Pressure-Dependent Leak Detection Model and Its Application to a District Water System

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Abstract: Cost-effective reduction of water loss is a compelling but challenging task for water utilities. This paper presents a model-based optimization method for leakage detection of water distribution systems. Leakage hotspots are assumed to exist at the model nodes identified. Leakage is represented as pressure-dependent demand simulated as emitter flows at selected model nodes. The leakage detection method is formulated to optimize the leakage node locations and their associated emitter coefficients such that the differences between the model predicted and the field observed values for pressure and flow are minimized. The optimization problem is solved by using a competent genetic algorithm. The leakage detection method is developed as an add-on feature of the optimization-based model calibration tool. This enables engineers to undertake leakage hotspot optimization as an independent task or combine the task with hydraulic model calibration, subject to suitably varied field data. Two case studies are discussed in this paper including an example from literature and a district water system in the United Kingdom. The results obtained illustrate that the optimization model for predicting leakage hotspots can be effective despite the recognized challenges of model calibration and the physical measurement limitations from the pressure and flow surveys also referred to as field tests. It is found that the method is effective at being applied for hydraulic conditions that occur in the early hours of the morning, often on water networks with excess design capacity and where hydraulic gradients are slack and loggers may sometimes be working close to their limits of accuracy.

DOI: 10.1061/(ASCE)0733-9496(2010)136:1(116)

CE Database subject headings: Water loss; Leakage; Water distribution systems; Hydraulic models; Algorithms; Optimization.

Author keywords: Water loss; Leakage detection; Water distribution system; Hydraulic model; Genetic algorithm; Optimization.

Introduction

Water utilities provide clean water to local communities and charge for the service by metering water consumptions or basing charges on the ratable value of customer's properties. However, not all water produced reaches the customers and generates revenue for water companies. Instead, a significant portion of it is lost, due to leakage from water mains and unauthorized water use. Water loss represents a major fraction of nonrevenue water (NRW). A World Bank publication (Kingdom et al. 2006) reports that the annual NRW volume lost has been estimated at a staggering 50 billion cubic meters from an annual production of 300 billion cubic meters of potable water treated. According to the International Water Association (IWA)'s best practice recommendations (IWA 2000) for water balance studies, more than 65% of NRW arises from unauthorized water consumption, meter inaccuracies and leakage from the water mains source-to-taps infrastructure. On average, more than 15% of water produced is lost in the United Kingdom. The Water Management 2005–06 Report by the House of Lords' Science and Technology Committee (House of Lords Science and Technology Committee 2006) stated that the level of leakage from the distribution network was unacceptably high in parts of the United Kingdom and this was having a negative impact on the public's attitude to sensible water use. The report called on the Office of Water (Ofwat) to sanction increased water company expenditure in the United Kingdom on reducing leakage. Leakage targets, taking into account environmental and social factors, as well as economics, are set as a key part of water utilities measured performances. Severe financial penalties can be incurred if targets are not met. Ofwat's report (Ofwat 2008) on service delivery published in October 2008 included statistics for each U.K. water company's water production and leakage. For United Utilities (UU), the total water delivered in 2007–08 was 1849.4 Ml/d and the total leakage of 462.2 Ml/d was within the set target of 465 Ml/d. More recently, Ontario Sewer and Watermain Construction Association (Zechner 2007) in Canada reported that as much as $1 billion worth of drinking water disappears into the ground every year from leaky municipal water pipes, and that 20–40% of all the water pumped through municipal water systems never reaches consumer taps and in some cases the loss is as high as half of all treated water. The fact that water companies and municipalities are losing such large quantities of water through leaky pipes undermines the conservation messages that the water utilities are championing. The AWWA Water Loss Control Committee [America Water Works Association (AWWA) Water Loss Control Committee 2003] reports that water loss reduction and the associated revenue loss

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Note. This manuscript was submitted on April 30, 2008; approved on May 11, 2009; published online on December 15, 2009. Discussion period open until June 1, 2010; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, Vol. 136, No. 1, January 1, 2010. ©ASCE, ISSN 0733-9496/2010/1-116–128/$25.00.

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recovery stand among the most promising areas of water resources improvements in North America. Reduction of these losses also provides opportunities for water companies to reduce their carbon footprint and improve water infrastructure sustainability.

There are several techniques for detecting where leakage is occurring in a distribution system. These include (1) random or regular sounding surveys; (2) step-testing of subsystems; and (3) acoustic loggers surveys. Regular or random sounding surveys are time consuming and not always effective in focusing on areas with potential leaks. This is because leakage technicians may end up looking for leaks in sections of the network where they are not prevalent. Step-testing needs to be conducted branch by branch and is generally undertaken during the period of minimum night flow (MNF) which often occurs between 1:00 a.m. and 5:00 a.m. One reason for this is to avoid supply interruptions to the majority of customers. Acoustic loggers can be either installed across a network or deployed at certain points as part of planned leakage reduction activities. These options can be expensive in terms of the amount of apparatus required or repeated deployments of more limited amounts of equipment. The effectiveness of acoustic loggers in sensing leaks can also be impaired by any planned pressure reduction in operation and/or the replacement of ferrous mains with plastic ones. Both factors limit the amount of noise generated by leaks and subsequently reduce the acoustic logger's capacity to "hear" the leaks. Although the IWA Water Loss Task Force has developed the concept and method for system wide water balance calculations (Lambert and McKenzie 2002) based on water asset physical data, the statistics of pipe bursts, service connections and underground conditions, the method is not able to pinpoint where leaks are located in a distribution system. However, it has been possible for many years to represent the impact of a known leak in a network model. Hence, a need has arisen to develop a model-based systematic approach for predicting likely leakage hotspots, which will enable leakage engineers to identify leaky mains quickly in turn leading to timely repairs.

Literature Review

Over the last decade, leak detection has been the focus of a significant amount of research. A variety of techniques, including inverse transient analysis (Liggett and Chen 1994), Bayesian identification method (Poulakis et al. 2003), flow statistical analysis (Buchberger and Nadimpalli 2004) and belief-rule-based expert system (Xu et al. 2007), have been applied to quantitatively identify leakage with inverse transient modeling having been the most active research area. Liggett and Chen (1994) first proposed this technique for leakage detection and calibration since when much productive research has been carried out in this area. The technique is based on the deliberate generation of transient waves or impulses at one location and the measurement of the propagated transients with highly sensitive pressure transducers at other locations in the system. The observed transient pressures are used to identify model parameters including leakage and pipe roughness. Brunone (1999) has reported on the laboratory results to confirm the reliability and validity of the inverse transient analysis for a long pipeline. Ferrante and Brunone (2003) have derived the analytical expression for the piezometric head spectrum at the downstream end of a pipe during transients, and the wavelet transform was used to detect local singularities in the pressure time history due to the presence of a leak in a single pipe system. Vítkovský et al. (2000) applied a genetic algorithm (GA) to the inverse transient model of a hypothetic pipeline system to calculate the changes in demand (the leaks) by minimizing the difference between the simulated transient pressures and measured transient pressures. Some other leak detection approaches (Wang et al. 2002; Kapelan et al. 2004; Beck et al. 2005; Covas et al. 2005; Covas et al. 2003; Lee et al. 2005; Taghvaei et al. 2006) have also been reported in literature based on time and frequency analysis. Nixon et al. (2006) have carefully studied the range of validity of the inverse transient analysis method and found that its applicability is limited to the instantaneous small amplitude disturbances within simple reservoir-pipe-valve type configurations or reservoir-pipe-reservoir systems. Holnicki-Szulc et al. (2005) proposed a theoretical formulation of leak detection based on the Virtual Distortion Method that was originally developed for structural damage identification. The formulation is based on steady-state flow and generalized as a quadratic programming problem solved by a gradient-based optimization tool.

The reason for using transient methods, instead of steady state ones, is that transient simulation is less sensitive to the pipes' roughness coefficients than in a steady state simulation. Hence, transient inverse analysis initially appears to be more attractive than steady state inverse analysis for leakage detection. However, to date, there are no reports in the literature about successful application of the inverse transient methods to water mains distribution systems. As these networks are often highly looped and contain many valves, tanks, and pumps, any induced transients will become heavily damped. This will probably prevent the success of transient induction as a general method for leakage location predictions. In addition to the damping, it is difficult to distinguish the transient wave reflections caused by possible leaks from the reflections caused by pipeline fittings and those arising from demand changes. There is also the risk of inducing ingress and contamination into the network from the generated transients.

One alternative approach for achieving cost-effective leakage detection is to leverage the well-established hydraulic modeling technology. Pudar and Ligget (1992) first looked into the inverse steady state analysis approach for detecting leaks in pipe networks. A leak is determined by using the orifice formula with an equivalent orifice area. Two solution methods were formulated to solve for the leaks of both overdetermined and underdetermined cases. The former represents the scenario in which the number of field observed data points is greater than the number of leaks. It can be solved by using an explicit method that minimizes the difference of the observed and calculated nodal hydraulic heads. For the latter scenario, the number of the field observed values is less than the number of leaks. This case is solved by an iterative procedure that minimizes the L_2-norm of the leakage area vector. The results indicated that the main challenge was the unknown or imperfect pipeline roughness used for solving the inverse steady state analysis problem. However, the velocity of flow in the test examples (Pudar and Ligget 1992) was generally greater than 1.5 m/s in most of the pipes. This does not emulate the hydraulic characteristics of real systems, especially during the low-demand conditions from midnight to the early morning. It is well known that the greater the velocity, the greater the head loss caused by pipe roughness, and thus the greater the uncertainty for leakage detection within inverse steady-state analysis.

Hydraulic network modeling techniques have improved over the last two decades. These have included the introduction of flow emitters, which may be adopted to model leakage, as implemented in EPANET2 (Rossman 2000) or the generalized pressure-dependent demand analysis models (Kapelan et al. 2007; Todini 2006; Wu et al. 2006; and many others). In addition to the

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technical improvements to modeling software, the capture of pressure and flow trending data has also been improved as a result of advances in SCADA systems either for routine monitoring of the mains network, or for more detailed field surveys required to support activities such as network model calibration. Additional temporary data loggers can also supplement SCADA data. This means that opportunities have now arisen to make even more improvements to the modeling software including the use of optimization techniques to predict leakage hotspots. As the new optimization methods become more commonplace, it is likely that the water industry will need to review the current custom and practice data trending methods in order to evaluate how much more advantage can be derived from the newly emerging optimization methods.

Sage (2005) has reported previously on a leakage detection method based on the redistribution of leakage demands and some successes were achieved for detecting leakages in a number of district meter areas (DMA). The total leakage demand for a DMA was calculated as the difference between the field metered inflow and the modeled demand, the later being based on a combination of metered and estimated consumption. The leakage across each DMA was then attributed to junctions in direct proportion to the numbers of properties or mains lengths associated with each junction. The leakage demands in the earlier method were not in any way related to emitter functionality or pressure-dependent considerations. However, the local leakages were assumed to comprise of background leakage and burst leakage. The background leakage for each node and pipe was calculated by an empirical formula, based on the internal condition factor (ICF), a function of pipe age. The ICF was normalized as a value between 0 and 1. The older a pipe is, the greater the ICF, thus the greater the background leakage. The difference between the total leakage and background leakage was treated as the total burst leakage. A heuristic search algorithm was used to assign the burst leakage across the network nodes such that the difference between the modeled pressures and the observed pressures was minimized. However, there were a number of limitations with the earlier method (Sage 2005) as follows:

- The method was not able to distinguish between a big leak and clusters of small leaks due to the leakage optimization model and the implementation of the search algorithm.
- Leakage detection modeling was separated from the model calibration process, while ideally, leakage detection should be included as part of model calibration.
- Leakage was not represented as a pressure-dependent demand.
- The method was not part of a well-supported and maintained modeling package, thus the leakage hotspot prediction analysis first required transfer of data from a different modeling application.

In comparison, the GA-based parameter optimization approach (Wu et al. 2002) has been developed as an integrated GA-based optimization calibration tool embedded into a proprietary modeling package (Haestad Methods, Inc. 2002). It allows modelers to optimize the nodal demand by multiplying a demand multiplier with the total original demand. This provides a basic function for detecting leakage as node demand. The demand calibration approach has been applied to two systems (Wu and Sage 2006, 2007), including (1) a simple test case with simulation-generated field data and (2) a complex district water system with real field data. Promising results have been obtained for both examples. The GA-based model calibration was able to identify the deliberately allocated leaks in the simple test system and provided good indications of where the leaks were for the second example of the real water system. The study concluded that the GA-based model calibration tool showed good potential for the development of an effective leakage detection method based on the network hydraulic model.

In this paper, leakage is represented as pressure-dependent emitter flow at a node. However, the method developed is a departure from background and burst estimation analysis as originally introduced by Lambert (1994) or the hydraulic modeling of leakages distributed across a system according to the numbers of local connections (or length of mains) as adopted in previous emitter based pressure-dependent leakage studies (Burrows 2003). Rather, the leakage prediction model has been generalized to optimize leakage emitter locations and corresponding leakage flows such that the difference between the observed and the simulated values (flows and pressures) is minimized. The problem is solved in the same module as an existing model calibration algorithm. This has made it possible to implement the leakage detection method as an extended feature of the existing optimization-based model calibration tool. Hence, it has been integrated within a modeling package widely adopted by the water industry. As mentioned earlier, two examples are presented in the paper to demonstrate the new leakage prediction method. The first example is a simple water system from literature while the second example is a real district water system in the United Kingdom. Historical leakage records of the real water system are compared with the leakage hotspots predicted by the optimization model to illustrate the effectiveness and robustness of the innovative method for leak detection.

Formulation

It is a well-known fact that leakage is pressure dependent, the greater the pressure, the greater the leakage. Leakage is one type of pressure-dependent demand that can be modeled as an emitter flow given as

$$Q_{i,l}(t) = K_i[P_i(t)]^{\alpha} \tag{1}$$

where $Q_{i,l}(t)$=leakage aggregated at node i at time t; $P_i(t)$=nodal pressure at node i at time t; K_i=emitter coefficient at node i; and α=exponent that can be flexibly set to any desired value. Although the exponent may vary from 0.5 to 2.5 due to different pipeline materials, the exponent is found to be close to 0.5 for detectable leaks and bursts on metal pipes (Lambert 2002). Eq. (1) indicates that a positive emitter coefficient will result in leakage demand at a node. Therefore, it is the emitter coefficient K_i that is to be optimized as the indication of possible leakage. When its optimal value is greater than zero at a node, that node is referred to as a leakage node or leakage hotspot indicating that leaks may exist on the pipes connected with the node.

In order to identify leakage nodes or leakage hotspots, an optimization model needs to be formulated to optimize the node emitter coefficients. However, in a typical all-mains network model of a real water distribution system this could require the optimization of hundreds or even thousands of emitter coefficients to include all possible demand nodes. There is not an optimization algorithm that can efficiently and effectively solve for a problem with thousands of decision variables. But it is the nature of leakage that the sizable and restorable leaks can often be associated with no more than a few dozens of leakage hotspots. The task of leakage management is to find the hotspots and stop leaks as quickly as possible should it be economical to do so.

In general, a water distribution network can be divided into different subsystems, each of which may represent similar pipeline conditions and water consumption characteristics. The nodes within a subsystem can be aggregated into one demand group. Thus, all the nodes in a large water distribution network can be aggregated into a number of demand groups. Each demand group is specified to identify a given maximum number of leakage nodes at which the emitter coefficients fall within prescribed limits. The actual number of leakage nodes is determined by the optimized node indices where the emitter coefficients are found to be greater-than-zero. The prediction of identified leakage nodes should be repeatable for subsequent analyses of the same scenario. Likewise, for cases where pipe hydraulic roughness has been changed, the new sets of predicted leakage nodes, although they may vary from the previous predictions, should remain the same for any subsequent analyses using the modified pipe roughness conditions. In addition, any nodes with negative pressures should not be selected as leakage nodes because the flow emitters at such nodes would indicate inflows into the system, instead of leakage. Thus, the leakage detection model is generalized as

$$\text{Search for}: \quad \vec{X} = (LN_i^n, K_i^n); \quad LN_i^n \in J^n; n = 1, \ldots, NGroup$$
$$i = 1, \ldots, NLeak^n \tag{2}$$

$$\text{Minimize}: \quad F(\vec{X}) \tag{3}$$

$$\text{Subject to}: \quad 0 \leq K_i^n \leq \overline{K^n} \tag{4}$$

$$P_i^n > 0 \tag{5}$$

$$\sum_{n=1}^{NGroup} NL_{dup}^n = 0 \tag{6}$$

where LN_i^n=leakage node index for leakage node i within demand group n; K_i^n=emitter coefficient for leakage node i in group n; J^n=set of nodes within node group n; $NGroup$ is the number of node groups; $NLeak^n$=number of the specified leakage nodes to be identified for node group n; $\overline{K^n}$=maximum emitter coefficient for group n; P_i^n=pressure head at the detected leakage node i within group n; NL_{dup}^n=number of the duplicated nodes that are identified as leakage emitters in one solution for group n; and $F(\vec{X})$=objective function given as follows.

Objectives

The goodness-of-fit or fitness of a leakage detection solution is evaluated by using the same objective functions as the optimization-based model calibration (Wu et al. 2002). The objective function is defined as the discrepancy between the model simulated and the field measured junctions' hydraulic gradient lines, (HGLs) and pipe flows. In order to equivalently consider both HGL and flow contribution to the dimensionless fitness, the goodness-of-fit score is calculated by using two user-specified conversion factors, namely the hydraulic head per fitness point and the pipe flow per fitness point, which convert the head difference and flow difference into a dimensionless fitness value. Three fitness functions are then defined as

1. Objective Type I: minimize the sum of difference squares

$$F(\vec{X}) = \sum_{t=1}^{T} \frac{\sum_{nh=1}^{NH} w_{nh}\left[\frac{Hs_{nh}(t) - Ho_{nh}(t)}{Hpnt}\right]^2 + \sum_{nf=1}^{NF} w_{nf}\left[\frac{Qs_{nf}(t) - Qo_{nf}(t)}{Qpnt}\right]^2}{NH + NQ} \tag{7}$$

2. Objective Type II: minimize the sum of absolute differences

$$F(\vec{X}) = \sum_{t=1}^{T} \frac{\sum_{nh=1}^{NH} w_{nh}\left|\frac{Hs_{nh}(t) - Ho_{nh}(t)}{Hpnt}\right| + \sum_{nf=1}^{NF} w_{nf}\left|\frac{Qs_{nf}(t) - Qo_{nf}(t)}{Qpnt}\right|}{NH + NQ} \tag{8}$$

3. Objective Type III: minimize the maximum absolute difference

$$F(\vec{X}) = \arg\max_{t,nh,nf}\left\{\left|\frac{Hs_{nh}(t) - Ho_{nh}(t)}{Hpnt}\right|, \left|\frac{Qs_{nf}(t) - Qo_{nf}(t)}{Qpnt}\right|\right\} \tag{9}$$

where $Ho_{nh}(t)$=designates the observed hydraulic grade of the nhth junction at time step t; $Hs_{nh}(t)$=model simulated hydraulic grade of the nhth junction at time step t; $Qo_{nf}(t)$=observed flow of the nfth link at time step t; $Qs_{nf}(t)$=simulated flow of the nfth link at time step t; $Hpnt$ notes the hydraulic head per fitness point; while $Qpnt$=flow per fitness point, both are the user-specified coefficients to convert pressure and flow differences into dimensionless values, and also can be applied as weighting factors for pressure and flow calibration; NH=number of observed hydraulic grades; and NQ=number of observed pipe discharges; W_{nh} and W_{nf}=normalized weighting factors for observed hydraulic grades and flows, respectively. They are given as

$$W_{nh} = w\left(Hloss_{nh}/\sum Hloss_{nh}\right) \tag{10}$$

$$W_{nf} = w\left(Qo_{nf}/\sum Qo_{nf}\right) \tag{11}$$

where $w(\,)$=function which can be linear, square, square root, log or constant; and $Hloss_{nh}$=head loss at observation data point nh. An optimized calibration can be conducted by selecting one of three objectives above and the weighting factors between junction hydraulic heads and pipe flows.

Solution Methods

The optimization model formulated as Eqs. (2)–(11) is an implicit nonlinear search problem. It is solved by using the competent genetic algorithm (Wu and Simpson 2001). The method is implemented and incorporated into a powerful parameter optimization tool (Bentley Systems, Incorporated 2007) that searches for the leakage locations and the size of each possible leakage as part of model calibration process. Although leakage detection optimization has employed the same objective functions as model calibration and solved by using the genetic algorithm, the extra constraints given by Eqs. (5) and (6) must be carefully handled.

Constraint Handling

The constraints given by Eqs. (5) and (6) are required for the GA to effectively search for good solutions of the leakage detection problem. During the optimization process, nodal pressure may become negative when too much demand is assigned to a node. It

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is necessary to ensure that a leakage detection solution that includes nodes with negative pressures is not selected for producing the next generation of solutions during GA optimization. On the other hand, it is highly desirable not to have the duplicated nodes to be identified as leakage nodes in one solution. This is guarantied by satisfying the constraint of Eq. (6), which states that the identified leakage nodes are unique for one solution.

The leakage detection constraints are implicit nonlinear constraints that are handled by using the approach of penalty function given as

$$F_{leak}(\vec{X}) = F(\vec{X}) + f_{\text{penalty}}\left[\left|\sum_{n=1}^{NGroup}\sum_{i=1}^{NLeak^n}\min(0,P_i^n)\right| + \sum_{n=1}^{NGroup} NL_{dup}^n\right] \quad (12)$$

where f_{penalty} = penalty factor prescribed as one of the optimization option parameters. For leakage detection solutions that meet both constraints, the fitness values are the same as the model calibration objectives given as Eqs. (7)–(9), otherwise, an extra penalty term is calculated and added to the solution fitness by Eq. (12). It is the fitness penalty that deteriorates the solution optimality and thus reduces the likelihood for an infeasible solution to be selected as a parent individual for creating the next generation of solutions.

Solution Representation

A possible leakage solution is represented as a number of leakage nodes with positive emitter coefficients. Two variables are used for one leakage node, namely a node identifier and an emitter coefficient. To search for a total number of *NLeak* nodes, two *NLeak* variables are required for being coded as one GA solution individual. A binary code is used for encoding the GA solution while the node identifier is designated as a node index and the emitter coefficient is encoded with a value between zero and the prescribed maximum value based on the specified increment. The solution representation is flexible and effective for applying the method to a large water system. By using the solution representation scheme, the maximum number of leakage nodes is specified by the modeler and does not have to be the same as the number of nodes. The optimized number of leakage nodes, where the calculated emitter coefficients are greater than zero, should be less than the specified maximum number of leakage nodes to be detected, otherwise, the maximum number of leakage nodes should be increased and the model should be rerun for leak detection.

Integrated Implementation

The leakage detection method is implemented as the extension of the model calibration framework. It consists of a user interface, evaluation module, competent GA optimizer, hydraulic simulation model, and a database system. A user interface provides users with the ability to manage the field observed data and set up optimization runs with different data including the baseline demands, corresponding boundary conditions, and optimization criteria. All the input data and the results are consistently presented in a modeling database along with the simulation model. This permits engineers to revisit the optimization runs at any time in future, and so help them to better manage a modeling project and facilitate the maintenance of model accuracy in the longer term.

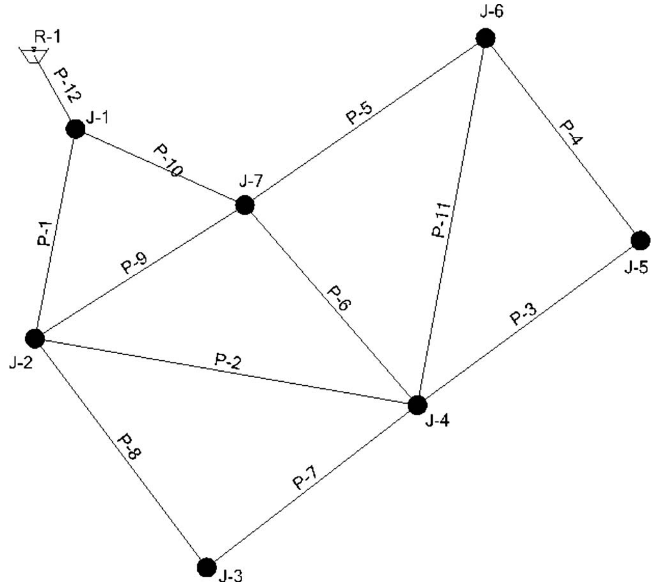

Fig. 1. Layout of Example 1 water system

A leakage detection run is initiated by loading a hydraulic model and field observed data. After selecting the corresponding optimization criteria, it proceeds with presenting the data to the GA optimizer to automatically search for the optimal and near optimal solutions. With the GA optimizer, possible solutions are automatically generated and progressively improved during the optimization process. Each trial solution, along with the selected data sets, demand loading and boundary conditions, is submitted to the hydraulic network analyzer for predicting the hydraulic responses. The model simulated results are used to calculate the fitness and penalty term given by Eqs. (7)–(12) for each solution. The solution with better fitness namely less distance value than another solution is more likely to be selected to be the parent solution to reproduce a new solution for next generation. The GA-optimizer evolves the leakage detection solutions (emitter node locations and the corresponding emitter coefficients) generation after generation. An optimization run is terminated when the maximum number of trials or the minimum tolerance of the acceptable fitness value is reached.

Applications

Two examples are illustrated for applying the solution method of water distribution leakage detection. The first example is a trivial system while the second example is a real district water system in United Kingdom.

Example 1: Simple System

This example, as shown in Fig. 1, is based on the system used by Pudar and Liggett (1992) for testing the leak detection approach based on steady state modeling. The original system is significantly modified for better emulating the condition of a real water system. The node and pipe data of the modified system is given as in Tables 1 and 2. The leakages are assumed to be lumped and modeled as pressure-dependent emitter flows at node J-2, J-4, and J-7 with the emitter coefficient of 0.8 $\mathrm{L/s/m^{0.5}}$ and the emitter

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Table 1. Nodal Data for Example 1

Node ID	Elevation (m)	Demand (L/s)
J-1	0.0	0.00
J-2	0.0	0.00
J-4	0.0	0.00
J-5	0.0	10.00
J-6	0.0	10.00
J-7	0.0	0.00
J-3	0.0	20.00
R-1	40.0	0.00

exponent of 0.5, which results in leakage demand of about 5.5 lps according to Eq. (1). The leakage detection runs are undertaken for the following two scenarios:

1. Perfect pipe roughness. In this case, a hydraulic model run is performed for the assumed leakage at node J-2, J-4 and J-7 with Hazen-William C value of 130 for all pipes. The simulated pressures at node J-3, J-5 and J-6 along with the flow of pipe P-12 as listed in Table 3 are taken as field observed data to detect the three known leaks at node J-2, J-4, and J-7. The leakage detection runs are performed using the same *C* value of 130 for all pipes to emulate the case of perfect pipe roughness. Seven optimization runs are undertaken with the different artificial field data combinations of pressures and the system inflow, including one run using the pressures at three nodes (J-3, J-5, and J-6), three runs using the pressures at two of three nodes and three runs using one pressure at each of three nodes, respectively.
2. Imperfect pipe roughness. This is similar to scenario 1, except that optimization runs are carried out with pipe roughness errors of 10%, namely, *C* value of 117 for all pipes.

The optimized emitter coefficients for each case of two testing scenarios are given in Tables 4 and 5 while Figs. 2 and 3 illustrate the average of the optimized emitter coefficients using the same number of observed pressures with and without pipe roughness error.

Without introducing any errors to the pipe roughness coefficients, as shown in Table 4 and Fig. 2, three nodes J-2, J-4, and J-7 are identified as leakage nodes by the optimization run using three observed pressures at node J-3, J-5, and J-6 although the optimized emitter coefficient at each node is different from the known value ($0.8\ \mathrm{L/s/m^{0.5}}$). When using two observed pressures, the number of the unknown is greater than the number of the known and the problem becomes underdetermined. However, the results obtained from most of the optimized leakage detection runs indicate that fairly high leakages occur at the node J-2, J-4, and J-7, and occasionally at J-3, J-5, and J-6. With one observed pressure, the results are less definitive than two and three observed pressures. However, nodes J-2 and J-7 are still consistently identified as leakage node.

Table 2. Pipe Data for Example 1

Pipe ID	Diameters (mm)	Length (m)	H-W C
P-1	215	1,000	130
P-2	215	1,000	130
P-3	215	1,000	130
P-4	215	1,000	130
P-5	215	1,000	130
P-6	215	1,000	130
P-7	215	1,000	130
P-8	215	1,000	130
P-9	215	1,000	130
P-10	215	1,000	130
P-11	215	1,000	130
P-12	600	100	130

Table 3. Observed Field Data for Example 1

Elements	Attributes	Values
P-12	Discharge (L/s)	54.58
J-6	Hydraulic grade (m)	36.50
J-5	Hydraulic grade (m)	36.40
J-3	Hydraulic grade (m)	36.32

To test the performance of the solution method with unknown pipe roughness, Hazen-Williams *C* values for all the pipes are reduced by 10%, namely *C* value of 117 for all pipes. The optimization runs are conducted for the different combinations of the observed pressures and system inflow. As illustrated as Table 5 and Fig. 3, a similar performance is observed to for all the testing cases. Nodes J-4, J-1, and J-6 are identified as leakage nodes. It indicates that if pipes are hydraulically rougher than they should be, the increased hydraulic resistance forces the optimization to favor the solutions in which leakage is expelled toward the upstream of the network such as node J-1. This is because the greater-than-expected leakage near the source reduces the flow within the system, which consequently reduces the head losses to match the observed pressures.

The test results for the trivial system appear to indicate that exact leakage emitter coefficients cannot be determined, but the most likely leakage nodes are definitively identified by the solution method. Under the scenario of perfectly known pipe roughness, three nodes J-2, J-4, and J-7 are clearly found to be the nodes with the significantly large emitter coefficients. For all the analysis cases using imperfect pipe roughness, nodes J-1, J-4, and J-6 are consistently detected as leakage nodes with the relatively large emitter coefficients. Considering the nodes J-2 and J-1 are the adjacent nodes, so are the nodes J-6 and J-7, it can be seen that, for a real system, determining one node as a leakage node would indicate to engineers that the connected pipes should be investigated for leaks.

Example 2: District Water System

This example as shown in Fig. 4 is a real district water system in the United Kingdom, which had historically high leakage records (Sage 2005). The system serves an area of more than 15 km^2 and about 3,000 properties. The hydraulic model is comprised of 1,122 pipes, 841 nodes, and one variable head reservoir. The hydraulic model was constructed and maintained by the UU' modeling team. It is one of the models that UU has provided for testing out the optimization-based approach for leakage hotspot detection.

Key Challenges

Traditionally, hydraulic model calibration includes the allocation of leakage across the modeled nodes in proportion to the base demand or the number of properties served by a node. Factors are then applied to differentiate between leakage at MNF and that

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Table 4. Results of Leakage Detection Optimization for Example 1 Using Perfect Pipe Roughness

Observed pressures	Solution No.	Optimized leakage emitter coefficients ($L/s/m^{0.5}$)						
		J-3	J-4	J-2	J-7	J-1	J-5	J-6
J-3 J-5 J-6	1	0.0	0.7	1.0	0.6	0.0	0.0	0.1
	2	0.0	0.5	1.0	0.7	0.0	0.0	0.2
	3	0.0	0.5	1.0	0.7	0.0	0.0	0.2
J-5 J-6	1	0.0	0.0	1.0	0.9	0.0	0.2	0.3
	2	0.0	0.0	1.0	0.9	0.0	0.3	0.2
	3	0.9	0.0	0.3	1.0	0.0	0.2	0.0
J-3 J-6	1	0.0	0.8	0.6	1.0	0.0	0.0	0.0
	2	0.0	0.8	1.0	0.6	0.0	0.0	0.0
	3	0.0	0.9	0.5	1.0	0.0	0.0	0.0
J-3 J-5	1	0.0	0.8	0.6	1.0	0.0	0.0	0.0
	2	0.0	0.0	1.0	0.8	0.0	0.0	0.6
	3	0.0	1.0	1.0	0.4	0.0	0.0	0.0
J-3	1	0.1	0.3	0.8	1.0	0.0	0.2	0.0
	2	0.1	0.3	0.8	1.0	0.0	0.2	0.0
	3	0.1	0.3	0.8	1.0	0.0	0.2	0.0
J-5	1	0	0.4	0.8	1.0	0.0	0.2	0.0
	2	0.8	0.0	1.0	0.4	0.0	0.2	0.0
	3	0.8	0.0	0.8	0.6	0.0	0.2	0.0
J-6	1	0.0	0.0	1.0	0.8	0.0	0.6	0.0
	2	0.0	0.0	1.0	0.8	0.0	0.6	0.0
	3	0.0	0.0	1.0	0.8	0.0	0.6	0.0

which occurs in the working day and evening. This "custom and practice" method of handling the leakage demand generally ignores any large leakage hotspots in a distribution network and represents a significant challenge for calibrating a hydraulic model. This is because for any model calibration exercise for which large leaks have not been correctly located, pipeline roughness values are often over or underadjusted to compensate for head loss components caused by large leaks. For example, the pipe roughness upstream of a large leak can be overroughened while the pipes downstream of a leak can be made too smooth. As part of the water utility's standard model maintenance procedures, the model for this example was calibrated prior to the existence of

Table 5. Results of Leakage Detection Optimization for Example 1 Using Pipe Roughness Coefficients of 10% Errors

Observed pressures	Solution No.	Optimized leakage emitter coefficients ($L/s/m^{0.5}$)						
		J-3	J-4	J-2	J-7	J-1	J-5	J-6
J-3, J-5, J-6	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3
J-5 J-6	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3
J-3, J-6	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3
J-3, J-5	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3
J-3	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3
J-5	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3
J-6	1	0.0	0.8	0.1	0.0	1.2	0.0	0.3
	2	0.0	1.0	0.0	0.0	1.2	0.0	0.2
	3	0.1	0.8	0.0	0.0	1.2	0.0	0.3

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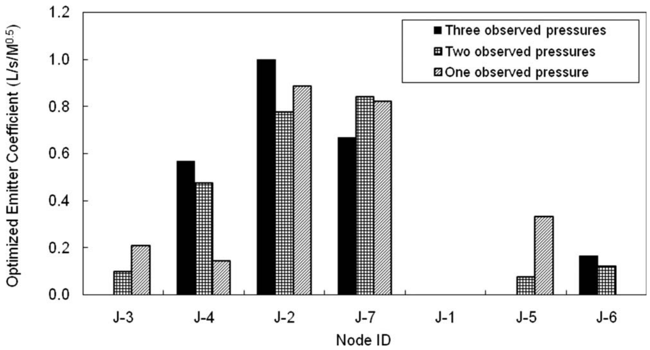

Fig. 2. Averages of optimized emitter coefficients at nodes using perfect roughness coefficient

any knowledge about leakage hotspot Leak A as shown on Fig. 5, and as also illustrated on Fig. 5, many of the pipes downstream of the leak were calibrated with unexpectedly low roughness values. This seems to be a general problem that is difficult to avoid when using custom-and-practice manual methods for model calibration in which leakage demands have been allocated according to such factors as property density or local mains lengths associated with each node. The imperative task is to correctly apply the optimization method to identify and represent the leaks in the distribution system. The results would assist engineers for not only quickly locating the leaky pipes but also achieving effective model calibration.

Optimization Results

The field tests were carried out in May 2003 by UU with a higher density of pressure loggers than usual as part of the project to test out the earlier leakage prediction method (typically UU deploys one pressure logger per 200 houses). The observed data contains the time series for flows into the system and the pressures at 28 locations as shown in Fig. 4. The data sets of flows and pressures were collected and prepared every 30 min. A total of 48 field data sets over 24 h from midnight (noted as hour 0) to midnight have been imported into the optimization modeling tool. Each data set represents a complete snapshot of system conditions including the observed reservoir level as the boundary condition, the observed inflow into the DMA and the 28 pressures used as calibration targets for evaluating the trial solutions. For example, the field data set for 6:30 a.m. contained the observed reservoir water level, DMA inflow and 28 pressures collected at that time. Mul-

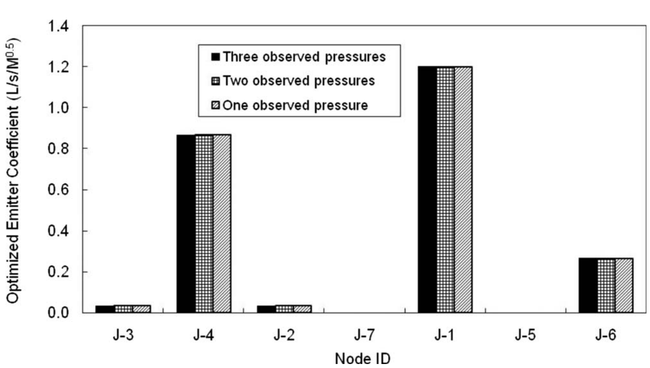

Fig. 3. Averages of optimized emitter coefficients at nodes using the roughness coefficient of 10% errors

Fig. 4. Layout of the district water system with 28 pressure logger locations

tiple snapshots of data sets can be selected for leakage detection, but each data set will require one hydraulic simulation to produce the simulated responses for evaluating the fitness objective function. The more snapshots activated for one optimization run, the longer it takes to complete the analysis.

To apply the proposed method to the district water system, all the nodes were aggregated as one demand group and leakage detection optimizations were conducted for the field data at times of low demand, that is, from midnight to 4:00 a.m. This was because, during this period, the pressure was higher than that in the day and so was the pressure-dependent leakage but the other demands (daytime demands) were lower. Multiple optimization runs were conducted to test the robustness of the method with two sets of pipeline roughness values including (1) the default roughness assigned according to the pipe installation year and pipe material and (2) the roughness values previously obtained for the calibration case when leakage was allocated in proportion to the properties served by each node. Both sets of roughness values were provided by UU. The default pipe roughness values, based on Colebrook White, were generally in the range from 0.5 to 1.0 mm while those for the calibrated model, shown in Fig. 5, tend to have values between 0.2 and 0.5 mm, especially toward the downstream parts of the model.

While all three objective functions given in Eqs. (7)–(9) are suitable for leakage detection optimization, the objective function

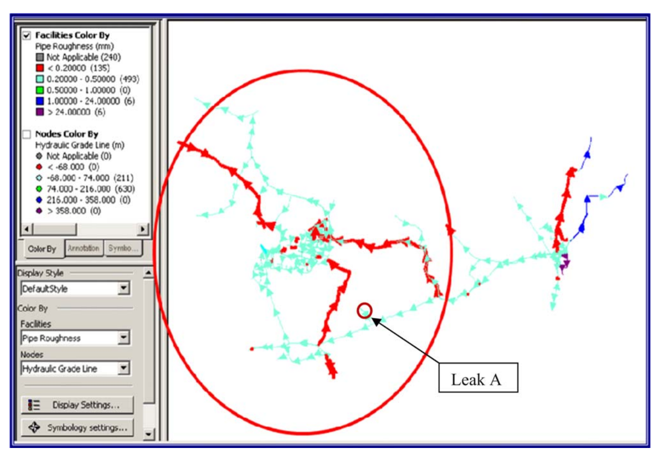

Fig. 5. Previously calibrated model prior to knowing large leaks such as Leak A (J-840) results in low roughness values for most of the downstream pipelines

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Table 6. Results of Leakage Detection Optimization for Example 2 with Different Roughness Values

Best-fit solutions with calibrated roughness				Best-fit solutions with default roughness			
Solution 1		Solution 2		Solution 3		Solution 4	
Detected node	Emitter coefficient ($L/s/m^{0.5}$)	Detected node	Emitter coefficient ($L/s/m^{0.5}$)	Detected node	Emitter coefficient ($L/s/m^{0.5}$)	Detected node	Emitter coefficient ($L/s/m^{0.5}$)
J-554	1.00	J-554	1.00	J-402	1.00	J-402	1.00
J-402	0.90	J-402	0.95	J-554	0.65	J-554	0.65
J-840	0.40	J-840	0.40	J-840	0.40	J-793	0.40
J-473	0.20	J-578	0.40	J-474	0.25	J-474	0.20
J-527	0.20	J-530	0.20	J-34	0.15	J-781	0.15
J-474	0.15	J-473	0.20	J-14	0.10	J-290	0.15
J-717	0.15	J-474	0.15	J-409	0.10	J-409	0.10
J-419	0.10	J-717	0.15	J-275	0.05	J-14	0.10
J-510	0.10	J-510	0.10	J-790	0.05	J-840	0.05
J-408	0.10	J-408	0.10	N/A	N/A	J-269	0.05
J-774	0.05	J-14	0.05	N/A	N/A	N/A	N/A
J-14	0.05	J-774	0.05	N/A	N/A	N/A	N/A

Note: N/A=not applicable.

used in this example is the goodness-of-fit based on the sum of difference square given as Eq. (7). All the optimization runs are executed with the maximum number of 25 leakage nodes and the maximum emitter coefficient set to 1.0 $L/s/m^{0.5}$. In general, it is expected that the actual number of the optimized leakage nodes (with greater-than-zero emitter coefficient) will be less than the specified maximum number of leakage nodes otherwise the optimization model will need to be rerun with a greater number of maximum leakage nodes. The fast messy GA-related parameters used for the optimization include population size of 100, maximum era of 6, era generation number of 150, mutation probability of 0.01, splice probability of 0.8, cut probability of 0.017, and penalty factor of 10. Ten best-fit solutions are saved at the end of an optimization run.

Table 6 presents the best-fit solutions from the optimization runs with different pipeline roughness values. Each solution consists of the identified nodes of positive emitter coefficients with the actual amount of leakage given by Eq. (1). The solutions of the detected leakage nodes are fairly similar in terms of leakage node location and emitter coefficient but there appears to be a slight tendency for more leakage hotspots to be predicted closer to the source node when optimizing with the calibrated set of pipe roughness. After careful investigation of UU's work management system, a list of 22 leak records have been retrieved from archives since the original field data test in May 2003. Table 7 presents the historically repaired leaks. The comparison shows that each of the leaks is associated with the node that has been detected as a leakage hotspot by the optimization-based method.

Four best-fit solutions listed in Table 6 are illustrated in the maps as shown in Figs. 6–9. Each solution represents a set of nodes detected as leakage hotspots and compared with the actual leaks. For instance, Fig. 6 illustrates the comparison of the detected nodes of Solution 1 compared with the historical leaks. It shows that five detected nodes including J-14, J-840, J-717, J-510, and J-402 are closely associated with the actual leaks. Similar comparisons of Solution 2, 3, and 4 are presented in Figs. 7–9, which show that the detected nodes of the optimized leakage solutions are well correlated with the historical leaks reported and repaired. A challenging test was to correctly predict the leakage hotspot named Leak A (at node J-840) as indicated in Fig. 5. It had not always predicted by analysis runs from the previous method (Sage 2005) and took many man-hours to find in the field as the previous method was still at its testing stage when Leak A was actually located and repaired. As shown in Figs. 6–9, junction J-840 has been consistently detected by the new method as the leakage node near Leak A. It should be noted that the new method predicted Leak A even when the originally calibrated pipe

Table 7. Comparison of Historical Leak Records with the Detected Nodes for the District Water System

Historical leaks repaired and reported	Leaky pipes	Nodes connected to leaky pipes and detected by optimization method
A	P-50	J-840
B	P-267	J-510
C	P-606	J-510
D	P-606	J-510
E	P-267	J-510
F	P-345	J-578
G	P-220	J-717
H	P-181	J-717
I	P-327	J-290
J	P-119	J-14
K	P-323	J-275
L	P-119	J-14
M	P-267	J-510
N	P-263	J-793
O	P-327	J-290
P	P-433	J-402
Q	P-119	J-14
R	P-249	J-717
S	P-233	J-717
T	P-420	J-578
U	P-304	J-269
V	P-324	J-290

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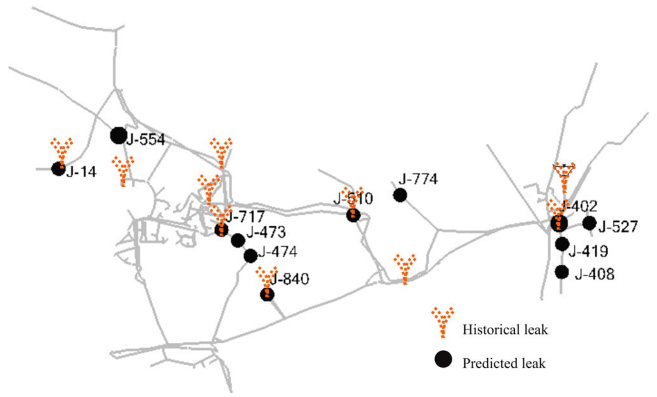

Fig. 6. Comparison of historical leaks with Solution 1 the optimized leakage hotspots with calibrated roughness values

Fig. 8. Comparison of historical leaks with Solution 3 the optimized leakage hotspots with default roughness values

roughness data sets were used, that is, the roughness set adversely influenced by the lack of knowledge about Leak A. It had not been possible to predict Leak A using this same pipe calibration data with the old method but only when recourse was made to the original data set.

Subsequent investigation of the leakage hotspots predicted by the new method for both the default pipe roughness and calibrated pipe roughness indicates a useful correlation with the leakage and burst repair work carried out in the field since the original field test in May 2003. The pressure-dependent leakage detection method appears to be more effective at detecting leakage hotspots than the previously reported method. In addition, the new pressure-dependent method is possibly going to predict leaks that have been hard to find using the traditional field survey methods. Predicting leaks prior to going to the field can be very useful for leakage engineers, as they can then concentrate their field investigations in the identified area and quickly locate the exact leakage hotspots. Fig. 10 shows the field recorded inflows from 2003 to 2005. It indicates that an amount of 10 lps was saved after fixing the leak at J-840, equivalent to more than $6{,}000\ \mathrm{m}^3/\mathrm{week}$. It is also apparent that a relatively small number of leaks reduce MNF by a significant amount as soon as they are repaired. This is not atypical of leakage management in which the repair of one leak often leads to a significant fraction of the saved water then be lost from other nearby leaks. However, it does seem that leak "*L*" repaired in June 2004 was large enough to reduce MNF although not as much as leak "*A*" did the year before.

The other trend in MNF that is of note is the steady reduction that occurred in August 2004. A search of the work management data did not reveal any obvious explanation for this and nor did enquiries about possible changes in the night time consumption patterns of any commercial and/or industrial users in the study area. However, an analysis of the prevailing weather conditions was revealing. July 2004 was a hot month in the United Kingdom as was the first part of August but the hot weather broke down after that with heavy rain being frequent toward the end of August. It did appear that there was a correlation between the hot daytime temperatures and the MNF with a 7°C drop in average temperatures to 18°C being associated with a 4 lps drop in MNF to 5 lps. This behavior has been noted before in the United Kingdom and may be more pronounced than in other parts of the World. This is because many U.K. water distributions are only partially metered with large numbers of customers still being charged according to the ratable values of their properties.

The new optimization modeling tool includes functionality for the hydraulic model to be updated with the identified leakage nodes and emitter coefficients. An extended period simulation (EPS) analysis is completed with the updated hydraulic model and the inflow comparison is illustrated as in Fig. 11. The model simulated flow with the detected leakage emitters matches much better than the original modeled flow over 24 h. A typical comparison of the observed and simulated hydraulic grades is also given in Fig. 12 for hour 0. It illustrates that the differences at most of the observed junctions are less than 1% and the maximum

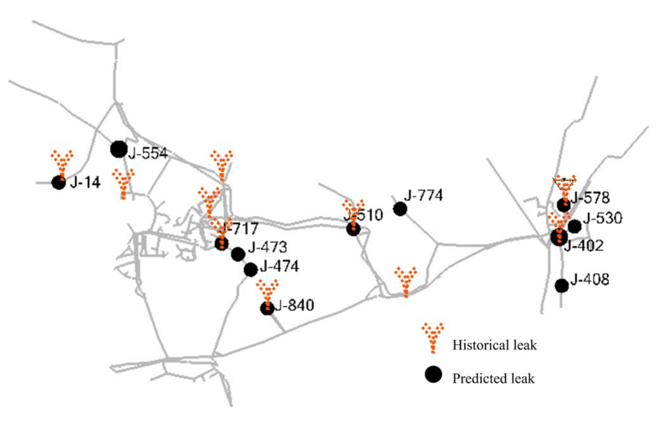

Fig. 7. Comparison of historical leaks with Solution 2 the optimized leakage hotspots with calibrated roughness values

Fig. 9. Comparison of historical leaks with Solution 4 the optimized leakage hotspots with default roughness values

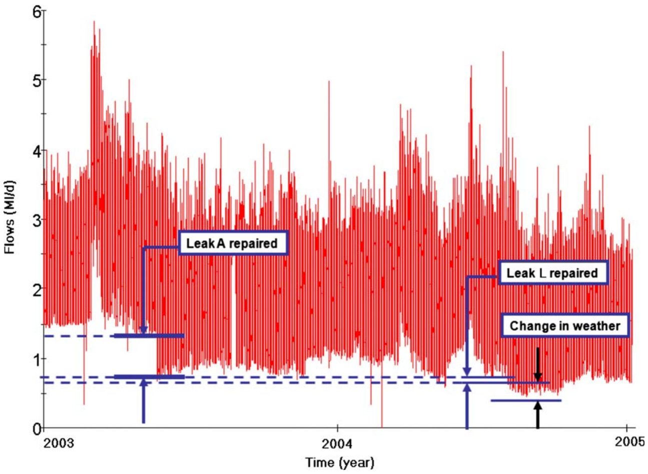

Fig. 10. Field recorded flow comparison before and after repairing the detected leakage Leak A

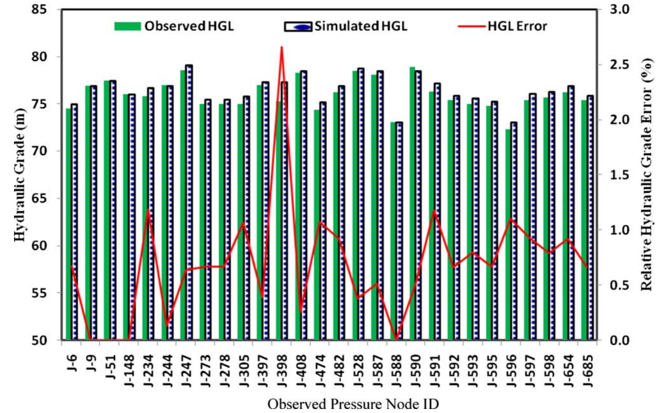

Fig. 12. Comparison of the observed and simulated HGL for the optimized leakage detection solution at hour 0

relative difference is less than 3% at one node. Although this does not represent a fully calibrated model, it serves as a very good baseline for further calibration of the EPS model. This implies that the leakage detection method developed in this paper not only facilitates leakage detection but also contributes to model calibration.

Discussions

The district water system example is relatively small compared to many large distribution systems. However, the leakage hotspot prediction for the example represents a typical case for UU that owns and manages around 2,750 DMAs across its regulated region in northwest England. Following the successful application of the leakage detection method to the district system, Hayuti et al. (2008) conducted a comparative study. A number of DMAs were tested and the results were compared for the previously developed method (Sage 2005) and the new pressure-dependent leakage detection model. Positive feedback has been received on the use of the pressure-dependent leakage detection method. It has been found that the new method is more efficient and effective than the previous method in predicting leakage hotspots, especially those leaks that proved to be hard to find. The leakage hotspots found using the new method are closer to the actual leaks than those indicated by the previous method. The new method also predicted leaks missed by the previous method. Recent work by Moorcroft (2008) has suggested that leakage hotspot optimization may become a useful support tool for helping manage leakage on new plastic pipe systems. This is because there are indications that acoustic loggers are sometimes struggling to predict leaks on such systems because of relatively less leakage induced noise from plastic pipes accompanied by general reductions in pressure. Therefore, the pressure-dependent leakage detection tool is practically beneficial for helping leakage detection staff to better identify the hidden leaks across the whole operational region. A particular advantage of the new technique is its ability to predict "hard-to-find" leak locations. It is expected that the leakage detection model discussed in this paper will soon start to prove to be a valuable tool in helping water companies reduce leakage and achieve their annual targets as agreed with the water industry regulator.

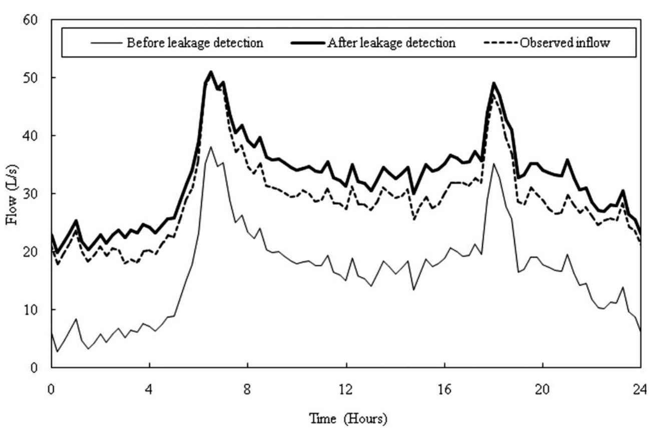

Fig. 11. Simulated flow comparisons before and after leakage detection

The method is also applicable to leakage detection in a large water distribution system. This is because the dimension of the leakage detection optimization is determined by the maximum number of leakage nodes, instead of the total number of model nodes. The maximum number of leakage nodes is specified by the users so the number of optimization variables is much less than the number of model nodes. For the DMA example discussed, if every node is treated as an independent optimization variable for the district water system, it would result in a search problem of 841 decision variables. Experience indicates that the number of actual leakage hotspots for such a water system often comprises no more than several dozen nodes. Thus, instead of optimizing 841 emitter coefficients, the new solution method reduces the optimization dimension by searching for 25 leak nodes and 25 emitter coefficients. A total of 50 decision variables were employed for the leakage detection optimization. In general, the engineer specifies the maximum number of possible leak nodes, noted as $NLeak^n$ for nodal demand group n. The genetic algorithm searches for the best combination of $NLeak^n$ leakage nodes (node index and emitter coefficient) within demand group n and a total number of $2\sum_{n=1}^{Ngroup} NLeak^n$ variables are optimized for leakage detection. Comparing to the optimization formulation that just considers emitter coefficients without optimizing the leakage node locations, the proposed solution method avoids assigning one decision variable to one node, for which the optimization

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dimension increases exponentially with the number of nodes in a system. It ensures the scalable efficiency based on optimization of the given number of possible leakage spots.

A drawback of the proposed method is that a user has to prescribe the maximum number of possible leaks but this is a minor limitation. The optimization runs, based upon the competent genetic algorithm can be effectively completed for a few dozen (up to hundreds) of decision variables (leakage nodes), which should adequately represent the leakage hotspot locations in many water distribution systems. For very large systems, it is recommended that multiple optimization runs be performed with different maximum numbers of possible leakage nodes and that the results are compared to see if similar leakage locations are identified. If leakage hotspots are identified repeatedly from series of multiple runs, it is likely that the pipes in the identified areas will be worthwhile candidates for subsequent leakage investigation on site.

Field data are always essential for applying any modeling method in practice. The current custom and practice field test in the United Kingdom. can be considered as "passive." The requirement to make use of night-time data means that the optimization algorithms often have to process small HGL differences that can approach the accuracy of the loggers being used. It is increasingly clear that alternative hydrant opening interventions could be used to provide more varied "active" data collection. It is expected that this would further facilitate mathematical optimizers in order that they could then be used to more clearly distinguish between leaks induced hydraulic gradient losses and those arising from other causes. In the mean time, an improved data collection procedure is also desirable for correctly identifying the status of any inline valves that may inadvertently have been left closed, for example, after pipeline rehabilitation projects. Therefore, UU has initiated a new field data collection pilot program that will combine two field testing modes and adopt a much shorter time step than the 15-min-step used currently. Future research will investigate the impact of this refined field data on the improvement of the solution quality for both leakage detection and model calibration

It should also be noted that water utilities in the United Kingdom have started to introduce discrete pressure areas (DPAs) within their existing DMA. The DPAs are often subject to additional local managed pressure reduction in addition to any reduction that may have been introduced at the inlet into the DMA. The future research in leakage detection and management needs to take DPAs into account in order to further develop and test new methods for such conditions.

Conclusions

An optimization model has been developed for identifying leakage hotspots. It utilizes pressure-dependent flow emitters to represent the leaks at nodes. Leakage emitters emulate the physical leak holes allowing water to flow out of a system. The emitter flow or leakage is an exponential function of nodal pressure. The relationship acknowledges the importance of pressure reduction on leakage reduction policy. The leakage detection model is not limited to the size of a model or the type of pipe materials to identify the likely leakage hotspots so that it is practically applicable to large water systems. The integrated optimization tool includes improved means of updating hydraulic models. Thus, the additional time spent on modeling leakage detection is relatively small. Benefits can be immediately realized from the application for the water utility.

The research has made some promising progress in developing a method for solving a long-standing problem of leakage allocation within a network model. In doing so it has provided a tool for assisting leakage detection engineers to predict leakage hotspots and thereby provide them with a focus on where to search for leaky pipelines. The results obtained for the case studies are consistent with one another and illustrate that the integrated optimization method is effective at supporting water companies for cost effective leakage reduction. In general, it is not often possible to exactly locate the water losses or leakages by just using the integrated optimization tool. Nevertheless, the tool has been shown to be able to help engineers to narrow down the possible areas of water loss (including leakages, unmetered and illegal consumptions etc.) and thus enables more efficient leakage reduction programs.

The method has fulfilled two purposes these being leakage detection and hydraulic model calibration. The work presented in the paper has shown that leakage detection optimization essentially improves the accuracy of the hydraulic model calibration by identifying the unknown leakages and the other NRW consumptions. It leverages the usage of the hydraulic model and also the flow and pressure data that are originally collected for model calibration. However, a need for improved field data collection is indicated whereby the logging of continuous flow and pressure trends are combined with measurements associated with controlled hydrant discharges. It is expected that such data sets will enhance the solution quality of leakage hotspot prediction and facilitate model calibration (pipe roughness adjustments and predictions of any unknown closed or open valves). This will eventually enable technical staff to carry out leakage hotspot prediction as an independent task or combine such analysis with other water network model calibration work. It is also important that pressure loggers are accurate or that any under or overrecording of pressures are consistent such that they can be corrected by valid offsets for each instrument.

Finally, the applied research demonstrates to regulators that water utilities can exploit the latest innovations of modeling technology with its supply chain partners to manage, detect, control and reduce water leakages, and to mitigate some of the current concerns being expressed by government agencies about the lack of technical progress with leakage reduction. The lessons are valuable for utilities' owners, operators, and consulting engineers to reduce the water losses by using the latest optimization modeling approach.

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