longer shift and the groups remain stable.

In practice, this method is highly effective for identifying hidden structures within data without requiring prior labels or categories. It is commonly used for tasks such as segmenting datasets into meaningful groups, identifying patterns in sensor data, or simplifying images by grouping similar colours together. By minimising variation within each cluster, the algorithm provides a more organised summary of complex information that would otherwise be difficult to interpret manually.

To partition a dataset into k distinct clusters, the k-means algorithm uses an objective function designed to minimise the total distance between data points and their respective cluster centres. The goal is to find a set of k clusters, $S = (S_1, S_2, \dots, S_k)$, that minimises the within-cluster sum of squares. The objective function is presented in Eq. (10) where x represents a specific data point belonging to set S_i, and u_i is the geometric mean (centroid) of all points assigned to that cluster.

$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \|x - u_i\|^2 \tag{10}$$

Once the points are assigned, the algorithm updates the position of each centroid by calculating the mean of all points currently in that cluster. By repeating these steps, the algorithm reduces the total error until the assignments no longer change, signifying that the optimal centres for those specific groups have been found.

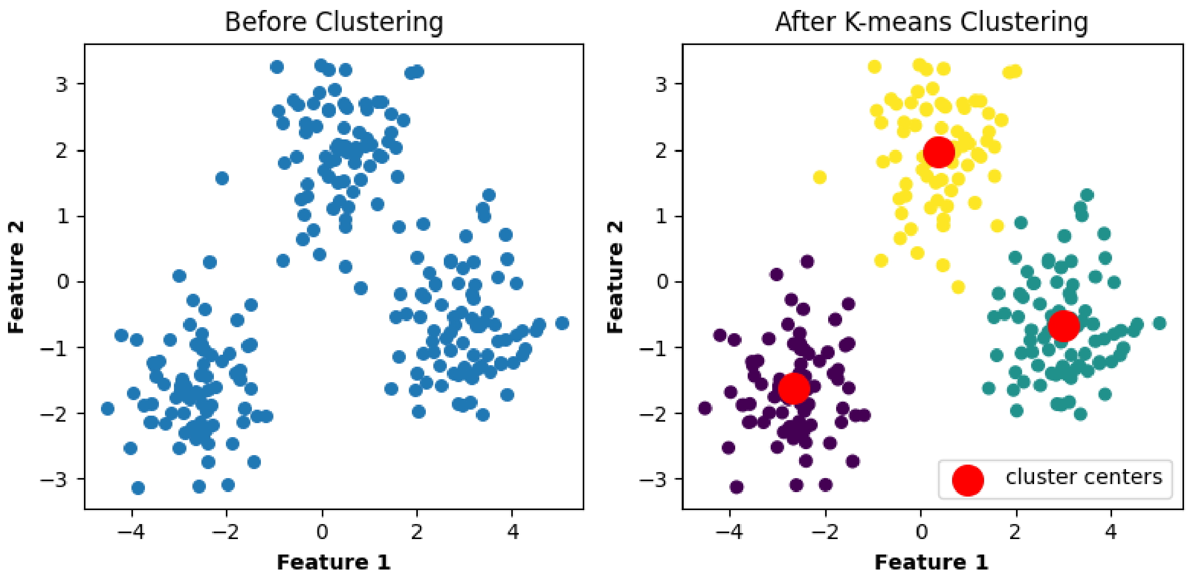

Figure 8 – Example of k-means clustering algorithm on a dataset with two features.

3 Results

3.1 Study Households

Table 2 summarises the characteristics of the nine households that participated in the study. Household H6 discontinued participation soon after monitoring commenced and has therefore been excluded from the analysis.

The study houses were located across five Victorian suburbs, representing four water network utilities: Barwon Water, Greater Western Water, Yarra Valley Water and Southeast Water. Household occupancy ranged from one to ten occupants, with an average occupancy of 4.11. The houses contained between two and six bedrooms (average 3.89), and between one and four bathrooms (average of 2.50).

Table 3 presents water heating systems, pipe materials and pressure control devices installed at the property boundary. Heated water systems were categorised as either “instantaneous” (three houses) or “storage” (six houses), across a mixture of gas, electric element, and heat pump technologies. Plumbing materials were classified as copper (metallic), plastic, or mixed with four, three, and two houses in each category, respectively.

Of the nine houses, only two had active pressure management devices installed at the property boundary, and none had backflow prevention devices at the property boundary.

Table 4 presents the number of fixtures per house, ranging from 10 to 24, with an average of 16.9 fixtures.

Table 2 – Study house details

ID	Location	Year Constructed	Occupants	Bedrooms	Bathrooms
H1	Geelong	1980	4	5	2
H2	Geelong	1930	2	4	2.5
H3	Geelong	2023	4	3	2
H4	Lalor	1990	10	6	3
H5	Lalor	1985	4	3	2
H6					
H7	Narre Warren	1995	2	2	1
H8	Point Cook	2024	4	4	4
H9	Bacchus Marsh	2000	4	5	2
H10	Geelong	1980	3	3	3
		Average:	**4.11**	**3.89**	**2.50**

Table 3 – Plumbing heated water system, pipe materials, pressure control devices at property boundaries for study houses

ID	Water Heating		Pipe Material	Property Boundary Control Device
	Heat Source	**Category**		
H1	Electric	Storage	Copper	None
H2	Gas	Instantaneous	Copper	None
H3	Heat Pump	Storage	Plastic	None
H4	Heat Pump	Storage	Mixed	None
H5	Gas	Instantaneous	Mixed	None
H6				
H7	Heat Pump	Storage	Copper	PRV
H8	Electric	Storage	Plastic	None
H9	Gas	Instantaneous	Mixed	PLV
H10	Electric	Storage	Copper	None

Notes:
PRV = Pressure Reducing Valve
PLV = Pressure Limiting Valve

Table 4 – Plumbing fixtures present in study houses

ID	Showers	Baths	Toilets	Taps	Washing Machine	Dishwasher	Outdoor Taps	Total
H1	2	0	2	5	2	2	11	24
H2	3	1	3	6	1	1	2	17
H3	2	1	2	5	1	1	3	15
H4	3	0	3	5	1	1	2	15
H5	2	1	2	5	1	1	4	16
H6								
H7	1	1	1	3	1	1	2	10
H8	4	0	5	6	1	1	3	20
H9	2	1	3	6	1	1	3	17
H10	3	1	3	7	1	1	2	18
Avg:	**2.44**	**0.67**	**2.67**	**5.33**	**1.11**	**1.11**	**3.56**	**16.89**

3.1.1 Data Loss

Pressure data were collected from nine houses, across 15 different monitoring locations (two locations per house except for houses H1, H7 and H10).

Data collection from house H6 was unsuccessful. H6 had experienced persistent internet connectivity issues, resulting in only a limited number of days of intermittent data being transmitted to the cloud platform. As of May 2026, the research team had been unable to retrieve the DAQ devices from H6 to access data stored locally on the devices.

For houses H1 and H7, data from one of the DAQ devices (the same unit used during different monitoring periods) exhibited extreme measurement noise during certain hours of the day. To ensure the accuracy of the results presented, data from this device have been removed from the study dataset.

For house H10, the monitoring device was intermittently switched on and off, resulting in insufficient data for meaningful comparisons between the two monitoring locations within the house.

3.2 Diurnal Pressure Profile

Figure 9 and Figure 10 present the mean hourly pressures, calculated from 10-second aggregate data for each hour of the day across all monitoring days for each house. Cold and heated water services are analysed separately. The dataset includes pressure data collected from nine houses across 15 monitoring locations, with two locations per house except for H1, H7 and H10.

For cold water pressure data, mean hourly pressures ranged from 300 to 680kPa. Three houses (H1, H2 and H10) recorded mean pressures at or above the 500kPa limit set by AS/NZS 3500 for all hours of the day. These houses are located in the Geelong region (Barwon Water), where higher water mains pressures were observed compared to other water utilities. Pressure variations ranged from 22 to 108 kPa from the maximum hourly average to the minimum hourly average.

For heated water pressure data, mean pressures ranged between 300 and 780kPa. Houses with storage-based water heating systems (solid lines, Figure 9) recorded pressures above the 500kPa limit specified in AS/NZS 3500 for extended periods throughout the day. This behaviour is attributed to thermal expansion, where water increases in volume as it is heated, forcing an increase in pressure. This pressure is only released when a fixture is used (e.g., tap turned on), or when the water storage Temperature and Pressure Relief Valve (TPR) is activated.

In contrast, houses with instantaneous water heating systems (dashed lines, Figure 9) generally exhibited similar pressures to those observed in the cold-water service.

Figure 11 presents daily pressure profiles (10-second aggregated data) for two houses: one with heated water storage (house H3, Figure 11a) and one with instantaneous water heating (house H9, Figure 11b), highlighting the differences in their pressure profiles.

It appears that heated water storage systems can remain near the TPR valve limit for extended periods (i.e., several hours) with either the pressure slowly decaying after water heating has stopped or being rapidly released when a fixture is used.

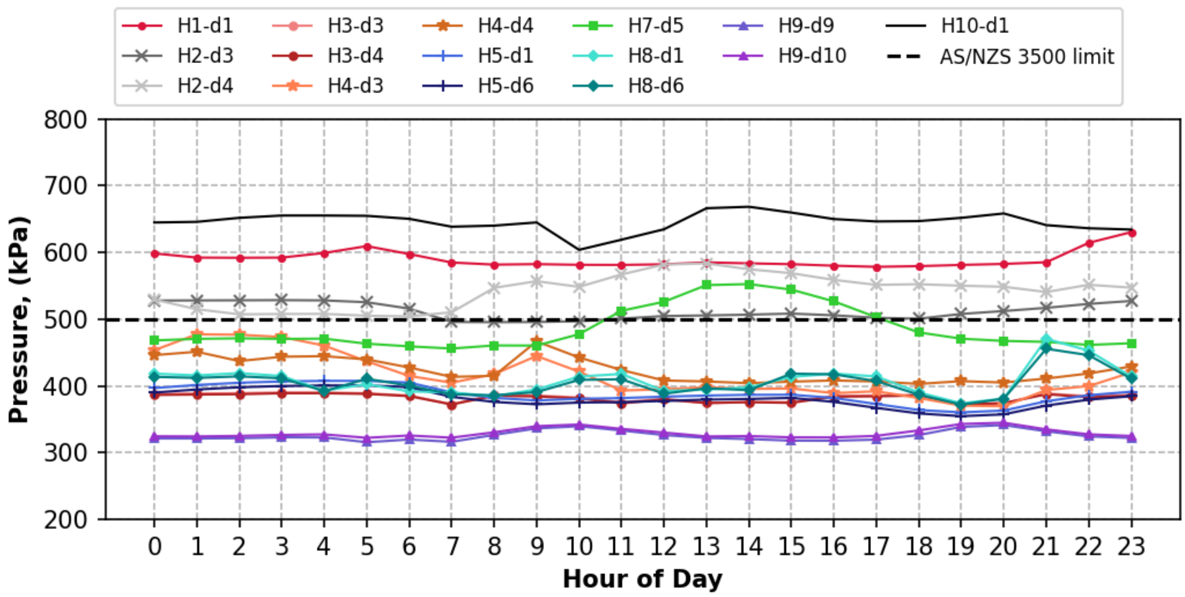

Figure 9 – Mean hourly pressure for monitored cold water services in nine households and 15 different fixture locations, (designation for each house H1-d1 = House id - DAQ device id).

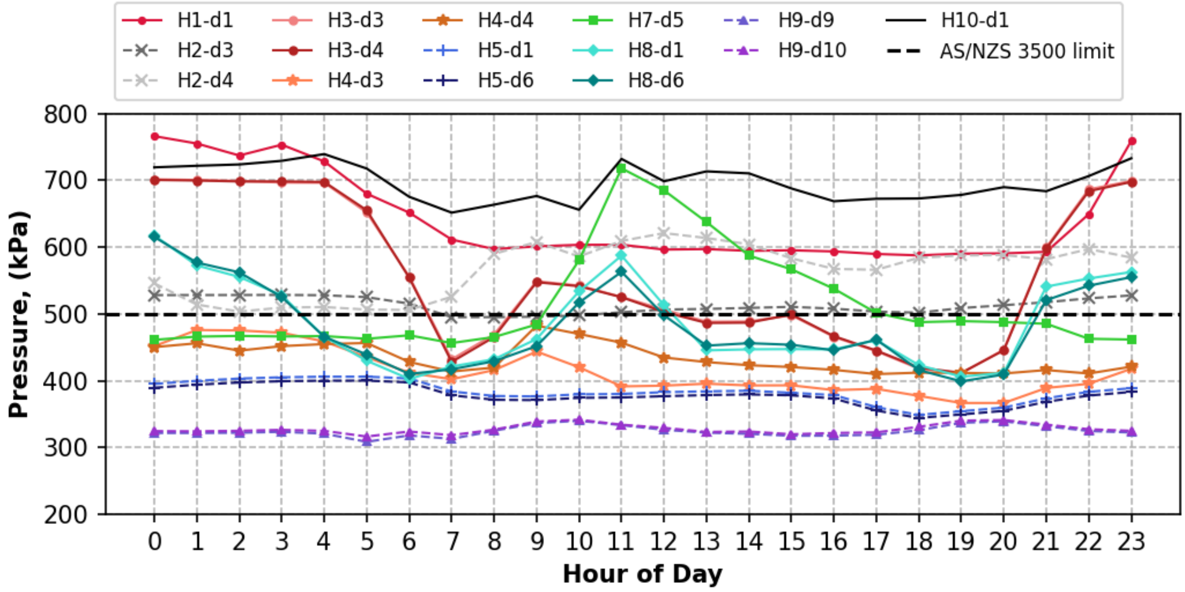

Figure 10 – Mean hourly pressure for monitored heated water services in nine houses and 15 different fixture locations, solid lines represent houses with storage water heating, dashed lines represent houses with instantaneous water heating, (designation for each house H1-d1 = House id - DAQ device id).

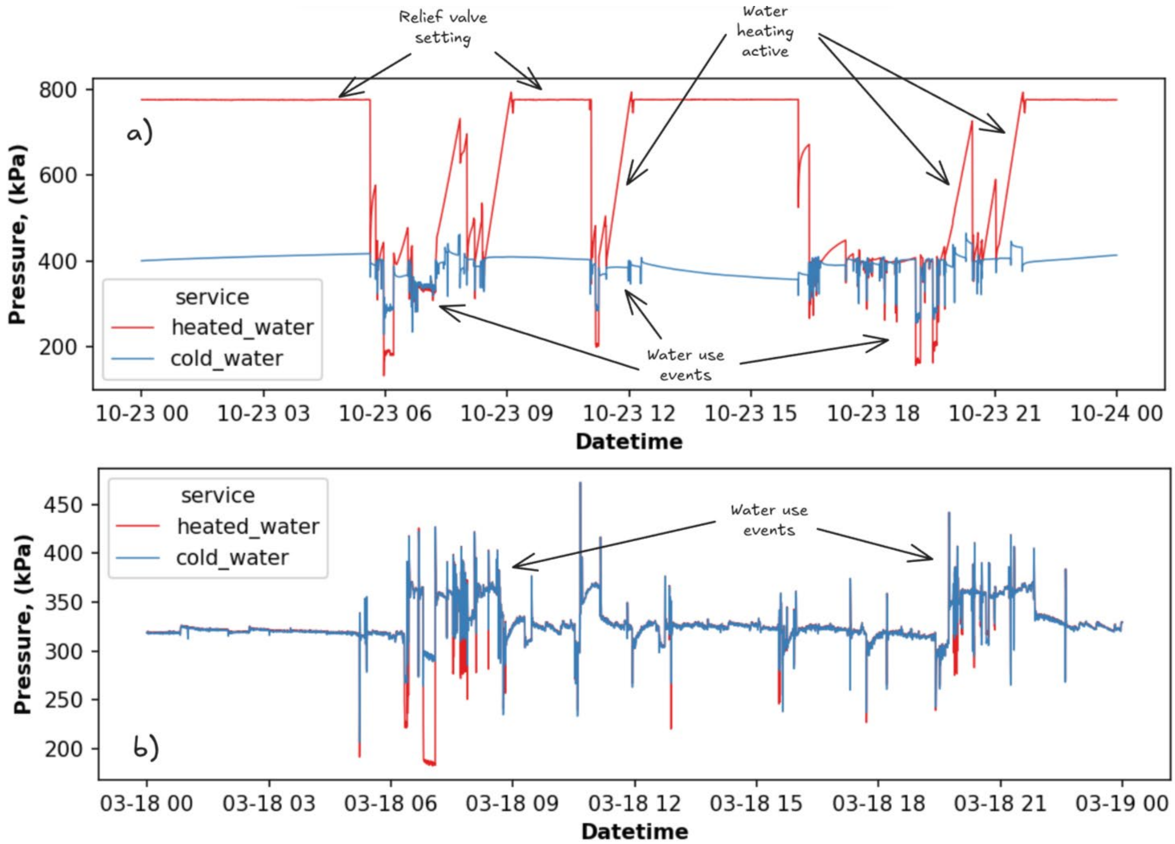

Figure 11 – Daily pressure profiles for a) a house with heated water storage and b) a house with instantaneous water heating for a single day.

3.3 Compliance with AS/NZS 3500 Pressure Requirements

Table 5 presents the percentage of time each DAQ device recorded cold and heated water service pressures within the 50-500kPa range specified in AS/NZS 3500. Houses located in Geelong exhibited the worst performance, with two houses (H1 and H10) recording pressures above 500kPa for 100% of the monitoring period. House H2 in Geelong rarely met this performance requirement, with performance ranging between 21-28% across its two DAQ devices. While house H3 demonstrated good compliance (100%) for cold water pressures entering the property, compliance for the heated water service was significantly lower (55%). This further highlights the impact of water heating and storage systems, which can elevate pressures above 500kPa for extended periods.

The remaining five houses demonstrated better compliance, spending between 67-100% of the time within the allowable pressure range. Analysis of data from these five houses suggests that incoming service pressures are generally below the 500kPa limit, and that characteristics of the internal plumbing systems such as heated water storage and valves are contributing to the periods during which pressures exceed 500kPa.

Table 5 – Percentage of time each house and monitoring device was observed between AS/NZS 3500 pressure requirements of 50-500kPa.

ID	Location	Device 1		Device 2		Water Heating		Pressure Device
		CW %	HW %	CW %	HW %	Type	Category	
H1	Geelong	0.3	0.0	N/A	N/A	Electric	Storage	No
H2	Geelong	28.0	25.3	21.6	26.8	Gas	Instant.	No
H3	Geelong	100.0	55.4	100.0	55.9	Heat Pump	Storage	No
H4	Lalor	92.7	92.7	90.3	85.0	Heat Pump	Storage	No
H5	Lalor	100.0	100.0	100.0	100.0	Gas	Instant.	No
H6								
H7	Narre Warren	72.8	71.1	N/A	N/A	Heat Pump	Storage	PRV
H8	Point Cook	92.8	67.6	92.9	67.7	Electric	Storage	No
H9	Bacchus Marsh	100.0	100.0	100.0	100.0	Gas	Instant.	PLV
H10	Geelong	0.0	0.0	N/A	N/A	Electric	Storage	No

When comparing data from houses H4 and H5, which are located within a five-minute drive from each other in the Lalor area, the key difference in their plumbing systems is heated water storage in H4 and instantaneous water heating in H5, with H5 being fully compliant for both DAQ devices. While broader network topology is not discounted, these findings provide supporting evidence that incoming mains cold water pressures are acceptable for the Lalor area.

However, when examining data for house H4, compliance for the cold-water service drops to 90-92%. This reduction is attributed to observable pressure increases in the cold-water service that follow trends in the heated water service (Figure 12), suggesting pressure transfer (or "creep") from the heated water the cold-water service.

Theoretically, the cold and heated water services should be isolated from each other, as the heated water system is fitted with a check-valve installed before the heated water tank to prevent reverse flow. The observed pressure rise therefore indicates a potential failure in this isolation, likely due to either improper installation or a faulty check valve that is not fully preventing interaction between the two systems.

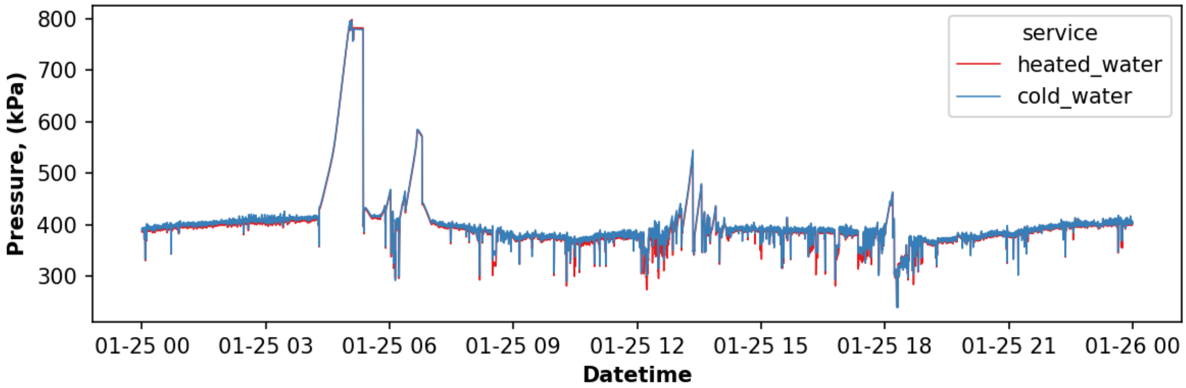

Figure 12 – Daily pressure profiles for H4 for cold and heated water pressure monitored at the kitchen sink.

When evaluating data for houses H7 and H9, both properties have pressure control devices installed at their property boundaries. The data indicate that these devices are effective at protecting the house from excessive pressure in the cold-water distribution system (before the water meter) but are less effective at mitigating large pressure spikes and transient events that are generated within the house.

Figure 13 presents 10-second aggregated time series data for house H7 over a selected day (MM-DD HH). H7 is fitted with a pressure reducing valve (PRV) at the property boundary. During the early hours of the morning, the pressure is maintained below 500kPa, suggesting the PRV is actively working. However, at approximately 10am, a series of significant cold-water pressure spikes is observed, coinciding with dishwasher operation. These spikes occur when the dishwasher completes its fill cycle and the solenoid valve quickly closes, elevating the pressure to well above 500kPa). Examination of the raw pressure signal indicates the transient pressure generated from dishwasher fill cycles are stored within the system and slowly dissipate, with release occurring when a downstream fixture is opened (e.g., during another fill event).

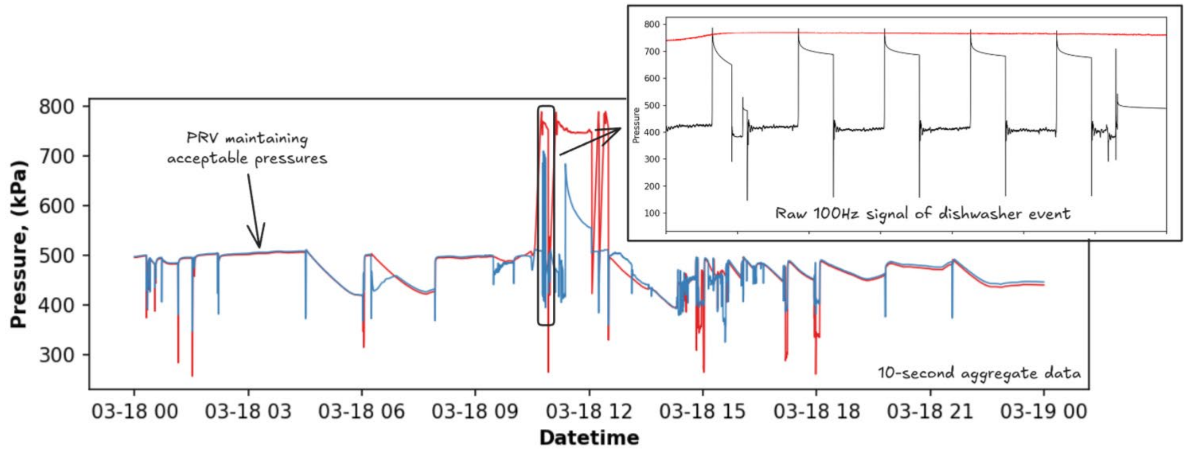

Figure 13 – Daily pressure profiles for H7 for cold and heated water pressure monitored at the kitchen sink and raw signal pressure data for a series of dishwasher fill cycles events.

It is hypothesised that the observed storage of transient pressures is associated with modern "mini-stop" taps (cistern valves) (Figure 14), which incorporate a check-valve mechanism to prevent reverse flow and ingress of contaminants into the plumbing system. Transient pressure (water hammer) waves have both positive and reverse flow components. When a downstream fixture (such as at the end of a braided flexible hose) closes rapidly, flow is abruptly halted, resulting in an initial pressure spike. This increased pressure cannot be balanced by the lower static pressure in the system because the check-valve mechanism prevents negative (reverse) flow, effectively trapping the transient pressure within the house's plumbing system.

Figure 14 – Example of internal check-valve in "mini-stop" tap.

This phenomenon is also evident in house H2, where pressures in an upstairs bathroom (Figure 15b) exceed those at a ground floor washing machine (Figure 15a). When considering hydraulic principles, pressures at higher elevations should be lower because of the additional energy required for vertical transfer. However, the data suggest that transient pressure waves generated elsewhere in the system (via positive flow) can enter the braided hose after the "mini-stop" tap but are prevented from dissipating because of the check-valve mechanism. As a result, because the built-up pressure is slow to dissipate, and successive transient events can lead to cumulative further pressure increases (Figure 15b). This behaviour explains the reduced compliance between device 1 and device 2 for house H3, as reported in Table 5.

The research team has reproduced this trapped transient pressure behaviour under controlled conditions, and these findings this is presented in section 4.3 (Trapped Transients and Check-Valves).

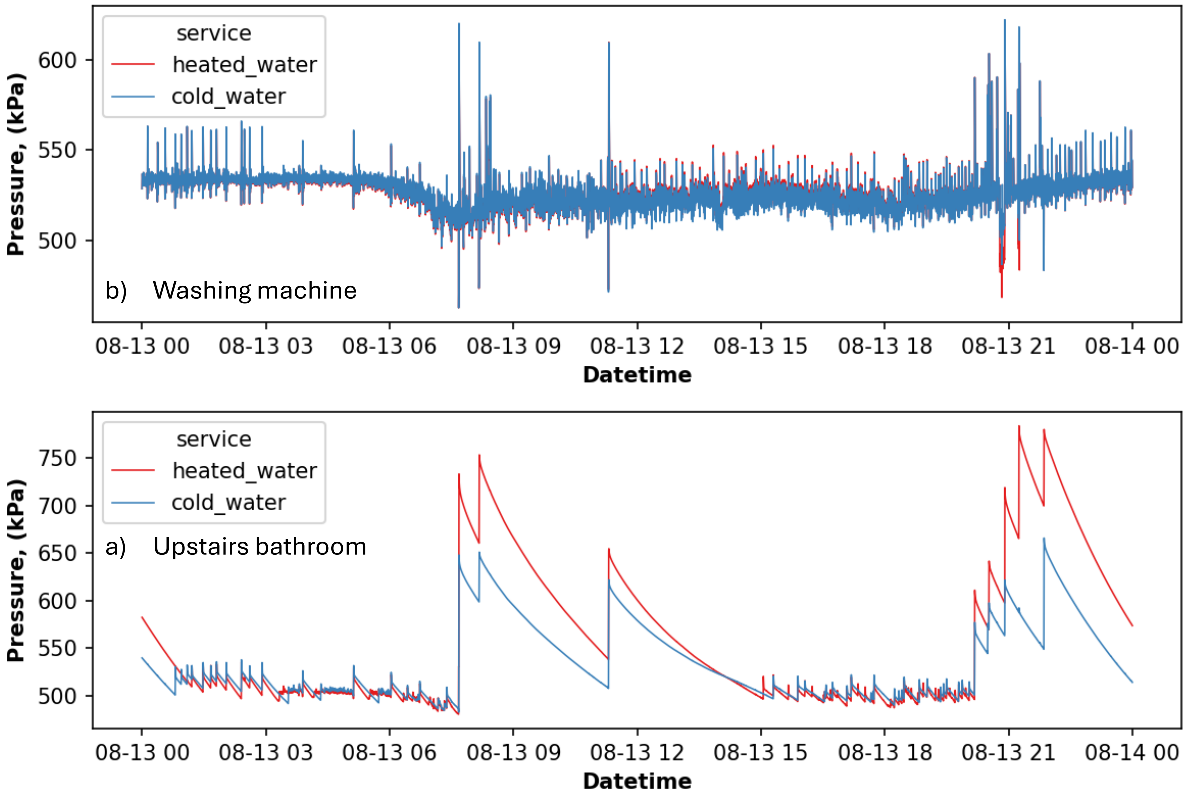

Figure 15 – Daily pressure profiles observed for a select day at H2 for cold and heated water pressure monitored at a) washing machine on the ground floor and b) basin in an upstairs bathroom.

3.4 Damage Index

Figure 16 and Figure 17 present the calculated damage indices (Damage Index) for copper and PEX pipework, respectively, for both cold and heated water services. For copper (metallic) pipework, the damage index incorporates the Copper Pipe Impact Scaling (CPIS), which accounts for dynamic stress cycles generated by water hammer events (i.e., transient pressures). In contrast, PEX (cross-linked polyethylene, or plastic) pipework is better able to absorb short-term pressure spikes as the pipe wall can expand. Consequently, the primary concern for damage in PEX systems is long-term “creep” associated with sustained static pressures.

The pressures and associated stresses observed in houses with copper or mixed (copper and PEX) pipework (Figure 16) were mostly insignificant, with all recorded hoop stresses remaining below copper’s endurance limit of 60MPa (10^7 cycles). This suggests that pressure spikes associated with water hammer events contribute minimally to the reduction of the overall service life of copper pipework. This finding is not surprising as type B DN20 pipe has a safe working pressure of 3970kPa (International Copper Association Australia, 2021), and maximum pressures observed were less than 25% of this. As noted previously, pipe degradation is influenced by multiple factors including water quality, flow velocity, and quality of construction. The data therefore suggest that transient pressures are unlikely to be the dominating factor in reducing the service life of copper pipework in these systems.

Periods of highest water use within the house correspond to increased CPIS activity. In contrast, minimal activity was observed during early morning and late evening hours. Cold water services (Figure 16a) generally exhibited greater transient activity and increased impact compared to heated water services (Figure 16b).

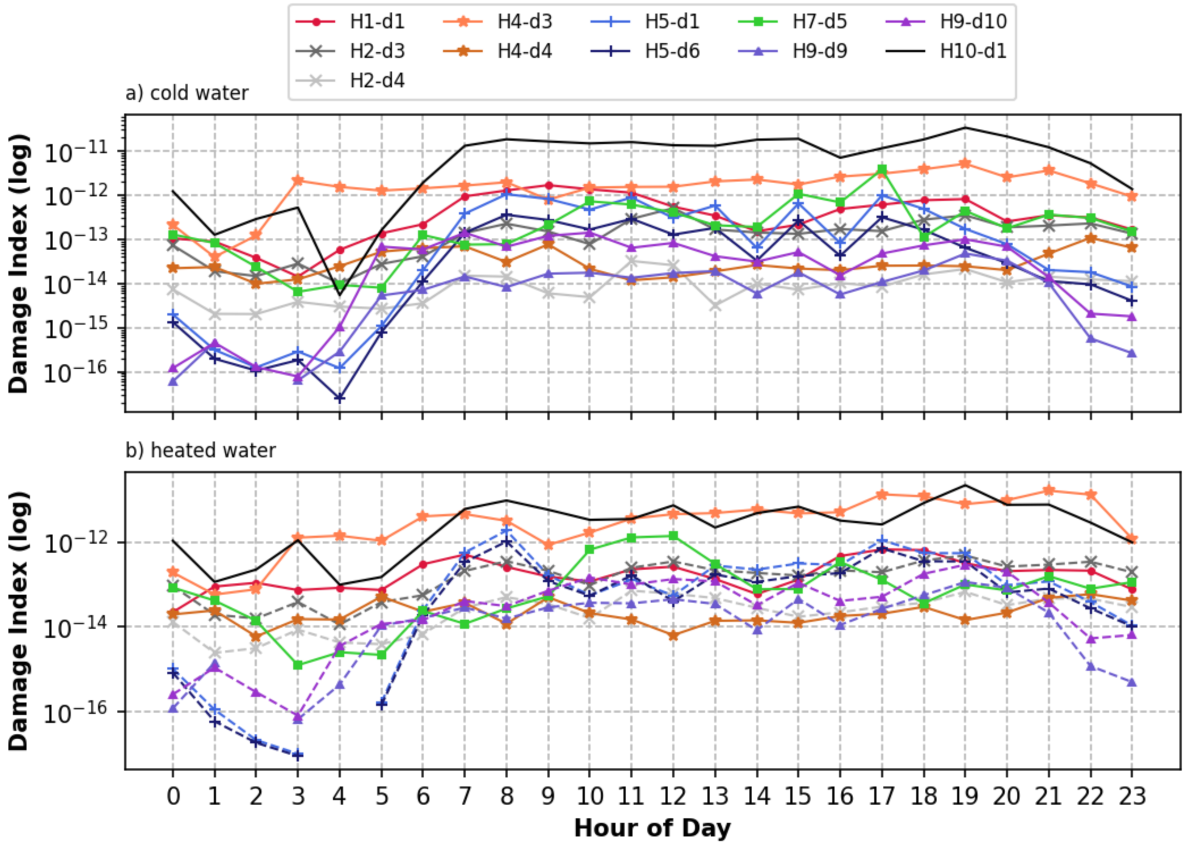

Figure 16 – Damage index for copper pipework in for a) cold water and b) heated water service in in 9 households and 15 different fixture locations, solid lines represent houses with storage water heating, dashed lines represent houses with instantaneous water heating, (designation for each house H1-d1 = House id - DAQ device id).

Mean hourly static pressures, derived from 10-second aggregated data for houses, are compared against the allowable static pressure limits for PEX pipework in both cold and heated water systems. A value of 1.0 indicates that that mean static pressure is at the allowable threshold for achieving a 50-year service life; values below 1.0 indicate a longer expected service life, while values above 1.0 indicate a reduced service life. As PEX is temperature sensitive, its allowable pressure decreases with increasing temperature and is “de-rated” as temperature increases.

For cold water services (Figure 17a), the calculated damage index ranged between 0.3 and 0.6 and remained relatively stable throughout the day. Even in houses with low compliance relative to the 500kPa limit specified in AS/NZS 3500, the observed static pressures remain within acceptable limits for PEX pipework. Heated water services (Figure 17b) exhibited elevated damage indices compared to cold water services. This is attributable to: 1) the lower allowable pressure for PEX at 65°C (795kPa) compared to 23°C (1,055 kPa), and 2) the higher static pressures observed in houses with heated water storage systems (solid lines).

Overall, the observed pressures are generally low enough to remain within allowable limits for PEX pipework. It should be noted, however, that heated water pipes are not expected to operate at a fixed temperature continuously; higher temperatures typically occur only during and shortly after water use, before cooling over time. Furthermore, the damage index for heated water systems assumes that the system is operates correctly and prevents temperatures from exceeding the specified limits.

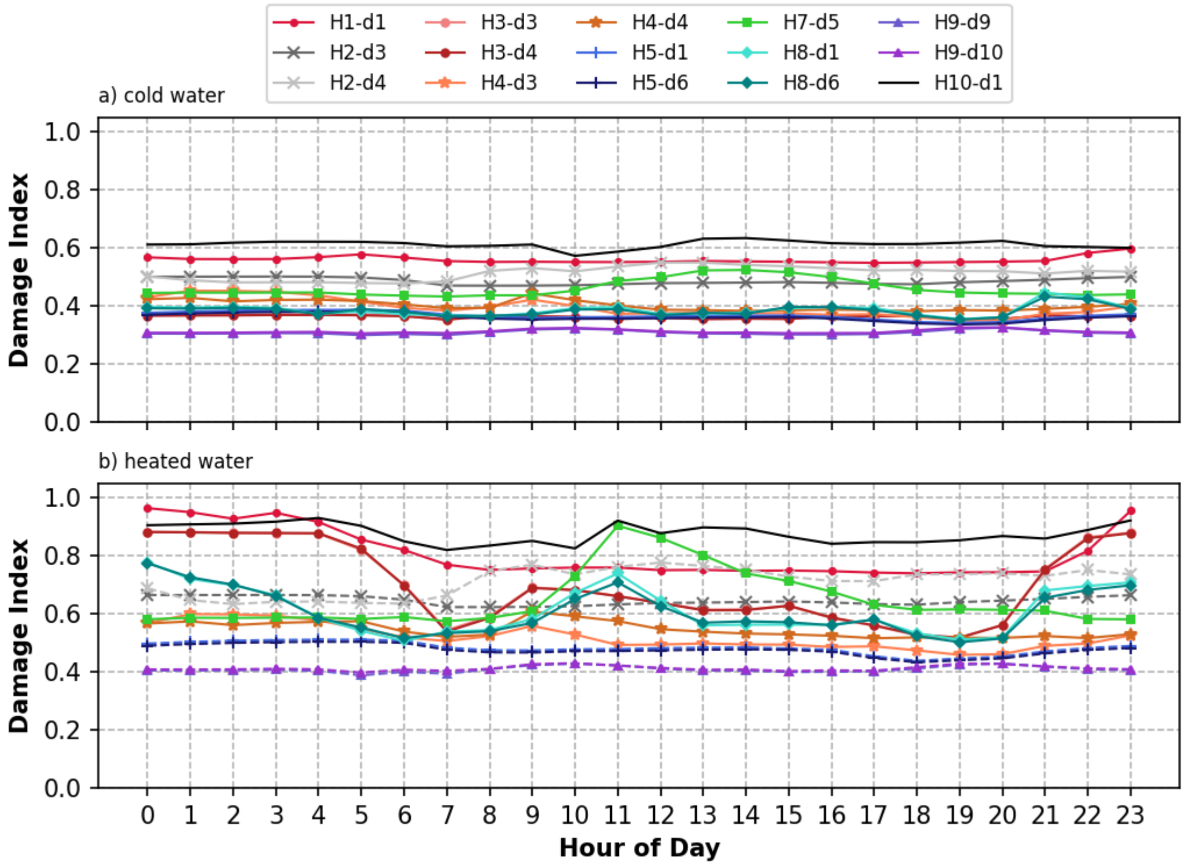

Figure 17 – Damage index for PEX pipework in for a) cold water and b) heated water service in in nine households and 15 different fixture locations, solid lines represent houses with storage water heating, dashed lines represent houses with instantaneous water heating, (designation for each house H1-d1 = House id - DAQ device id).

3.5 Event Detection and Characterisation

3.5.1 Household Event Tagging

Households were asked to log date and time stamps for fixture events using an online platform developed by the research team (see Figure 4). Each household was requested to record five examples of each fixture type, which was expected to yield approximately 720 fixture events across the nine houses. In practice, households generally logged a small number of events at the beginning of the study; however, participation declined over time, with several households ceasing to record events as the study progressed. In total 249 events were recorded across the nine houses. Table 6 presents a summary of logged events for each house.

Although beyond the scope of this study, the intention of collecting tagged events was to enable the application of pattern matching algorithms to identify similar signals within the dataset for use in supervised machine learning models.

Among the recorded data, washing machines and dishwashers produced some of the most notable events, generating successive water hammer events through repeated fill cycles. Figure 19 shows a dishwasher cycle comprising 12 repeated events over a 90-second window. Figure 20 presents the extracted signals, both down surge (valve opening) and upsurge (closing) responses.

Table 6 – Summary of tagged fixture events from households.

Fixture	**Number of Events**
Tap	101
Shower	55
Toilet	54
Washing Machine	15
Dishwasher	12
Garden Hose/Outdoor Taps	9
Bath	3
Total:	249

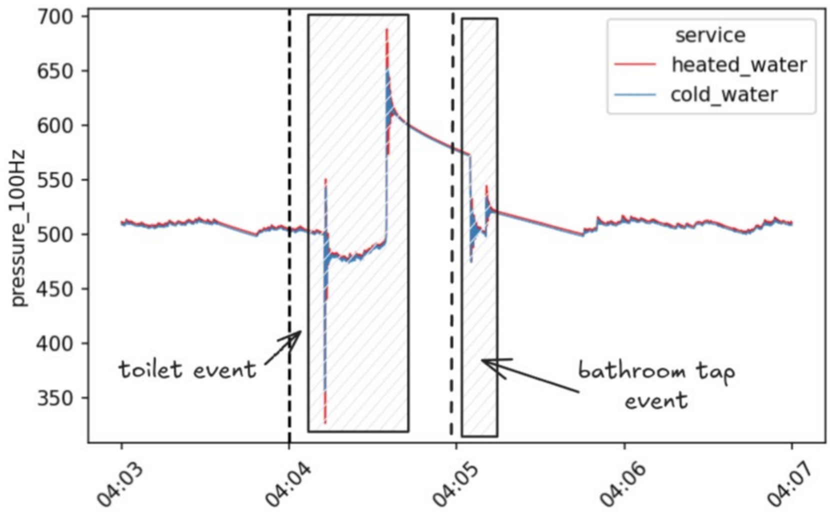

Figure 18 – Example of tagged household events using online platform to timestamp fixture use.

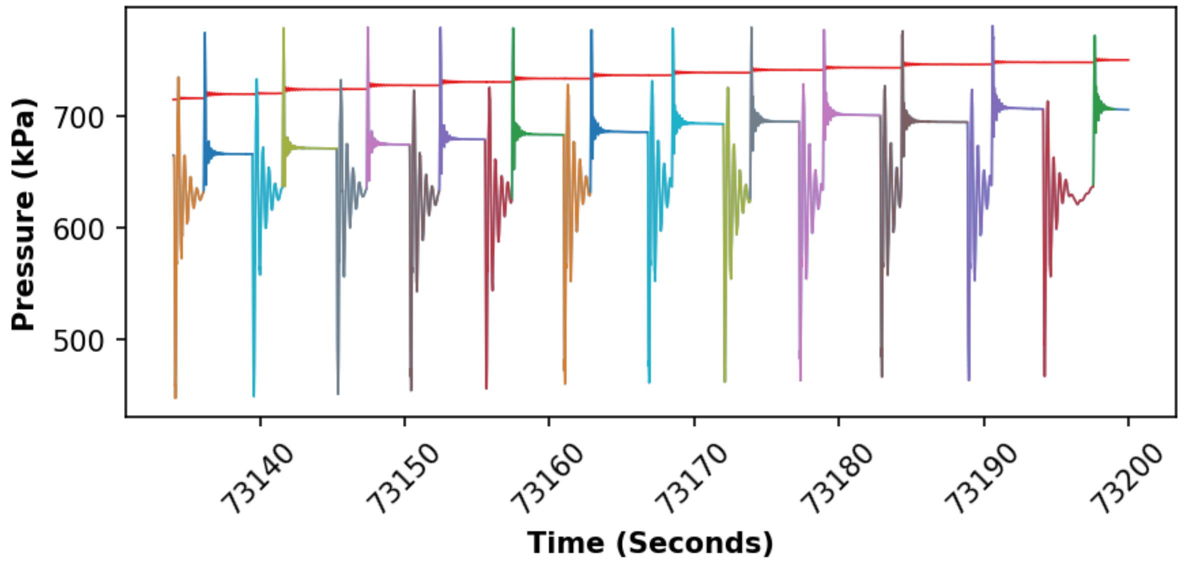

Figure 19 – A tagged dishwasher event with 12 fill cycles over a 90-second window generating repeated water hammer events.

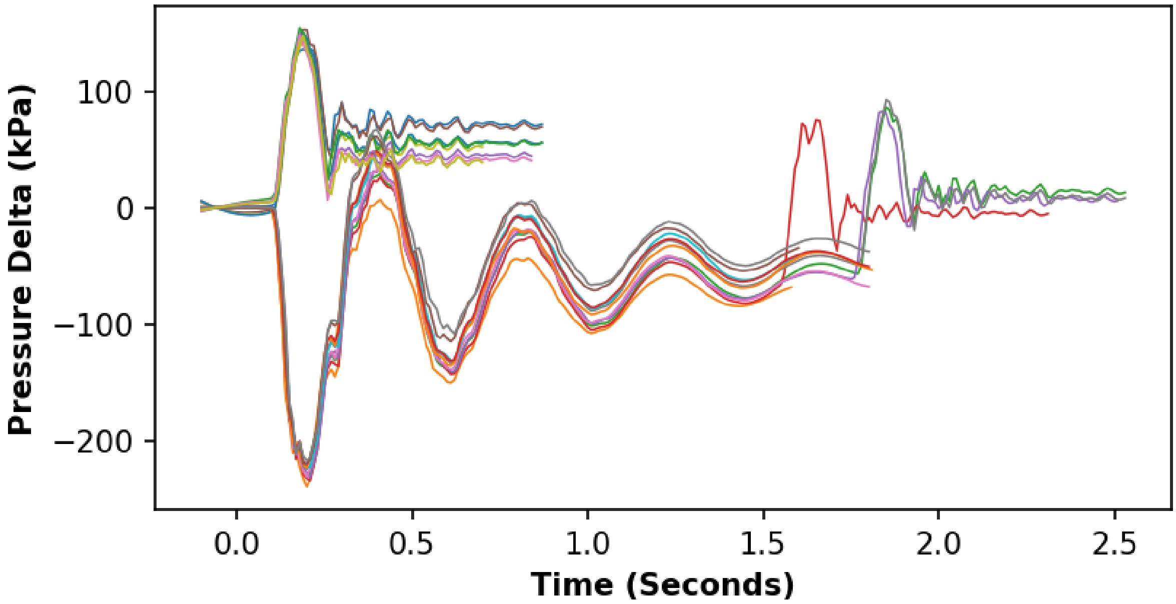

Figure 20 – Extracted pressure signals from the dishwasher event shown in Figure 19.

3.5.2 Event Detection

For each house, the event detection algorithm was applied to the first seven full days of collected pressure data. The number of detected events varied significantly across houses and devices, ranging from 144 (house H2, device 4) to over 2,300 events (house 5, device 1). The relatively low number of events detected for H2 (device 4) is attributed to the trapped transient pressures within braided hoses, reducing transient activity at this specific monitoring location. For most other houses, the number of detected transient events ranged between 900 and 2,300 over the seven-day period (approximately 128-257 events per day). Generally, houses with higher occupancy rates exhibited greater numbers of transient events.

However, not all detected events were attributable to fixture or appliance operation and could be the result of fluctuations in mains pressures. This effect was mostly evident at house H2, which is located very close to the Geelong CBD, where pressure fluctuations up to 50kPa over one-minute intervals were consistently observed throughout the day.

Detected transient events generated by fixtures and appliances typically had durations of two to five seconds, with maximum or minimum pressures reached approximately 0.2 seconds after initial detection. Figure 21 presents 2,300 transient events detected for house H5 over a seven-day period. Pressure fluctuations, both positive and negative, exceeded 600kPa just prior to the event. Large pressure drops in the heated water system were associated with the release of stored heated water storage being released when a fixture or appliance was activated.

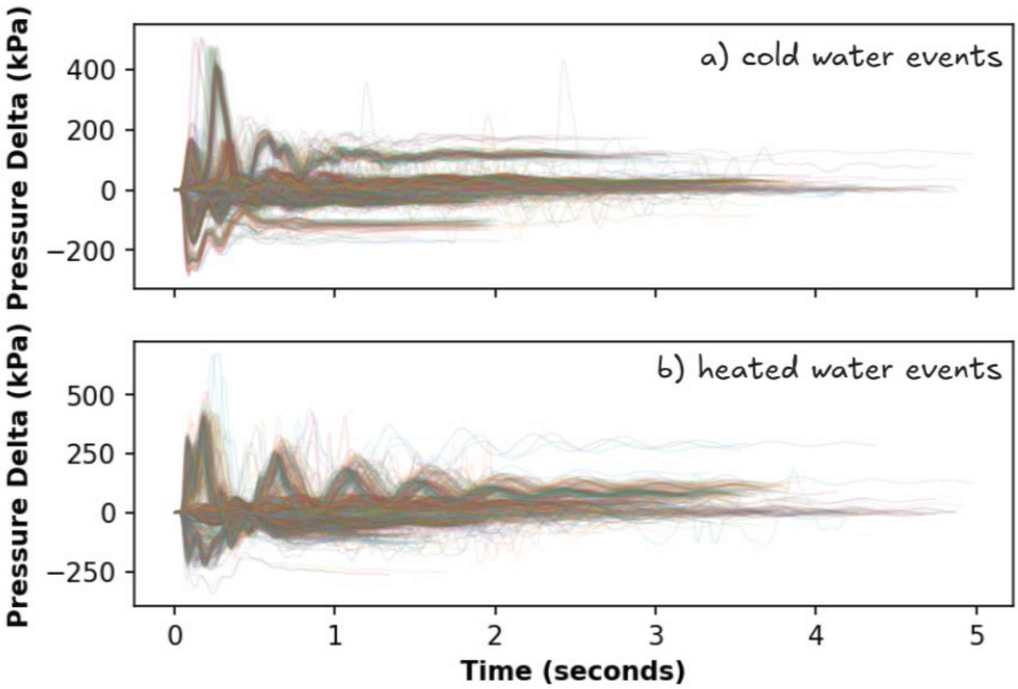

Figure 21 – Transient (water hammer) events detected for cold and heated water services in house H5 over a seven-day period.

3.5.3 Event Clustering

K-means clustering was applied to each household dataset to identify discernible patterns based on statistical, time domain and frequency domain features extracted from detected transient events. An initial run with all features included in the model's parameter were run. From this, the inertia and silhouette score were calculated to determine the number of clusters that produced the most meaningful separation (low inertia and greater silhouette score). Then, the model is re-run with the preferred number clusters, and the top 5 features that create the most distance from other clusters centroids were selected to re-run the model with this reduced feature space.

In several houses, the clustering was effective in identifying distinct patterns in transient pressure behaviour. As shown in Figure 22, k-means analysis identified nine response clusters that capture distinct pressure-deltas across cold and heated water conditions. Several clusters are clearly defined, characterised by strong cold water-dominant or heated water-dominant transients, including response groups with large early spikes, sustained offsets, or pronounced damped oscillations. Other clusters correspond to weaker or near-baseline responses.

Overall, the clustering results appears well supported, with clear separation in both the silhouette analysis and principal component analysis (PCA) projections, suggesting that most clusters represent meaningful structure rather than arbitrary partitioning (Figure 23). The key factors influencing cluster formation include pressures in adjacent water services, response amplitude, oscillatory behaviour, and transient direction. It is noted, however, that one small, low-quality cluster (cluster 4) may represent infrequent or low-signal events rather than a robust standalone cluster.

The heat map presenting the calculated distances using dynamic time warping (DTW) (Figure 24) further supports that the identified clusters represent meaningful response structures across both cold and heated water services. Signal distances are ordered by cluster, with strong diagonal blocks of low distance values indicating strong cluster cohesion. The heated-water panel shows stronger contrast across several cluster blocks, suggesting that heated-water responses contribute more strongly to separation. In contrast, the cold-water panel highlights a subset of clusters with particularly distinct cold-response profiles.

The cold-versus-heated difference map provides additional insight, demonstrating that some clusters are defined not only by their overall signal shape but also by the noticeable change in pressure response in the adjacent water system over the same time period. Of note, Cluster 3 (cold water) and Cluster 1 (heated water) form clear horizontal and vertical bands, indicating that these clusters are more distinct from others. This distinction aligns with the large initial pressure spikes observed in these clusters.

The k-means algorithm was less effective in houses where transient signals did not exhibit a typical water hammer response, characterised by sharp and distinct pressure changes (e.g., Figure 19). In some houses, transient events were significantly dampened and displayed gradual upward trends rather than abrupt spikes. The gradual changes made it more challenging to detect clear event start and end points. They also resulted in less variance across extracted features and calculated distances using DTW, limiting the algorithm's ability to distinguish between patterns.

It is hypothesised that these behaviours are influenced by pipe material (e.g., plastic) and associated valves and fittings, which may dampen transient responses. Further investigation into the specific configurations of the plumbing systems within these houses is needed to better understand the observed signal characteristics.

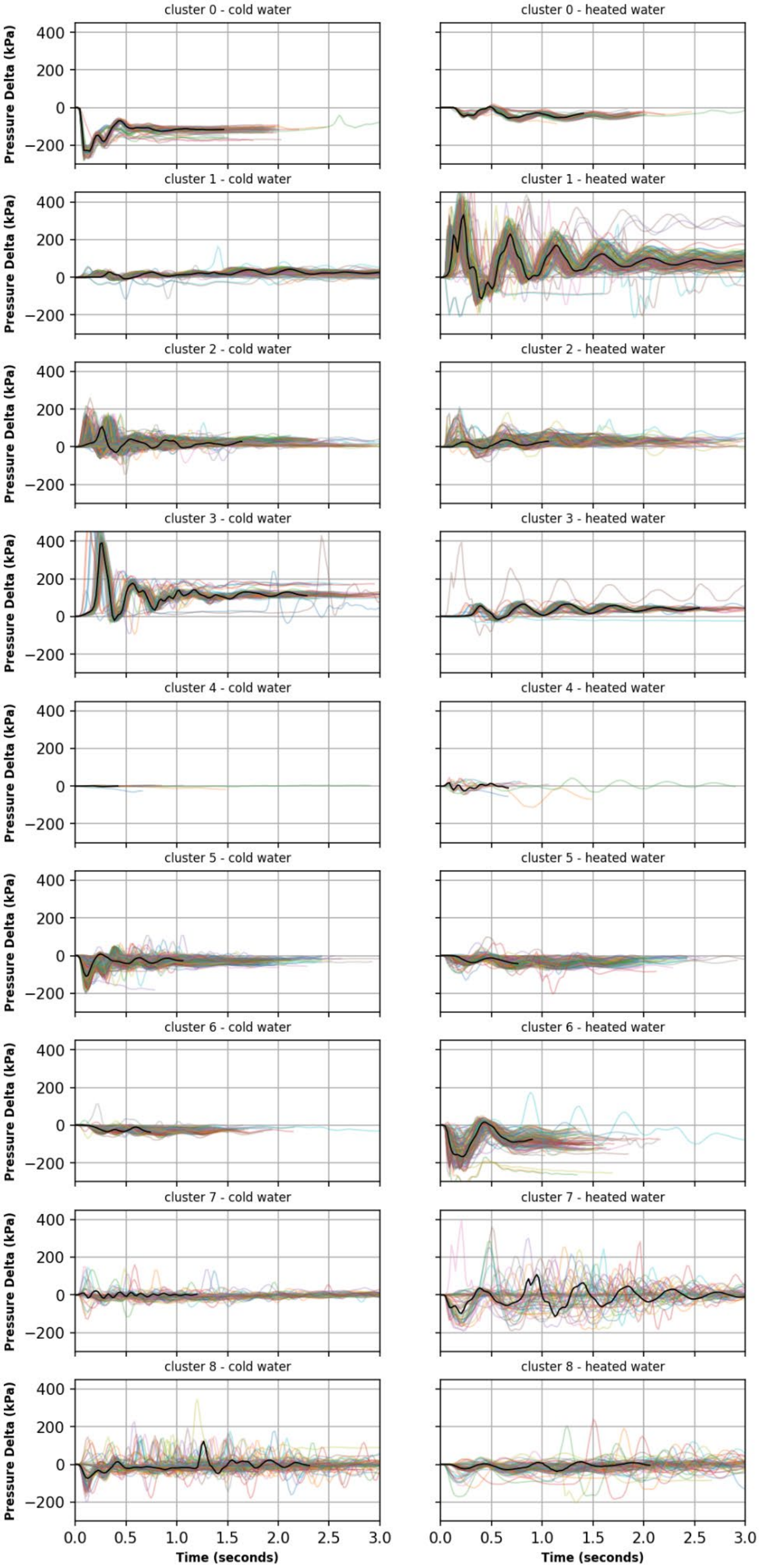

Figure 22 – Clustered transient signals using the k-means algorithm (k=9) for detected cold and heated water transient events in house H5, device 1.

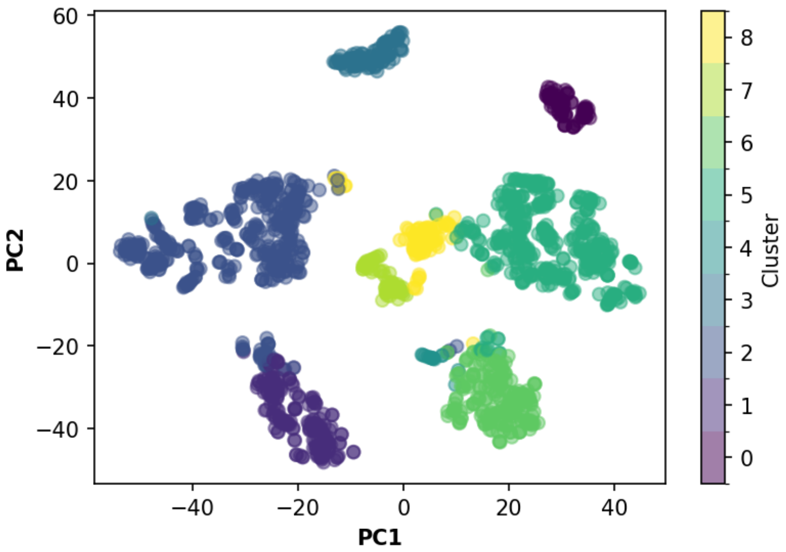

Figure 23 – Principal component analysis (PCA) of clusters for transient events detected for house 5.

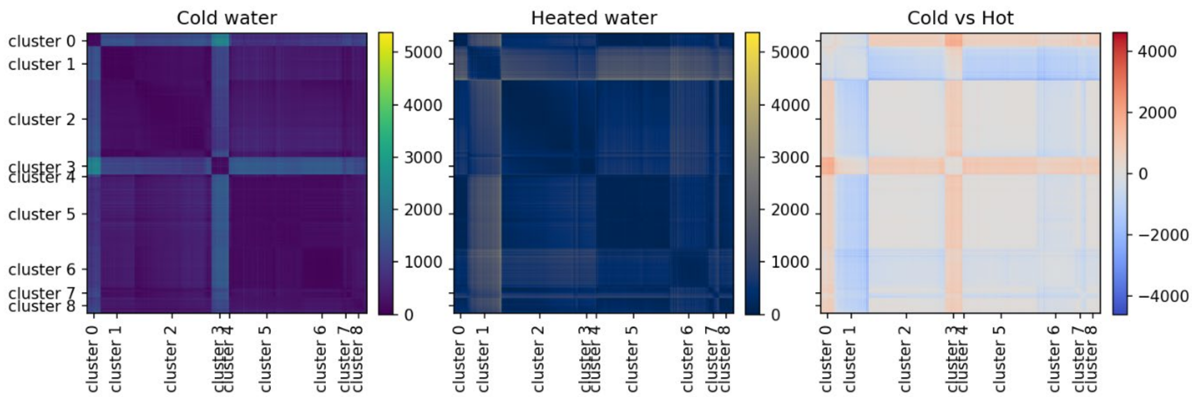

Figure 24 – Heat map of clustered pressure signals from calculated distances from dynamic time warping.

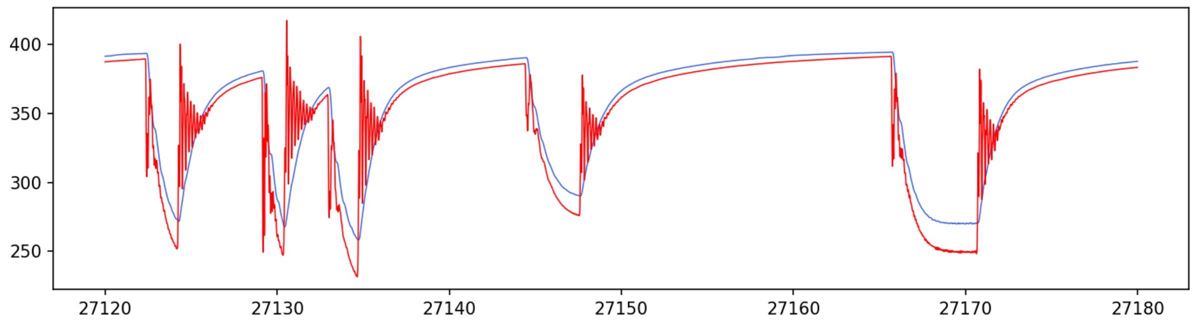

Figure 25 – Example of a series dampened upward pressure transients observed in H8.

4 Discussion

4.1 Compliance with Pressure Limits

Compliance with the 500kPa limit set within AS/NZS 3500 was highly variable across the nine-study houses. Houses in the Geelong region demonstrated the poorest compliance, with some exceeding the prescribed limit for the entire monitoring period due to elevated mains pressure. In contrast, in areas with lower mains pressure, such as Lalor, instances of non-compliance were primarily attributed to internal factors, including heated water storage systems and the presence of trapped transient pressures.

Current design guidance and industry practice recommend the installation of a pressure limiting valve (PLV) or pressure reducing valve (PRV) at the property boundary when a plumber identifies a specific property is deemed at risk of exceeding the 500kPa limit. This approach is generally an effective means of regulating the incoming cold-water service. However, there appears to be an anecdotal perception within the plumbing industry that installing a pressure control device at the property provides a complete solution to excessive pressures issues within residential systems. The findings of this study suggest otherwise.

While pressure control devices at the property boundary improve compliance with AS/NZS 3500 requirements, the data indicate a need for additional measures to effectively manage transient pressures events generated from within residential plumbing systems. Several solutions are currently available, including:

1. Water hammer arrestors, installed near specific fixtures and appliances with fast acting valves, which absorb the initial transient shock.
2. Cold water expansion valves (ECVs), that regulate pressure and temperature from the cold-water inlet to heated water storage systems and act in conjunction with temperature and pressure relief valves of heated water storage systems. ECVs can also reduce energy losses by limiting the discharge of heated water.
3. Pressure vessels, that are a tank with a bladder full of compressed air that can rise and fall with the pressure fluctuations of plumbing systems to maintain a consistent pressure level. Pressure vessels are recommended as secondary pressure control devices in AS/NZS 3500.4 (heated water standard) for regions with lesser water quality that may induce malfunction of the heated water storage temperature and pressure relief valve.

A review of the literature indicates that relatively few studies have examined transient pressures in premise plumbing systems (Marsili et al., 2023). Existing work is largely exploratory, focusing on understanding impacts and risk (Batterton, 2006; Lee, 2008, 2015), with limited experimental evidence evaluating the effectiveness of pressure control devices in mitigating the impacts of water hammer events in the context of complex plumbing systems.

To improve plumbing system longevity and reduce the risk of water ingress and associated property damage, further research is needed to evaluate effective pressure management strategies within premise plumbing systems. Such work would support the development of robust, evidence-based guidance for plumbing practitioners and system designers.

4.2 Modern Plumbing Systems Pressure Resilience

Newly constructed or renovated residential plumbing systems increasingly favour cost effective and environmentally sustainable solutions. This shift has driven a transition from copper (metallic) pipework to plastic materials such as cross-linked polyethylene (PEX), Polybutylene (PB). While this transition offers benefits in terms of cost, reduced environmental impact, and improved corrosion resistance, it also reflects trade-offs between convenience and long-term durability.

Copper pipework possesses a robust endurance limit, enabling it to remain highly resilient against transient pressure spikes. In contrast, plastic pipes are viscoelastic; although they are effective at dampening the magnitude of water hammer through lower wave speeds, they are susceptible to creep and mechanical fatigue when subjected to repeated stress cycles over time. These material characteristics introduce pressure-related vulnerabilities that are less critical in legacy copper systems.

Analysis of pressure data in this study indicates that, while mean operating pressures generally fall within allowable limits for a nominal 50-year service life, the safety margin is narrower in plastic systems compared to copper. This limitation is more pronounced when considered alongside the operational characteristics of modern water heating technologies. The increasing electrification of the home has led to the widespread adoption of heat pump water heaters. Unlike instantaneous systems that heat water on demand, heat pumps rely on storage tanks and require multiple passes of water to reach target temperature. This storage-based approach results in thermal expansion within a closed system, frequently forcing internal pressures to reach the operating limits of temperature and pressure relief (TPR) valves for extended periods.

Under these conditions, plastic pipework is subjected to sustained high static pressures and temperatures, which have the potential to accelerate material ageing and degradation. Consequently, system longevity becomes increasingly reliant on the mechanical integrity of the TPR valve. If these safety components become faulty or scale up, plastic pipework has less residual capacity to withstand further stress compared to metallic pipework.

AS/NZS 3500.4 provides some guidance on pressure expansion control as a means of protecting temperature and pressure relief (TPR) valves rather than maintaining system pressures below the regulatory 500 kPa limit. However, this is not a mandatory requirement, and adoption is based on known water quality parameters at the time of installation which may not be readily available to plumbing contractors in a residential setting.

Residential plumbing systems are inherently complex, involving interactions between material properties, hydraulic conditions, and water quality that collectively contribute to systemic degradation over time and influence long-term performance. This research does not advocate for a specific pipe material, but rather it highlights the implications of evolving construction practices using high-resolution monitoring and data-driven analysis.

By opting for cost-effective, flexible materials combined with energy-efficient heat pump and heated water storage, modern plumbing may have inadvertently sacrificed the over-engineered pressure resilience of legacy copper systems in favour of a design that operates much closer to its design and performance limits. Consequently, effective pressure control is far more critical in contemporary plastic-based systems than it was for traditional metallic installations.

4.3 Trapped Transients and Check-Valves

A key finding of this study was the occurrence of "trapped transient pressure" associated with the use of “mini-stop” taps. These fixtures incorporate check-valve mechanics to prevent backflow and the ingress of contaminated water into the house plumbing system, particularly in applications such as kitchen taps with spray hoses and toilet cisterns.

Transient pressure (water hammer) waves consist of both positive and reverse flow components. It is hypothesised that the closure of the water fixture at the downstream end of the braided flexible hose will stop the flow and generate a pressure jump, and this increased pressure cannot be balanced by the lower static pressure in the system because the check-valve mechanism prevents negative (reverse) flow. In addition, transient waves generated elsewhere in the system (positive flow and pressure) can still enter into the braided line, resulting in a "ratchet effect", whereby successive transient events elevate pressure well above the baseline of the system (see Figure 15b).

To investigate this behaviour, the research team conducted a controlled trial by installing pressure transducers both upstream (Figure 26a) and downstream (Figure 26b) of a tap, recording pressures simultaneously. In Figure 27 the black line represents the pressure before the tap (i.e., the true system pressure), while the red line shows the pressure within the braided hose downstream of the tap. Pressures within the braided hose were consistently higher due to the accumulation of transient events and the inability of the system to relieve pressure via reverse flow. Repeated transient events generated elsewhere within the house can enter the braided line and further elevate these pressures until eventually dissipating after a period of no water use activity.

Braided flexible hoses are a known "weak point" within premise plumbing systems and are frequently implicated in pipe failures and water damage insurance claims (Chubb, 2019). The elevated pressures observed in this study, due to transient events and pressure accumulation, may represent a contributing mechanism underlying these failures.

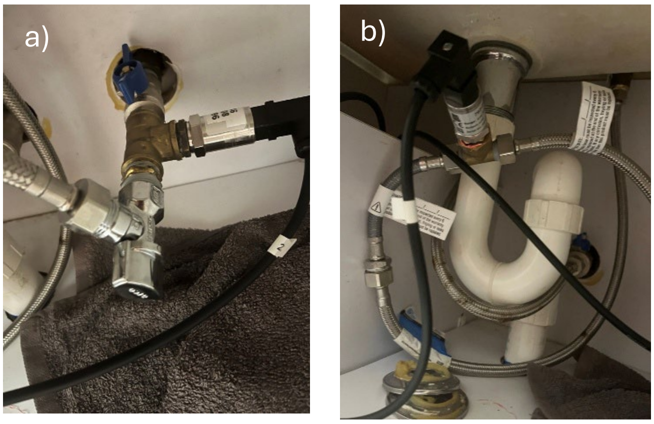

Figure 26 – Installed pressure transducers installed a) before (upstream) of the tap, and b) installed after (downstream) of the tap.

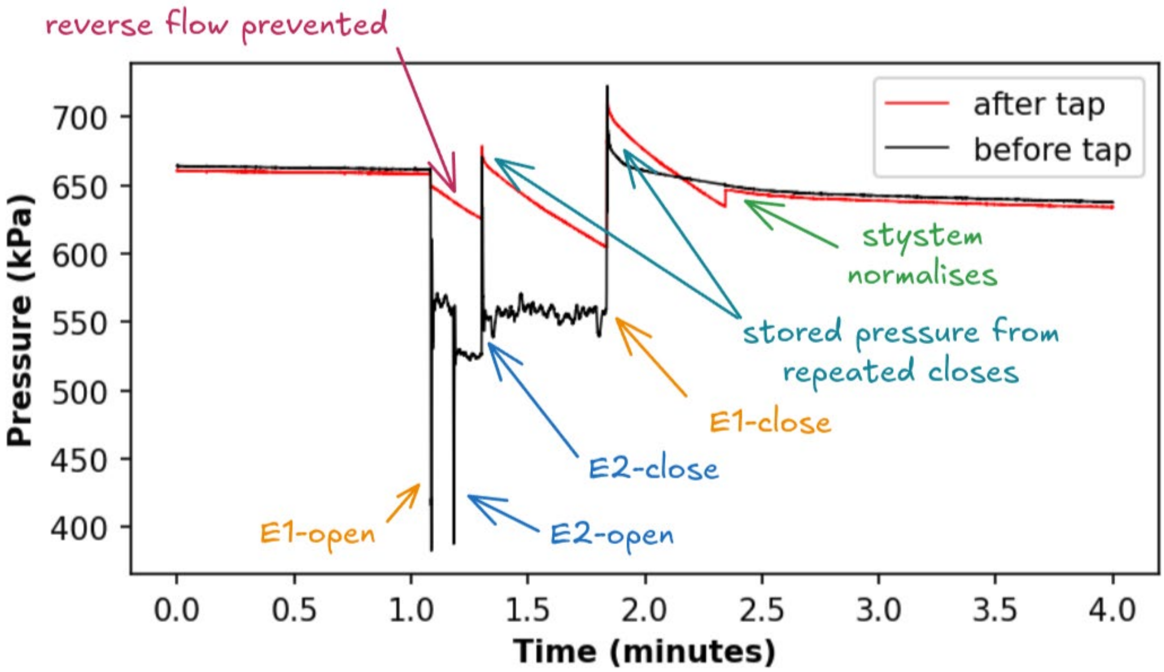

Figure 27 – Example of stored transient pressures upstream and downstream of a "mini-stop" tap after repeated transient events generated elsewhere in the house.

4.4 Event Detection and Characterisation

The implementation of a modified cumulative sum (CUMSUM) algorithm proved effective in identifying transient pressure events across the diverse study houses. By aggregating high-frequency 925Hz data to 100Hz and applying piecewise approximation, the research team successfully captured both the down-surge responses associated with fixture opening and up-surge responses associated with valve closure. The detection frequency varied significantly between houses, ranging from as few as 144 to over 2,300 events per week.

Challenges in developing a generalised over-arching event detection algorithm arise from the wide variability in pipe materials and system configurations. The collected pressure data provides valuable insight into the behaviour of modern plumbing systems. Unlike metallic pipes, the viscoelastic nature of plastic materials dampens high-frequency pressure waves, which effectively "blurs" the signal and making transient events less distinct.

Future iterations of the event detection methodology will require further investigation into the variation and noise each house exhibits as a baseline. This will enable the development of more robust and detectable thresholds for transient events and improve the reliability of transient event identification across differing plumbing configurations.

4.5 Machine Learning and Clustering Performance

The k-means clustering algorithm, supported by Dynamic Time Warping (DTW) for pattern alignment, was effective in categorising transient events into repeatable signal signatures. In higher performing cases (e.g., house H5), the analysis identified nine distinct clusters characterised by features such as response amplitude, oscillatory behaviour, and the direction of the transient. Clusters associated with lower amounts of transient activity in the heated water service may provide insight for identifying cold-water only fixtures, such as toilets, or the repeated fill cycles generated by dishwashers and washing machines.

When considering tagged fixture events, the research team employed dynamic time warping across detected fixture events to extract more of the same signals from the data sets. This proved to be an unsuccessful task, as results returned many similar patterns, but were not the fixture in question. Plumbing systems are inherently noisy, and the transient response is a result available pressure, flow and valve open and closure time. Even when examining more consistent fixtures (i.e., toilets), known tagged examples were shown to vary greatly, making extractions of repeatable patterns was difficult.

Future work should focus on developing pattern recognition techniques capable of accounting for the variability and noise inherent in residential plumbing systems.

5 Policy Considerations and Future Work

5.1 Policy Considerations

Based on the findings of this study, several considerations are identified for policy makers in the review and development of standards and regulations:

1. **Pressure Control in High-Pressure Zones:** In regions where water mains pressure consistently exceeds 500kPa (e.g., parts of Geelong), the implementation of boundary pressure reduction may need to be reinforced for both new and existing properties. This issue is likely more pronounced in existing buildings, which may have complied with regulatory requirements at the time of commissioning (either prior to the introduction of the 500kPa limit or under historically lower mains pressures). There remains uncertainty regarding responsibility for ensuring that pressures downstream of the water meter are maintained within prescribed limits over the asset lifecycle, and further clarification of roles between water authorities, regulators, and property owners may be required.

2. **Standards for Plumbing Components with Check Valves:** Existing standards for plumbing components incorporating check-valve mechanisms may warrant review in light of the observed "trapped transient pressure" phenomenon. Consideration could be given to design modifications, such as incorporating localised expansion capacity or pressure relief features, to facilitate pressure dissipation. The review should extend beyond “mini-stop” valves (as investigated in this study) to include all relevant plumbing components with integrated backflow prevention mechanisms.

3. **Pressure Management for Heated Water Storages:** Standards for pressure management in domestic water heater storage systems may require strengthening. For houses with heated water storages, the installation of expansion control valves or expansion tanks could be more explicitly required or more strongly enforced to mitigate extreme pressure rises associated with thermal water expansion. Enhanced guidance or mandatory requirements in this area may help reduce the risk of prolonged exposure to elevated pressures within residential plumbing systems.

5.2 Future Work

Future research phases may focus on the following areas:

- **Mitigation Strategy Development and Evaluation:** Evaluate the effectiveness of different pressure reducing and pressure limiting valves for controlling pressures at the property boundary. Investigate strategies to manage pressure expansion in storage-based heated water systems, as well as approaches to mitigate transient pressures generated by fast acting valves and the "trapped transient" phenomenon identified in this study.
- **Machine Learning Refinement:** Develop more advanced methods for event detection and classification, including improved feature extraction and model optimisation. Leverage logged fixture event data to support the development of more robust machine learning models for automated anomaly detection, such as leak identification or valve failure.
- **Broader Demographics:** Expand the study to include a wider variety of housing types, plumbing configurations and geographic regions to ensure the findings are representative of broader residential plumbing conditions and infrastructure.

6 Conclusion

This research has demonstrated how IoT-based sensing, combined with machine learning and AI-enabled data analytics, can be used to develop a practical Smart Plumbing System framework for residential cold and heated water services. Through the deployment of high-frequency pressure monitoring devices across nine study houses, the research collected detailed cold and heated-water pressure data that captured both steady-state conditions and transient pressure (water hammer) events associated with fixture and appliance use. These data were analysed to assess pressure compliance, characterise water hammer behaviour, and evaluate pressure-related risks across different plumbing configurations. The development and application of event detection, feature extraction, and k-means clustering showed that pressure signals can be used to identify repeatable patterns of normal system behaviour and distinguish unusual or potentially problematic events. In doing so, the research provides a clear proof of concept for using connected sensing and intelligent analytics to improve the design, operation, condition assessment and proactive maintenance of residential plumbing systems.

The monitoring program revealed that residential plumbing systems are subject to a wide range of pressure conditions. In several cases, pressures regularly exceeded the 500 kPa maximum limit specified in AS/NZS 3500. These exceedances were attributed to multiple factors, including elevated incoming mains pressure, pressure increases associated with heated water storage systems, and localised pressure build-up caused by trapped transient pressures. These results indicate that pressure issues in residential settings are not solely driven by the incoming water supply but may also be generated or amplified within the internal plumbing system.

The study further demonstrated that transient pressure events can be reliably detected using high-frequency pressure data. The modified cumulative sum (CUMSUM) event detection method proved effective in identifying rapid pressure fluctuations associated with fixture and appliance usage. These findings support the potential for IoT-based pressure sensing as a practical and scalable monitoring tool for residential plumbing systems.

The machine learning component of the study demonstrated that detected pressure events can be grouped into consistent and repeatable signal patterns. The k-means clustering approach, supported by dynamic time warping, was effective in identifying distinct event clusters in some houses. This finding suggests that pressure signals contain meaningful features that may support future fixture characterisation and anomaly detection.

However, the results also highlight the challenges associated with developing a generalised event detection model for all houses. Residential plumbing systems vary in layout, pipe materials, pressure control mechanisms, fixture types and water use behaviours. These factors influence the clarity, consistency and repeatability of pressure signals. In particular, systems with plastic pipework tend to dampen transient pressure waves more significantly, further reducing signal distinguishability.

A key finding of this study was the identification of trapped transient pressures associated with certain plumbing components, particularly mini-stop taps with check valves. These components can prevent normal pressure dissipation, allowing localised pressure build-up within connected braided flexible hoses. This finding is important because braided flexible hoses are widely recognised as a vulnerable component in residential plumbing systems. Further investigation is required to determine the prevalence of this issue and to assess whether modifications to component design, installation practices, or regulatory standards are warranted.

Overall, this research demonstrates that smart plumbing systems have the potential to provide real-time or near real-time insights into the performance of residential plumbing systems. Such systems may support improved pressure management, earlier identification of abnormal behaviour, and more informed decision-making for plumbers, designers, regulators and property owners.

While further work is required before this approach can be applied broadly, the findings demonstrate the important role that pressure monitoring and data analytics can play in improving the design, operation and maintenance of residential plumbing systems.

Future research should focus on expanding the sample size and diversity of monitored houses to improve the robustness and generalisability of the findings. Further work is also needed to enhance event detection methods across a range of pipe materials and system configurations, and to develop more reliable approaches for linking pressure signals to specific fixtures and appliances.

In addition, targeted testing of pressure control devices, check-valve components, and heated water storage systems would provide stronger evidence to inform standards, regulatory frameworks and plumbing practices.

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8 Appendices

Appendix A: Plain Language and Consent Forms

PLAIN LANGUAGE STATEMENT AND CONSENT FORM

TO: Participants

Plain Language Statement

Date: March 2025

Full Project Title: Smart Plumbing Systems for Households: Monitoring and Analysis of Transient Pressure

Principal Researcher: Dr James Gong, Senior Lecturer of Water Engineering, School of Engineering, Deakin University.

Associate Researcher(s): Mr. Brendan Josey, Associate Research Fellow, School of Engineering, Deakin University.

Student Researcher(s): Mr Muhammad Bilal, PhD Candidate, School of Engineering, Deakin University.

Purpose of Research

Deakin University is undertaking research to explore how sensors that monitor pressure (in your home's plumbing system), combined with machine learning and artificial intelligence driven data analysis, can be used to create smart plumbing systems that could help residents and homeowners detect and address potential plumbing issues before they become major and potentially expensive failures (such as leaks or pipe bursts).

Funding Source and Amount

This research project is funded by the Victorian Building Authority through their research grant program. The total amount of funding awarded is $58,000.

What Participation Involves

The project will install pressure monitoring devices that include pressure sensors and microcontrollers to your cold and heated water plumbing network. These devices will continuously record pressure data at a high frequency. The installation will be minimally invasive and performed by a plumber who is licensed through the Victorian Building Authority in water supply work.

Plain Language Statement & Consent Form to Participants
[2025/HE000004]: version R1: [26/03/2025]

Page 1 of 5

Participants will:

1. Allow the research team to install/remove pressure monitoring devices at designated locations in their homes (e.g., under the kitchen sink, connectors to washing machines/dishwashers). Install/removal is expected to take 2 hours (4 hours total).
2. Pressure monitoring devices will log pressure data for 4 weeks (study period).
3. Complete a short survey on household fixtures and plumbing appliances at the beginning and end of the study period.
4. Periodically log specific water use events (e.g., using taps or appliances) via an online platform.

Risks and Benefits

Risks

- Minor inconvenience during sensor installation and data logging.
  - The research team expect study participants will need to commit ~8 hours of their time over the 4-week study period.
- Installing sensing equipment will mean temporary modifications to your homes plumbing network. This means there is a risk of leaks and water damage because of failed plumbing work.
  - To mitigate this risk, the research project will use high quality materials/product for sensing equipment. All sensing equipment will be installed by a licenced plumber.
- Possible misunderstanding of installed pressure device's purpose and capabilities:
  - The study's main goal is to collect the relevant information and pressure data that will support the development event detection algorithms for **future** smart plumbing systems.
  - This means, in their current state, the installed pressure sensing devices **do not** alert you to problems such as leaks or faults within your home's plumbing network.
- Identification of excessive plumbing pressures:
  - The study may discover that your plumbing network is subject to unusually low or high pressures.
  - The research team will do their best to notify study participants of any pressure related concerns that arise during data collection and analysis.
  - However, it the study participants responsibility to decide what actions to take in response, i.e. engage a licensed plumbing contractor to investigate.
  - The research team cannot provide advice, repairs, or financial support, and will not be responsible for any costs related to repairs or further investigation.

The identified risks are considered "Lower Risk" to participants with respect to safety and privacy.

Benefits

- Access to real time data of your household plumbing system performance via our online platform for the duration of the study period (4 weeks).
- Increased awareness of water uses and potential plumbing issues.
- Contributing to research that may lead to improved plumbing standards and smarter water management.
- Potentially identify any unknown problems (excessive pressure) with your plumbing system while it is being monitored. This means household can intervene before the potential failure of a specific component leading to a more sinister outcome.

Voluntary Participation

Participation is entirely voluntary. Participants can withdraw at any time without penalty before the end of the monitoring period by filling and sending back the Withdrawal of Consent Form. If a participant withdraws, they can opt to have collected data excluded from the research and will be removed from data repositories.

Privacy and Confidentiality

All data will be collected and stored securely, in accordance with Deakin University's Privacy Policy and the Privacy and Data Protection Act 2014 (Vic). Personal details will not be published or shared. During the project, participants will only be identified by a unique code in the dataset. Personal details and the code key will be destroyed at the conclusion of the project (18 months).

Data Management

Data collected will be stored securely on Deakin University's servers within its Research Data Store (RDS) for a minimum of 5 years. De-identified data may be used for future research projects that are extensions of, or closely related to, the original project or in the same general area of research. De-identified data may be shared with other researchers internal or external to Deakin University for research collaboration. De-identified data may be made available to the public during the publication process. The data will not be attributable to any individual and no implications are expected. For more information, please request a copy of the project's data management plan.

Research Monitoring

The research will be monitored by Deakin's Human Research Ethics Unit through annual and final reports.

Published Outputs Requests

Participants can contact the researchers to request a copy of any published outputs.

Contact Information

For any questions about the project, please contact:

Mr. Brendan Josey

Associate Research Fellow

E

P

Complaints

If you have any complaints about any aspect of the project, the way it is being conducted or any questions about your rights as a research participant, then you may contact:
The Human Research Ethics Office, Deakin University, 221 Burwood Highway, Burwood Victoria 3125, Telephone: 9251 7129, research-ethics@deakin.edu.au
Please quote project approval number [2025/HE000004].

This study has received Deakin University ethics approval, reference number: 2025/HE000004.

PLAIN LANGUAGE STATEMENT AND CONSENT FORM

TO: Participants

Consent Form

Date:

Full Project Title: Smart Plumbing Systems for Households: Monitoring and Analysis of Transient Pressure

Reference Number: 2025/HE000004

I have read and I understand the attached Plain Language Statement.

I freely agree to participate in this project according to the conditions in the Plain Language Statement.

I have been given a copy of the Plain Language Statement and Consent Form to keep.

The researcher has agreed not to reveal my identity and personal details, including where information about this project is published, or presented in any public form.

This study has received Deakin University ethics approval, reference number: 2025/HE000004.

Participant's Name (printed) ……………………………………………………………………………

Signature ……………………………………………………… Date ………………………………

Appendix B: Household Demographics and Fixture Stocktake Survey

Survey – Household Demographics and Fixture Stock Take

[Below is a list of proposed survey questions we wish to ask study participants.

A research team member and licensed plumbing contractor will assist the study household in completing this survey at the time of installing sensing equipment.

We intend for the survey to be completed in a paper format.]

Introduction

Thank you for participating in Deakin University's Smart Plumbing Systems research project. Your insights are invaluable in developing innovative solutions to detect adverse plumbing conditions and prevent potential failures. Please take a few moments to complete this survey. If you are unsure of an answer or prefer not to respond, kindly use "N/A." All responses will remain anonymous and will only be used for research purposes.

Survey Questions

Please enter the following details:

Household Number: ______________________

Date of survey completion: ______________________

List your preferred location to have sensing equipment installed: ______________________

Demographics and Household Information

1) Please provide the number of household members in each age range:
   0 – 10 years :______________
   11-20 years :______________
   21-30 years :______________
   31-40 years :______________
   41-50 years :______________
   51-60 years :______________
   61-70 years :______________
   70+ years :______________

Survey – Household Demographics and Fixture Stock Take

Property Information

2) Please estimate the age of your property, rounded to the nearest 5 years:
3) How many bedrooms does your house have?
4) How many bathrooms/ensuites does your house have?
5) What material are the plumbing pipes in your property primarily made of (e.g., copper, PEX, polybutylene)?
6) What water service is your property connected to? (Select all that apply):
   - ☐ Town Mains
   - ☐ Water Tank
   - ☐ Other, please list
7) Is there an active rainwater tank on your property? If yes, please describe its primary uses:
8) How is your water heated? (Select all that apply)
   - ☐ Gas
   - ☐ Electric
   - ☐ Solar
9) If your property has heated water storage, please specify the tank size in liters and the setting for the pressure relief valve:
10) Does your property have a backflow prevention device installed at the water service connection point?
11) Does your property have a pressure-reducing or pressure-limiting device installed at the water service connection point?
12) What is your average water consumption each month?
13) Has your property ever experienced a plumbing related failure? If so, please list the failure and the approximate cost to repair.

Fixture Stock Take

The following section will help the research team to identify the water fixtures and appliances within your home.

Taps

Please list all taps, their location, type, and whether they supply cold water, hot water, or both.

Please refer to the images below for information on how to classify your taps.

Item	Description	Location	Type	Cold / Hot / Both
E.g.	*Kitchen Sink*	*Kitchen*	*Mixer*	*Both*
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

Tap Types

Mixer (Combined)

Lever (Individual)

Turn (Individual)

Survey – Household Demographics and Fixture Stock Take

Showers and Baths

Please list all showerheads and baths, their location, and type. Please refer to the images below for information on how to classify your taps.

Item	Description	Location	Type
E.g.	*Shower 1*	*Main Bathroom*	*Mixer*
1			
2			
3			
4			
5			

Tap Types

Mixer (Combined)

Lever (Individual)

Turn (Individual)

Toilets

Please list all toilets, their location, flush volumes (half and full).

Item	Description	Location	Volume Half Flush	Volume Full Flush
E.g.	*Toilet*	*Main Bathroom*	*3 Liters*	*4.5 Liters*
1				
2				
3				
4				
5				

Survey – Household Demographics and Fixture Stock Take

Washing Machine

Please list the following information about your washing machine:

Make/Model: ______________________________

WELS star rating (e.g. 4 stars): ______________________________

(The research team can look up the WELS star rating can be found if you supply the make and model of your appliance)

Please list the three most common wash cycles you use on your washing machine. For each cycle, please list the cycle duration, temperature and estimated percentage of total washing machine use.

Cycle Name	Duration	Temperature	Percentage of use
Full Load 60	*60 minutes*	*40℃*	*70%*

Dishwasher

Please list the following information about your dishwasher:

Make/Model: ______________________________

WELS star rating (e.g. 4 stars): ______________________________

(The research team can look up the WELS star rating can be found if you supply the make and model of your appliance)

Please list the three most common wash cycles you use on your dishwasher. For each cycle, please list the cycle duration, temperature and estimated percentage of total washing machine use.

Cycle Name	Duration	Temperature	Percentage of use
Eco 50	*2 hours, 15 minutes*	*50℃*	*80%*

Outdoor Taps

Please answer the following questions about your home's outdoor taps.

Are outdoor taps installed on your property? ______________________________

If so, how many outdoor taps are present? ______________________________

Are any outdoor taps connected to an irrigation system? ______________________________