Design of an Observational Study for Investigating the Impact of Pressure Transients on Pipe Failures in Water Supply Networks

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ABSTRACT

A system-wide investigation into the impact of quasi-steady and unsteady state pressure variations on the structural degradation and ultimate failure of pipes is critical for prioritising operational and capital expenditures. Such investigations rely upon an optimally designed observational study and the availability of metrics, which accurately capture the physical phenomena. The objective of this paper is to explore advances in causal inference and statistical methods in order to develop a sampling survey methodology that is required to differentiate the impact of pressure variations and transients, and other causal factors on pipe deterioration and failures.

Keywords: Observational study, high-resolution pressure logging, pressure transients

1 BACKGROUND

Pipe failures in water supply network are attributed to the individual or combined impact of factors associated with pipe material and diameter (e.g. age, manufacturing defects, wall thickness), environmental and operational loadings (e.g. temperature, ground movement, soil shrink and swell, road traffic, pipe hydraulics), installation practices and workmanship during installation and repairs, and external factors (e.g. a third party damage). While many of these factors are beyond the control of operators for existing infrastructure, the optimal management (reduction) of the diurnal steady-state pressure, which is represented by the Average Zonal Pressure (AZP), has been recognised as a cost-effective method for reducing leakage and burst frequencies ([1], [2]).

In addition to AZP, cyclic pressure variations under steady and unsteady state hydraulic conditions could significantly contribute to both pipe failures and the structural degradation of pipelines by accelerating the fatigue crack growth rate. Recent studies ([3], [4]) have highlighted the adverse impact of pressure variations on pipe deterioration and failures. Consequently, it is of critical interest to operators the degree to which the dynamic pressure variations due to quasi and unsteady-state pipe hydraulics are a risk factor for pipe failures and pipe deterioration; and whether this knowledge could significantly enhance the performance of existing pipe burst deterioration models.

The assessment of whether dynamic pressure variations, which include quasi-unsteady state pressure variations and pressure transients, are a causal factor in a pipe burst is rather complex. Firstly, on-site information gathered during pipe repairs is of low quality and a forensic analysis to identify the causes of pipe failures is rarely carried out. A “fire-fighting” (reactive) model for dealing with incidents and the lack of protocols for pipe failures analyses have so far limited the on-site data collection during and after pipe repairs. Secondly, technologies [11] for continuously monitoring the pressure with high temporal and spatial resolution, and metrics to quantitatively capture the fatigue-induced stress (e.g. the cumulative pressure induced stress, [12]) have only been recently developed and made available to pipeline and network operators [14]. Thirdly, pipe failures are likely the result of the joint effects of a number of factors, which makes it difficult to differentiate the contribution(s) of the dynamic pressure variations to a pipe failure. The so-called "Swiss cheese model" of accident causation [13] describes that failures occur because of a combination of different events, which collectively change the behaviour of a system or a physical process. This model acknowledges that a structural failure has a multiple of possible causes that may not function independently, thus resulting in a fairly complex causal structure. Therefore, understanding the role of a critical individual factor such as the dynamic pressure variations, which is one of the very few factors an operator could proactively control, may bring significant operational benefits and expand the life cycle of pipe assets.

The causality analysis of a pipe failure (or a cohort of pipe failures) requires good understanding and control of the various causal factors in making comparisons and assessments for different management strategies. Therefore, to assess the degree to which dynamic pressure variations increases the probability of a structural failure in a pipe, the design of the data collection and analysis should account for the correlation between the multiple additional factors, referred to as confounding factors, and the dynamic pressure variations as the causal factor of interest.

A common experimental approach that limits the influence of confounding factors is the randomised control trial. However, the deliberate introduction of dynamic pressure variations will be unacceptable for water operators. Consequently, most of the data that is collected for such analysis are part of an observational study, which draws inferences from a sample to a population. In this case, the independent variable (dynamic pressure variations) is not under the control of an investigator and specific design-for-data-collection methods are needed to balance the impact of confounders on the comparison of pipe segments with and without the causal factor of interest, namely the dynamic pressure variations. By using such methods, water utilities can better assess the corrective actions, and the OPEX vs CAPEX trade-offs to reduce pipe failures due to sub-optimal pressure management.

In this paper, methods for the design of an observational study for investigating the impact of dynamic pressure variations on pipe burts are studied in order to support the design and execution of a large scale investigation by a UK water company. The paper is structured to, firstly, provide a background review on the data collection methods, followed by a review of various categories of probability sampling methods. A calculation of sample sizes for this investigation is then presented, together with methods for a stratified random sampling and a two-stage sampling procedure.

2 HIGH RESOLUTION PRESSURE DATA COLLECTION

The long-term impact of dynamic pressure variations on water pipes is not well understood. Urgent cost-effective investigations are required to establish whether hydraulic dynamics increases the probability of pipe failures in order to take this into account when optimising capital and operational expenditure plans. One reason for this poor knowledge is the lack of long-term pressure data with high temporal and spatial resolution. Recent technological developments can now address this challenge. A pressure monitoring device, a data management system and a set of analytical methods developed at Imperial College London, InfraSense Labs, [3,11] and licensed to [14], are used for continuously monitoring the dynamic hydraulic behaviour within a water supply network and deriving the cumulative pressure induced stress [12] for each pipe and a control asset. CPIS is calculated from the frequency and amplitude of cycles and the average pressure for which these cycles occur for a specific pipe diameter. High frequency pressure data (up to 128S/s, Samples per second) has been acquired at over 480 monitoring locations across a water supply network within 2.5 years (and this programme of work continues). A carefully designed device placement programme (the sampling programme) was integral to support the deduction of causal inferences from observational data and extrapolating such inferences to similar pipe segments.

2.1 Sampling programme (device placements) for an observational study

We investigate the impact of dynamic pressure variations on pipe failures by combining experimental research under controlled laboratory conditions (e.g. pipe samples investigated for crack initiation and propagation) and observational studies from operational networks. Each of these methods has its own advantages and limitations; and therefore, it is essential that the two methods are combined. This paper focuses on the design of an observational study.

Our initial approach, which is becoming a common practice for UK water companies, included case studies where pressure data with high spatial and temporal resolution were acquired for individual pipes and sub-sections of a network following a pipe failure. We refer to this approach as "hunting for transients". While this approach addresses specific operational problems, it lacks the rigour of answering system level questions such as: to what extent and under what circumstances dynamic pressure variations impact the pipe deterioration and failures, should these dynamic pressure variations be included in pipe burst prediction models, and what pressure monitoring and control actions should be implemented for hydraulically calm networks. Consequently, our work evolved to include causal inference and observational studies methods from epidemiology, medicine and statistics such as case-control, cross-sectional and cohort methods [10]. The device placement (sampling) method described here is designed to support a cross-sectional observational study, for which sections of uniform metallic pipes with historic failures, performance indicators (e.g. pressure from extended period simulation models and leakage) and specific confounding factors (e.g. soil type) were divided into "pipe subjects". Nearly 114,000 pipe repair records were available for a time period of 10 years. The device placement method aimed to determine the prevalence of the cumulative pressure induced stress (CPIS) as a metric for the dynamic pressure variations. Prevalence equals the number of pipe subjects with measured CPIS in the population at a given point in time (e.g. a duration of two weeks).

For the cross-sectional observational study, two approaches for the placement of devices (sampling) were considered: probability and non-probability sampling methods. In probability samples, each pipe subject from the population has a known and non-zero chance of being chosen, while in non-probability samples, it is not known for certain whether each pipe subject has non-zero probability of being selected. Probability sampling methods, which were investigated, include [5] a simple random sampling (SRS), stratified sampling, systematic sampling and multi-stage sampling.

In simple random sampling, the desired number of pipe subjects (pipe samples) to be investigated for their CPIS (e.g. analysed for the dynamic pressure variations) are randomly selected from the population. For the stratified sampling, the pipe subjects are ranked and stratified, and then a list of pipe subjects to be investigated are randomly selected from the different strata. In systematic sampling, every i^{th} member of the list with ranked pipe subjects is selected. Multi-stage sampling involves using a combination of two or more of the sampling techniques highlighted above.

In our study, a stratified random sampling has been applied to utilise a smaller sample size and minimise the use of under-representative samples. Two categories of stratified random sampling were investigated: proportionate stratification and disproportionate stratification of the derived pipe subjects [6]. In proportionate stratification, the sample size of each stratum is proportionate to population size, i.e. each stratum has a similar sampling fraction. The sampling fraction may vary for each stratum in disproportionate stratification. The disproportionate stratification could lower the cost of the study as various assumptions are accommodated without significantly affecting the statistical rigour of the analysis. For instance, using this method, the sampling could be more heavily biased towards a stratum where the size of the stratum or its variability are large.

2.2 Sample size

There are various factors affecting the number of pipe subjects from the whole population, for which CPIS should be experimentally determined. These factors include the acceptable level of precision, confidence interval, variability within the strata and cost considerations. In order to calculate the sample size for random sampling without replacement, the population size, confidence level, margin of error and standard deviation are required. The sample size is determined from [6]:

$$n = (z - score)^2 \times SD \times (1 - SD)/(MoE)^2 \quad (1)$$

where n is sample size, SD is standard deviation and MoE is Margin of Error. Value of 0.5 is assumed for the standard deviation. For stratified random sampling, the sample size in each stratum is calculated as [7]:

$$n_h = \frac{n \times \frac{(N_h \sigma_h)}{\sqrt{c_h}}}{\sum \frac{(N_i \sigma_i)}{\sqrt{c_i}}} \quad (2)$$

where n_h is the sample size for stratum h, n is total sample size, N_h is the population size for stratum h, N is total population size, σ_h is the standard deviation of stratum h, and c_h is the direct cost to sample an individual element from stratum h. In this study, it is assumed that direct cost of each sample (e.g. the deployment of an InfraSense device) is the same across various strata, and in order to maximise precision given a fixed sample size, Neyman allocation, [5], is used to provide the sample size for stratum h, as:

$$n_h = \frac{n \times (N_h \sigma_h)}{\sum (N_i \sigma_i)} \quad (3)$$

There are approximately 24,000km length of metallic pipes as part of this study with approximately 0.5 million pipe segments, and a large proportion smaller than 5m in length. Based on the transient dissipation characteristics for metallic pipes, we assumed that a monitoring location can be representative of the CPIS characteristics for a pipe length of 1km, 500m length upstream and downstream direction. This reduces the total population to 24,000 pipe subjects; it should be noted that this topological simplification for the purpose of device placement provides the largest number of pipe segments.

By applying the Neyman allocation, and considering a standard deviation of 0.5, sample sizes (n) are calculated for various confidence intervals and margins of error (Table 1).

Table 1 Sample size got various Confident Intervals (CI) and Margin of Error (MoE)

α	CI	$z - score$	MoE	SD	n
0.05	95%	1.96	10%	0.5	96
0.02	98%	2.33	10%	0.5	136
0.1	90%	1.645	5%	0.5	271

0.05	95%	1.96	5%	0.5	384
0.02	98%	2.33	5%	0.5	543

Considering the network size, uncertainties in data used for the sampling design, and resource constraints (number of devices and man hours), a confidence interval of 95% and margin of error of 5% are considered, resulting in a minimum sample size of 384 monitoring locations.

3 STRATIFIED RANDOM SAMPLING (SRS)

The developed stratified random sampling consists of two stages (Figure 1). Stage 1 assigns the pipe subjects (population members) to individual strata, and in stage 2, the random sampling from each stratum is carried out.

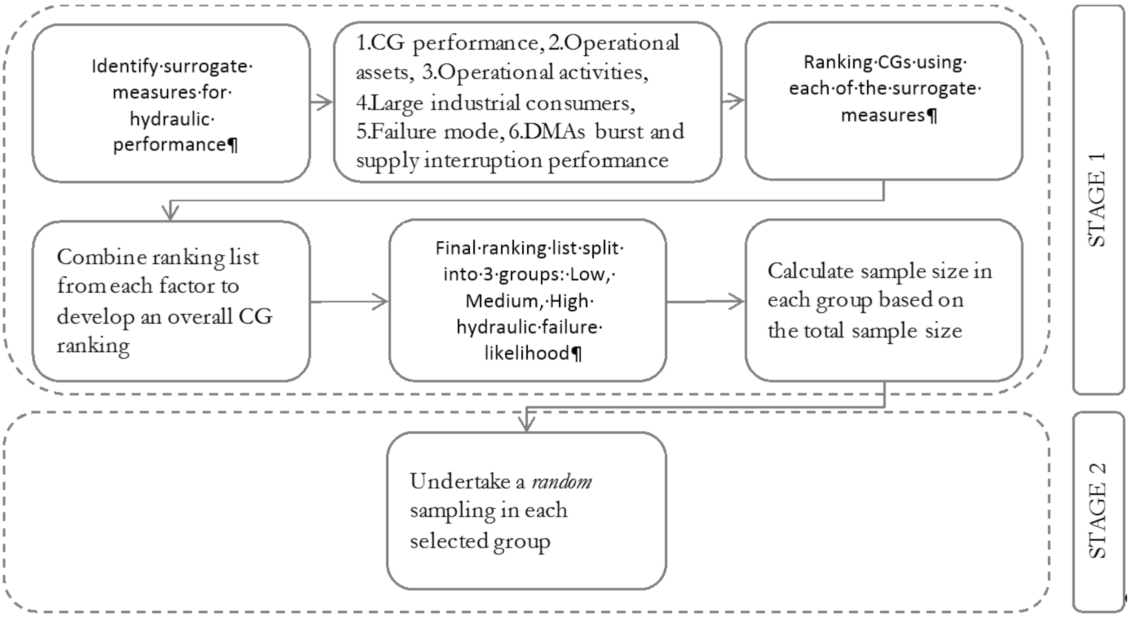

Figure 1 placeholder - Statified random sample procedure

3.1 SRS Stage 1

In stage 1, three strata with low, medium and high hydraulic failure likelihood are defined. This stratification process attempts to capture the spatial variations in the network performance based on topological, operational characteristics and historic performance. The hydraulic failure likelihood utilises information from "classic" pipe burst prediction modelling methods, which do not take into consideration the dynamic pressure variations, together with additional hydraulic-based performance indicators. In this investigation, the topological hierarchy of the network has also been considered. For example, the stratification included Control Groups (CG). A control group is a set of 30-60 DMAs (District Metered Areas) with the same supply sources.

The additional hydraulic-based performance indicators, which were included in the hydraulic failure likelihood, take into consideration areas and assets with high probability of occurrence of pressure transients. These include pipe assets in proximity to pumps, electrically operated valves and large industrial consumers. The hydraulic performance measures used for stage 1 ranking are based on the control group ranking, type of control assets, historic pipe failures, predicted pipe failures and historic supply interruptions. A performance table is then used to rank all CGs. For instance, analysing historical bursts per pipe length in each CG, Table 2, results in CG ranking based on this factor.

Table 2 Example of CG ranking based on CG pipe failure rate

CG reference	Number of burst (2003-2013)	Length of mains(km)	Bursts/ 1000km	CG ranking	CG level
CGEM23	837	246.9	3390	3	H
CGEM16	146	75.5	3258	4	H
CGEM03	288	152.7	1886	51	M
CGEM24	2840	1521.8	1866	52	M
CGEM47	434	321.9	1349	96	L
CGSV03	242	180.7	1339	98	L
…	…	…	…	…	…

A weighted CG rank list is then computed from the six CG ranking lists, which are derived using the various indicators. Methods such the Round Robin, Raw Score and Linear Scaling [8] can be applied to combine the ranked lists. For this study, a Raw Score method is utilised. A local score for each list is calculated for defining the ranking in the combined list. CGs are assigned a weighting based on their ranking in each list. Then, a linear combination of weights for each CG is calculated and used to develop a final ranking list. In this final list, each CG has a CG level (H, M, L), which stands for High, Medium, or Low, in order to indicate its hydraulic failure likelihood.

3.2 Stratum sample size

The outcome from stage 1, which is the three strata of the CGs with low, medium and high level of hydraulic failure likelihood, is summarised in Table 3.

Table 3 Characteristics of the Strata result from stage 1

Stratum	Number of CGs	Population (pipe segments)
Low	43	477,304
Medium	43	318,018
High	43	456,905

A stratum with low hydraulic failure likelihood represents areas of the system that have not experienced hydraulic failures (e.g. pipe failure, supply interruption, etc.), have a low probability of predicted pipe failures (based on a “classic” pipe burst modelling method) and where the likelihood of dynamic pressure variations is low. Consequently, the stratified sampling results in a larger number of samples from areas with a higher likelihood of hydraulic failures.

The Neyman allocation is expanded to account for this sample adjustment weighting:

$$n_h = \frac{n \times (N_h \sigma_h) \times SW}{\sum (N_i \sigma_i) \times SW_i} \quad (4)$$

where n_h is the sample size for stratum h, n is total sample size, N_h is the population size for stratum h, σ_h is the standard deviation of stratum h and SW is sample adjustment weighting. As standard deviation for each stratum is not known, value of 0.5 is used. For n=384, σ_h=0.5 and considering population proportion (weighting factor to promote areas with a higher likelihood for hydraulic failures); the number of samples in each stratum is calculated, as shown in Table 4.

Table 4 Distribution of sampling points in each stratum

Stratum	Mains length (km)	Population (pipe segments)	Sample adjustment weighting	N_h	n_h
Low	10,193	477,304	0.2	95461	62
Medium	13,909	318,018	0.3	95405	62
High	19,473	456,905	0.5	228453	148

3.3 SRS Stage 2

At SRS stage 1, the list of CGs and number of samples in each stratum is determined. At stage 2, a random sampling is undertaken from the number of samples within each stratum. The device placement (deployment) locations are randomly selected within each stratum, taking into account various practical constraints and deployment restrictions. Some of these restrictions include: (i) a limited number of pressure tapping points on large diameter (trunk) mains, valves and pumps; (ii) a restricted access to certain locations (traffic management, private properties, etc.); (iii) discrepancies between available assets data from the GIS and the actual network configurations.

4 ANALYSIS OF THE SAMPLING (DEVICE PLACEMENTS)

A total of 480 locations have been monitored as part of this initial study, which exceeded the minimum sample requirement of 384 device placements. The proposed sampling methodology for the observational study was further analysed in order to examine whether the assets selected for placing a device had similar distributions in comparison with the distributions of all pipe assets for the entire population. For instance, as illustrated in Figure 2, the distribution of sites logged, follow a similar distribution of the assets for the entire network. This is true for both physical properties (e.g. pipe age and soil properties) of the network and its hydraulic characteristics (e.g. maximum pressure).

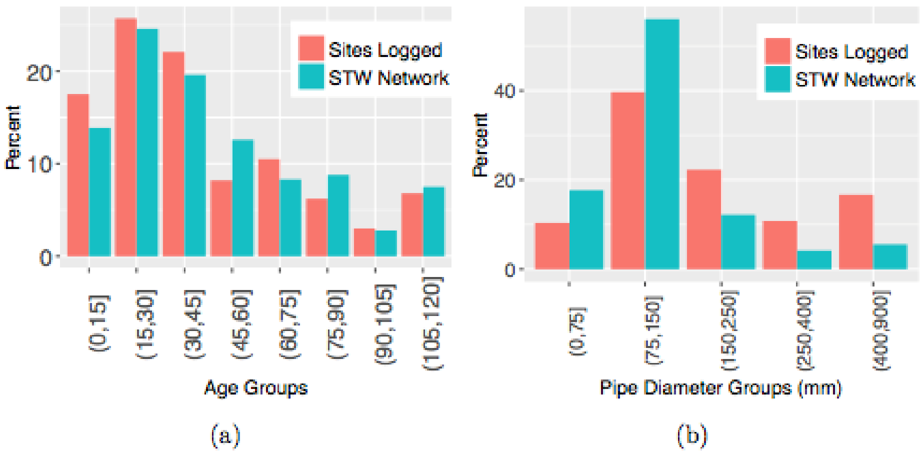

Figure 2 Comparing distribution of assets logged versus all pipes at (a) age groups (b) pipe diameter groups

5 CONCLUSIONS

The total expenditure model (TOTEX) and the recently introduced quality of service and outcomes-based incentives by the water regulator (Ofwat) are forcing UK water utilities to gain much better understanding and control of the hydraulic performance of their networks, and causes of pipe failures.

This paper describes the design of an observational study, which informed the sampling programme (the placement of pressure monitoring devices) for a unique large scale investigation into the impact of quasi-unsteady and unsteady-state (transients) pressure variations on pipe failures. The size of the networks under investigation is 43,000km of pipes. The quality and strength of evidence provided by the study, which is outside the scope of this paper, is determined largely by its sampling design. This paper discussed the principles and methods that guided the design of the observational study.

The presented observational study and sampling method empower the transition towards a more holistic pressure management approach for hydraulically calm networks, which includes the reduction of both AZP and dynamic pressure variations

6 ACKNOWLEDGEMENT

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