

Computer Aided Leak Location and Sizing in Pipe Networks

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The Urban Water Security Research Alliance (UWSRA) is a \$50 million partnership over five years between the Queensland Government, CSIRO's Water for a Healthy Country Flagship, Griffith University and The University of Queensland. The Alliance has been formed to address South-East Queensland's emerging urban water issues with a focus on water security and recycling. The program will bring new research capacity to South-East Queensland tailored to tackling existing and anticipated future issues to inform the implementation of the Water Strategy.

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Cover Photograph:

Description: Leak through a perforation caused by corrosion on a mild steel pipe.

Photographer: Melbourne Water.

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FOREWORD

Water is fundamental to our quality of life, to economic growth and to the environment. With its booming economy and growing population, Australia's South East Queensland (SEQ) region faces increasing pressure on its water resources. These pressures are compounded by the impact of climate variability and accelerating climate change.

The Urban Water Security Research Alliance, through targeted, multidisciplinary research initiatives, has been formed to address the region's emerging urban water issues.

As the largest regionally focused urban water research program in Australia, the Alliance is focused on water security and recycling, but will align research where appropriate with other water research programs such as those of other SEQ water agencies, CSIRO's Water for a Healthy Country National Research Flagship, Water Quality Research Australia, eWater CRC and the Water Services Association of Australia (WSAA).

The Alliance is a partnership between the Queensland Government, CSIRO's Water for a Healthy Country National Research Flagship, The University of Queensland and Griffith University. It brings new research capacity to SEQ, tailored to tackling existing and anticipated future risks, assumptions and uncertainties facing water supply strategy. It is a \$50 million partnership over five years.

Alliance research is examining fundamental issues necessary to deliver the region's water needs, including:

- ensuring the reliability and safety of recycled water systems.
- advising on infrastructure and technology for the recycling of wastewater and stormwater.
- building scientific knowledge into the management of health and safety risks in the water supply system.
- increasing community confidence in the future of water supply.

This report is part of a series summarising the output from the Urban Water Security Research Alliance. All reports and additional information about the Alliance can be found at <http://www.urbanwateralliance.org.au/about.html>.



Chris Davis

Chair, Urban Water Security Research Alliance

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1. INTRODUCTION

Prior to the wet weather experienced since December 2007, South East Queensland (SEQ) experienced marked reductions in seasonal rainfall over the past decade and as a result water storages in the region had reached unsustainably low levels. In response, water conservation measures were adopted across the region, augmented with programs for water recycling and stormwater harvesting. In this environment, losses from the potable water distribution system were brought under scrutiny especially as audit information indicated application of leak detection and rehabilitation technologies in SEQ had the potential to save 36,000 ML or \$27 M worth of water annually. The economic benefit of applying such technologies depends on the cost of leak detection and location technologies. With a view to reducing these costs, this report describes research that was done in the development of a novel technique for leak detection and predicting leak location, involving the analysis of pressure sensor readings by a support vector machine (SVM). The research aimed to develop a novel technique useful to water authorities for restricting the range of locations that have to be searched to find a leak.

Initial research, reported in the first edition of this Technical Report, focused on pressure measurements. However, due to the technical limitations of detecting small pressure changes against high background levels, the SVM analysis procedure was modified for execution through flow rate measurements using orifice plates in combination with a differential pressure gauge. This Technical Report updates the previous report and presents the findings of this additional research to examine the effectiveness of SVM-based leak detection methodology using flow rate measurements.

2. BACKGROUND

2.1. Leakage in Australian Cities

Although the primary objective of a water distribution system is to provide water at a sufficient pressure and quantity to all its users, in most distribution systems a significant percentage of water is lost in transit from bulk storages to consumers. As shown in Figure 1, losses range from less than 10% in countries with well managed infrastructure to greater than 40% in poorly managed systems. Australian cities average about 12%, ranging from about 4% in Canberra to 15% in Brisbane.

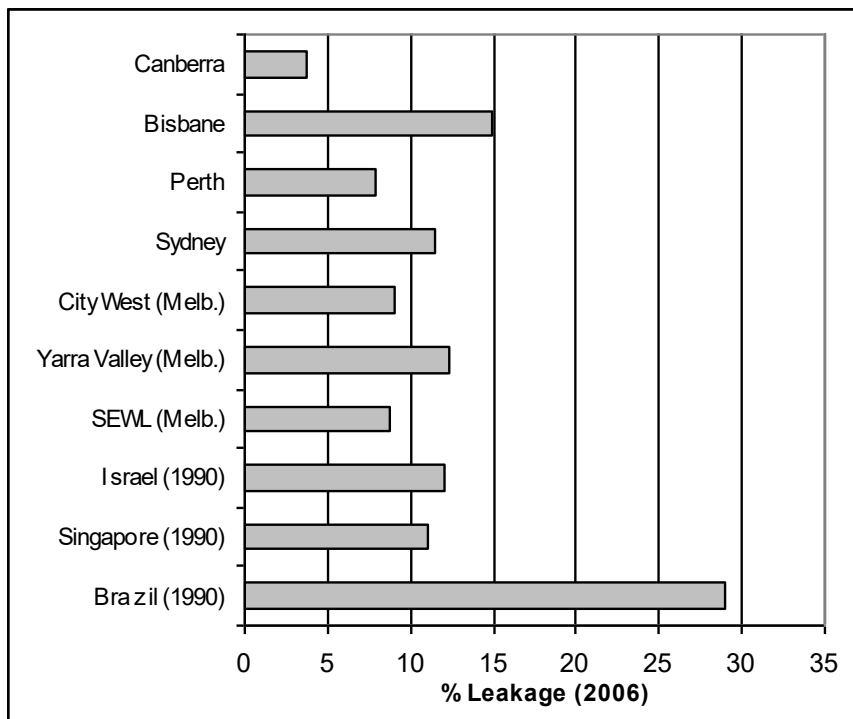


Figure 1: Leakage levels in Australian cities and overseas (from WSAA NPR 2008 and Cheong 1991).

The types of pipes in a distribution network largely determine the extent of losses, with older metallic pipes in corrosive soils generally being more prone to leaks than newer plastic pipes. Australian networks typically have a mix of pipe types ranging from the older cast iron and asbestos cement pipes to the more recent ductile iron, polyvinylchloride, polyethylene and mild steel pipes. While leakage rates specific to different pipe types have not been reported, a property described as the leakage parameter has been derived in an analysis of leakage control data in Melbourne. In this study, the leakage rate was given by the leakage parameter multiplied by the number of pipe joints, the pipe joint circumference and a pressure correction factor. Table 1 compares the leakage parameters calculated for different water pipeline materials in the Melbourne study (Desilva *et al.*, 2005).

Table 1: Leakage Parameters for different pipe types.

Material	Nominal Installation Year	Leakage Parameter (Litres/minute)
Metallic (predominantly Cast Iron)	1925-1975	0.0059
Asbestos Cement	1935-1970	0.0080
Plastic (PVC and Polyethylene combined)	1971 onwards	0.0006

The significantly higher leakage parameters for cast iron and asbestos pipes shows that reticulation networks that have these older pipe materials will contribute disproportionately to the overall leakage rate. In most Australian cities older suburbs have a higher proportion of older pipe types and consequentially higher leakage, while plastic pipes with lower leakage will predominate in newer subdivisions. A similar pattern of leakage can be expected from pipe types in water distribution and reticulation networks in SEQ.

2.2. Quantification of Network Leakage

Leakage in a network is quantified by a top down water balance of total supply against total metered consumption, with allowances for maintenance (i.e. flushing, cleaning), fire fighting, metering errors and unauthorised/illegal consumption as detailed in Equation 1.

$$Leakage = TS - [MC] - [MT_{Allwnc} + FF_{Allwnc} + ME_{Allwnc} + IC_{Allwnc}] \quad (1)$$

where TS = Total supply, MC = Metered Consumption, MT_{Allwnc} = allowance for Maintenance, FF_{Allwnc} = allowance for Fire Fighting, ME_{Allwnc} = allowance for Metering Errors and IC_{Allwnc} = allowance for Illegal Consumption.

Leakage in smaller areas can also be quantified by measuring minimum night flows in District Metered Areas (DMAs, also known as District Metered Zones or DMZs) as shown in Figure 2. After allowances for customer night flow, the balance of the flow is assumed to be due to leakage.

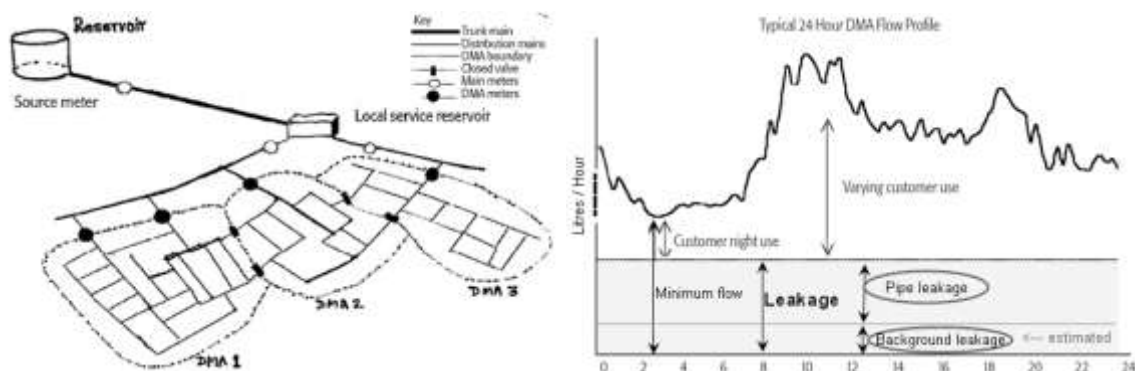


Figure 2: Leakage quantification through measurements in DMAs (Morrison, 2004).

Utilities employ a variety of measures to reduce leakage ranging from routine renewal of assets, reduction of service pressures and location of leaks by acoustic methods with follow up repairs (known as active leakage control). The level of leakage reduction achieved depends on the investment in detection and rehabilitation. While savings, direct and indirect, justify the expenditure up to a point, beyond a critical level, the benefits of leakage reduction are less than the costs. Included in these non-economic leaks are smaller ones that cannot be detected by current technologies. Referred to as background leakage, these are generally very slow, including joint leaks or seepage from small cracks and perforations.

An index developed by the International Water Association (IWA) referred to as the Infrastructure Leakage Index (ILI), based on the ratio of total leakage losses to the background leakage (Eq. 2), is used by most Australian utilities to assess the performance of their leakage abatement activities. An ILI of 1 would indicate the best outcome from a technical viewpoint, but is dependent on the method of estimating background or unavoidable levels of leakage. Figure 3 illustrates the relationship between the different leakage levels and the economic leakage level.

$$\text{Infrastructure Leakage Index (ILI)} = \frac{\text{Current Annual Real Losses (CARL)}}{\text{Unavoidable Annual Real Losses (UARL)}} \quad (2)$$

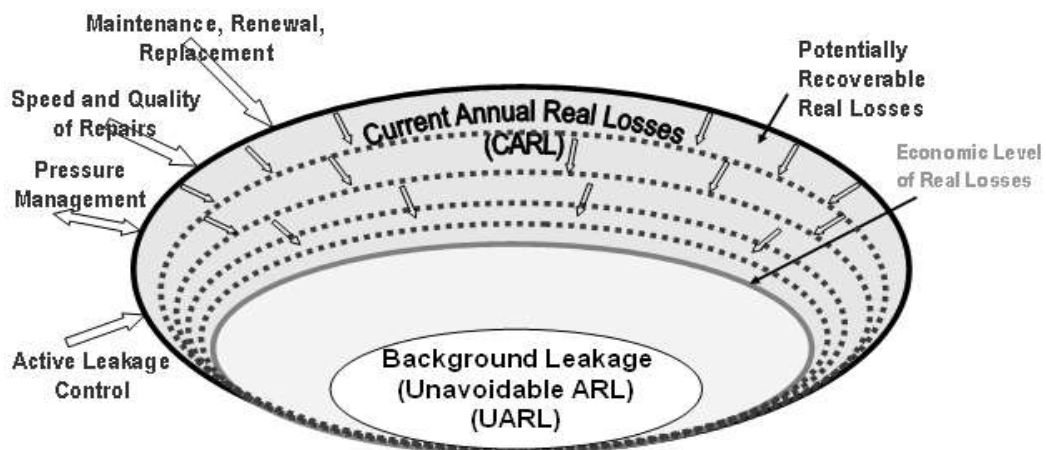


Figure 3: Relationship between CARL, UARL and Economic Level of Leakage.

A more direct indicator of leakage can be derived from measurements of water losses in terms of litres/connection/day. As shown in Figure 4, due to differences in auditing methods the two indices show slight differences when comparing utility performance.

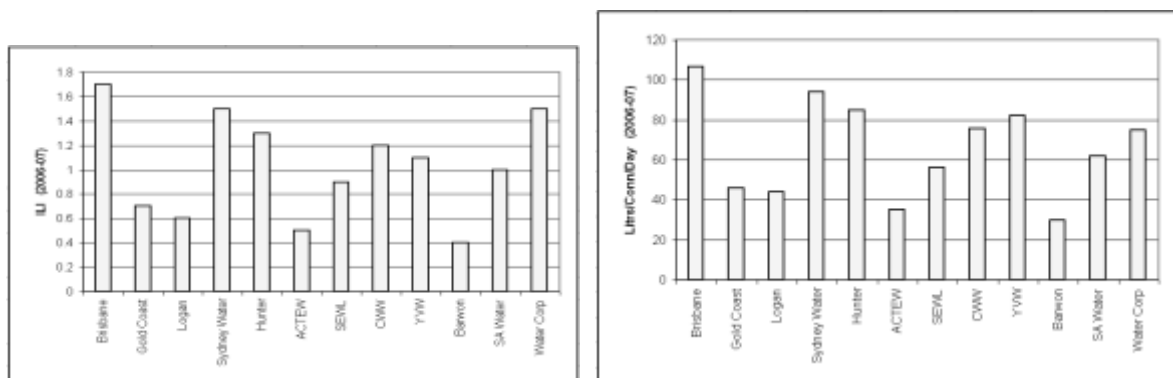


Figure 4: ILI and losses per connection/day for major Australian utilities (2006-07, from WSAA NPR 2008).

Note: As the IWA formula for calculation of UARL is based on UK leakage rates, some Australian utilities with new networks report ILI values <1. Theoretically the ILI should be ≥ 1 .

To some extent, leaks plague all water distribution systems. While water audits provide the scope of the problem, the control involves location of leaks across the distribution network. The next section reviews the evolution of leak detection in water networks and research and development to advance the science in future.

3. LEAKAGE DETECTION METHODS

Methods of identifying leak sites based on acoustic principles have been practised from the inception of pressurised water distribution networks. However, over the past two decades, new detection techniques have been under development based on analysis of hydraulic characteristics of water within the pipe, ranging from measurement of hydraulic characteristics in the steady state, to measurements in the transient state (Pudar and Liggett, 1992, Liggett and Chen, 1994). Although considerable research has been directed towards the development of techniques based on transient flow methods, the most commonly used method in the water distribution industry continues to be acoustic leak detection.

3.1. Acoustic Detection Methods

Acoustic leak detection is based on monitoring the noise and vibration generated by a fluid under pressure escaping through a leak site. While wooden listening sticks were utilised for this purpose in the early to mid 1900s, with the advent of microphones and the electronic age in the 1960s the accuracy of acoustic detection was enhanced. Further improvements followed with the development of correlators in the late 1970s (Grunwell and Ratcliffe, 1981) and the methods currently used by the water industry range from the electronic version of the listening stick (Pilcher, 2003) to advanced correlators with computerised signal analysis (Gutterman, 2009). Area surveys are also carried out using acoustic loggers. These are battery powered acoustic sensors that are installed permanently or for limited periods on the network to record noises during low consumption hours at night and identify areas of potential leakage for further investigation.

All these techniques are labour intensive; the listening sticks are manually operated whereas correlators and loggers require sensors to be placed directly on the pipe or fittings at street level (Fantozzi and Fontana, 2001). The sensors are usually installed at fittings via simple magnetic couplings, and they require minimal maintenance as they have built-in battery power. Signals from loggers monitored through a receiver module, hand-held or mounted in a patrolling vehicle, are used to identify the location of units indicating a leak condition, and thus the approximate position of a likely leak. More recent techniques deploy a tethered sensor inside the pipeline using special insertion equipment and monitor signals through the tethering ‘umbilical’ cord and surface probes (Bond and Rees, 2001). A free floating sensor has also been developed recently (Kurtz, 2006, Fletcher, 2008). These in-pipe sensors are more suited for large pipes (>300mm) such as trunk mains and require specialised deployment-retrieval equipment. Figure 5 shows the timeline for development of acoustic detection techniques and other related water audit methods.

1850s	1880s	1920s	1930s	1965	1978	1980s	1990s	1990s	2001	2001	2002	2003	2006
Manual sounding	Deacon meter (waste metering)	Helical Vane meters	Step testing	Ground microphones	Leak noise correlator	Electronic step tester, DMAs	Acoustic loggers	Ground penetrating radar	Combined acoustic logger & correlator	Tethered Hydrophone	Digital correlator	Advanced ground microphones	Free floating hydrophones

Figure 5: Timeline for development of acoustic detection technology (adapted from Pilcher, 2003).

As previously noted, these techniques are based on detecting sound waves generated by the escaping water propagating through the water as well as through the pipe material. The sound waves propagating along the pipe wall are detected by non-intrusive microphones, also referred to as accelerometers, attached to the outer surface of the pipe wall or to valves and hydrants. The detection of the sound waves in the water itself is accomplished by using hydrophones inserted into the water stream. However, as the location of hydrophones within pipes requires specialised insertion equipment and techniques, surface detection by accelerometers is usually the preferred option. Contamination issues associated with hydrophones also have to be considered as the water industry is averse to use of methods that increase the risk of bacteria or pathogens entering the water stream.

The disadvantages of the basic acoustic listening techniques have been well documented (Fuchs and Riehle, 1991). Some of these disadvantages include:

- Interference through noise signals from traffic, water use, ground movement and wind;
- Variations in pipe pressure conditions due to varying pipe materials, and thus changing sound propagation within different pipe sections;
- Leak characteristics: size and the soil environment determine the strength of the signal;
- Presence of multiple leaks;
- Signals in plastic pipes are difficult to detect due to acoustic attenuation; and
- Operator fatigue: in spite of experience, concentration decreases with time, and weakly audible leaks may not be detected.

The cross correlation method (Long *et al.*, 2003) minimises the effects of some of these limitations by estimating the position of a leak to within a metre if signals are taken at two points bracketing the leak (Fantozzi and Fontana, 2001). Correlators were not widely accepted in the 1970s as a leak detection technique, with the most harsh criticism originating from the American Water Works Association which found that a correlator method effective within two or three feet was far too expensive and time consuming for commercial use (Shaw-Cole, 1979). To respond to these problems, the following improvements to the correlator technique were made:

- Reliance on operator experience to be replaced by an objective detection system;
- Suppression of interference noises from the environment and from the network itself; and
- Ability to monitor the sensor responses remotely.

By the 1990s, systems such as LOCAL (Fuchs and Riehle, 1991), Leaktec (Seaford, 1994) and later HEARLEAK (McNulty, 2001) had been developed and were available for commercial use, although the systems were relatively expensive, each costing upwards of US\$60,000 (Smith, *et al.*, 2000). Current computer technology permits the completion of the processing within a short time frame on small portable devices. Systems that detect and locate leaks of 1.2 mL/s (4.3 L/hr) with sensor spacing 30m apart have been reported (Tafari, 2000).

Typically, leaks in cast iron, ductile iron and steel pipes can be detected at a maximum distance of 250 metres with accelerometers and up to 600 metres by hydrophones. However, acoustic techniques are not equally effective with every type of pipe as they have been primarily developed for metal pipelines and difficulties have been encountered with plastic (Hunadi *et al.*, 2000) and with asbestos cement pipelines (SubSurface, 2009). The high attenuation in plastic pipes requires the accelerometers to be placed at greatly reduced distances (Hunaidi *et al.*, 1999) which can be partly offset by using hydrophones as water-borne noise is not damped to the same extent. The typical length of plastic pipes, such as PVC or polyethylene (high and low density), that can be sampled accurately with accelerometers is 50 metres and this can be increased to 120 metres when hydrophones are used (Fantozzi and Fontana, 2001). As this entails a greater number of access points on plastic pipes compared to metal ones, the method is sometimes not a practical option with plastic. To overcome this difficulty, the effectiveness of sensors placed at ground level has been investigated (Lockwood *et al.*, 2005). Further improvements on the standard cross correlation techniques through the development of a signal processing procedure tailored specifically for plastic pipes has been described by Brennan *et al.* (2006).

3.2. Transient Analysis (TA) Methods

Because of the difficulties and expense associated with acoustic techniques, it is worthwhile investigating non-acoustic techniques of leak detection in pipe systems that include methods based on:

1. Injection of tracing substances into the fluid stream;
2. Electro-magnetic inspection of the pipe from the inside;
3. Analysis of quasi-static signals detected by sensors built into the pipe system such as pressure sensors, flow rate sensors and temperature sensors;
4. Analysis of transient signals detected by sensors built into the pipe system e.g. pressure wave analysis;
5. Analysis of leak generated temperature variations using infrared thermography by sensors located outside the pipe system; and
6. Identification of radar or radio frequencies emitted from transmitters located inside the pipes and permeating outside through cracks.

As most leak detection methods had their inception in the oil and gas industry, only a few of these are suitable for potable water systems. Furthermore, some techniques are expensive (i.e. 2, 5 and 6) and in addition, others are intrusive into the water stream (i.e. 1, 2 and 6) increasing the risk of contamination. For these reasons, only techniques 3 and 4 are considered in this report.

Techniques 3 and 4 seek to determine the pipe system state from the measured parameters of pressure, flow rate and sometimes temperature at various points in the pipeline system and at various times.

In technique 4 when a transient pulse, such as a pressure wave, is introduced in a pressurised pipe system, a hydraulic transient event propagates through the system. The presence of leaks, variations in pipe diameter, pipe material, pipe geometry, elevation or air pockets, introduces changes in the hydraulic transient event propagation. A leak creates a pressure drop; a change in pipe size or geometry creates reflections; an air bubble creates a pressure drop followed by a pressure increase. Detection of these signals allows identification and location of the source that caused the change (Covas *et al.*, 2004).

Several techniques based on transient analysis have been described in the literature, including: reflected wave or timing methods (Brunone, 1999; Covas and Ramos, 1999); frequency response analysis (Jonsson and Larson, 1992; Mpesha *et al.*, 2001; Lee *et al.*, 2006); input response analysis (Lee *et al.*, 2007); inverse transient analysis (ITA) (Liggett and Chen, 1994, Vitkovsky 2003, 2007); genetic algorithms (Vitkovsky *et al.*, 2000) and pressure damping (Wang *et al.*, 2002). Each of these leak detection techniques has its advantages and disadvantages, with all methods detecting features of reasonable size. The major question for each technique is identification of the type of feature; is it a leak or some other feature such as a bend in the pipe, air bubble, etc. The accuracy of leak identification depends on the knowledge of other features in the system. For example, in a comparison of reflected wave and ITA methods to detect leaks in laboratory and quasi-field conditions, the ITA method was more successful (Covas *et al.*, 2004). In a separate investigation, the observation was made that the ITA method requires all boundary conditions, system properties and the transient model to be well defined (Vitkovsky *et al.*, 2007) and this poses practical difficulties for implementation in the field. Limitations of the reflected wave method have also been noted by Wang *et al.* (2002), where they observe that while being simple to use and apply, it does not have the flexibility of other methods (i.e. the ITA) and it is not generally applicable to a complex system such as a pipe network.

As in the case of acoustic detection methods, a range of factors influence the transient analysis techniques. These include:

- Pipe characteristics: in addition to leaks, the pipe diameter, material changes, tee junctions and air pockets introduce changes in the transient signal. Uncertainties in these also influence the wave speed, which is the determining parameter for leak location;
- Topography: changes in pipe elevation have to be considered in numerical solutions;
- Leak characteristics: leak size, location, state of surrounding soil;

- State of flow: the generation of the transient event requires the use of well controlled valve closure/opening procedures; and
- Data collection: the pressure sensors need to be next to the site of transient generation within reasonable proximity to the leak. Signals from leaks located far from the measurement site tend to be dissipated within the pipe.

The method of transient analysis, initially proposed by Pudar and Liggett (1992) for networks in the steady state, was extended by Liggett and Chen (1994) to transient events by combining the inverse method with transient analysis on the basis that large volumes of measurement data could be provided by electronic monitoring devices. It was expected that this method could give more accurate calculation of the friction factor of pipes, which in turn leads to improved accuracy in the prediction of leaks. The ITA method has proved, at least numerically, to have the capability of simultaneous leak detection and network calibration (Covas and Ramos, 2004). As pressure waves are less affected by pipe friction factors, the ITA method is less dependent on accurate knowledge of those properties in the pipe network.

The method takes as a starting point the equations of transient flow in pipelines that can be solved numerically by the method of characteristics. In the ITA method, parameters such as leak area are adjusted to obtain a best fit to the observed transient pattern of pressure. The solution parameter set is determined by minimising an objective function that represents the match between the numerically modelled heads and measured heads. The objective function is derived from maximum likelihood estimators with the least squares criterion:

$$E = \sum_{i=1}^M (H_i^m - H_i)^2, \quad (3)$$

where E = objective function, H_i^m = measured head, H_i = numerically modelled head and M = total number of measurements.

The optimisation technique used by Liggett and Chen was the Levenberg-Marquardt gradient method (Nash and Karney, 1999). A genetic algorithm (GA) search method was implemented by Vitkovsky *et al.* (2000). This method is more robust and less likely to get caught up in local minima than the Levenberg-Marquardt method. The GA technique was shown to be effective at finding leakage locations and magnitudes and simultaneously finding the friction factors for different measurement pipe lengths. Further developments that explored the effects of data and model error, including strategies to minimise their effects using compensation techniques and ITA implementation approaches, were reported by Vitkovsky *et al.* (2007). After these improvements, experimental observations in a simple laboratory pipeline demonstrated the detection and quantification of both single and multiple leaks. Further discussion of the ITA method can be found in Kapelan *et al.* (2003) and Covas *et al.* (2003).

As stated previously, these methods require a good understanding of the system, including unsteady friction, pipe roughness, precise geometry and other considerations such as minor leaks (Lee *et al.*, 2007). Such knowledge constitutes a very high hurdle to overcome and, even if known, may be difficult to include in the mathematical equations governing system behaviour (Lee *et al.*, 2007). A solution is to benchmark against a leak-free system, which is obviously a problem if the system is not known to be leak-free. As an alternative, Lee *et al.* (2005) and Sattar and Chaudhry (2008) have used impulse response and frequency response functions in order to perform leak detection in pipes by analysing transient signals in the frequency domain. When the transient signal is generated by a wide band signal fed into the pipe system, it generates a response at a wide range of frequencies simultaneously. When a pipeline system is excited by such a signal, a quantity called the frequency response function is generated that is defined by:

$$H(\omega) = \frac{Y(\omega)}{X(\omega)}, \quad (4)$$

where $X(\omega)$ and $Y(\omega)$ are the Fourier transforms of the input and output signals respectively.

The presence of a leak within a single pipeline induces changes in the shape of the frequency response diagram (FRD) and this can be used as a means of identifying the position of the leak within the system. Lee *et al.* (2005) presented two methods of leak detection in pipeline systems; the inverse resonance method; and the resonance peak sequencing method. The former is related to the method of inverse transient analysis of Liggett and Chen (1994) but operates in the frequency domain and carries out a parameter estimation process by fitting the FRD from a numerical model to a measured FRD. The resonance peak sequencing method involves a comparison of the shape of the FRD and known shapes generated by leaks at various positions in the pipe. This comparison can be affected by summarising the shape of the FRD in a sequence of harmonic peaks ranked in order of magnitude. These functions provide a unique relationship between an injected transient event and a measured pressure response. The feasibility of applying impulse response and frequency response functions for leak detection has been shown experimentally (Lee *et al.*, 2006: 2007). Independent assessment of these methods was not found in the literature.

A method for leak detection in oil transport pipelines based on pressure wave transients was described by Zhang *et al.* (2005). The method uses Enhanced Independent Component Analysis (EICA), a powerful tool for blind signal separation with better generalisation properties than independent component analysis, in combination with SVM. Their leak detection method is based on examining pressure traces with the EICA/SVM system to determine if a negative pressure wave characteristic of a leak has occurred. The method includes two steps: (i) EICA based feature extraction; and (ii) SVM based classification of EICA features. The classification system operates on $N \times N$ pressure trace images where, for the experiments in their paper, $N = 30$. They considered 5,380 images as a sample set in which 1,600 images contained a negative pressure wave. 1,500 images (containing 500 with a negative pressure wave) were chosen as a training set and the remaining images were used for testing. The EICA/SVM method was found to have an accuracy of 97% when compared to 91% for direct SVM. They state that the reason for this improved performance is that the EICA can explore edge information in the image data and that, by using EICA features instead of the original image data, the number of support vectors for the SVM is reduced, resulting in lower detection errors.

Another method for detecting pipeline leaks by analysing pressure wave transients has been described by Hu *et al.* (2007). Their method detects negative pressure waves using the Interactive Self-organising Data Analysis Technique Algorithm (ISODATA), an unsupervised learning method which is a clustering procedure, in which they define a feature space of 10 components which is reduced to 4 by applying the Karhunen-Loeve transformation.

Leak detection methods utilising transient behaviour are very complex and they do not work well for pipe networks or for field conditions. They have been mainly tested on single pipes in laboratory conditions, as the requirement for detailed fluid flow hydraulic modelling and associated significant computer processing capabilities contributes to limitations in applying transient analysis methods to field studies in real networks. The underlying uncertainties associated with the application of TA methods for leak detection and location in real life systems was discussed by Covas *et al.* (2004: 2005). They observe that, although TA based techniques have been shown to be successful in the detection and location of 'reasonable' size leaks provided hydraulic characteristics of the system are quantified, practical difficulties exist in the implementation of the proposed techniques in real life systems.

Because of these limitations, detection techniques based on hydraulic characteristics have yet to enter the mainstream leak detection industry (Savic *et al.*, 2005). The slow progress in the development of practical TA based leak detection techniques appropriate for leaks in real networks has prompted discussion among practitioners of proven acoustic techniques on the direction and priorities of research in this domain (Waldron, 2005).

4. PATTERN RECOGNITION APPROACHES TO LEAK DETECTION IN PIPE NETWORKS

4.1. Analysis through Neural Networks

As discussed previously, the analysis of transient events in relation to water pipeline leaks requires detailed hydraulic modelling of fluid flow and significant computer processing capabilities. The modelling requirements and, to a limited extent, the computer processing requirements, can be partly overcome by using Artificial Neural Networks (ANN) to monitor the status of piping networks. The ANN is trained on different sets of input data, which characterise the states of the fluid network under normal and abnormal (i.e. with leaks) operating conditions. Then it acts as a classifier in order to estimate the actual system status and pinpoint leaks, based on available information, thereby solving the stated inverse problem. The ANN recognises patterns among measurement data from pressure and flow rate sensors distributed on the network branches and nodes, and classifies them to identify and locate the leak.

Neural networks are computational systems that model the operation of the human nervous system and are made up from a collection of nodes linked by a number of connections or arcs. Each connection is associated with a real number referred to as its weight. Neural networks define a mapping between input patterns and output patterns and are trained on a collection of training cases called a training set. During training, the weights are adjusted to minimise the mean square error between the predicted output and the actual output pattern, a procedure referred to as 'back-propagation'. Through training, a neural network can learn a mapping between input patterns and output patterns without an explicit model for the mapping being provided. The training allows some of the computational processing to be carried out offline, reducing significantly the real time processing and detailed fluid flow modelling required in transient analysis.

Neural networks operating on quasi-static pressure and flow readings have been used for leak detection in pipe systems. Caputo and Pelagagge (2003) have described an approach to detecting spills and leakages from pipeline networks using a multilayer perceptron back-propagation ANN. The system analyses data from pressure and flow rate information in order to determine the location and size of leaks in the pipe network using a two level architecture composed of a main ANN at the first level and several branch specific second level ANNs. The branch in which the leakage occurs is estimated by the main ANN while a specific second level ANN is activated to estimate the magnitude and location of the leakage in the selected branch. The methodology is based on two main phases:

- Evaluation of pressure/flow rate conditions (effects) by simulation imposing the piping network's boundary conditions (causes); and
- Correlation of effects with causes by ANN.

Using this process, a series of patterns characterising the system status in several conditions of normal or abnormal operation are determined and the ANN is trained successively on the data sets representing the system status (i.e. pressures and flow rates) in different operating conditions, either with or without leakages. Satisfactory leakage identification and location performance was obtained using their system; in particular, the ANN was always able to correctly identify the leaking branch.

A similar approach only utilising pressure readings was described by Shinozuka *et al.* (2005). The methodology described identified the location and severity of damage in a water delivery system by monitoring water pressures on-line at some selected positions in the system. The ANN employed in the study was trained on data originating from a simulation of the water supply network. A trial system was produced having only one location of damage and three monitoring stations. The ANN was given further training with the pressure variation at the three monitoring stations as inputs and the location of break and damage index as outputs. Finally, the ANN was tested on the simulated data with the result that it was effective for the purpose of damage identification.

Another application of ANNs operating on steady state process parameters for leak detection in pipe systems was delivered by Belsito *et al.* (1998) describing an approach to leak detection in liquefied gas pipelines. In order to generate data for ANN training, they used a computer simulation based on a deterministic model using equations for mass conservation, momentum conservation and energy conservation. A numerical simulation was used to generate a series of patterns corresponding to the presence or absence of leaks. Two different neural networks were implemented: one for leak detection and sizing; and one for leak location. The simulated patterns were used to train and test the leak sizing network and field data used for validation. The values of pressure at thirteen monitoring stations and the inlet and outlet flow rates were used as inputs to the ANN and trained on steady state values rather than transients. The leak location ANN came into operation only if the leak detection and sizing network was activated. The output layer of the leak location ANN contained a number of neurons, with the leak location information provided by the highest activation neuron. The system was able to detect leaks as small as 1% of the flow rate without generating spurious alarms. The ANNs performed very well in leak locations when noise was not present or when the leak was large.

A neural network for leak detection operating on sound signals emanating from a pipe network was used by Zhang *et al.* (2004). Their work described a method for detecting gas leaks in pneumatic pipe systems. The neural networks employed operated via detection of sound signals emanating from the pipe system.

As well as neural networks, the domain of pattern recognition includes the areas of fuzzy logic and fuzzy neural networks. A system using fuzzy logic acting on flows in a pipe system for leak detection was described by Da Silva *et al.* (2005). Their system was used for the detection of leaks in petroleum pipelines. The system was composed of three modules: Fuzzy Rules Design; State Recognition; and Deviation Evaluation. The authors reported an accuracy level greater than 90% in leak detection.

A number of systems utilising fuzzy neural networks for leak detection in pipeline systems have been described. Gabrys and Bargiela (1999) addressed the problem of effective interpretation of water distribution network state estimates, calculated on the basis of measurements and pseudo measurements (consumption estimates) that have significant uncertainties associated with them. System state interpretation is particularly relevant to the diagnosis of leakages and other operational faults occurring in water distribution networks. They proposed and evaluated an approach based on the examination of patterns of state estimates by a general fuzzy min-max neural network (GFMM). The GFMM classification and clustering was incorporated into a two-level fault diagnosis system. The measurements on which the state estimates had been based were flows and pressures in the network at a number of instants in time. The procedure for the quantification of the inaccuracy of the state estimates caused by the input data uncertainty was initially developed by Barjiela and Hainsworth (1989) and was termed the confidence limit analysis (CLA).

Feng and Zhang (2006) described an approach to pipeline leak detection using a Discrete Incremental Clustering (DIC) fuzzy ANN. The input to the fuzzy ANN was a set of features extracted from raw sensor information. The fuzzy ANN was made up of six layers: Input; Condition; Rule-base; Normalisation; Consequence; and Output. The raw sensor information consisted of pressure readings and flow readings at terminals along the pipe. The experimental results for this method indicated better than 90% classification accuracy.

Another fuzzy ANN system for fault detection in water supply systems was described by Izquierdo *et al.* (2007). Their method was based on a mathematical model of the system and the application of a fuzzy neural network. The mathematical model was used to generate fuzzy estimated states which were then used to train the ANN. The ANN was based on multidimensional cells. It was found that this system had good classification accuracy for large leaks.

In summary, the methods discussed in this section have involved: the analysis of transient signals, in particular pressure waves; the analysis of steady state (quasi-static) signals such as process parameters and sound signals by neural network; and the analysis of steady state signals by fuzzy and fuzzy ANN systems. Of these, the most straightforward to implement, given a suitable pipe network simulation system, is the analysis of steady state process parameters by an ANN.

The analytical methods involving transients do not generalise well to pipe networks with more than one pipe or to field conditions. Pattern recognition techniques using automated learning techniques are perhaps preferable in such circumstances. This leads to the possibility of processing frequency response functions by neural network rather than using inverse resonance theory or the peak sequencing method. However, as mentioned above, frequency response functions are not trivial to obtain and the definition of the frequency response function of a pipe network is not entirely straightforward. Such an approach would be complex with no clear benefit.

Therefore, a promising direction seems to be the analysis of steady state process parameters by ANN, fuzzy or fuzzy ANN systems. As well as being the simplest, the analysis by ANN of these parameters promises to successfully detect leaks as reported in the paper by Caputo and Pelagagge (2003).

4.2. Analysis through Support Vector Machines (SVM)

SVMs are learning machines that can perform binary classification (pattern recognition) and real value function approximation (regression estimation) tasks. They are related to neural networks and can be considered to be a type of neural network and have a number of properties that make them superior to (conventional) neural networks. Firstly, they can operate successfully on very high dimensionality input spaces and secondly, SVMs are able to deal with small samples for training and testing.

Neural networks have inherent drawbacks such as:

- Local optima;
- Lack of generalisation; and
- Uncontrollable convergence.

SVMs are less sensitive to these factors and additionally they have yielded excellent generalisation performance on a range of problems including:

- Bioinformatics (Brown *et al.*, 2000);
- Text categorisation (Kapoutsis *et al.*, 2004);
- Fault diagnosis (Zhang, 2008);
- Image detection (Roohi *et al.*, 2007);
- Power systems (Moulin *et al.*, 2004); and
- Financial analysis (Chen and Hsiao, 2008).

A SVM can be established by assigning a few parameters, such as the kernel function and the loss function, in contrast to the large number of parameters that need to be decided upon in constructing an ANN. It has been shown in experimental studies that a SVM achieves superior performance in comparison with other methodologies (Ramesh *et al.*, 2001; Kwok, 1998; Mukherjee *et al.*, 1997). Also the use of a SVM guarantees a global minimum of the error surface, while with an ANN there is always the possibility of getting trapped at a local minimum.

Therefore, this report will test the use of SVMs for leak detection using the method of Caputo and Pelagagge (2003), specifically by training the SVMs to act on steady state process parameters such as pressures and flows.

5. LEAK DETECTION AND SIZING USING SVMS

As described above, SVMs are statistical pattern recognisers that can be used for regression or classification. When acting as a classifier, the output is a predicted class associated with an input pattern. When acting as a regressor, the output is a real number associated with an input pattern. A SVM acting as a regressor is acting as a function approximator. SVMs are trained on a training set consisting of a number of input patterns and the associated output values or categories. They can then be evaluated on a testing set to determine the relevant performance metric, that is, classification accuracy in the case where they are acting as a classifier or the Mean Squared Error (MSE) and correlation coefficient (R) when they are acting as a regressor.

The SVM method used for leak size and location prediction monitored the pressure at a number of nodes in the pipe network under consideration and fed these pressure values into SVMs trained to predict various sizes of leaks and locations in the pipe network.

As SVMs require 100s or possibly 1,000s of cases in their training sets, it was not feasible to generate the training sets by introducing actual leaks into the real pipe network. To overcome this, the training sets were obtained by simulation of the pipe network under consideration using the simulation tool EPANET, which is a computerised simulation model produced by the Environmental Protection Agency of the USA that predicts the dynamic hydraulic and water quality behaviour within a drinking water distribution system operating over an extended period of time. Leaks of various sizes were simulated in EPANET and the resulting pressures and flows in the network were calculated. In this project pressure was the sole criterion considered in the SVM training and predictions.

In order to generate the large number of cases required for the SVM training set the running of EPANET was automated by developing a program which calls EPANET many times with various values of the leak size.

5.1. Modelling Leakage in EPANET

Although EPANET is primarily designed for modelling network supply and water quality issues, the emitter property in EPANET designed to model fire hydrants/sprinklers can be adapted to model leaks and associated pressure variations.

The definition of the emitter is based on the classical Torricelli equation for flow through an orifice:

$$Q = C.A.P^B \quad (5)$$

where Q is flow rate, C is a given coefficient, A is aperture area, P is pressure and B is a pressure exponent typically measured as 0.5 for circular apertures.

Based on this equation, EPANET applies a simple definition for the emitter coefficient:

$$\text{Emitter Coefficient} = Q/P^B \quad (6)$$

The emitter coefficient is given in terms of flow rate per unit pressure. EPANET permits the value of the Emitter Coefficient to be specified for individual leak sites, but the pressure exponent (also referred to as the Emitter Exponent) can be specified only for the entire network.

Equation 6 indicates that the desired low leakage rates of 50-100 litres per hour can only be achieved by specifying emitter coefficients in the order of 0.001 in combination with an emitter exponent value of 0.5. Hydraulic simulations through EPANET are affected by very low values of emitter coefficient and convergence could only be reached by changing the system accuracy to 0.00075.

Investigating the effects of leakage in water distribution systems has shown that the pressure exponent depends on the geometry of the orifice (Van Zyl and Clayton, 2007; Greyvenstein and Van Zyl, 2005). Table 2 shows that corrosion areas in metal pipe correspond to the highest values of the exponent, and in plastic pipe, depending on the orientation of the leak defect, the exponent can take different values.

Table 2: Leakage exponents found in experimental study (Van Zyl and Clayton, 2007).

Failure Type	Leakage Exponent* for pipe materials		
	uPVC	Asbestos Cement	Mild Steel
Round hole	0.52	-	0.52
Longitudinal Crack	1.38 -1.85	0.79 – 1.04	-
Circumferential crack	0.41 – 0.53	-	-
Corrosion cluster	-	-	0.67 – 2.30

*These values are for turbulent flows and with the leaks to the atmosphere.

Soil will also have an effect on the leakage rate because it exerts a back pressure at the leak site (Van Zyl and Clayton, 2007). The pressure in the soil will affect the leakage rate directly by lowering the available head, i.e. the higher the soil pressure, the lower the leakage rate. However, soils can't withstand large pressures, and the behaviour outside a leak seems to be very complex. It is likely that the soil will not affect the exponent, but might affect the coefficient (Van Zyl, 2009). In the absence of experimental evidence to the contrary, the EPANET simulations for this study were carried out with the exponent value set at 0.5.

5.2. Development of the SVM Analysis Method

The EPANET model was applied to simulate the pipe network in an area in South Eastern Melbourne shown in Figure 6 which had been developed from the mid 1970s through to the mid 1980s. Almost all the pipelines in the area are PVC and the supply to the zone is from a pumped system connected to a reservoir. The site was selected with a view to validating simulation outputs with *in-situ* measurements later in the project.

The first experiment carried out was to determine how effectively an SVM regressor predicts emitter coefficient values when a given fixed node is leaking. Leakage from 0 to a high rate of approx. 3 L/s (litres per second) was modelled in these experiments. The EPANET driving program was used to generate a data set of 300 cases with the emitter exponent set at 0.5. In each case, the node Nd73 (see Figure 7) was leaking and its emitter coefficient value was varied from 0 to 0.3 in steps of 0.001, and the pressure monitored at six nodes located in different parts of the network (nodes 46, 16, 23, 59, 70 and 36). From these, 200 cases were randomly selected to form a training set and 100 cases selected to form a testing set. The training converged very rapidly and when the trained SVM was applied to the testing set the MSE and the squared correlation coefficient (R^2) were:

$$\text{MSE} = 4.47569\text{e-}005; \text{ and}$$

$$R^2 = 0.994289.$$

Thus, the testing results were very good. As the SVM was acting as a regressor (function approximator), its accuracy was not measured as a percent accuracy but by the MSE and R^2 values due to the fact that its outputs were given as floating point numbers (leak sizes, i.e. emitter coefficient values) rather than discrete classes.

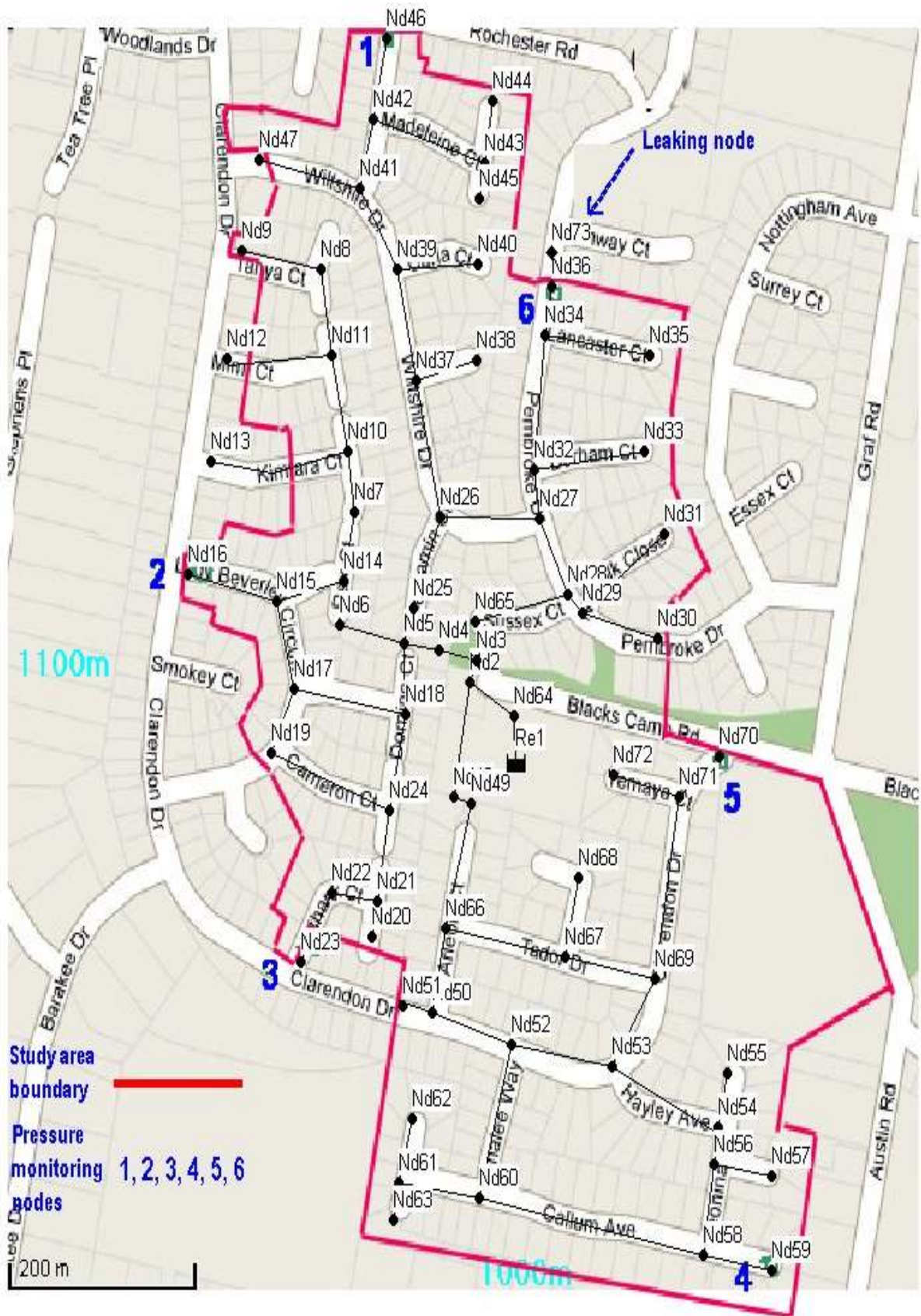


Figure 6: The study area indicating node distribution.

The next experiment carried out was to determine the effectiveness of using an SVM classifier for leak location. Ten nodes were selected from the pipe network under consideration as candidate leak nodes (Nd45, Nd41, Nd8, Nd10, Nd14, Nd17, Nd21, Nd52, Nd55 and Nd31). The EPANET driving program was used to generate data representing the pressures at the six monitoring nodes for the case when exactly one of the candidate leak nodes was leaking for emitter coefficient values increasing from 0 to 0.3 in steps of 0.002. Ten data sets of 150 cases each were generated. The data sets were then amalgamated and 1,000 cases randomly selected to form a training set. The remaining 500 cases were used as a testing set. The cases in the training and testing sets contain representatives for a variety of leak locations and leak sizes.

When the SVM was trained with its default parameter settings, it achieved a testing accuracy of 19%. If it were guessing randomly it would have had an accuracy of 10%. The training parameters were then adjusted in order to optimise the testing accuracy. The best testing accuracy that was achieved was 76.8%. The training parameters are the misclassification penalty parameter (C) and the kernel function parameter (γ). The misclassification penalty parameter specifies the penalty applied during training to a misclassified case. The kernel function parameter specifies the spread of the Gaussian in the radial basis function kernel for the SVM. The testing accuracy for various values of these parameters is shown in Table 3. The default value for γ is $1/k$, where k is the number of attributes in the input data.

Table 3: Testing accuracies with 10 candidate leak nodes.

C	γ	% Accuracy
1000	Default	60.2
10000	Default	67.6
100000	Default	72.2
1000000	Default	75.2
10000000	Default	76.8
100000000	Default	74.8
10000000	0.001	73.4
10000000	0.0001	68.4
10000000	1	76
10000000	10	74.4

It should be noted that the leak location prediction was carried out for all emitter coefficient values in the range from 0 to 0.3, including very small emitter values. It seems reasonable that the accuracy would be better for higher emitter values. To test this hypothesis, a histogram of prediction accuracy versus emitter value was generated. This analysis was carried out for the case of the ten candidate leak nodes described above. Emitter values ranged from 0 to 0.3 in steps of 0.002. A training set of 900 randomly selected cases and a testing set of 600 randomly selected cases were obtained. The accuracy histogram is shown in Figure 7. The interval from 0 to 0.3 has been divided up into 40 histogram cells. It can be seen that accuracy is low for small leak sizes ($< (5/40)0.3$ emitter value). There does not seem to be a trend for other values of the emitter value, just random variation.

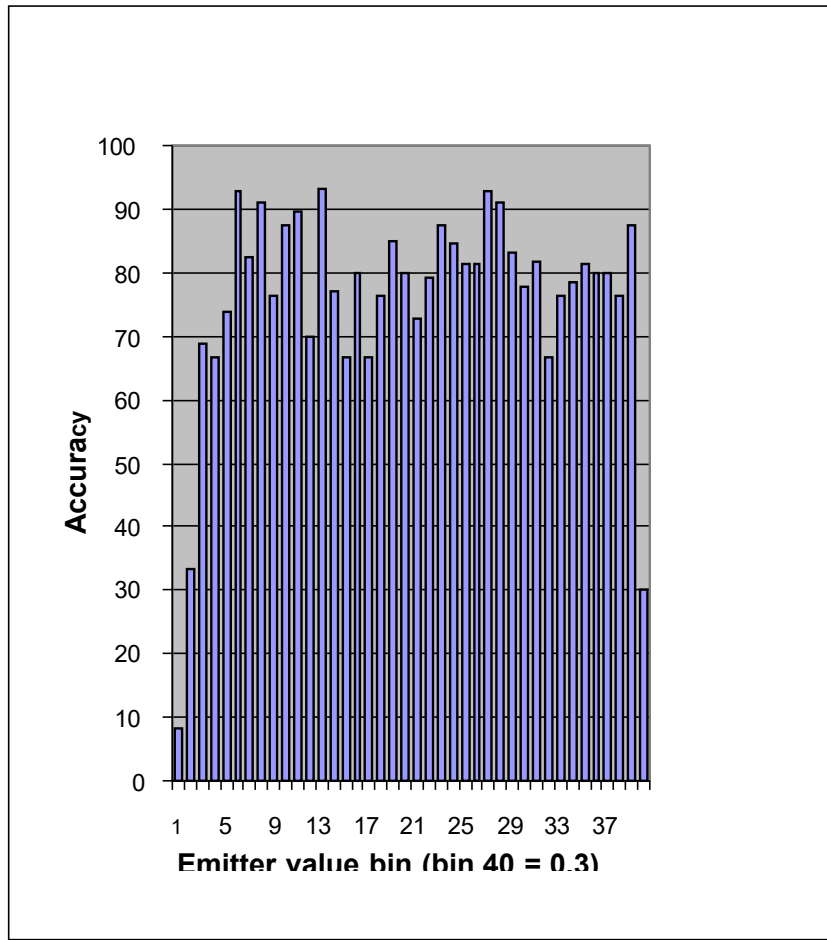


Figure 7: Histogram of accuracy versus emitter value.

The accuracy of using the SVM for leak location with 20 and 40 candidate leak nodes was then determined. The EPANET driving program was run 20 times with leaking nodes Nd45, Nd41, Nd8, Nd10, Nd14, Nd17, Nd21, Nd52, Nd55, Nd31, Nd3, Nd6, Nd19, Nd50, Nd60, Nd69, Nd72, Nd27, Nd33 and Nd38 respectively, with emitter values going from 0 to 0.3 in steps of 0.002 to generate 3000 cases. A training set of 2000 was randomly selected and the remaining 1,000 cases were used as a testing set. After manually optimising the training parameters, the testing accuracy was 77.2%. The accuracies obtained for various values of the training parameters are shown in Table 4.

Table 4: Testing accuracies with 20 candidate leak nodes.

C	γ	% Accuracy
10000000	Default	76.6
1000000	Default	75.2
1000	Default	51.1
100000000	Default	75
9000000	Default	75.5
11000000	Default	76.2
10000000	0.001	71.7
10000000	0.01	74.6
10000000	0.1	77.2
10000000	1.0	76.4

Then, in addition to the above mentioned leaking nodes, the following nodes were used as candidate nodes for leaking: Nd39, Nd40, Nd11, Nd13, Nd7, Nd24, Nd20, Nd51, Nd67, Nd4, Nd25, Nd37, Nd29, Nd26, Nd32, Nd35, Nd30, Nd56, Nd53, Nd66, making a total of 40 candidate leak nodes. 6000 cases were generated by applying the EPANET driving program 40 times and a training set of 4000 cases was randomly selected. The remaining 2000 cases were used for testing. After manually optimising the training parameters the testing accuracy was 57.25%. The accuracies obtained for various values of the training parameters are shown in Table 5. If the SVM was guessing randomly then it would get the right answer 2.5% of the time. Therefore an accuracy of 57.25% for 40 candidate leak nodes is satisfactory.

Table 5: Testing accuracies with 40 candidate leak nodes.

C	γ	% Accuracy
10000000	Default	57.25
1000000	Default	55.2
1000	Default	32.85
100000000	Default	56.75
9000000	Default	57.1
11000000	Default	56.75
10000000	0.001	53.45
10000000	0.01	55.15
10000000	0.1	56.15
10000000	1.0	56.4

While the system is not correctly predicting the actual leaking node in 42.75% of the cases it would be useful to determine if the predicted leaking node is near to the actual leaking node. A histogram of the distance between the predicted leaking node and the actual leaking node for the case of 40 candidate leaking nodes with the testing set of 2,000 cases is shown in Figure 8. The interval between 0 and 1,500 was divided up into 15 histogram bins (the diameter of the study region is 1,243.4 m).

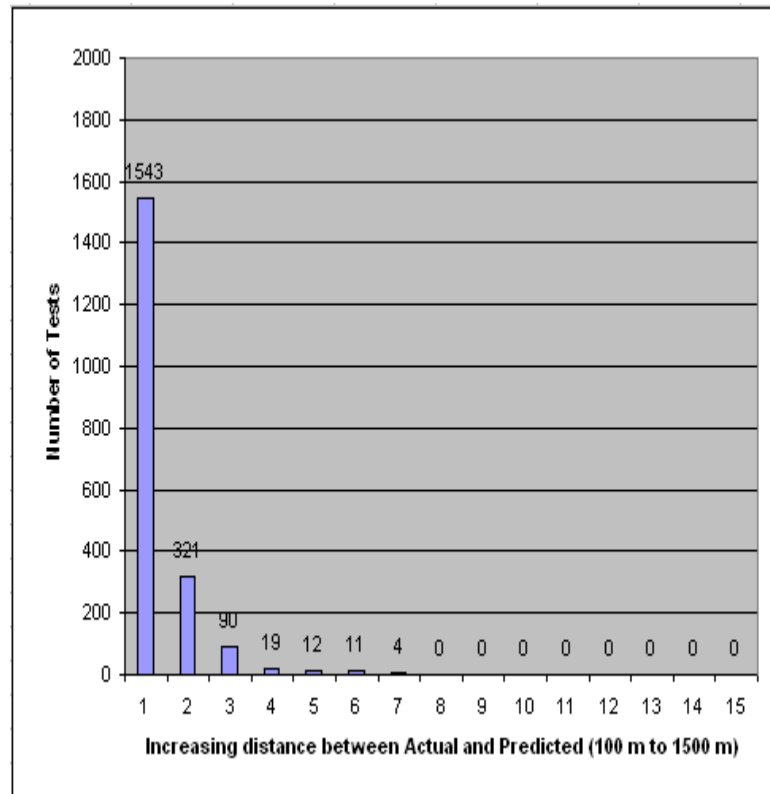


Figure 8: Histogram of distance between predicted leaking node and actual leaking node.

The predicted node equals the actual node in 57.25% of the cases. However, Figure 9 shows that the predicted node is within 100 metres of the actual node in 77.5% of the cases, within 200 metres of the actual node in 93.2% of the cases and within 300 metres of the actual node in 97.7% of the cases. Thus the prediction would provide useful information for the water authority in order to appropriately direct its search for the leaking node.

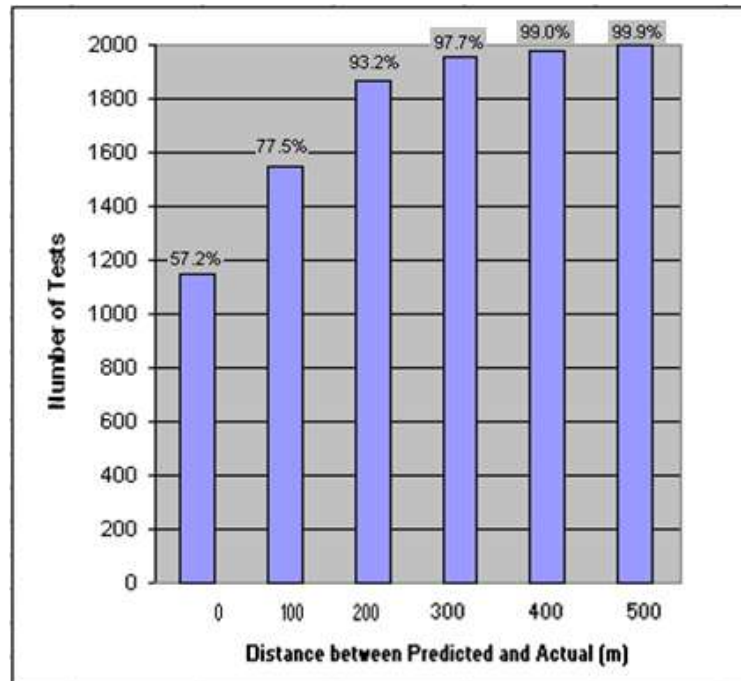


Figure 9: Histogram of percent accuracy within a nominated distance between actual and predicted leaking node.

5.3. Applying the SVM Analysis Method for Detecting Low Leak Rates

Having established the procedure to generate the required data through EPANET and apply the data to train the SVM to predict the position and size of leaks, the next step was establishing the limits of the procedure to detect small leaks.

The combination of emitter coefficient of 0.3 and emitter exponent of 0.5 correspond to a leakage level of 2.5 L/s. As this represents leak volumes up to 10,000 L/hr, additional experiments were conducted to:

- Determine the modelling limits of EPANET to successfully converge with low emitter coefficients equivalent to leakage levels of 50 to 100 L/hr;
- Generate data sets through EPANET using low emitter coefficients that successfully converge;
- Select data sets that have sufficient variation for use as training sets for SVM analysis; and
- Determine the optimum accuracy attainable from SVM analysis.

5.3.1. Using Pressure as the Monitoring Property

EPANET trials with a series of low emitter coefficients (with the emitter exponent fixed at 0.5) indicated the lowest leakage successfully processed was at a coefficient of 0.0001, equivalent to a leakage rate of 3.45 L/hr. Following this, the EPANET driving program was used to generate data representing the pressures at the six monitoring nodes in the case when exactly one of the candidate leak nodes was leaking for emitter values going from 0 to 0.0001 in steps of 0.00001. For this, ten data sets of 150 cases each were generated.

The results showed there was no difference in pressure from the no leak scenario in any of the simulations. In other words, the EPANET sensitivity was not sufficient to register the small difference in pressure. The experiment was repeated many times while progressively increasing the upper limit of the coefficient from 0.0001 until a pressure difference registered on the EPANET output. From this, it was found that the lowest emitter coefficient that could produce a pressure difference in EPANET was 0.0025. This was equivalent to a leakage of 90 L/hr.

The EPANET driving program was then applied to generate data while changing the emitter coefficient from 0 to 0.0025 in steps of 0.0001. The output data was used as the training data set for SVM analysis. The training set was limited to ten data sets. The analysis showed that prediction of the exact location had a 35% success rate. As the distance between actual and predicted location increased, the success rate increased. A 100% success rate was predicted by 500m (Figure 10).

The accuracy at shorter distances could be improved, but at the expense of increased leakage volume. Experiments with an emitter coefficient of 0.005 produced a success rate of 56% for prediction of exact location, a 60% increase in accuracy from the analysis with the emitter coefficient at 0.0025. As shown in Figure 10, the prediction accuracy at other distances also improved.

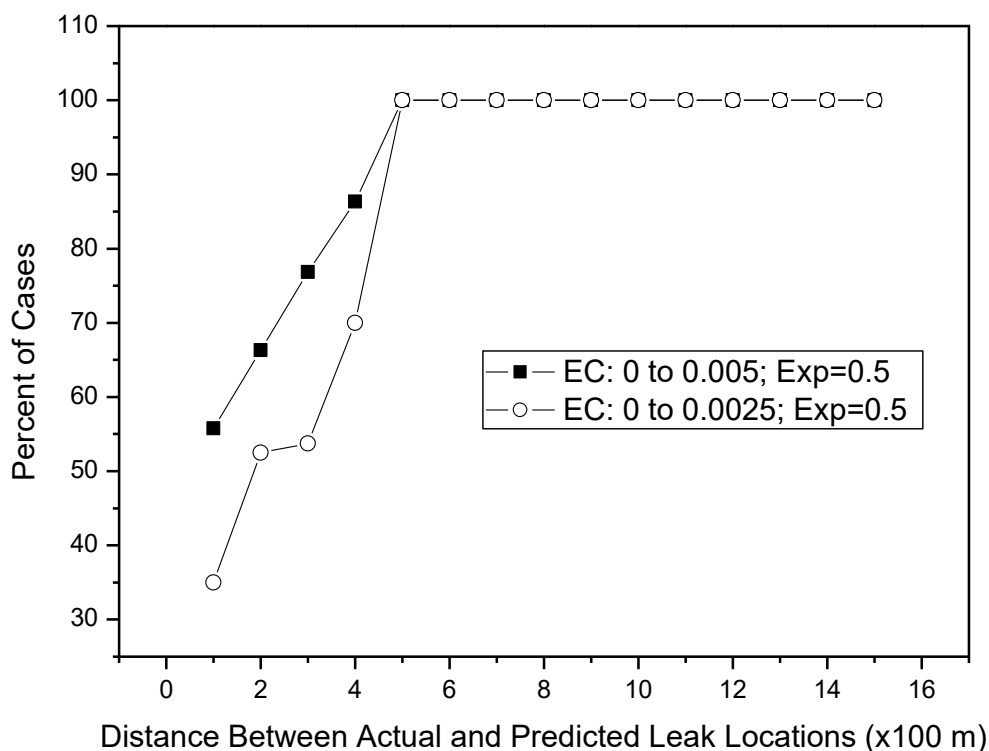


Figure 10: Prediction accuracy based on pressure with Emitter Coefficient 0 to 0.0025 (max leak size 90 L/hr) and Emitter Coefficient 0.005, (leak size 180 L/hr), exponent 0.5 [EC=Emitter coefficient].

5.3.2. Using Flow Rate as the Monitoring Property

An alternative analysis approach is to monitor flow values in the network. EPANET can be used to simulate the flows in a pipe network for a given leak and these simulations can be used to train an SVM. Monitoring flow values rather than pressure values has a distinct advantage. With pressure values, when a leak is present the pressure value is only a small fraction of a percent different to the pressure value when there is no leak. On the other hand, with flow values, the no leak or small leak situation corresponds to a zero flow or a very small flow as compared to a comparatively large flow when there is a leak.

Flow rate training data was generated by having one of the 10 candidate leak nodes in the study area leaking with emitter coefficient ranging from 0 to 0.0025 in steps of 0.00005. Six pipes were used to monitor the flow. We randomly selected 410 cases to form a training set and the remaining 100 cases were used as a testing set. Five-fold cross validation was used to select the best values for the training

parameters with the best found values being $C = 110,000$ and $\gamma = 0.08$. The testing accuracy for these values was 41% for exact location of the leaking node and 92% at a 500m distance (leakage of 90 L/hr). The prediction accuracy for various values of the distance between predicted leaking node and actual leaking node is shown in Figure 11.

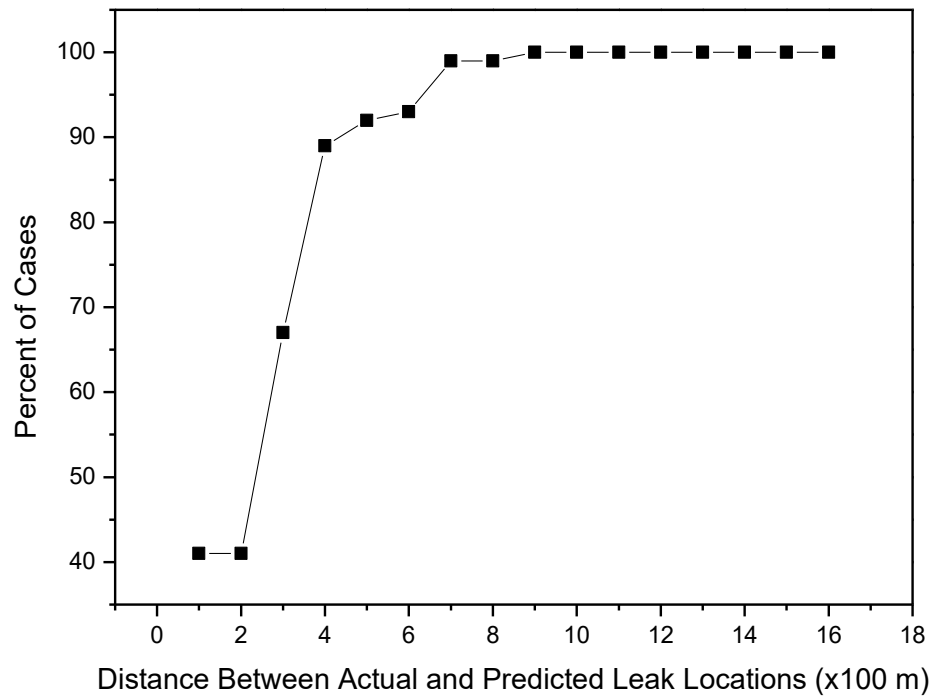


Figure 11: Leak prediction accuracy based on flows with Emitter Coefficient 0 to 0.0025 (max leak size 90 L/hr), exponent 0.5 (41% for exact location and 92% within 500m).

The result is similar to the result of training the SVM on pressure values. Therefore, measurement of either pressure or flow could be the basis of SVM training and subsequent prediction of leak size or position. In the prediction procedure, the variation in the pressure or flow from a no-leak scenario is matched with the SVM training data set to identify the location within the uncertainty in distance as indicated by the analysis of the training data.

5.4. Practical Aspects of Applying the Method in Field Measurements

The practicality of designing a leak detection method using SVMs depends on monitoring the pressure or flow rate changes which are traceable to leaks.

The output from the EPANET driving program for emitter coefficients from zero to 0.0025 indicated the pressure changes registered at the nodes are in the order of 0.0001 kPa to 0.0008 kPa in 100mm diameter pipes. Therefore, pressure changes of that order are required to be monitored in order to detect leaks in the range of 90 L/hr (equivalent to an emitter coefficient of 0.0025) in 100mm pipes. As the background pressure in a distribution network is generally not less than 250 kPa, the viability of leak detection using SVM based pattern recognition depends on instrumentation with the required sensitivity to measure extremely low pressure changes against the relatively high background pressure environment.

A survey of accurate pressure meters designed to operate from zero to 500 kPa (or to 1,000 kPa) indicated they typically have an accuracy of $\pm 0.1\%$ of calibrated span, or ± 0.5 kPa to 1.0 kPa, in 0-500kPa or 0-1,000kPa meters. As this is about 10^3 to 10^4 times the pressure change that has to be monitored, the sensitivity of these meters will not be adequate to monitor the variations in pressure required for leak detection through SVM driven pattern recognition.

An alternative was to use differential pressure meters which measures the difference in pressure between two points. These meters are capable of monitoring differential pressures as low as 0.001 kPa across two points in a pipeline even when the background water pressure is up to 1,000kPa. Although the differential pressure does not provide a direct method of determining the absolute pressure at the location, it does provide a basis for calculating the flow rate. Therefore a test program was designed to explore the feasibility of using a differential pressure gauge as described in the following section.

5.4.1. Using a Differential Pressure Gauge for Leak Location

As the sensitivity of differential pressure gauges is in the order of 0.001 kPa, (1 Pa) they were not suitable for monitoring the low flows (i.e. 90 L/hr) associated with small leaks. However, by using an orifice plate it is possible to magnify the differential pressure to levels detectable by a differential pressure gauge.

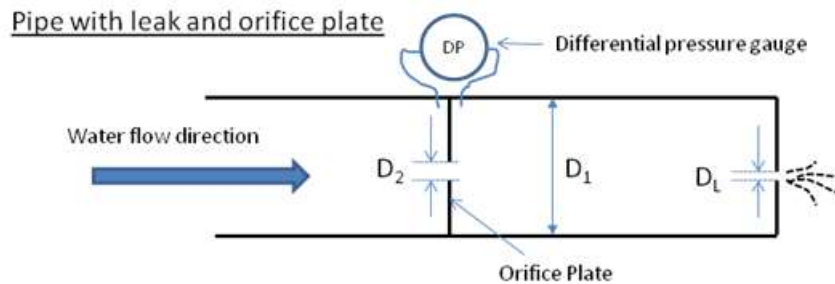


Figure 12: Illustration of a pipe fitted with an orifice plate and a differential pressure gauge.

An orifice plate is simply a thin plate with a hole in the middle placed in a pipe through which the water flows (Figure 12). When the water reaches the orifice plate, it is forced to converge to go through the small hole; the point of maximum convergence actually occurs shortly downstream of the physical orifice, at the so-called *vena contracta* point. As it does so, the velocity and the pressure changes based on the radii of the pipe and orifice. The principal of an orifice plate is explained by combining the Bernoulli equation (Equation 7), and the continuity equation (Equation 8),

$$P_1 + \frac{1}{2} \rho \cdot V_1^2 = P_2 + \frac{1}{2} \rho \cdot V_2^2 \quad (7)$$

$$Q = A_1 \cdot V_1 = A_2 \cdot V_2 \quad (8)$$

From those the pressure differential (PD, in Pa) across an orifice plate is represented by,

$$PD = (P_1 - P_2) = \frac{1}{2} \rho Q^2 \frac{1}{A_1^2} \left[\frac{A_1^2}{A_2^2} - 1 \right] \quad (9)$$

(Q =volumetric flow rate, m^3/s , A_1 =cross-sectional area of pipe, m^2 , A_2 =cross sectional area of orifice, m^2 , P_1 = water pressure upstream from orifice plate, Pa, P_2 = water pressure after orifice plate, Pa, ρ =density of water, kg/m^3)

As $A = \pi r^2$ and $A^2 = \pi^2 r^4$ (r = radius of pipe)

$$PD = \frac{1}{2} \rho Q^2 \frac{1}{\pi^2 r_1^4} \left[\frac{r_1^4}{r_2^4} - 1 \right] \quad (10)$$

(r_1 =radius of pipe, m , r_2 =radius of orifice, m)

As Equation 10 indicates, the pressure difference across the orifice plate is a function of the radii of the pipe and the orifice. By applying this equation to a 100mm pipe and orifice plates of different sizes, and with different flows through the pipe, it can be shown that the pressure difference increases exponentially as the orifice size decreases (Figure 13). This allows magnification of the pressure difference to detectable levels by selecting the orifice size.

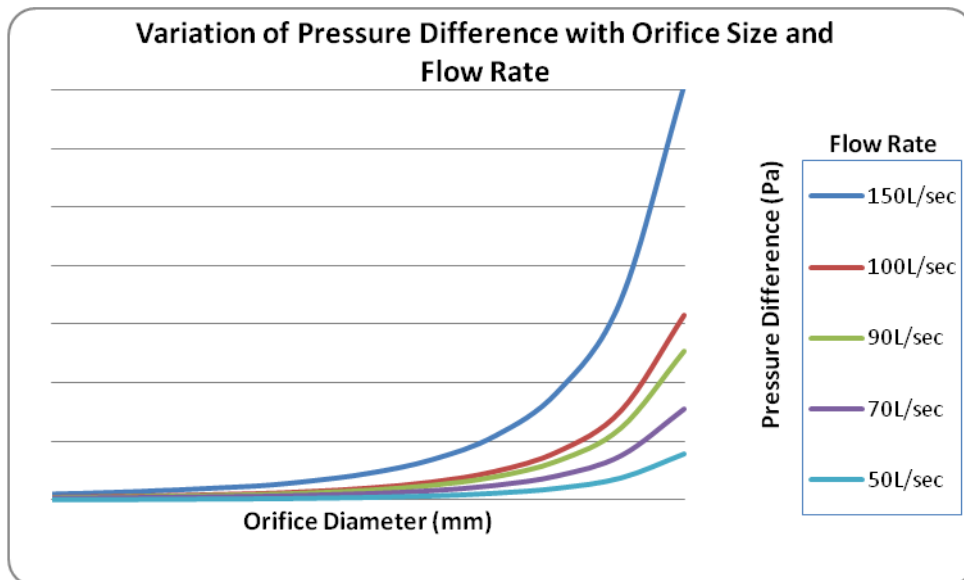


Figure 13: Variation of Pressure difference across an orifice plate in a 100 mm pipe, at different orifice sizes and flow rates.

While Equation 10 provides a theoretical basis to determine differential pressure, the pressure difference measured in a fabricated orifice plate will depend on several other factors, among which are the profile of the orifice and the positions of pressure measurement points relative to the orifice. As it is difficult to accurately model those effects, they can be determined by calibrating the orifice plate-differential pressure gauge setup with known flow rates and generating reference curves. The curves can then be used to determine the flow rate directly from the pressure difference reading. As explained in Section 5.3.2, the measured flow rate is matched with SVM training data to identify the leak location within the experimentally established limits of uncertainty. On that basis, an experimental program was undertaken to refine a measurement method using a differential pressure meter as describes in the next section.

5.4.2. Differential Pressure Measurements

A 100mm diameter, 450mm long section of pipe was fabricated with the ends blanked off and fitted with valves; one for connection to mains pressure water and the other to simulate leaks of different magnitudes. A flanged joint midway on the pipe was provided to attach an orifice plate. Openings either side of the flange were provided to connect the inlet and outlet of a differential pressure gauge. Figures 14 and 15 show a diagrammatic view and a photograph of the experimental setup.

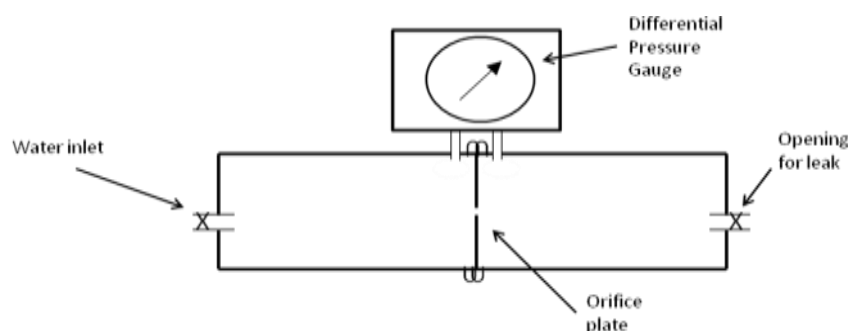


Figure 14: Diagram of experimental pipe for differential pressure measurement.

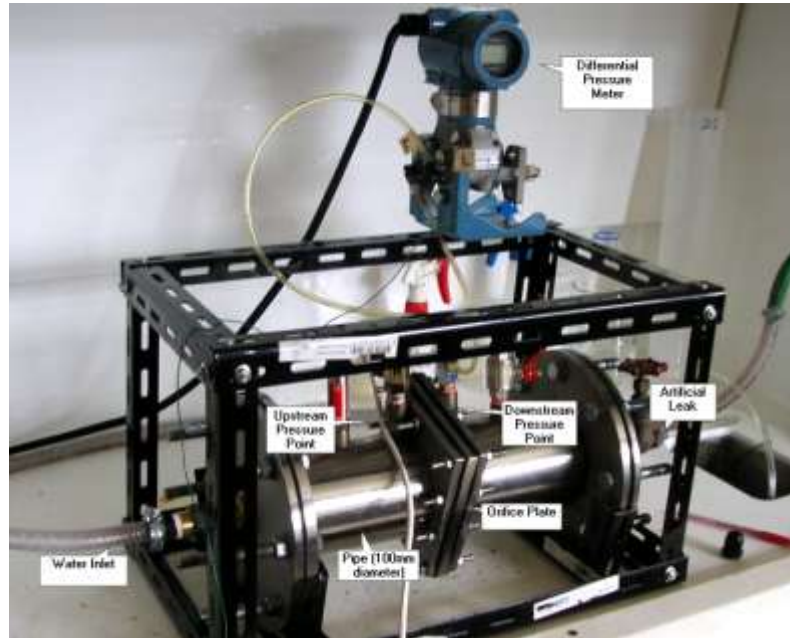


Figure 15: Photograph of experimental setup.

The test unit was connected to mains pressure maintained at 600 kPa and the leak adjusted to the desired flow rate by timing a volumetric measure. Mains pressure was monitored by a separate meter.

The system was allowed to stabilise for 15 minutes and readings were taken from the differential pressure gauge. Table 6 and Figure 16 show the results from a range of orifice plates (6mm, 7mm, 9mm, 12mm, 15mm and 20mm) and flow rates as low as 45 L/hr up to 180 L/hr.

Table 6: Measured pressure difference values from a range of orifice plates and flow rates.

Orifice Plate orifice diameter mm	Pipe Internal diameter mm	Flow Rate L/hr	Input Pressure (median) kPa	Press Difference (median) Pa
6	100	45.00	621.16	130.25
		60.00	628.75	229.39
		72.00	615.99	333.81
		85.20	619.69	496.56
7	100	60.00	634.28	143.075
		90.00	629.83	333.38
9	100	90.00	627.38	119.43
		120.00	616.64	220.34
		180.00	619.09	511.64
12	100	90.00	621.95	31.89
		120.00	620.52	61.20
		180.00	603.66	154.84
15	100	90.00	618.63	5.03
		120.00	619.66	15.71
		180.00	607.7	48.07
20	100	90.00	622.70	2.64
		120.00	620.48	8.09
		180.00	617.06	21.94

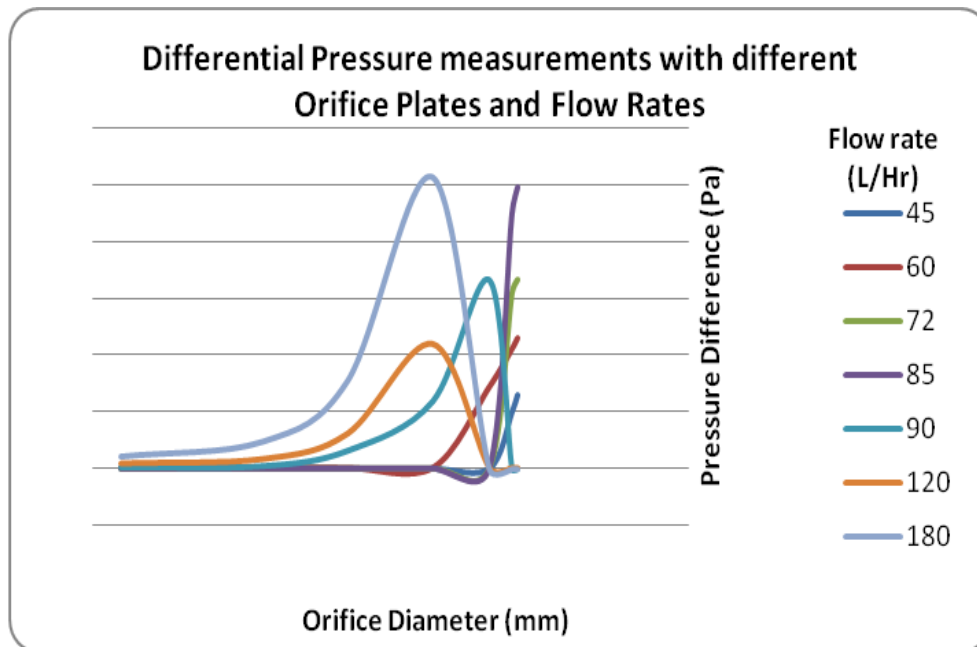


Figure 16: Calibration curves for the Differential Pressure – Orifice Plate measurement unit.

The results show that the differential pressures created by flow rates equivalent to low volume leaks (i.e. 45 L/hr to 180 L/hr) can be monitored using commercially available differential pressure gauges. In this particular exercise based on a 100mm pipe, low flow rates produced differential pressure within the detectable range with 6mm to 10mm orifice plates. While 100mm pipes are generally the smallest reticulation pipes in a typical network, larger pipe sizes will increase the magnification effect of orifice plates, increasing the sensitivity.

6. ANALYSIS AND DISCUSSION

The experimental setup demonstrated the feasibility of using differential pressure gauges to monitor low flows. Calibration curves produced from those results were the basis of the data for SVM analysis. The lowest flow rate tested was 45 L/hr. A 6mm orifice plate produced a pressure difference of 130 Pa while a higher flow rate of 85 L/hr produced a 500 Pa pressure difference. At the other extreme, a flow of 180 L/hr together with a 20 mm orifice plate produced a pressure difference of 22 Pa. However, the SVM model development indicated that EPANET sensitivity limits flow rates to 90 L/hr and above in the training datasets. Consequently, although by selecting the correct orifice plate it is possible to monitor very low flow rates (down to 45 L/hr), the inability to generate training datasets prevents detection of flows less than 90 L/hr by SVM analysis.

It is not practical to have orifice plate flow meters on a distribution network on a permanent basis, as (a) the restricted flow through an orifice plate will be far below normal supply requirements, and (b) planned maintenance operations of pipelines, such as air souring, require the pipe bore to be unrestricted. Consequently, the orifice plate need to be on a section of parallel pipe that can be brought on-line as required. A simple arrangement of a system is illustrated in Figure 17. Closing valve A and opening valves B and C diverts the flow through the by-pass line with the orifice plate and DP gauge for measurement. After monitoring the pressure over the 2am to 3am period the valve A is reopened for normal flow. Several of these by-pass systems are necessary in the network under investigation.

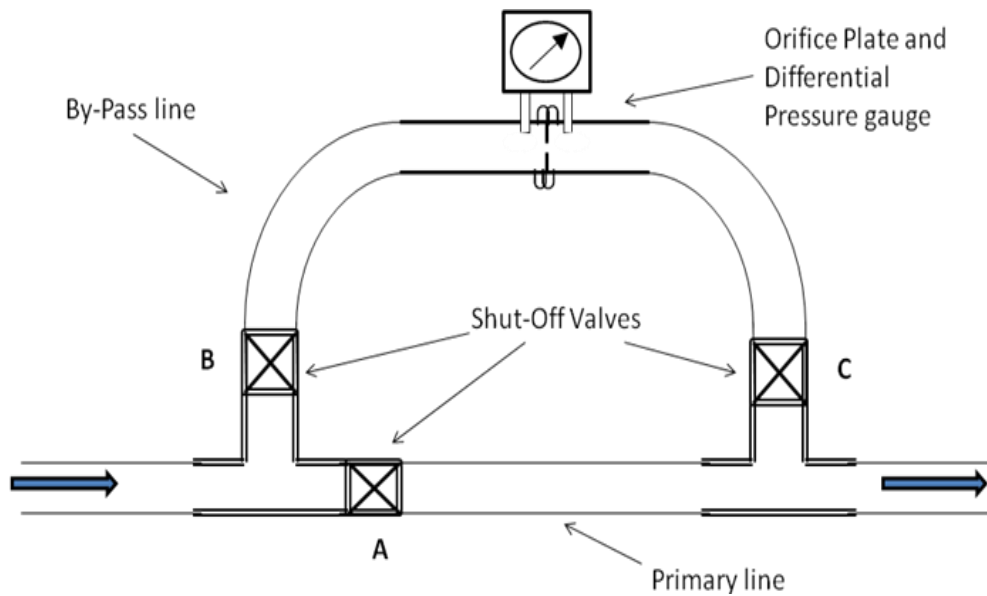


Figure 17: By-pass line with orifice plate and Differential Pressure gauge to monitor low flow rates.

The SVM analysis relies on obtaining low flow for a small leak in relation to zero flow from a no leak situation. If the system being investigated already has small leaks, it will be necessary to treat them as background levels or isolate them prior to the study. If the background flow is within the calibrated range of the orifice plates, any new leaks can be detected by the SVM method. However one has to be certain that the low flow is due to leaks, and not from consumption. Minor leaks within customer premises, i.e. dripping taps, will be confounding factors. A method for filtering the flows from those sources needs to be identified.

The effectiveness of the method in application to real pipe networks would depend on the validity and correctness of the EPANET simulation. Differences between the EPANET model behaviour and the actual network behaviour will affect the leak detection results. The training data set needs to be generated on EPANET modelling with accurate representation of variations in network geometry, location topography and pipe roughness coefficients depending on material and age in different sections of the network. While EPANET has functionality to model these attributes, it has not been tested if the information is available from a real network with the required accuracy. The numbers arising as flow rates from the EPANET simulation of small leaks are extremely small and have a very low number of significant figures. They are sensitive to inaccuracies in the modelling of properties of the pipe network by EPANET. If inaccurately modelled flow rates are used as inputs for training an SVM, then the result is likely to be inaccuracies in the prediction of the SVM.

Considering these issues, the successful application of the SVM leak detection technique to real networks is unlikely. The greatest hurdle will be simulation of a real network in EPANET with the accuracy required for detection of small leaks.

7. CONCLUSIONS

Hydraulic data simulated through EPANET and analysed using the SVM has demonstrated the feasibility of detecting and locating leaks in the order of 90 L/hr. Although initially based on pressure measurements, due to the technical limitations of detecting small pressure changes against high background levels, the SVM analysis procedure was modified for execution through flow rate measurements. A method of monitoring small variations in flow rates was successfully implemented using orifice plates in combination with a differential pressure gauge. The procedure will be based on calibration of the measurement unit.

To apply the technique to real pipe networks, simulation of the network by EPANET would be necessary to generate training sets for the SVM analysis. Measurement of leak flows, or their absence, has to be affected through a by-pass line fitted with an orifice plate-differential pressure meter arrangement. The procedure requires background flows to be filtered from the measured values. While most of the background effects could be minimised by collecting data between 2:00 and 3:00 am, the total elimination cannot be guaranteed. Therefore a method of identifying the contributions from non-leak events is required.

The success of the method would depend on the accuracy of the EPANET simulation of real pipe networks accounting, among others, for variations in pipe roughness, undulations on the landscape and bends in the pipes. While this is possible with experimental pipelines, it is unlikely the EPANET simulation will capture network details necessary to provide data on small variations in flow with the required precision. This uncertainty, combined with the uncertainty in eliminating background noise during measurements, does not warrant the SVM-based leak detection methodology to be developed further.

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