NOVEL METHODS FOR RANKING DISTRICT METERED AREAS FOR WATER DISTRIBUTION NETWORK MAINTAINENCE SCHEDULING

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Abstract

To prevent the accumulation of material in pipes which leads to the potential for discolouration events to occur, UK water companies often operate five year cleaning schedules. To organise the schedule District Metered Areas (DMAs), the case study water company assigns a score based on several key performance indicators and water quality levels, which are used to place each DMA into one of three categories: good, poor and urgent. This paper investigates alternative methods of ranking DMAs in order to generate better maintenance schedules. We demonstrate how DMAs can be both partially and totally ordered with methods from multi-objective optimisation, and show how it is possible to prioritise and progressively apply Discolouration Propensity Modelling (DPM) to help guide interventions in the most effective and efficient way. Results obtained from sample DMAs show a good correlation between the DPM scores and the rankings produced by the multi-objective methods. We apply both methods to water networks from a UK water company and demonstrate that used in combination the power index and DPM, have advantages over the current ranking method.

Keywords

Asset management, performance evaluation, discolouration risk, water quality

1. INTRODUCTION

Potable water distribution networks require regular scheduled maintenance to provide clean, clear water. However, over time material accumulates in pipes leading to the potential for discolouration events to occur [4]. Methods such as the Cohesive Transport Model [5, 6] have been developed to help understand the causes of this material build-up and provide modelling facilities to analyse the potential of pipes within a network to contain and store discolouration-causing material.

It is possible to mitigate this effect by cleaning pipes within the network, which is usually split into District Metered Areas (DMAs) in the UK, using techniques such as flushing. However, due to the size of distribution networks in the UK it is not usually feasible to clean all the DMAs of a network at the same time. Therefore, a schedule of cleaning operations is usually required, lasting around 5 years where those DMAs that have a high risk of leading to discolouration should be attended to first. In this study we examine a scoring system currently employed by a UK water company in which DMAs are assigned a ranking based on recorded key performance indicators (KPIs) and water quality levels. The DMAs are then placed into one of three categories (good, poor and urgent) based on these scores and maintenance is scheduled accordingly, placing emphasis on those in the urgent category. However, after the prioritisation of the poorer quality DMAs the current three category system no longer provides sufficient distinction between the DMAs – the majority of which are classified as good.

This paper investigates alternative methods of ranking DMAs in order to generate better maintenance schedules. First, we demonstrate how DMAs can be partially ordered using the Pareto dominance relation; an approach with which they can be sorted into categories based on their relative performance. This is extended using the power index, which is a method that provides a full ordering of DMAs. Once a ranking of DMAs is produced it is then possible to prioritise and progressively apply Discolouration Propensity Modelling (DPM) to help guide interventions in the most effective and efficient way. Results obtained from sample DMAs show a good correlation between the DPM scores and the rankings produced by the power index.

Having applied all three methods to the water company's water networks we demonstrate that, used individually, the two new methods each have advantages over the current method. DPM is useful for prioritising flushing schedules and highlighting those DMAs that require extra flushing, as well as being independent of the KPIs and any noise contained within the collected data used to produce them. Pareto sorting and power index ranking provide an intuitive way of scheduling maintenance, requiring only the information present in the KPIs. Additionally, the power index operates equally well with or without weighting the individual KPIs. By carefully considering which KPIs are included, the benefit of using the power index could be enhanced. We show that by combining all three approaches, water companies have the best information on which to base their decisions.

2. CURRENT MAINTENANCE SCHEDULING SCHEME

In [7], a study was conducted that collected samples from "over 1000 hydrants in 79 DMAs from ten [UK] water companies." The results from this early study were used to inform the construction of a DMA ranking system for one UK water company's maintenance priority scheduling. The system ranks DMAs into three categories (urgent, poor and good) based on the following input data: DMA region[1] iron (Fe) and manganese (Mn) pickup; bursts per 200; complaints per 200; proportion of unlined ferrous iron pipes; and the number of pressure control valve (PCV) failures. Each of these KPIs are compared to a set of threshold values which have been adjusted each year as the overall performance of the networks improve. For each DMA, the count of those KPIs which exceed their threshold is assigned as the DMA's score and used to sort all the DMAs, from best (0) to worst (6), which are then categorised into good, poor and urgent.

While the ranking system initially provided a suitable method with which to prioritise the case study water company's maintenance scheduling, continual improvement in DMA performance has led to the need to introduce a more granular ranking. In 2009, even with more stringent threshold levels, 69.77%, 28.68% and 1.55% of the company's DMAs were categorised into good, poor and urgent respectively. Although the urgent category and poor categories are suitably small, enabling sufficient prioritisation for these worst cases, it is difficult to make a distinction between the majority of DMAs in the network, which are all categorised as equally good.

3. MAINTENANCE SCHEDULING WITH RANKING

A common way of measuring relative performance between the individuals in a population, such as the DMAs in a network, is to rank them. As each DMA is described by a set of K KPIs it is possible to draw on ranking methods from multi-objective optimisation. Central to multi-objective optimisation is the dominance relation. An individual is said to *dominate* a second individual if it is no worse than the second individual on any KPI and better on at least one. An individual is *non-dominated* if no other member of the population dominates it, and two individuals are *mutually non-dominating* if neither dominates the other.

The entire population can be placed into ranked *shells* with these principles, using *Pareto sorting* [1]. Pareto sorting provides a partial ordering of individuals categorising the individuals from best to worst, where the non-dominated individuals are in the best, first shell, and the most dominated individuals reside in the worst, last shell. To rank the population, the non-dominated individuals are assigned a Pareto rank of 1 and placed in the first shell and temporarily removed from the population. Next, those individuals which were dominated only by rank 1 individuals are now themselves non-dominated and are given a Pareto rank of 2, placed in the second shell, and removed. This procedure continues until all individuals have been placed in a shell.

Pareto sorting can be used as the starting point for an intuitive visualisation of a multi-objective population [2] as demonstrated in Figure 1 for a network of DMAs. The set of DMAs is presented as a graph in which a DMA is a

[1] The water company's DMAs are grouped into local regions based on water sources and network topography.

node and the directed edge between two DMAs indicates that the DMA at the start of the arrow dominates the one at the end. The DMAs have been sorted into Pareto shells, each of which is shown as a column, and for clarity only the dominance relationships between adjacent shells are show. Whilst it is clear to see that a DMA in the jth shell is better than DMAs in shell j+1, and so on, it is not possible to determine which is the superior DMA between those within the same shell. To do this, we require a finer ordering of the population and therefore consider the *power index* of individuals.

A variety of ranking methods are capable of ordering populations with multiple KPIs (see [2] for a recent review). In determining the rank of an individual the power index [2] takes into account not only the number of individuals dominated but also their quality; thus an individual which dominates other powerful individuals is more powerful than one which dominates weaker individuals. To evaluate the power index we first consider the *probability of dominance*, which is the probability that an individual beats another in a tournament on a randomly chosen KPI. We construct an adjacency matrix $\boldsymbol{W}$ between all of the individuals in which W_{ij} is the probability that individual i dominates individual j:

$$\boldsymbol{W}_{ij} = \frac{1}{K}\left(\sum_{k}^{K} I\left(x_i^k < x_j^k\right) + \frac{1}{2}\left(\sum_{k}^{K} I\left(x_i^k = x_j^k\right)\right)\right) \tag{1}$$

where I is the indicator function, returning 1 if its argument is true and 0 otherwise and x_i^k is the score of the ith individual on the kth KPI. Without loss of generality, all KPIs are assumed to be minimised. The power index is computed by following the iterative procedure $\boldsymbol{u}^t = \boldsymbol{W}\boldsymbol{u}^{t-1}$. For $\boldsymbol{u}^1$, ordering the DMAs so that the DMA with the n^{th} largest value of $\boldsymbol{u}^1$ has rank n, results in the *average rank* [3], which ranks DMAs by each KPI independently and then finds the average of these K ranks. This scheme, whilst providing a finer ordering than Pareto sorting in a high-dimensional space, can lead to ties. Continuing to the limit as $t \to \infty$ results in the power index, which can be found as the right eigenvector of $\boldsymbol{W}$ [2].

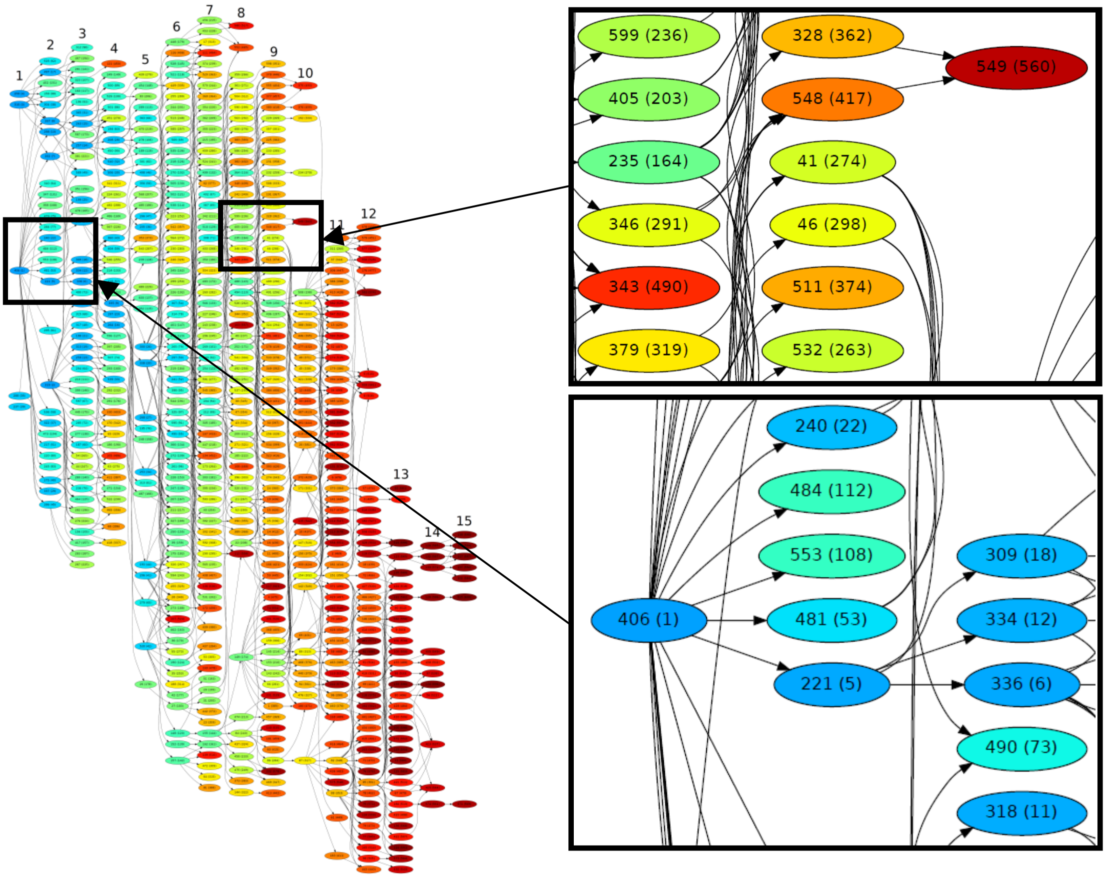

Figure 1. A rank-based visualisation of the DMAs. The population has been sorted into Pareto shells, and each DMA is coloured by its power index. The top panel shows two of the DMAs of interest (548 and 459) and the bottom panel shows the most powerful DMA(406).

In Figure 1, the power index has been used to colour the DMAs. The DMAs have been ranked by the power index such that a low rank indicates high power; dark colour is used to show a powerful DMA and light colour shows a weaker DMA. Colouring in this way more easily allows interesting observations about the DMAs to be made. For example, DMA 105 is in the fourth of fifteen Pareto shells, placing it in the top third of all DMAs, however it has a poor power index. This implies that it is performing very well on one KPI and poorly on the remainder – known as an *outlier*; further to this, an individual may have a better power index than one in a better shell if it is not dominated by the individual with higher Pareto rank. It is also interesting to observe that those DMAs with the highest power index tend to be those which dominate more in the subsequent shell; DMA 406 in shell 1 and DMA 319 in shell 2 for example.

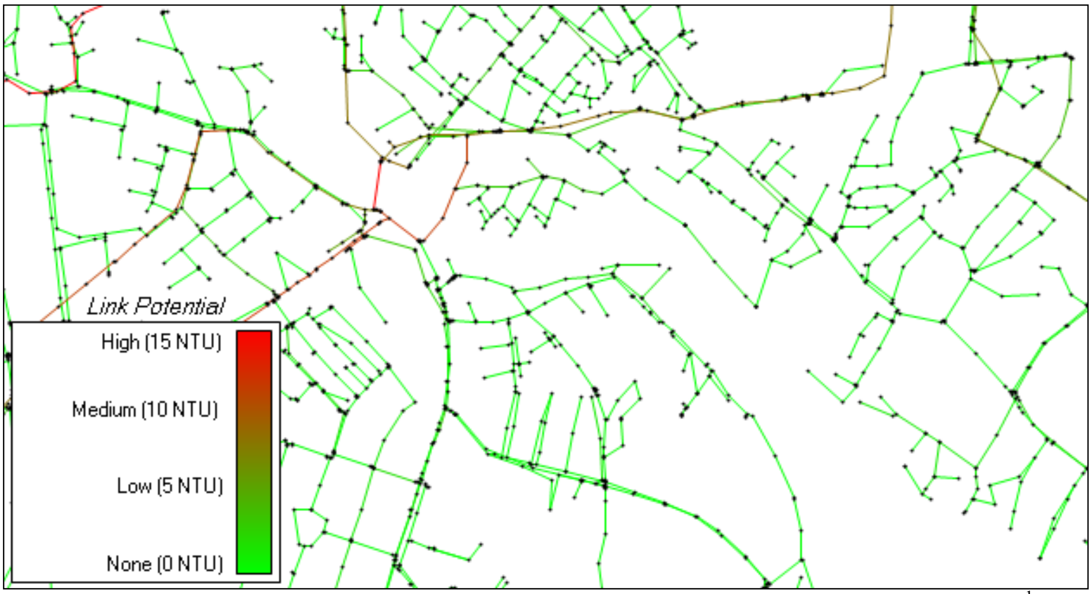

Figure 2. A coloured map visualising discolouration propensity. Red indicates pipes with 15NTUm^{-1} or more.

4. DISCOLOURATION PROPENSITY MODELLING

Prior to the development of the cohesive transport model, a number of approaches have been explored in order to better model discolouration events and material accumulation in potable water distribution networks. These include models developed in countries other than the UK, such as the particles sediment model (PSM) [8] and other methods applied in the Netherlands [9]. However, only a handful of discolouration risk modelling (DRM) tools are accessible by UK water companies at present. Perhaps the most notable of these are the PODDS models, of which there have been a number of iterations, developed by the University of Sheffield [5, 6] and the DRM software developed by Mouchel [10]. More recently a successor to the DRM software, the discolouration propensity model (DPM) [11], was developed in order to provide high level risk assessment to aid asset management and maintenance scheduling.

Similarly to the PODDS model, the DPM system implements the cohesive transport model to analyse discolouration risk using a shear stress approach, whilst also providing the opportunity to introduce non-hydraulic factors, such as the KPIs described above, to refine the DMA level risk models. Using the well known EPANET software [12] to calculate the dynamic hydraulic conditions of each network, the DPM system extracts the shear stress values to assess the relative risks of pipes within a DMA storing potentially discolouring material. Example DPM results from the case study network is shown in Figure 2.

As outlined above, the DPM system uses a cohesive transport model to calculate the volume of accumulated material; which is measured as turbidity (expressed in Nephelometric Turbidity Units, NTU). In addition to calculating the potential material stored in a network, this model can also be used to calculate the volume of material mobilised given specific hydraulic events in the network – such as valve closure and pipe bursts.

However, in theory, the impact of mobilised material from one pipe is proportional to and limited by the material stored within it and so, in this study, only the potential material is considered.

The implementation of the discolouration model is based upon the shear stress equations outlined in [5, 6] which calculates each pipe's maximum shear stress value (known as the daily conditioning shear stress [13]). The daily conditioning shear stress is then used to derive the material (measured as turbidity in NTU) stored in each pipe in a network. The daily conditioning shear stress values are calculated based on the hydraulic gradient values calculated by EPANET. Appropriate NTU values are then calculated given the proper calibration of the constants k and b; set to 2 and 1 respectively based upon calibration data given in [6].

5. COMBINED RANKING

The results of the DPM system can be used to rank both pipes within a DMA and also the DMAs themselves. For example, as shown in Figure 2, the relative risks of each pipe in the network can be used to identify high risk areas of a DMA. This information can then be used to guide the construction of more effective flushing schedules and potentially reduce the number of pipes in a network that are regularly flushed – providing the opportunity to introduce quicker, more targeted flushes between the longer term complete flushes. Furthermore, by scoring each DMA based on their overall potential to store material it is possible to provide another ordered ranking of DMAs, outlined below in Table 1. The DMA's DPM score is calculated by summing the total potentially stored material of all pipes in each DMA, normalised by the total length of pipe in the DMA; in effect reducing the impact of the larger networks with many low risk pipes.

Using DPM, each of the DMAs can be analysed and the overall trend of the network to store potential material can be calculated. Combining these results with the power index described above in §3, the results of the DPM can be used to determine if the cause of the problem is due to the daily conditioning shear stresses, i.e., the normal hydraulic conditions, or perhaps another external cause, such as excessive upstream sediment sources. Furthermore, these results can be used to aid the decision making process, influencing which type of intervention to apply. For example, in a network that is prone to storing high levels of material, in addition to prioritising the network for more frequent flushing, operational changes such as relocating boundary valves and altering the flow of the network could provide more long term and cost effective results. Conversely, networks that are not expected to retain high levels of material could possibly score poorly on the recorded KPIs as a result of some non-hydraulic factor (such as corrosion) again suggesting some additional intervention may be required or more information gathered through more in-depth field analysis of assets expected to be contributing to the problem.

DMA	Original Group Position	Pareto Shell	Power Index Rank	Length Normalised Potential (DPM Score)	NTU Rank (Relative)
548	1 (GOOD)	9	417	3.429×10^5	1
551	1 (GOOD)	9	481	5.276×10^5	2
550	2 (GOOD)	13	528	19.608×10^5	3
549	2 (GOOD)	10	560	100.908×10^5	4
547	2 (GOOD)	11	521	261.094×10^5	5

Table 1. Five DMAs from a DMA region ordered by DPM score from best to worse (descending).

5.1 Discussion

The orderings produced by both Pareto sorting and the power index appear to correspond with that of the original grouping. As shown in Table 1, all of the group 1 DMAs are ranked better than the group 2 DMAs by both the Pareto shell and power index. In this case study, DMA 549 again demonstrates the occurrence of outliers, residing in a higher Pareto shell than its power index would indicate. This implies that it scores very well on a single KPI and poorly on the remainder which makes it difficult for other DMAs to dominate it whilst having a poor overall performance.

In an initial examination of one region with five DMAs, the results from the DPM and power index methods suggest some correlation in scores, summarised in Table 1. The relative ordering by the power index and DPM DMAs match, with the exception of DMA 547. On closer inspection, DMA 547 is reported to contain a lower proportion on unlined iron compared with the other five DMAs in the region. Clearly, while the DMA is expected to produce less discolouring material from corrosion, the hydraulics (represented by the DPM score) indicate that the network is in fact at higher risk of accumulating discolouring material. It is this comparison of results that enables this kind of analysis which would suggest that alterations to the regular operations of the network could potentially reduce this risk at a much lower cost in contrast to traditional methods, such as relining. However, in its current configuration, DMA 547 should be prioritised for more frequent flushing compared to the cleaner DMA 548 which is unlikely to cause visible discolouration events.

6. CONCLUSION

In this paper we examine the power index as a method for ranking DMAs for rehabilitation and maintenance scheduling. Compared with a method currently used by a UK water company, the power index is shown to provide a more granular method of ordering DMAs based on real key performance indicators recorded in 2009. In addition, a second hydraulics driven discolouration risk modelling system was used, the Discolouration Propensity Model (DPM). DPM provides high level strategic risk analysis which, when combined with the power index, enables a more in-depth analysis of the causes of a DMA's performance. By combining both approaches and comparing both sets of results, decision makers can be provided with a better understanding of the risks associated with each DMA, and thus enable a more informed scheduling process and therefore more effective maintenance schedule.

References

[1] N. Srinivas and K. Deb, "Multiobjective Optimization Using Non-dominated Sorting in Genetic Algorithms", *Evolutionary Computation*, vol. 2, no. 3, Fall 1994, pp. 221—248.

[2] D.J. Walker, R.M. Everson and J.E. Fieldsend, "Ordering and Visualisation of Many-objective Populations" in *2010 Congress on Evolutionary Computation*, Barcelona, IEEE, 2010, pp. 3664—3667.

[3] P. J. Bentley and J. P. Wakefield, "Finding Acceptable Solutions in the Pareto-optimal Range Using Multiobjective Genetic Algorithms," in *Soft Computing in Engineering Design and Manufacturing*, P. Chawdhry, R. Roy, and R. Pant, Eds. Springer-Verlag, 1998, pp. 231–240.

[4] S. Husband, J. B. Boxall, and A. J. Saul, "Laboratory Studies Investigating the Processes Leading to Discolouration in Water Distribution Networks," *Water Research*, no. 42, pp. 4309–4318.

[5] J. B. Boxall, A. Saul, and P. Skipworth, "A Novel Approach to modelling sediment movement in distribution mains based on particle characteristics", *Water Soft Sys*, no.1, 2001, pp 263-273.

[6] J. B. Boxall, and A. J. Saul, "Modelling discolouration in potable water distribution systems", *Journal Environmental Engineering* ASCE, vol. 131, no. 5, 2005.

[7] S. M. Williams, "*Factors Affecting the Build-Up of Sediment in Water Mains*", Mayfield Consulting Ltd, Cheshire UK, November 2001.

[8] J. H. G. Vreeburg and J. B. Boxall, "Discolouration in potable water distribution systems: a review", *Water Research*, no. 41, 2007, pp 519–529.

[9] J. C. van Dijk and D. van der Kooij, "Water Quality 21 research programme for water supplies in The Netherlands", *Water Sci. Technol.: Water Supply*, vol. 5-6, no. 4, 2005, pp 181-188.

[10] N. Dewis and M.Randall-Smith, "Discolouration risk modeling", *Proc. of the 8th Int. Conference on Computing and Control for the Water Industry*, vol. 2, 2005, pp 223-228.

[11] K. McClymont, E. C. Keedwell, D. Savic and M. Randall-Smith, "Mitigating Discolouration Risk with Optimised Network Design", *Proc. of the 9th Int. Conf. on Hydroinformatics 2010 (HIC2010)*, China.

[12] Rossman L. A., "*EPANET users manual*", United States Environmental Protection Agency, 2000.

[13] D. Cook, "*Field Investigation of Discolouration Material Accumulation Rates in Live Drinking Water Distribution Systems*", PhD Thesis, University of Sheffield, 2007.