

# TACTICAL LEAKAGE TARGETING, A MODELLING AND CONTROL SYSTEM TO AID EFFICIENT LEAKAGE STRATEGIES

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## ABSTRACT

*Water companies are under increasing pressure to drive down their level of leakage. Furthermore companies are seeking to be more efficient in the way they manage and reduce leakage levels. We present a preliminary investigations into a new approach to leakage targeting at a district metered area (DMA) level. The approach enables modelling of leakage at component level: growth rates of leaks, leak sizes and leak run times. These components allow a bottom-up approach of defining the natural rate of rise (NRR) and allocation of resource within a network to provide an efficient approach for leakage targeting.*

**Keywords:** Leakage targeting, leak break out, leak growth

## 1 INTRODUCTION

Water companies are coming under increasing pressure to drive down their company level of leakage. Many utilities have outcome delivery incentives [1] (ODIs) that reward outperformance of leakage targets, whilst conversely being penalised for failing to meet targets. Maintaining control of leakage and ensuring that leakage levels are reduced in a cost effective manner are therefore, key operational objectives. Since the 1990's levels of leakage have been progressively reduced. There was initial sharp decrease in leakage and now to a point where many leakage targets are flat as companies strive to maintain their sustainable economic level of leakage [2]. Going forward the challenge is how to maintain the downward trend in leakage, whilst delivering leakage management in a more cost effective manner.

In this paper we focus on historic data at a granular level to improve the efficiency of leakage targeting and active leakage control, and therefore present a more focused approach on the analysis of large amounts of data using innovative and novel methods. The approach makes use of standard 15-minute average flow data from district metered areas (DMAs); net flow into discrete isolated sections of the network typically supplying between 500 and 2000 properties).

Understanding individual leaks provides a better comprehension of the effectiveness of the intervention. Leak repair types (e.g. mains bursts, communication pipes, fittings, customer supply pipes) can be used to create distributions of repair times. A simulated reduction in total leakage can be assessed by varying the bounds or shift in the repair times. This type of assessment can provide active leakage control (ALC) cost curves to determine the financial efficiency of different approaches. Once ALC cost curves are calculated by DMA, a dynamic approach to leakage targeting is formed. This will aid an improvement in ALC efficiency and effectiveness.

We present the core structures behind what could become a fully automated real time system. The simplicity of the input data means that this approach could be employed by many water companies,

and will provide a data driven decision making system for resource allocation. The tool also affords a method for allocating economic leakage targets at DMA level that are linked to delivering companies targets and a warning system to replace standard operating procedures for allocating resource for leak detection and repair.

## 2 METHODOLOGY

A bottom-up approach explores the key components of leakage, and their differences spatially and temporally at district metered area (DMA) level. Natural rate of rise [3] (NRR) is calculated at a DMA level via a novel approach. The standard method is a manual method of determining the slope of gradients between repairs. Our approach uses the standard minimum night flow (MNF) within a DMA [4] as a surrogate measure of leakage, and the specific drops in leakage related to repairs. NRR is the increase in leakage that would occur if no repairs were carried out, and therefore is the sum of the repairs plus the change in leakage over the year. The change in leakage over the year is an average of the first and last week in the year.

Next is an assessment of each of the individual leaks [5]. From the NRR analysis the drop is used as the terminal volume. Repair time is calculated as the number of days between detection/reporting and completion. At this stage the leak is deemed triangular in shape with the gradient determined from the height defined as volume drop and length defined as leak runtime. Though the repair time is a useful metric, it will always be shorter than the full runtime, due to it not being possible to detect the leak when flow is zero or very low. Breakout rates and runtimes are estimated by studying intervention intervals, the assumption is if the leak was not discovered in previous intervention it must have occurred since then, and hence a mid-way point is selected.

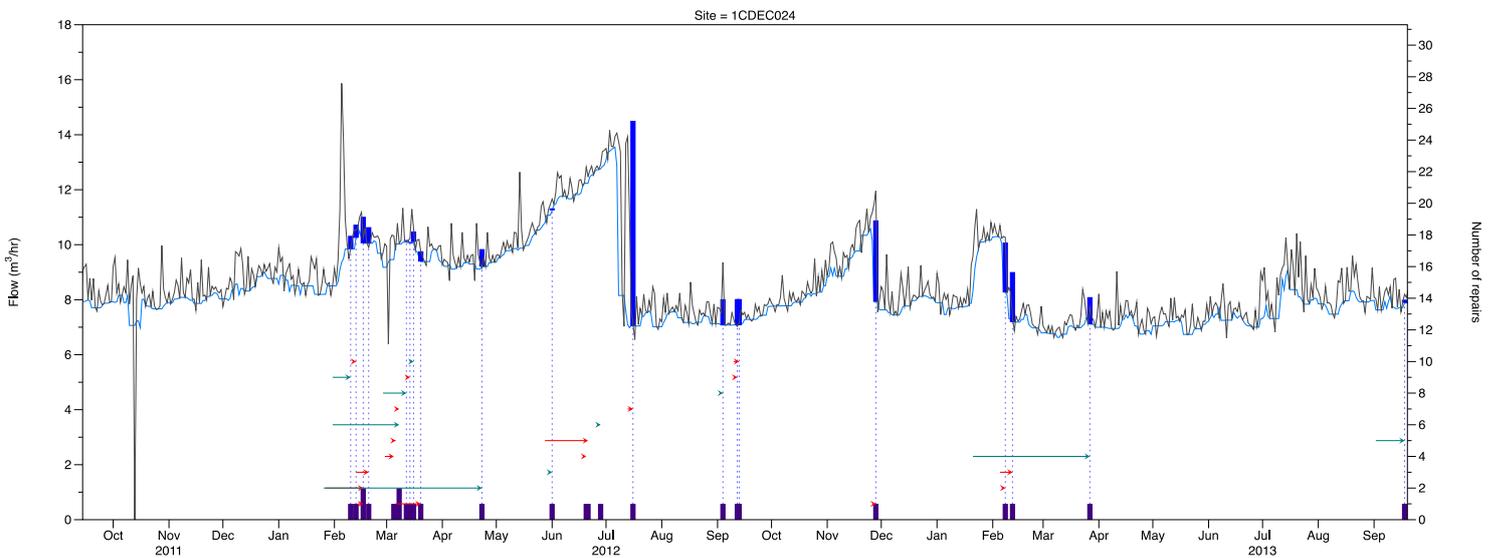
A more optimal leak fitting routine has also been investigated, which is an optimisation method that minimises the root mean squared error (RMSE) between the sum of individual leaks and the minimum night flow line. To identify each of the leaks a peak finding function is used, by detecting downward zero crossing the first derivative. An algorithm extracts the peak position, height, width, and area of each peak. These attributes inputs in the optimisation fitting procedure, with the exponential coefficients optimised for each leak to sum to the MNF profile [6]. Whilst the results seem promising, further work is needed to be able to apply this method across all DMAs, due to the high levels of complexity. Herein, data makes use of estimates from the triangular method, and presents some early results of the optimised curve fitting.

Probability distributions for each of the leak metrics are established, by any number of factors. An intervention function is developed over time, i.e. the probability of a repair being carried out in any given week over the year, again by a number of different factors dependent on the goals of the optimisation.

## 3 RESULTS

Stage one of the results is to determine the amount of volume associated with repairs. An example is shown in Figure 1. The grey line shows the MNF over the time series. The drops are calculated as the difference between the week before a repair, and the week after. There is considerable variation within the MNF line, and so the 15<sup>th</sup> percentile is displayed by the blue line as a graphical aid.

Different methods were trialled to best fit the drops to the repairs, and also the volume of the drop. The drop was captured by grouping declining leakage values and summing the result, so that minor variations do not disturb the calculations, within 7 days of the repair date. Detected repair times are



*Figure 1. Drops and repair times associated with repairs for a single DMA*

indicated by the red lines, and the reported repair times are shown by the blue horizontal lines. The purple bars illustrate the number of recorded repairs.

Figure 1 affirms the need to understand full runtime, rather than just the repair time. Background leakage is another consideration. Using the drops and repairs times alone to create the leak triangles will always underestimate leakage, and the sum will not reach the MNF line. However, the repair times are still an important factor as it is a component of each leak. Full runtime is estimated by halving the time between the last effective intervention and its own detection time.

An improvement to the triangular shapes and extraction of the metric from the MNF involves a peak finding and curve fitting routine. Results from this method are extremely promising as shown in Figure 2. The individual leaks were fitted using a reverse exponential pulse, a good fit with a long leading tail which simulates the increases from a low undetectable flow increasing rapidly once the leak becomes more active. This is followed by a sharp decline once the leak is repaired. Each individual leak is optimised so that the sum of the individual leaks equals the MNF; done by changing the height and shape of each of the curves.

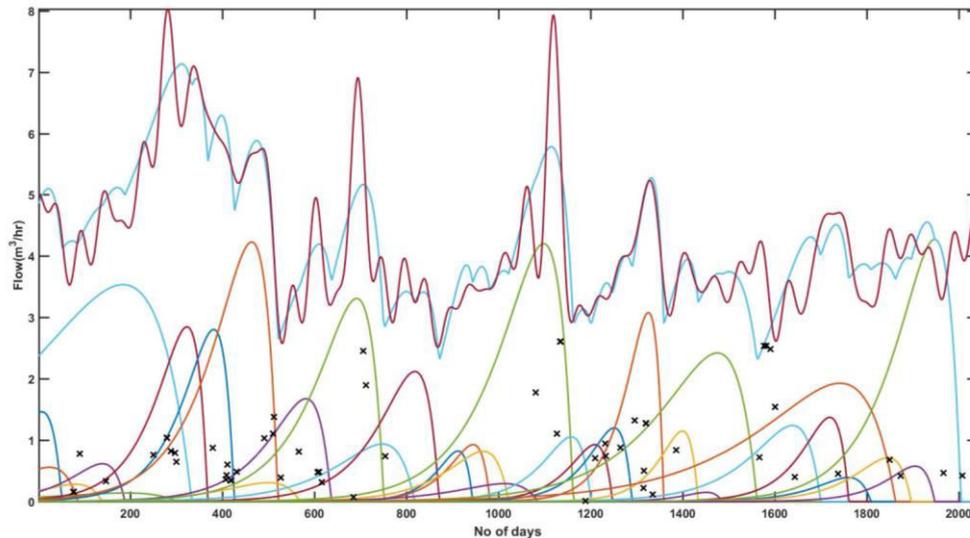


Figure 2. Reverse exponential pulse fitting to optimise the sum of leaks to fit MNF

The application of this optimisation tool is useful for several reasons. (1) Removal of the unknown level of background leakage, optimisation was run with zero background leakage, considering that background leakage is the sum of the undetectable volume of leakage from the long leading tails. (2) The possibility that background leakage consists of internal losses, any repairs are carried out by customers unbeknown to the company. When assessing the location of the crosses displayed in Figure 2, it is evident that many of the leaks identified using the curve fitting approach do not coincide with the repairs.

An advantage that this method has over the triangular approach is the ability to vary the shapes as well as the run time and terminal volume. It is possible that the shape itself could be modelled by pipe material, repair type or seasonally. Further improvements are under investigation to automate and explore this methodology.

The next step in the overall process following the curve fitting approaches is the Monte Carlo approach to optimise resource for leakage targeting. Once the key metrics for each leak are extracted, Monte Carlo is used to alter certain metrics and model the impacts on the total leakage levels, active leakage control (ALC), sustainable economic levels of leakage (SELL) and natural rate of rise (NRR).

A brief summary of some of the types of outputs and processes used in the Monte Carlo section are shown here;

Figure 3 shows an overall function of how the level of intervention changes throughout the year, actual values are displayed in blue, the solid red line shows the polynomial function fitted to the data points, and the dashed red line shows an example set of simulated figures are shown by the dotted re line where and normal error distribution has been fitted around the polynomial function. This is applied by DMA, repair type or other factor dependent on the optimisation required.

Time between intervention is used as a proxy for the portion of runtime that occurs before detection/ reporting. The distribution is log normal, and logical due to the long lead time before a leak reaches a detectable level. A log normal function is fitted to this data, and again can be segregated by many factors depending on focus of the optimisation.

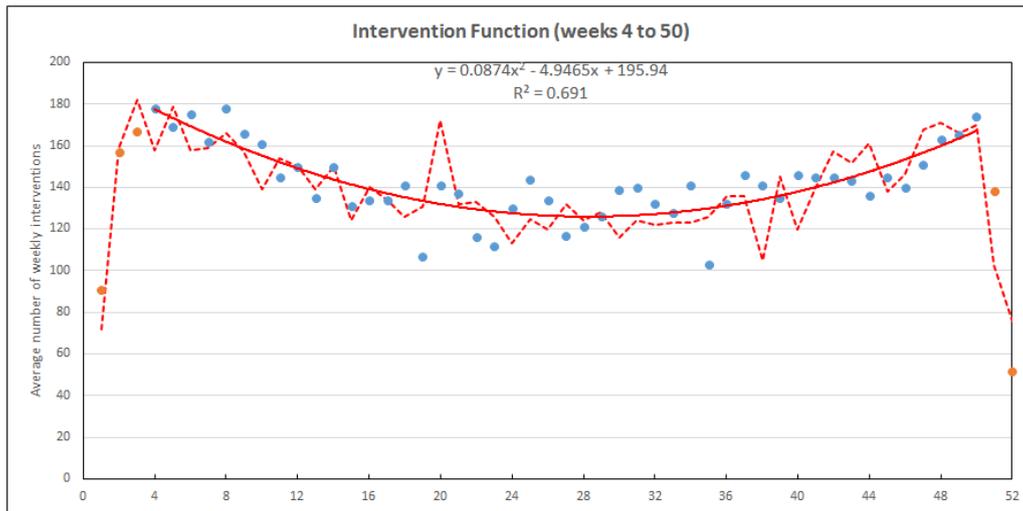


Figure 3. A seasonality function of the number of interventions occurring by week

Table 1. Example function and coefficients for the repair time (days between reported/ detected and job completion)

Functional Form	Leak type	a	b	Median Rt (days)	Average Rt (days)
$Rt \text{ (days)} = \text{gamma.inv}(p, a, b)$ $p = \text{rand}()$	Detected Mains	0.2794	16.1598	3	8
	Reported Mains	0.1154	23.5909	2	8
	Detected Comm Pipes	0.7838	13.4770	7	13
	Reported Comm Pipes	0.5140	18.4185	7	13
	Detected Fittings	0.4061	25.9208	7	17
	Reported Fittings	0.5297	23.2767	9	18
	Detected Supply Pipes	0.7821	56.5433	29	52
	Reported Supply Pipes	0.7455	48.4233	25	42

The repair time functions appear to best fit a gamma distribution, examples contained here are different shapes (coefficient a) and scales (coefficient b) of each of the eight common repair types.

Table 2. Terminal leak flow rates

Functional Form	Leak type	m	sd	Median Flow (m <sup>3</sup> /hr)
$\text{Leak Flow (m}^3\text{/hr)} = \text{Norm.Inv}(p, m, \text{sd})$ $p = \text{rand}()$	Detected Mains	-0.3800	1.0203	0.68
	Reported Mains	-0.4473	0.9902	0.64
	Detected Comm Pipes	-1.1153	1.0125	0.33
	Reported Comm Pipes	-0.7198	0.9114	0.49
	Detected Fittings	-1.2225	1.1153	0.30
	Reported Fittings	-0.7013	0.9522	0.50
	Detected Supply Pipes	-0.5577	0.8326	0.57
	Reported Supply Pipes	-0.6040	0.8903	0.55

As seen in Figure 1, there are a large number

of repair jobs without a resulting drop in leakage. This occurs for many reasons, and this set of

functions could be applied by different factors. The function is an important inclusion as for example, 19.2% of reported mains repairs have no impact on leakage. This is taken into account within the stochastic approach.

The terminal leak flow rates appear to fit a log-normal distribution (excluding zero flows), with the mean and standard deviation as inputs to form individual probability density functions for the leak types. The probability density functions for each repair type show very little difference between repair type, so if repair type was the focus of the optimisation this is not an ideal function to alter. This indicates that the terminal flow rate of the leak is not the best metric to target. Instead, runtime or repair time would be more appropriate with the terminal flow being a result of the run-time and repair time, which would in turn be reduced.

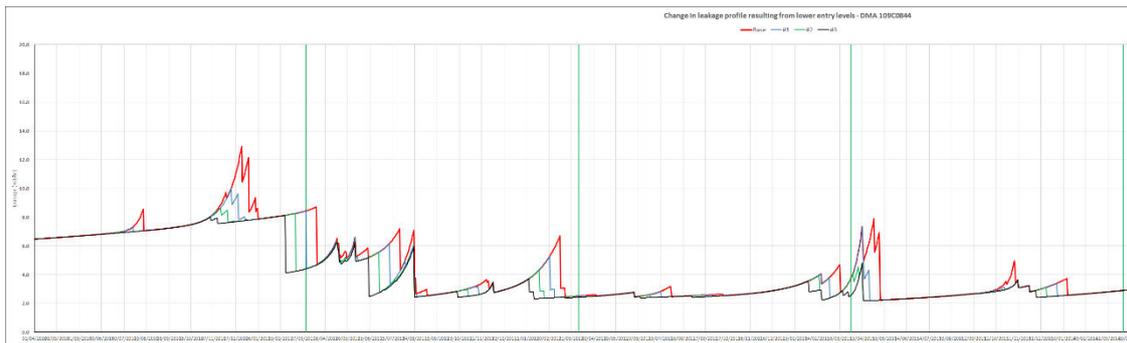


Figure 4. Example reduction in run-time for detected leaks

Figure 5 illustrates a five year time series of MNF. The red line shows the current dates of repairs and the blue, green and black lines show the impact of lowering entry levels into the DMA. In effect this shortens the time before detection and therefore the overall runtimes. The impact can be calculated by summing the area under the MNF and each of the scenarios however, this graph is for demonstration purposes of how the reduction would affect the MNF.

Scenario testing is displayed in Figure 6, this specifically targets a certain type of repair, and reduces the repair time by half by altering the scale factor for repair time. Figure 6 also shows the impact week by week basis as a mean repair volume. The baseline illustrated by the green line is compared to the scenario of the blue line. The difference between the two is displayed on the secondary axis, shaded blue area. The annual average saving for this scenario is 3 MI/day. There are many techniques to reduce leakage, we provide a few examples by way of this paper and some of the building blocks available from extracting the individual leak parameters.

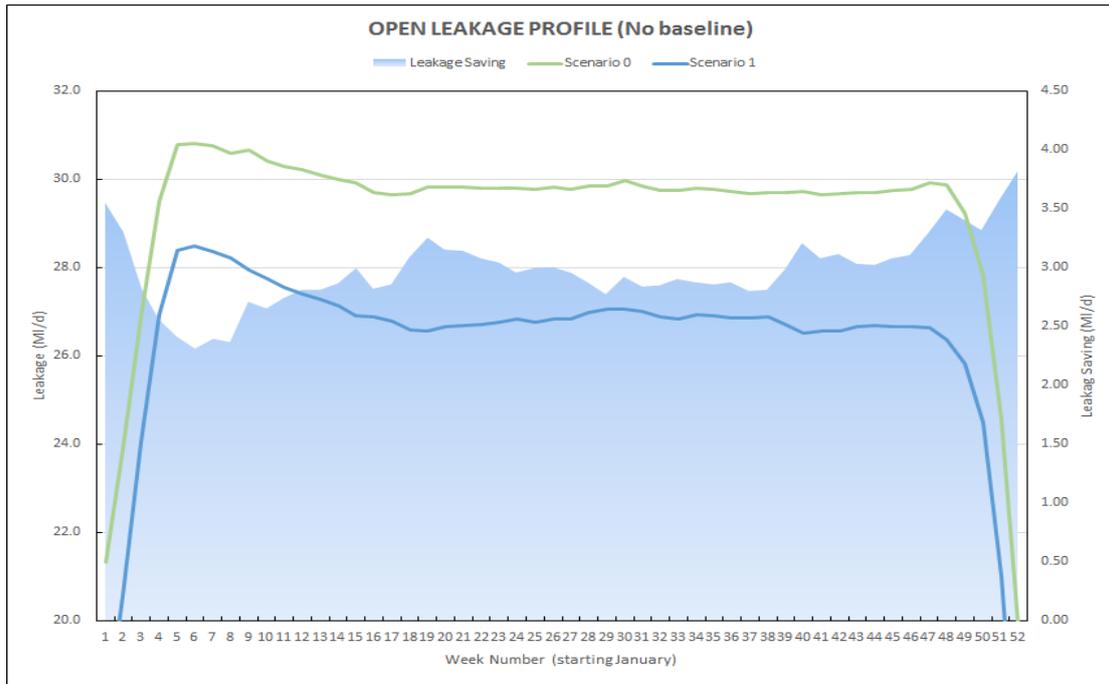


Figure 6. Another example scenario showing leakage reduction over the year

The scenarios built in this way can be directly fed into a DMA ALC cost curve, an example is shown in Figure 7. A set of scenarios are built and combined with static and variable cost of leakage repair, as well as the cost of water. This is used to find the best least cost option for maintaining steady state leakage.

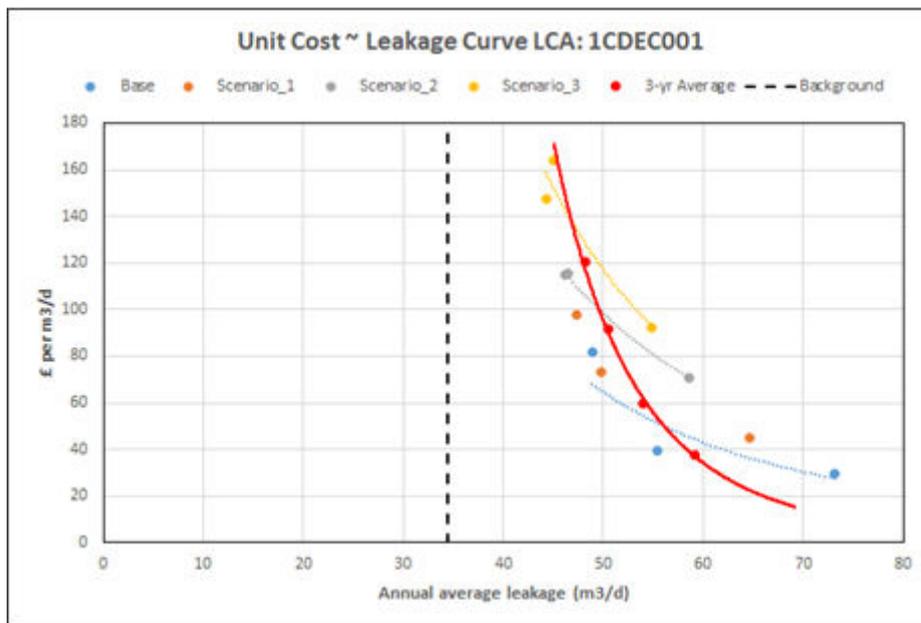


Figure 7. Example DMA ALC cost curve

### 3 CONCLUSION

We present our methods and outputs that are used to create optimal strategies for leakage targeting. These strategies are applied at DMA level in order to understand NRR and individual leaks. The leaks are used to understand and model the DMA characteristics by assessing leak runtime, repair time and terminal volume. We successfully trial a method using non-linear curve fitting for the

purpose of understanding all leakage below the MNF line, including background leakage and potentially internal losses. These steps lead to providing optimal ALC cost curves per DMA which can be used for strategic targeting by water companies.

Alongside this main work stream, there are many options for developing further work including; work basket optimisation, a new system for leakage targeting and a reporting structure to provide companies in depth visibility of what is happening within their water distribution system. Once the component parts are complete a fully automated approach with stochastic methods, real-time data and optimisation techniques will replace static targets and improve the efficiency of leakage management strategies.

The ultimate aim is to incorporate our approach into an operational planning tool that can inform DMA prioritisation and intervention levels with aim to achieve WRZ leakage targets at least cost. This novel approach provides a data led decision making system, optimised for the company's needs, whether that is cost reduction or leakage reduction. It provides a much needed statistical and mathematical approach to fully monitor and target the current leakage on the ground. This paper provides a platform and a set of tools which enable these challenges to be much more achievable.

## 4 ACKNOWLEDGEMENTS

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