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Experimental investigation into vibro-acoustic emission signal processing techniques to quantify leak flow rate in plastic water distribution pipes

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ABSTRACT

Leakage from water distribution pipes is a problem worldwide, and are commonly detected using the Vibro-Acoustic Emission (VAE) produced by the leak. The ability to quantify leak flow rate using VAE would have economic and operational benefits. However the complex interaction between variables and the leak's VAE signal make classification of leak flow rate difficult and therefore there has been a lack of research in this area. The aim of this study is to use VAE monitoring to investigate signal processing techniques that quantify leak flow rate. A number of alternative signal processing techniques are deployed and evaluated, including VAE counts, signal Root Mean Square (RMS), peak in magnitude of the power spectral density and octave banding. A strong correlation between the leak flow rate and signal RMS was found which allowed for the development of a flow prediction model. The flow prediction model was also applied to two other media types representing buried water pipes and it was found that the surrounding media had a strong influence on the VAE signal which reduced the accuracy of flow classification. A further model was developed for buried pipes, and was found to yield good leak flow quantification using VAE. This paper therefore presents a useful method for water companies to prioritise maintenance and repair of leaks on water distribution pipes.

1. Introduction

1.1. Leaks in water distribution systems

Leakage from water distribution systems (WDS) leads to a substantial loss of water, which can have high negative environmental and economic effects [1]. Typically, 20–30% of water pumped into the pipe network is lost through leakage, and can be as high as 50% in developing countries and older distribution networks [2,3]. This loss of water represents a substantial amount of energy loss, as pumping and treating water has been reported to use between 2 and 3% of the worlds energy consumption [4]. In the UK, leakage alone has been estimated to cost the government £7bn annually in street works, as well as further social and damage costs [5]. Typically, hydrophones or accelerometers are placed at some distance either side of a leak (Fig. 1) and the leak's location is found using Eq. (1):

$$L_1 = \frac{d - c\tau_{delay}}{2} \tag{1}$$

where d describes the distance between two accelerometers or hydrophones and c is the wavespeed of the leak noise on the pipe wall. τ_{delay} is the difference in signal arrival time between accelerometer 1 and 2, which is calculated from the peak in the cross correlation function.

The two accelerometers receive two inputs in the form of vibration, $x_1(t)$ and $x_2(t)$. It is possible to model the leak signal (S) and the background noise ($n_1(t)$ and $n_2(t)$) for accelerometer 1 (x_1) and accelerometer 2 (x_2) as:

$$x_1(t) = S(t - \tau_1) + n_1(t), \; x_2(t) = S(t - \tau_2) + n_2(t). \tag{2}$$

where τ_1 and τ_2 describe the travel time of the leak signal arriving at both accelerometers. The majority of leak acoustic modelling studies represent background noise as Gaussian and uncorrelated between sensors (see Gao et al. [6] for example) therefore the peak

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Nomenclature

τ_{delay}	difference in signal arrival time between accelerometer 1 & 2 (s)
$x_1(t), x_2(t)$	VAE signals at accelerometer 1 & 2
d	distance between accelerometer 1 & 2 (m)
c	wavespeed of propagating acoustic signal (m/s)
L_1, L_2	distance between leak and accelerometers (m)
$R_{x_1x_2}$	cross correlation between leak signals
$E[\cdot]$	expectation operator
q	leak flow rate (l/min)
C_d	discharge coefficient
g	acceleration due to gravity (m/s^2)
h	head (m)
α	exponent due to discharge
$X[k]$	discrete Fourier Transform
C	leakage coefficient

in the cross correlation represents the leak. The cross correlation of the signals is described by:

$$R_{x_1x_2} = E[x_1(t)x_2(t + \tau_{delay})], \tag{3}$$

where $E[\cdot]$ is the expectation operator and τ_{delay} describes the lag in time between both received signals. τ_{delay} is given as:

$$\tau_{delay} = \tau_2 - \tau_1. \tag{4}$$

where τ_1 and τ_2 describes the arrival time at accelerometer 1 and 2 respectively.

A number of variables have been reported to influence the leak's VAE signal received by the accelerometers, including pressure [7], flow rate [7,8], surrounding media [9], pipe material and pipe diameter [10]. Leak signals do not propagate long distances along plastic compared to metallic pipe. This is due to the viscoelastic nature of the material causing damping in the pipe wall [3], and higher frequencies tend to be attenuated or filtered as the plastic pipe acts as a low pass filter [11]. The propagation of waves in plastic pipes has been discussed elsewhere, for example Pinnington and Briscoe [12].

VAE still remains the most common method of leak detection in the UK and despite the ongoing research in improving the accuracy and capability of leak detection systems, the ability to classify a leak's flow rate accurately using VAE is still not yet possible. The lack of research into the quantification of leak flow rate on WDS is likely due to the complex nature of variables influencing the leak signal; yet the accurate quantification of leak flow rate using VAE would provide an excellent tool allowing water suppliers to prioritise maintenance thereby saving water and costs. The overall aim of this research therefore is to investigate signal processing methods to classify leak flow rate on plastic water distribution pipes using VAE.

1.2. Relationship between acoustic emission and leak flow rate

Increasing WDS pressure has been demonstrated to increase leak flow rate [13], and this in turn has shown to increase the amplitude of the VAE leak signal [7,8] as well as providing a more defined peak in the cross correlation [14]. This agrees with theory that for fixed sized leaks, higher pressure results in a higher leak signal amplitude due to increased leak flow rate [15]. Similarly, Papastefanou [16] and Pal et al. [8] demonstrated increasing signal amplitude with increasing pressure due to the strong influence of leak flow rate. Pal et al. [8] also found leak flow rate increased leak VAE frequency. Papastefanou [16] established an empirical relationship between leak size, amplitude and leak flow rate and continued to comment that it is easier to detect leaks of a higher flow rate compared to those at lower flow rates. A study by Humphrey [14] investigated the influence of leak flow rate on correlation performance, finding that leaks with flow rates of 0.5 m^3/h at a distance of 186 m from the leak had a low success rate in detection, whereas leaks at higher flow rates of 1 m^3/h at the same distance were detected more successfully. However, increasing the leak flow rate to 1.5 m^3/h and increasing the measurement distance to 316 m did not produce any successful correlations [14]. The information from the literature indicates that increasing the leak's flow rate is likely to result in an increase in leak amplitude, and it therefore seems logical to use signal parameters that will describe leak energy in order to quantify leak flow rate.

Traditionally, leak flow rate (q) has been shown to be sensitive to pressure through the orifice equation [17]:

$$q = C_d A \sqrt{2gh} \tag{5}$$

where g is acceleration due to gravity, C_d is the discharge coefficient, hole area (A), pressure head (h) and q is the flow rate through the leak. The equation can be simplified for the application of water distribution pipes and can be written as [17]:

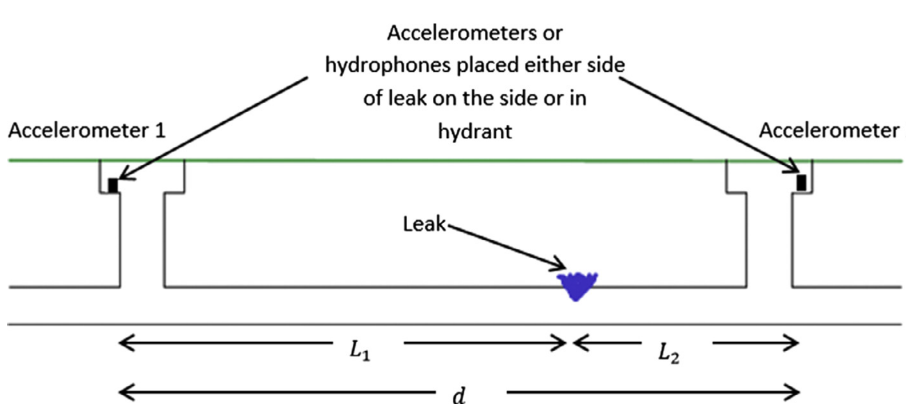


Fig. 1. Leak location schematic.

$$q = Ch^{\alpha} \tag{6}$$

where C is the leakage coefficient and α is an exponent of discharge and can vary due to leak hydraulics, pipe material, surrounding media and pressure [17].

1.3. Previous attempts to quantify leak flow rate

Few attempts have been made to quantify a leak's flow rate in WDS pipes using VAE, but there are some examples utilising methods other than VAE. Mashford et al. [18] demonstrated a relatively high degree of accuracy predicting a leak's size using EPANET modelling software and support vector machine. Salam et al. [19] continued to use EPANET modelling to classify leaks according to their size. Daoudi et al. [20] used wavelet analysis and artificial neural networks to classify leak size. Collecting 55 signals from iron and PVC pipe, they managed to distinguish between large and small leaks but did not demonstrate any convincing results.

Although there have been limited studies in the water industry, there have been several successful trials in other disciplines, and these can be divided into analytical methods based on known relationships between parameters and data driven comparative methods such as pattern recognition [21] and spectral comparison methods. Kim et al. [22] and Na et al. [23] both used fuzzy neural networks to classify leak flow rate caused by breaks in nuclear power plants. An investigation into a leaking steam ball valve and water ball valve by Yan et al. [24] demonstrated that signal amplitude is directly proportional to leakage rate. Khulief et al. [25] found that it was easier to detect differences in sound power levels using signal root mean square (RMS) when power levels are similar, when using acoustic emission of leaks in plastic pipes. Meland et al. [21] found a good relationship between leak flow rate and signal RMS from leaky shut down valves in the oil and gas industry. Kaewwaewnoi et al. [26,27] and Chen et al. [28] used VAE to investigate leak flow rate classification from gas leaks and hydraulic seals respectively, and both found good correlations between signal Root Mean Square and leak flow rate of a sample containing N samples, $x[0], x[1], \ldots, x[N-1]$

$$RMS = \left(\frac{1}{2}\sum_{n=0}^{N-1} x[n]^2\right)^{0.5} \tag{7}$$

The work by these authors shows that the VAE signal RMS can be related to the signal's energy content [28]. Kaewwaewnoi et al. [27] continued to develop an equation to relate VAE signal RMS from gas valve leakage to leak flow rate, although this was developed specifically for valve leakage in gas systems. Chen et al. [28] compared RMS with several other several signal-energy related parameters to quantify gas leak rate, including VAE counts and the magnitude of the peak in the power spectral density (PSD). Due to the success of the techniques presented in Chen et al. [28], similar methods are employed in this research. VAE counts is determined by setting a given threshold (for integrated electronic piezoelectric accelerometers the units would usually be in volts) and counting the number of times this threshold is exceeded. As leak flow rate is related to signal amplitude [7,8,16], it can be expected that higher leak flow rates result in a higher number of VAE counts. Mba [29] found good use of simple parameters such as VAE counts and RMS to detect defects in bearings within rotational machines. VAE counts are also a function of the sensor, damping characteristics of the material, signal amplitude and the chosen threshold level [30]. As a result, VAE counts are less applicable to the wider water industry due to the variety of sensors used to record leak signals. As leak signals are continuous signals [28] (i.e. non transient), the leak signal PSD can be used to represent the power of signals over different frequencies, and is defined by Marple [31] as:

$$P[k] = \frac{T}{N}|X[k]^2| = \frac{T}{N}\left|\sum_{n=0}^{N-1} x[n]\exp\left(-\frac{j2\pi kn}{N}\right)\right|^2, 0 \leqslant k \leqslant N-1, \tag{8}$$

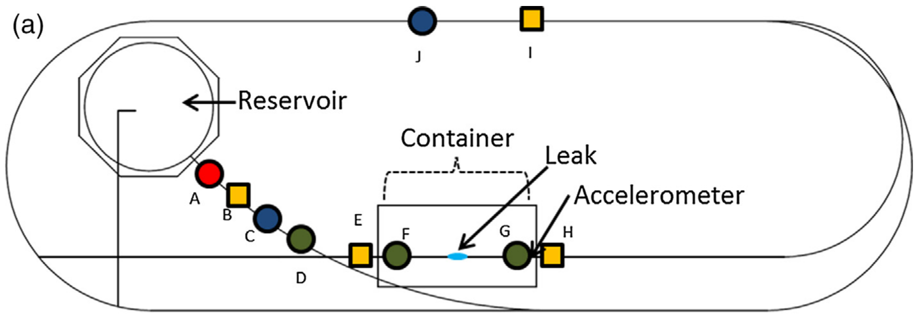
were $P[k]$ represents the PSD, T is the sampling period and $X[k]$ is the Discrete Fourier Transform of the recorded signal $x[n]$. Chen et al. [28] demonstrated that the magnitude of the peak in the PSD can be related to leak flow rate.

Other frequency domain methods such as octave banding can demonstrate the contribution of signal energy within given frequency bands and therefore may provide an alternate way of visualising leak flow rate in the frequency domain. Octave bands are commonly used in the description of VAE measurements, where the VAE is divided into several bands depending on the signal magnitude across frequency bands [32]. The bands are commonly referred to by their centre frequency, which is the average of the upper and lower frequencies so that the centre frequency equals $\sqrt{lower\ frequency * upper\ frequency}$. The majority of leak signals on plastic pipe have been demonstrated to be low frequency: Pal et al. [8] recorded leak frequencies of 20–250 Hz on leaks from MDPE pipe, Hunaidi and Chu [7] found leak signals on plastic pipe between 50 and 150 Hz using accelerometers on a buried test rig in Canada. Muggelton et al. [33] and Papastafaneou et al. [16] demonstrated leak signals well below the pipe ring frequency. Khulief et al. [25] found the production of broadband signals at the leak source, but many of these frequencies are quickly attenuated on the pipe wall [34], or lost to the surrounding media [3], resulting in lower frequency signals. Evidently, the literature suggests that leak signals from plastic pipe span the range of 20–500 Hz and therefore would lie in octave bands between centre frequencies 31.5 Hz and 500 Hz. Hunaidi and Chu [7] suggested that the frequency content did not differ significantly between leak types, so therefore it is possible that the leak signals of different leak types would occur in a similar frequency range and therefore grouping by octave bands represents a good way to investigate the influence of leak signals.

2. Experimental methods, data acquisition and signal processing

A 140 m long, 50 mm internal diameter Medium Density Polyethylene (MDPE) pipe loop known as the Contaminant into Distribution (CID) systems pipe rig (Fig. 2 and Table 1) at the University of Sheffield, UK [35] was used to study the influence of media and flow rate on the leak signals. A 3.5 kW variable speed pump drives water from an upstream reservoir and water recirculates around the pipe rig continuously. 3 pressure sensors (Gems 2200) were linked to a National Instruments DAQ board and LabVIEW software was used in order to process pressure data and system flow was recorded using an electromagnetic flow meter (Arkon Flow System Mag 900). The pressure sensors were used to solely measure system pressure and therefore were not used to measure the location of the leak.

Before testing, the rig was left to settle for 4 h to prevent viscoelastic effects interfering with the data [36]. A 1 mm diameter leak was drilled and originally discharged into atmosphere, located equidistant 36 cm between flange two plates. The leak discharged into a 125 cm × 61 cm × 61 cm container. Five different flow rates were measured manually using the positive displacement of the container liquid level and measured with a stopwatch. The pipe rig was left for a further 30 min between each flow adjustment. One accelerometer (Primayer Ltd. Enigma, sensitivity 10 V/g) was



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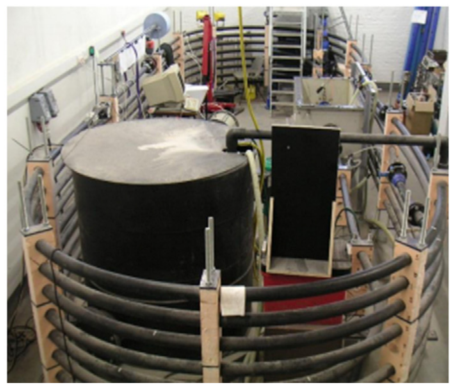

Fig. 2. (a) Schematic of the pipe test rig. A-pump; B-pump butterfly valve; C-pump flow meter; D-pump pressure sensor; E-upstream test section butterfly vale; F-Test section pressure sensor; G-Test section pressure sensor; H-downstream flow control valve; I-downstream flow meter. (b) Photograph of test rig.

Table 1
Pipe and leak details.

Pipe material	MDPE
Pipe diameter	63 mm
Pipe length	140 m
Pipe thickness	6 mm
Young's modulus	950 MPa
Wave speed	350 m/s
Leak hole diameter	1 mm

placed on the flange plate 36 cm next to the leak and recorded VAE signals at 4864 Hz for 60 s in accordance with the Nyquist sampling theorem. Due to the nature of the fittings, the accelerometers had to be placed horizontally. However, due to the strong coupling of the pipe wall and the fluid borne axis-symmetric wave [3] which dominates the leak noise in plastic pipes, there will always be a high degree of radial motion [12,33], were energy dissipates in around the pipe wall. Therefore, the orientation of the sensor should not matter to the recorded signal. The position of the accelerometers on the flange plate was also noted and the accelerometers were positioned in the exact same place for each test for reproducibility. Accelerometer signals were passed through an anti-aliasing filter, amplification and signal conditioning unit. The accelerometer has a built in DAQ system, and at the end of the measurement procedure the data is download to a laptop computer and processed using MATLAB. Signals were passed through a Hanning window and 10th order Butterworth filters in order to remove frequencies greater than 1000 Hz. Signal averaging was conducted in the frequency domain. The general measurement and analytical procedure is described in Fig. 3.

The pump speed was increased in order to increase system pressure and leak flow rate. Prior to the introduction of the leak, signals were measured at the different pump speeds so signals could be compared to a 'no-leak' scenario, where only background noise and pump noise exist, allowing for easier identification and more accurate characterisation of the leak signal (i.e. leak vs. no-leak).

The leak was initially discharged to atmosphere whilst developing the signal processing technique to quantify leak flow rate. In order to assess the influence of different external media types, tests were repeated with the pipe submerged to represent an idealised fluidised bed and with a geotextile fabric of 5 mm thickness (STABLEMASS 115) to represent a fully constrained porous media. A similar geotextile fabric was utilised in previous research by Fox et al. [37], and was found to represent an idealised unfluidised external media as the boundary condition is fully constrained therefore mobilisation of particles will not occur during fluidisation. The geotextile fabric was wrapped around the leak and pipe three times for each test and was wrapped all the way to the end of the container.

3. Results and discussion

3.1. Identification of leak signals

In order to fully characterise the leak noise, measurements of the system where initially taken in three states: pump off; pump on and no leak; and pump on with a leak. These results are shown in Fig. 4, which demonstrates the contribution of these sources to the measured signals. Background noise was most dominant at frequencies <50 Hz. It can be noted that both the pump and the leak contribute to the measured signal when compared to the background noise. The pump appears to produce signals dominated by low frequency components between, which are most powerful at frequencies <400 Hz. Results show that the contribution of the leak noise is greatest at the lower frequencies (between 0 and 410 Hz), well below the pipe ring frequency, which agrees with the majority of the literature for leaks on plastic pipes [8,9,34]. Ring frequency is estimated to be in the vicinity of 20 kHz based on Eq. (26) in Muggleton et al. [33]. Interestingly, the background

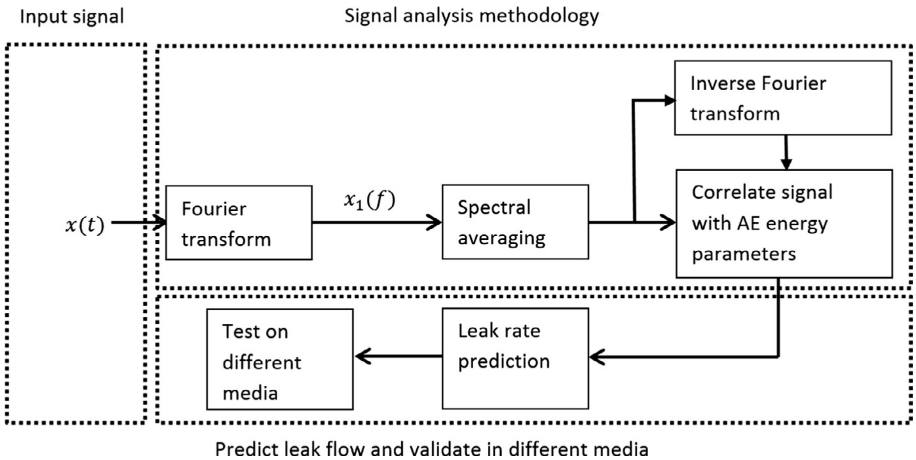

Fig. 3. Flow chart of methodological process.

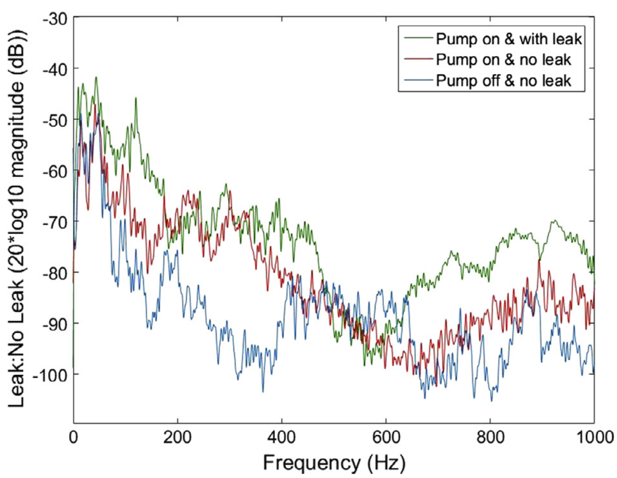

Fig. 4. Comparison of background noise, pump noise and leak signals.

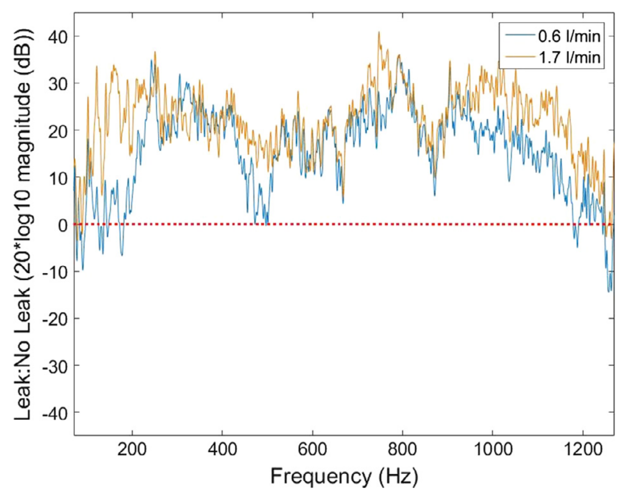

Fig. 5. Ratio leak and no-leak at leak flow rate 0.6 l/min and 1.7 l/min.

noise, pump and leak all showed similar spectra between 490 and 600 Hz. At frequencies >600 Hz, both the pump and leak noise can be separated from the background noise. However, the leak noise is shown to have amplitude signals in this range compared to the pump noise. Both the pump and the leak are therefore shown to influence the recorded signal.

During the tests, five different flow rates were investigated. The narrowband frequency spectrum for the ratio between leak and no-leak measurements at two different leak flow rates is illustrated in Fig. 5. The ratio between leak and no-leak demonstrates the visibility of the leak noise in the frequency domain at two different leak flow rates. Those magnitudes recorded at >0 dB are due to the leak noise and those signals around the zero dB mark represent either signals related to the pump or background noise. Increasing leak flow rate increased signal amplitude at specific frequencies for all five leak flow rates monitored. Notably, the frequency range 63–280 Hz and 920–1050 Hz showed higher amplitude at higher leak flow rate. However, those frequencies ranging from 280 to 920 appeared to be less affected by leak flow rate. The highest amplitude signal was recorded at the highest leak flow rate of 1.7 l/min.

3.2. Leak flow rate classification methods

Considering the results shown in Fig. 5 and a number of authors have demonstrated a leak's flow rate to increase signal amplitude [7,8,16], it is logical to investigate parameters that describe leak energy in order to estimate leak flow rate using VAE. This section compares four methods that have been shown by authors to describe signal energy in other disciplines. Initially, the signal processing methods will be developed with the pipe discharging into air.

3.2.1. Vibro-acoustic emission counts vs. leak flow rate

The accelerometer used in this study recorded outputs in raw voltage form, and the number of volts is proportional to the amplitude of the leak signal. The VAE count rate is defined in this measurement as the number of samples (VAE counts) that exceed a given voltage threshold. All VAE count rates are expressed as counts per second, thus VAE counts were divided by the signal duration in seconds. As this measurement is used very rarely in the field of leak detection on water distribution pipes, no guidelines exist as to the choice of threshold [28]. Similar to Chen et al. [28] different thresholds were tried and the threshold which produced the best results was 1.9×10^{-5} V (Fig. 6a), which provided a good correlation with leak flow rate. In order to assess a change in threshold, a floating threshold was used (Fig. 6b), whereby the RMS value of the signal in question was used to set the threshold of VAE count. Similar to Chen et al. [28], using RMS as a floating threshold for VAE counts did not perform well and is not suitable for quantifying leak flow rate.

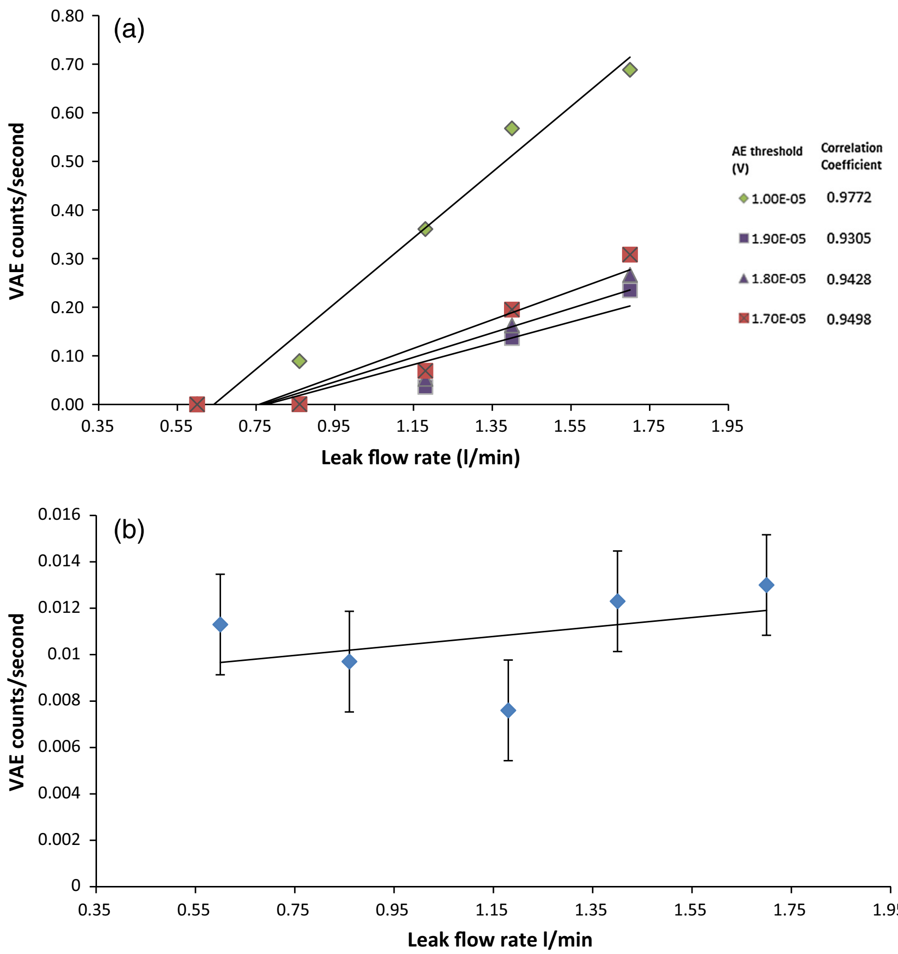

Fig. 6. VAE counts above a given voltage threshold; (a) manually set threshold and (b) floating threshold using RMS value. Error bars denote standard deviation.

3.2.2. Root mean square vs. leak flow rate

In accordance with Eq. (7) the signal RMS for different flow rates were calculated and a strong correlation between RMS and leak flow rate is observed in Fig. 7. Higher leak flow rates achieved higher RMS values compared to lower leak flow rates. The increase in RMS at the higher flow rates is likely due to an increased velocity and turbulence at the leak hole [27], and clearly demonstrates that RMS is a more suitable method for leak flow rate quantification compared to that of VAE counts (Fig. 6a and b).

3.2.3. Magnitude of peak in power spectral density vs. leak flow rate

The PSD of leak signals at different flow rates is shown in Fig. 8, with higher leak flow rates causing an increase in amplitude across specific frequency bands. The magnitude of the peak frequency in the PSD was tested to observe any correlation between leak flow rate and the magnitude of the peak frequency. Fig. 8 indicates no significant correlation between the peak magnitude of the PSD and leak flow rate exist. This method is therefore not useful in quantifying leak flow rate compared to the other methods

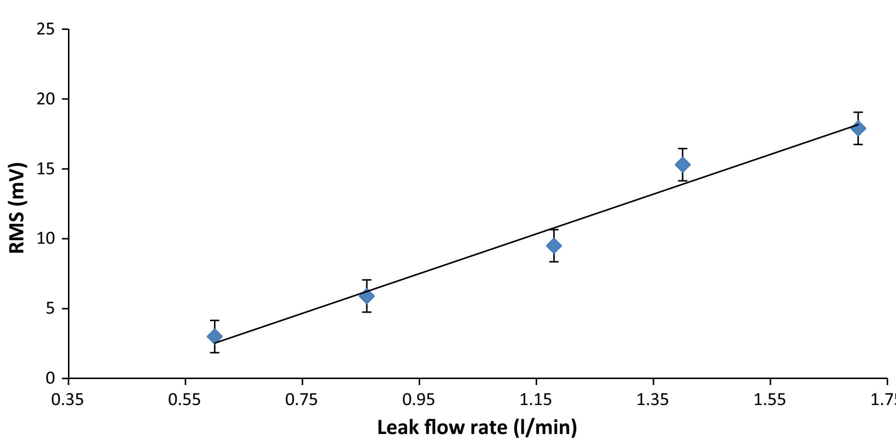

Fig. 7. RMS vs leak flow rate. Error bars denote standard deviation.

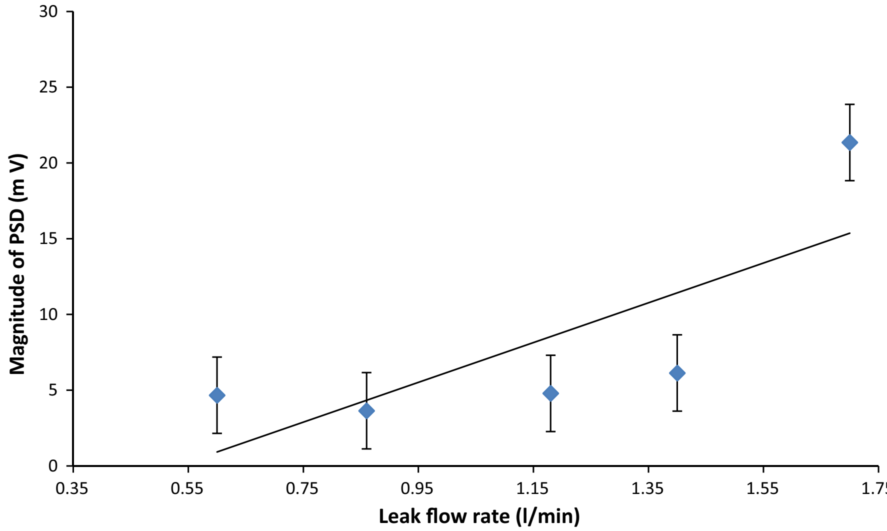

Fig. 8. Magnitude of the peak in the PSD vs leak flow rate. Error bars denote standard deviation.

investigated. The poor correlation observed in Fig. 8 is likely due to the observed changes in leak frequency and amplitude of these peak frequencies with leak flow rate (Fig. 5), and so there is no relationship between the amplitude of the peak frequency and leak flow rate.

3.2.4. Octave bands vs. leak flow rate

Fig. 9a shows the ratio between leak and no-leak measurements divided into octave bands. Octave bands show the intensity of the signal in certain frequency bands known as octaves, and the results demonstrate that the majority of leak energy is located in the first 4 octaves. The second octave band (centre frequency 125 Hz) appears to have similar magnitude for all leak flow rates. The division in magnitude becomes greatest in the 4th octave (i.e. the highest contribution of the leak noise is in the 4th octave, centre frequency of 500 Hz). The ratio of octave band 4 and 2 appears to describe leak flow rate well and could be a potential method to quantify leak flow rate (Fig. 9b).

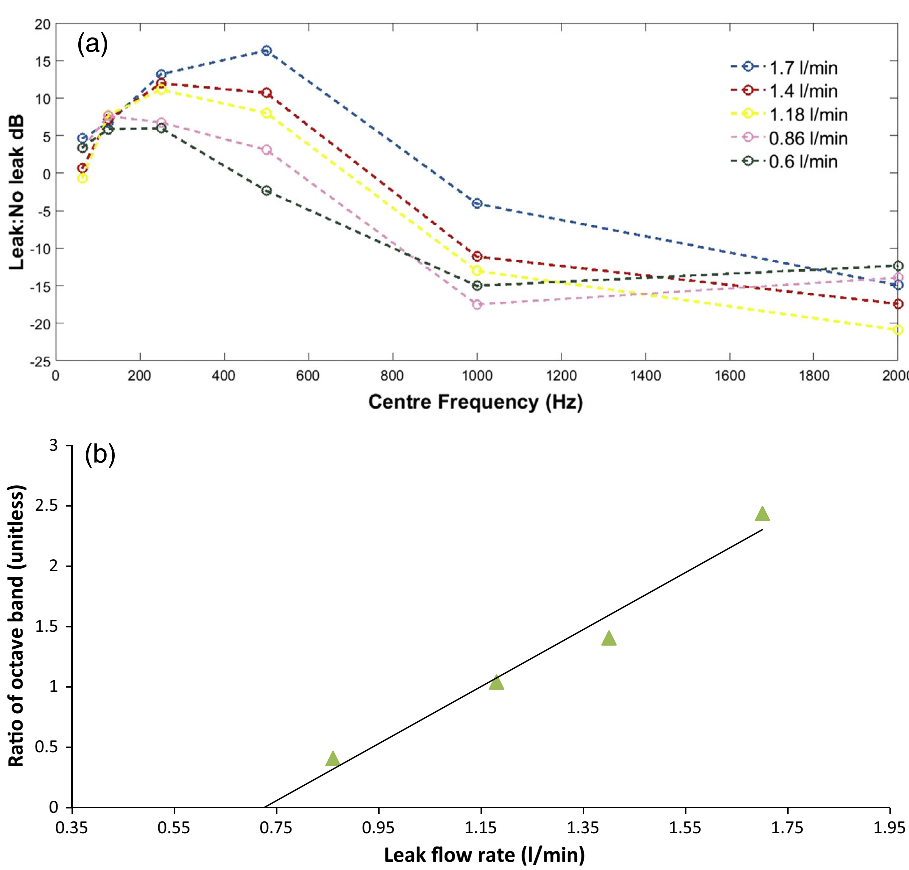

Fig. 9. (a) Ratio leak and no-leak signal describing the magnitude of the leak signal in different octave bands; and (b) ratio of the second octave band (centre frequency 125 Hz) and the 4th octave band (centre frequency 500 Hz).

3.2.5. Comparison of methods

All methods except for VAE counts and the magnitude of the peak in PSD with floating threshold achieved high correlations with leak flow rate and therefore appear to be good methods in quantifying leak flow rate using VAE (Table 2). The best performing method was that of RMS and this could provide good accuracy in predicting a leak flow rate. To quantify leak flow rate using VAE an RMS model with a leak discharging into air was derived in the following form:

RMS based model (discharging to air)

$$Q_{RMS} = 0.0686mV_{RMS} + 0.4406 \quad (9)$$

where Q_{RMS} is the flow rate leak flow rate (l/min) based on the RMS value and mV_{RMS} is the received RMS value (mV). In order to assess the applicability of this model, the pipe was submerged in water and a geotextile fabric in order to represent idealised surrounding media. The results for this model are demonstrated in Fig. 10.

The accuracy of the flow prediction model based on leaks discharging to air is demonstrated in Fig. 10 and Table 3, and was found to be affected by media type. For both the submerged pipe and the pipe wrapped in geotextile fabric, the model tended to perform well at lower flow rates but error margins became greater as the flow rate was increased. Overall, the accuracy of this model was generally poor when the media type was changed; highlighting a strong influence of the surrounding media. When the pipe was submerged, the air based model on average over-predicted leak flow rates by −37.96%, but at higher flow rates this error increased to −50.33%. When the pipe was covered in geotextile fabric, the model also tended to over-predict, on average by −37.33%. These results indicate that the surrounding media has a strong influence on the leak signal and therefore a model designed on data discharging into air will yield inaccurate results in a real life buried WDS.

Table 2
Comparison of different methods to quantify leak flow rate.

Leak flow rate identification parameter	Correlation coefficient
VAE counts >threshold (fixed)	0.9806
VAE counts >RMS (floating threshold)	0.4078
RMS	0.9877
Magnitude of peak in PSD	0.7654
Octave method	0.9854

Table 3
Prediction error of the leak flow rate prediction model when applied to different media types.

	Submerged pipe (%)	Geotextile fabric (%)
Maximum prediction error ±	−50.33	−54.25
Minimum prediction error ±	−24.21	−10
Mean prediction error ±	−37.96	−37.33

The resulting over-prediction of the air based model highlights the strong influence of surrounding media on the leak signal and the difficulty obtaining representative samples in a laboratory environment. This has also been highlighted by several other authors, who note a strong influence of the surrounding media on the leak signal [7,9,38,39]. The air based model performed poorly when the media type was changed due to lower RMS values in buried pipes. The reasons for the reduced RMS values within the submerged and geotextile samples are likely to be due to the extent of the impedance mismatch between the pipe and the surrounding media. When the leak discharges into air, the impedance mismatch is higher than when submerged and with geotextile fabric and therefore less leak energy is radiated into the surrounding environment. A lower impedance mismatch is present when submerging the pipe and wrapping it with geotextile fabric, where a low impedance mismatch generally represents efficient energy transfer [40], which will likely result in reduced leak signal energy recorded by the accelerometers.

Due to the strong influence of media on the leak's VAE signal and resulting over-prediction of the air based model, a further flow prediction model was derived (Eq. (10)), which is based on experimental data taken for the submerged pipe and the pipe wrapped in geotextile fabric. In order to verify this media based model, the experimental tests were conducted once more, where the pipe was resubmerged and wrapped in geotextile fabric. This data is now referred to as *validation data* and its purpose is to assess the accuracy of the media based model on new data sets.

RMS based model (discharging to media)

$$Q_{RMS} = 0.15127\ mV_{RMS} + 0.19893 \quad (10)$$

The performance of the media based model is further plotted in Fig. 11 and Table 4, and was found to provide a higher degree of accuracy in the flow rate prediction compared to the air based model. On average, the media based model caused only 4.17% and −1.01% error when applied to submerged and geotextile

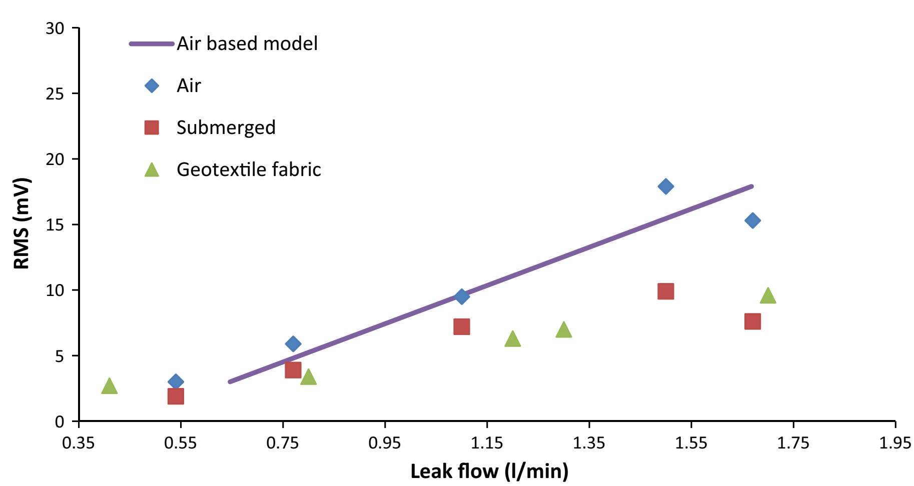

Fig. 10. Performance of the flow prediction model for leak flow rate prediction tested under different media types (discharging to air, submerged and wrapped in geotextile fabric).

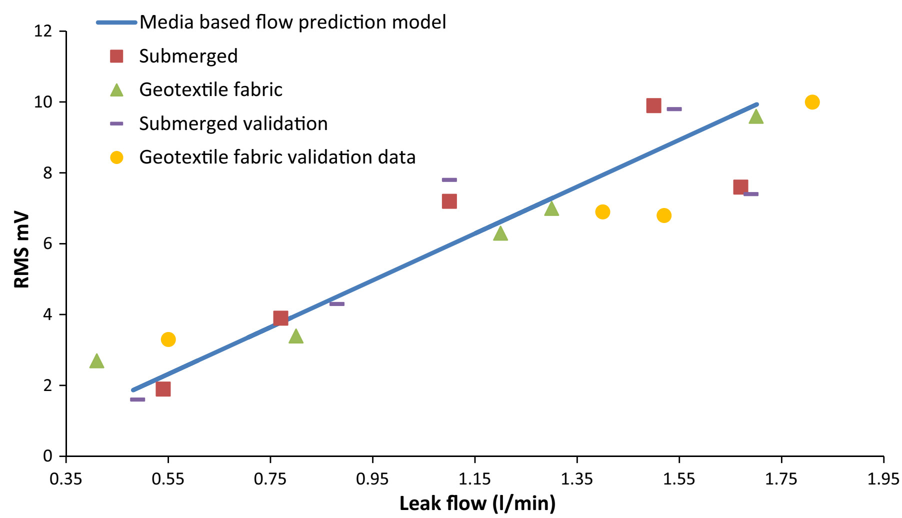

Fig. 11. Performance of the media based flow prediction model for leak flow rate quantification tested on validation data.

Table 4
Prediction error using the media based model, based on the assessment of secondary validation data.

	Submerged pipe (%)	Geotextile fabric (%)
Maximum prediction error ±	−2.86	−15.79
Minimum prediction error ±	−15.38	2.63
Mean prediction error ±	4.17	−1.01

secondary validation test data respectively. This suggests that the geotextile and submerged media types share similar RMS values, and therefore this model may be appropriate on real buried water distribution networks and could potentially be used on a wide variety of WDS due to a negligible effect of media type on the model

4. Conclusions

The purpose of this work was to investigate whether it is possible to derive a signal processing method which may help to quantify leak flow rate from leaks on plastic water distribution pipes using VAE. A variety of methods were tested and the most promising method was the use of the RMS value and from this value it was possible to derive a model based on experimental data with a leak discharging into air. The air based model was found to over-predict the leak flow rate when the pipe was buried under different media types representative of a real buried WDS, due to the strong influence of surrounding media on the leak's VAE signal. This highlights the importance of media in deriving information from leaks under different media types, and laboratory samples discharging into air are unlikely to result in representative signals of leaks on a real buried water distribution network. However, when comparing the two other media types with each other, the media type was found to have a negligible influence on RMS levels and therefore a second flow prediction model was developed based on the media data. This media based model was validated for a second time on the test rig and demonstrated high levels of accuracy in quantifying leak flow rate. However future research is required to validate this on a real WDS with different media and leak types. The results presented in this paper demonstrate a signal processing technique to quantify leak flow rate using VAE, which will provide a useful method for water companies to prioritise maintenance and repair of leaks in WDS.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apacoust.2017.01.002.

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