

Available online at [www.sciencedirect.com](http://www.sciencedirect.com)**ScienceDirect**

Procedia Engineering 119 (2015) 593 – 602

**Procedia  
Engineering**[www.elsevier.com/locate/procedia](http://www.elsevier.com/locate/procedia)

13th Computer Control for Water Industry Conference, CCWI 2015

## Advances in water mains network modelling for improved operations

**S. Sophocleous<sup>a\*</sup>, D. Savic<sup>a</sup>, Z. Kapelan<sup>a</sup>, Y. Shen<sup>b</sup>, P. Sage<sup>c</sup>**<sup>a</sup>Centre for Water Systems, University of Exeter, North Park Road, Exeter, EX4 4QJ, UK<sup>b</sup>Severn Trent Water Ltd, St. Martins Road, Finham, Coventry, CV3 6SD, UK<sup>c</sup>WITSConsult Ltd, Milton Rough, Acton Bridge, Northwich, CW8 2RF, UK

---

### Abstract

The traditional approach to water mains network model calibration is too coarse. System and data anomalies impact on the simulated pressures in the models. These include unknown status valves, incorrect pipe data including pipe roughness values and unknown leaks. A combination of smarter field testing and staged optimisation analyses provides a promising solution to solving this complex problem. An anonymous model has been used to demonstrate that inclusion in the field test of planned hydrant discharges and concurrent tactical valve operations will help detect the unknown status valves but also lead to more accurate pipe roughness values and leakage hotspots.

© 2015 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Peer-review under responsibility of the Scientific Committee of CCWI 2015

**Keywords:** Innovation; water mains network models; optimisation; leakage; unknown status valves; pipe roughness

---

### 1. Introduction

Currently, the UK Water sector is disadvantaged by the lack of major advances in water mains network modelling (WMNM). A consequence is compromised support for operational work at distribution mains level. Among possible uses of WMNM, the detection of unknown closed valves, unknown open cross connections and the location of leakage hotspots are important operational considerations. Large sums of money are spent by companies finding leaks but many remain undetected. One reason for this includes the current pressure calibration criterion for models, often set within a  $\pm 1$  metre range for simulated pressures (Savic et al., [1]). A lack of flow measurements from key mains within the WMNMs can also adversely affect calibration. Field testing pressure and flow criteria for

---

\* Corresponding author. Tel: +44(0)7927 928661.  
E-mail address: [ss694@exeter.ac.uk](mailto:ss694@exeter.ac.uk)

models were established in the mid 1980's when WMNM began to be used more widely, but they have remained unchanged despite the move to 'all mains' modelling in the 1990's and improved pressure transducer accuracy. Now, as the water industry moves towards a regulatory environment based on total expenditure, for which operational solutions are sought as well as traditional capital ones, the need for accurate WMNM to support operational activities becomes more important. Other traditional modelling techniques that can also compromise more accurate calibration include the assumptions for domestic demand and leakage. A homogenous distribution of domestic demand and leaks across the WMNM is adopted for the model that may not match real local demand in practice. It is also the case that many changes have been made to water mains distribution networks since water industry privatization. These have been associated with water quality driven mains rehabilitation, boundary modifications and leakage reduction strategies. This has raised the possibility of system anomaly issues regarding valves that may have been accidentally left closed (or open), perhaps for a long time. In turn, this may have led to data anomalies within corporate geographical information systems included in the water mains records used for network modelling. The paper objectives are:

- To raise the issues and challenges required to advance WMNM. These are associated with unknown status valves, incorrect pipe data including pipe roughness values and unknown leaks; In addition,
- To discuss methods for the improvement of unknown closed valve detection and leakage hotspot localization in the context of WMNM optimization analyses, by taking into consideration a desktop case study example from a real system.

Following a background section which reviews some key research studies and emphasizes the missing needs with regard to hydraulic network model calibration, the methodology for addressing the gaps mentioned is presented. Then, an application of the methodology is presented from a desktop-based case study. The subsequent sections provide a demonstration of the results, a discussion on the findings and issues raised, and finally a conclusion.

## 2. Background

WMNM optimisation studies, first undertaken to detect possible leakage hotspots, and then expanded to include preliminary detection of possible unknown closed (or open) valves, (Sage, [2]), identified a need for more research on network modelling field testing and calibration. This need arose from the gaps in current modelling assumptions that compromise existing calibration methods. Wu and Sage [3] applied optimization-based hydraulic model calibration to detect leakage hotspots, assuming that system states were perfectly known with respect to valve location and status. In reality, this is not certain. Similarly Sage et al., [4] applied a pressure-dependent calibration-based method associated with leakage hotspot optimization in a real system, reporting that outcomes for the detection of leaks were impacted by the sizes and ranges of the demand, pipe roughness and valve status groups. Wu et al., [5] stressed the imperative need of identifying the status and/or settings (degree of opening) of valves, in order to adequately calibrate a WMNM especially for those valves on critical flow paths. Walski et al., [6] suggested practical methods regarding field measurements collection, with the aim of calibrating models for leak location and finding the correct status of valves in the network. Moreover, various anomalies in model calibration for leakage detection have been found to originate from incorrect pipe roughness values. During traditional calibration these have often been assumed correct and do not take uncertainty into account (Alvisi and Franchini [7]). In a case study by Sage et al., [4], when modelled pipe roughness values were set too high, the location of simulated leakage hotspots moved upstream, while simulated inflows were less than those observed. The opposite effect occurred with smoother pipes. This raises various issues with traditional model calibration approaches.

The need for advances in WMNM led to a STREAM Industrial Doctoral Centre (STREAM, [8]) project that began in 2014, the purpose being to develop the next generation of WMNM tools to support network operators in the context of leakage detection. This paper outlines investigations that have been undertaken to establish the directions for this project, taking into consideration the aforementioned issues within calibration-based approaches.

## 3. Methodology

A methodology is presented to improve WMNM for the purpose of leakage detection, the aim being to locate leakage supported by improved reconciliation of observed pressure and flow data collected during Night Fire Flow

Field Tests (NFFFT). The methodology includes use of an optimization-based calibration approach taking into account the possible unknown status of valves in the network, as well as incorrect pipe roughness values. Hence a key methodology requirement is to overcome the uncertainty existing in traditional calibration-based approaches.

### 3.1. The software used

The Excel-based SolveXL optimization tool (Savic et al., [9]), was used for calibration of a WMNM for leakage detection, and is a non-dominated sorting genetic algorithm II (NSGA II) which is a computationally fast and elitist multi-objective evolutionary algorithm based on a non-dominated sorting approach (Deb et al., [10]). The EPANET2 software (Rossman, [11]) was used to carry out simulation analyses of the pipe network.

### 3.2. The optimization problem

The optimization algorithm considers as decision variables valve status, pipe roughness and leakage coefficients. The optimization-based calibration is defined as a nonlinear optimization problem with the single objective to minimize the function (“fitness”) for the weighted sum of absolute differences between the field observed and simulated values of junction pressures (hydraulic grades) and pipe flows for given boundary conditions, including valve status, pipe roughness and leakage emitter coefficients, as well as subject to implicit constraints defined by continuity (for every node) and energy loss equations (for every pipe). The optimization problem can be defined as:

$$\text{Search for: } \overline{X} = (K_i^n, f_j^g, s_{k,t}) \quad i = 1, \dots, NI; j = 1, \dots, NJ; k = 1, \dots, NK \quad (1)$$

$$\text{Minimize: } F(\overline{X}) = w_H \sum_{t=1}^T (|H_{\text{mod}} - H_{\text{obs}}|) + w_Q \sum_{t=1}^T (|Q_{\text{mod}} - Q_{\text{obs}}|) \quad (2)$$

$$\text{Subject to: } 0 \leq K_i^n \leq K_{\text{max}}^n \quad (3)$$

$$\overline{f}_j \leq f_j \leq \underline{f}_j \quad (4)$$

$$s_{k,t} \in \{0,1\} \quad (5)$$

Where  $\overline{X}$  represents a set of model parameters,  $K_i^n$  is the emitter coefficient for leakage node  $i$  in demand group  $n$  with 0 and  $K_{\text{max}}^n$  being the minimum and maximum values the emitter coefficient for group  $n$  can undertake,  $f_j^g$  is the roughness coefficient for pipe  $j$  in pipe group  $g$  with  $\overline{f}_g$  and  $\underline{f}_g$  being the upper and lower limits a roughness coefficient in that pipe group can undertake,  $s_{k,t}$  is the status of a valve  $k$  at time step  $t$ , belonging to a vector with values 0 and 1,  $NI$  is the number of the specified leakage nodes to be identified for node group  $n$ ,  $NJ$  is the number of roughness groups,  $NK$  is the number of uncertain status valves,  $F(\overline{X})$  is the objective function to be minimized, corresponding to weighted ( $w_H$ ,  $w_Q$ ) goodness-of-fit between the field observed values and the model simulated values for nodal heads ( $H_{\text{mod}} - H_{\text{obs}}$ ) and pipe flows ( $Q_{\text{mod}} - Q_{\text{obs}}$ ), respectively.

### 3.3. The calibration approach

A hydraulic simulation analysis was carried out in EPANET2 by considering the true state of the network, in order to create an artificial set of field (i.e. observed) pressure and flow measurements for calibration, without accounting for noise. The artificial data were collected by means of planned hydrant discharges during NFFFT. Water quality risks have been mitigated by considering the discoloured water theory (Boxall and Saul, [12]). Also, planned valves closures were introduced to the NFFFT while the hydrants were open. A restricted number of nodes and pipes of the network were assumed to have pressure observed and flow metered, respectively. Back tracing analyses were used to select the hydrants to be were opened at night to put the system under controlled hydraulic stress. This was to provide more varied field test observations than usual, but data tied to known hydrant demands at

otherwise low demand periods. The NFFFT observations were inserted into the optimization tool for calibration and detection of the true leakage hotspot locations and their emitter coefficients. In other words, the traditional demand driven leakage was replaced by a pressure driven alternative based on EPANET2's emitter coefficients. Two calibration problems were solved according to two case study specific cases outlined below.

#### 4. Case Study

##### 4.1. The "true" system state

The EPANET2 network layout of the study area is presented in Figure 1. It involves a real-life Discrete Pressure Area (DPA) system (Sage, [2]). The network comprises of 363 nodes, 180 pipes, 105 throttle control valves (TCVs) and a pressure reducing valve (PRV) with a downstream head set at 55.77m. Just upstream of the PRV, the modelled area's source inflow node has been considered as a service reservoir with a total head of 100m. The total mains' length is 7.887km. Flow from the source node varies between 4.45l/s at Minimum Night Flow and 8.81l/s at morning peak demand, but can be raised for short periods by planned hydrant discharges. The network model contains two closed TCVs (T58 and T196), one open cross-connection (TNUXCON) and three leakage hotspots (J202, J244, and J341). These adjustments were made for subsequent calibration purposes aligned with the paper's objectives. A fourth emitter was also introduced in the model, representing a fabricated leak at J343. This was to test the optimiser's capability to detect leakage hotspots using a perfectly calibrated test model (i.e. with known valve status and pipe roughness). The fabricated leak was set between 00:30 and 02:00 hours with an emitter of 0.296 (or 2.01l/s). The relevant emitter coefficient data and local pressures during minimum night flow and morning peak conditions for the three leakage hotspots are shown in Table 1 as are the total emitter leakages for 04:00 and 08:00. Finally, six chosen pipes from the base model, associated with three different pipe groups based on pipe material (e.g. four Cast Iron pipes (p734, p836, p1006, and p1008), one Polyethylene (PE) pipe (p1219) and one Asbestos Cement (AC) pipe (p592)) were considered for the calibration problem. Table 2 provides information for the pipe roughness (ks) values. The ks for each pipe in a group only represent the ks value of that particular group and not all pipes in the network of that material (Table 2). Limitations in the capacity of the optimization tool didn't allow for the inclusion of more pipes in each group. The larger number of pipes chosen for the Cast Iron (CI) group was based on the fact that historically CI pipes have caused the majority of model calibration problems, the reason being that CI pipes are associated with past corrosion and higher ks values. The location of the selected pipes in each group was based on: the contribution of flow to hydrants for CI group; the location of the AC pipe near node J343, feeding the fabricated leak; and that the PE pipe was the leading pipe into the network from the PRV.

**Table 1.** Leakage hotspot information

Label	True Emitter Coefficient	'Observed' Pressure at 04:30 (m)	Leakage flow (l/s)	'Observed' Pressure at 08:00 (m)	Leakage flow (l/s)
J202	0.160	33.23	0.92	33.14	0.92
J244	0.250	25.69	1.27	25.58	1.26
J341	0.230	40.67	1.47	40.60	1.47
		<b>Total</b>	3.66	<b>Total</b>	3.65

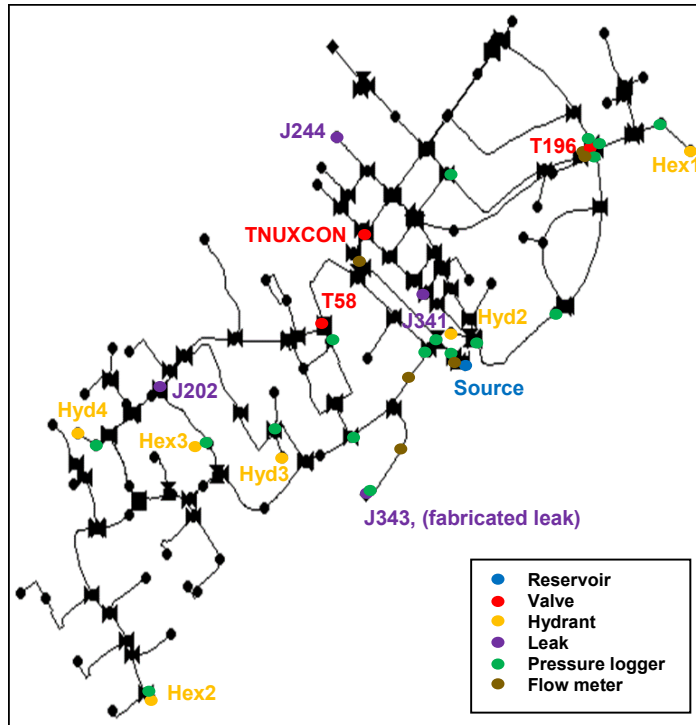
**Table 2.** Pipe information

Pipe	Material	True Ks coefficient (mm)
p734	CI	2.5
p836	CI	2.5
p1006	CI	2.5
p1008	CI	2.5
p1219	PE	0.01
p592	AC	0.8

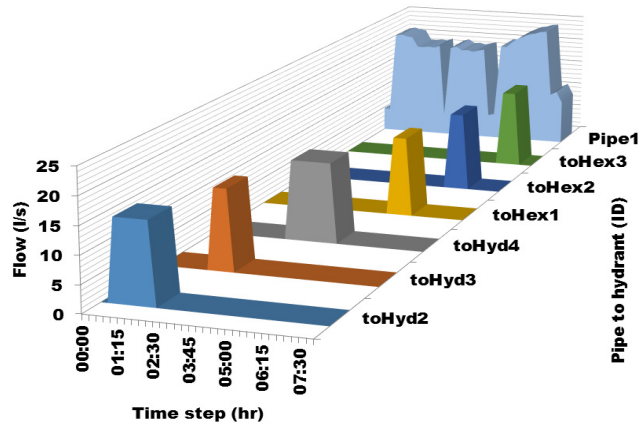
##### 4.2. Artificial measurements generation

Six planned hydrant discharges, included in the EPANET2 model as demands, were operated at 15l/s during Night Fire Flow Field Tests at Hyd2, Hyd3, Hyd4, Hex1, Hex2 and Hex3 (Figures 1, 2). A novel departure from the traditional 24-hour diurnal field regime was to include the planned discharges in a test period between midnight and 08:00. This was in order to mitigate the variation in legitimate demand occurring during the usual 24 hour field test. The hydrants were selected either within subareas of the network or at peripheral downstream network locations.

This was so that flow regimes could be created, from which the more varied hydraulic observations could be obtained. The fabricated field test data was obtained from 18 locations recording key pressures, such as those that



**Figure 1.** The true DPA system configuration illustrating the three TCVs of consideration for calibration, the six hydrants that were operated, the several pressure and flow measurement points and the four leaks to be identified .



**Figure 2.** 3-D plot demonstrating the order of hydrant discharge operation at 15l/s. The total incoming flow to the DPA system from the Source pipe (Pipe 1) and the flow from the pipes supplying the different hydrant discharges is shown at each time step between 00:00 and 08:00 hours.

occur near the PRV and hydrants as well as at locations along the key feeder mains. Inflow to the study area, hydrant discharges and flows from six key mains supplying the hydrants and substantial areas of the network were

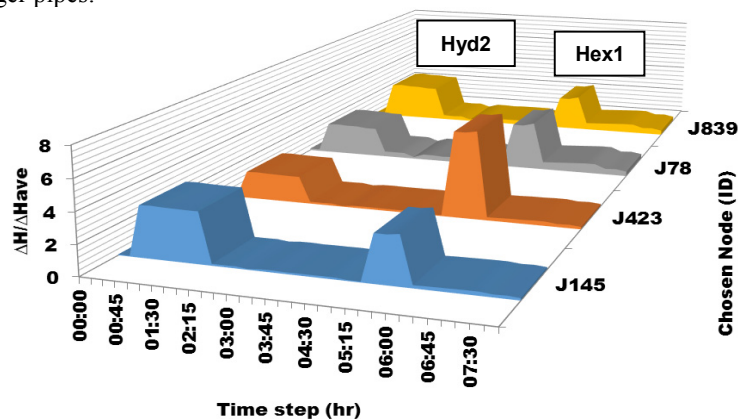
also obtained as fabricated data from seven flow metered pipes for model calibration purposes. The locations of the “collected” hydrant discharge data are shown in Figure 1.

#### 4.3 Case I

The Excel-based SolveXL optimization tool initiates the search process by randomly generating values for each decision variable, i.e. the valve status and pipe roughness, assumed to be the correct system configuration for the first calibration problem. The population of potential leakage nodes was restricted to those on pipes of length 50m or more to reduce the optimiser’s search space. This resulted into 91 candidate nodes, reduced from over 300 nodes. Consequently the optimization tool was run to detect the leakage hotspot characteristics, by calibrating the parameters of leakage emitters and their correct index within the network corresponding to the location.

#### 4.4 Case II

As in Case “I”, the optimisation process starts with decision variables taking randomly generated values, with respect to valve status and pipe roughness. However, a staged process was followed for the calibration. Firstly, the optimiser was used to detect the correct valve status. This involved calibrating for the valve status of the considered group of valves. The population of potential valves with unknown status was restricted to 13 candidates. The number of candidate valves was decided, based on Excel equation limitations in SolveXL, as well as EPANET2 hydraulic consideration of significant valves (which, in the past can could remain unnoticed with respect to the model hydraulics if they had an incorrect status) according to their location in the pipe network. For example, valves that feed dead ends, or lead to isolation of areas (i.e. zero-flow) were not taken into account. The remaining valves were sorted by descending flow and 13 valves were randomly chosen from the list. Then, following the valves’ status (imaginary) verifications with the true system state (Figure 1), the second stage was to calibrate for the correct pipe ks values in each pipe group, together with the emitter coefficients and indices of the group of candidate nodes, again restricted on longer pipes.



**Figure 3.** 3-D Field Test Scatter plot of the dimensionless head loss at each time step between 00:00 – 08:00 for randomly chosen nodes that are located along the supply route of Hyd2 and Hex1, demonstrating the effect caused on head loss from each the planned hydrant discharge during their operation period.

## 5. Results

### 5.1. Detection of correct valve status

A supporting visualization tool for locating unknown closed valves was through the construction of 3-dimensional scatter graphs, which reconciled the field data (Figure 3). Figure 3 illustrates and compares the dimensionless head loss plots for nodes ‘J145’, ‘J423’, ‘J78’ and ‘J839’, with respect to the time step during which



the hydrant discharges were operated. These were determined from the artificial field measurements and they reflect the effect caused from the planned hydrant discharges at ‘Hyd2’ and ‘Hex1’ shown in Figures 1 and 2, which are supplied by the above mentioned nodes. The existence of a closed valve at T196 (Figure 1) can be inferred from the large difference in head loss caused at the pressure logger locations due to the two hydrant discharges (Hyd2 and Hex1). A large increase in head loss is observed at node J423, which is located along the supply route to the discharging hydrant Hex1 (and nearby J839), relative to the rest nodes where no significant difference in head loss is noticed. Furthermore, the head losses at J78 were higher when Hex1 was open (Figure 2) indicating that the pipe route from that node was also contributing to the discharge at the hydrant, whereas the head loss at J839, which is located just upstream of valve T196, and is close to node J423, was very similar to that for earlier time when Hyd2 was discharging. A similar approach may be used to facilitate the identification of the location of pipes with uncharacteristically high ks coefficients.

### 5.2. Case I

Figure 4 illustrates the optimization outcome following the SolveXL analysis, for the task of calibrating for the correct leakage hotspot location and emitter coefficient, without considering either unknown valve status or increased pipe ks coefficients. With a fitness of 143, representing the scope of error between observed and simulated flows and pressures, the optimization process failed to calibrate the model. This resulted in severely wrong detection of leakage hotspot locations, as shown in Table 3. In addition, the optimizer overestimated the emitter coefficients at the leakage nodes, consequently overestimating the emitter’s discharges compared to the values, shown in Table 1.

**Table 3.** Optimization results for Case I

Label	Emitter Coefficient	Average Pressure (m H <sub>2</sub> O)	Leakage (l/s)
J40	0.296	36.8	1.80
J185	0.296	38.0	1.80
J308	0.296	37.8	1.80
J580	0.296	35.9	1.80
<b>Total</b>			<b>7.20</b>

### 5.3. Case II

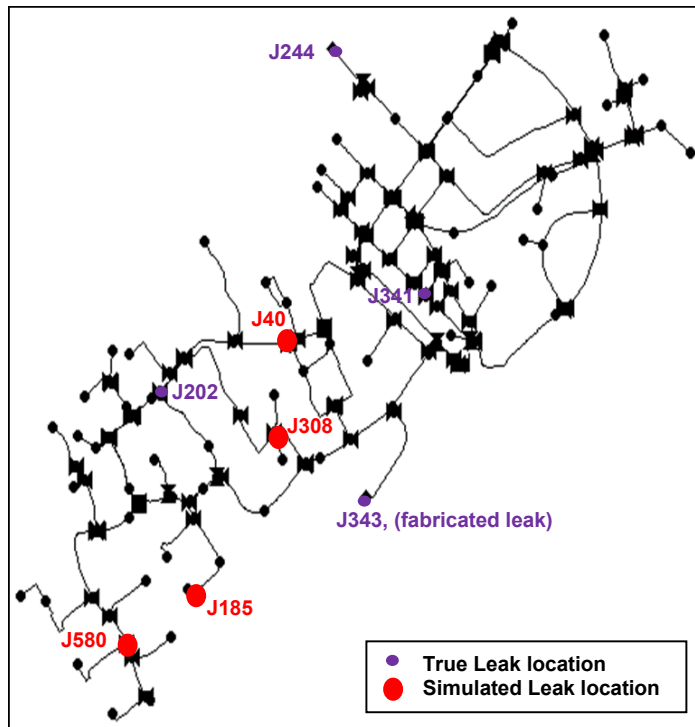
Following the staged optimisation, that detected the correct status for the unknown valves and the correct pipe ks values, good results were obtained for the leakage hotspots including a solution fitness of 0.1. This second stage took into account the correctly identified unknown closed valves and the open cross connection leading to successful identification of all the leakage hotspots. No false positives were detected by the optimizer. On the other hand, the optimization outcome for pipe ks coefficients did not lead on to correct calibration (Table 4). But the suggested ks values were significantly reduced illustrating that the pipes in the model should have been smoother. The three leakage hotspots locations (J202, J244, and J341 and fabricated leak at J343) were correctly detected, (Table 5).

**Table 4.** Case II results for pipe ks

Pipes	Material	True ks (mm)	Simulated ks (mm)
p734, p836	CI	2.5	0.5
p1006 & p1008	CI	2.5	0.5
p1219	PE	0.01	0.03
p592	AC	0.8	0.2

**Table 5.** Case II results for leakage hotspots

Label	Emitter Coefficient	04:00 Simulated Pressure (m)	Leakage (l/s)
J202	0.16	30.7	0.89
J244	0.25	26.7	1.29
J341	0.23	39.8	1.58
J343	0.3	24.2	1.46
<b>Total</b>			<b>5.21</b>



**Figure 4.** Calibration optimization problem solution for leakage hotspot location presented on the EPANET2 network layout along with their true location. This demonstrates the incorrect detection of leakage hotspot location, assuming a known status and ks coefficient for each valve and pipe, respectively.

## 6. Discussion

### 6.1 The need for shifting from custom-and-practice modelling approaches

The approach used in this desktop study helps demonstrate the benefits that could be secured by developing the optimization-based approach and next generation of models for WMNM calibration rather than pursuing the custom-and-practice methods that have now remained broadly the same for 20 years. However, there were several assumptions made in this work that impact on the calibration process, which are also applied to traditional modelling practices. One of these relates to the fact that all the “collected” artificial measurements in this study were noise-free. This is not the case in a real world, as measurement error includes an important component of model simulation uncertainty. Another assumption, unlikely in reality is that pressure measurements and hydrant discharges could be taken at any location within the study area. However, water companies often face situations where desired sampling points for field tests are inaccessible, thus causing the need to find alternative measurement locations to meet the calibration purpose.

Accurate flow and pressure field testing is a prerequisite of any modelling calibration exercise as is a need for more varied observations arising from known interventions. This is because a consequence of the traditional approach is that anomalies such as valves with unknown status are not necessarily identified during the calibration process. Also evident from work reported in recent years are opportunities to detect the hitherto undetected anomalies within the water distribution system. Steps can be taken to amplify pressure losses (or gains) arising from the anomalies thereby helping lead to the detection of those anomalies by the new optimisation-based modelling methods. The new modelling methods could also enhance the performance of smart network schemes. The improving opportunities for more successful detection of previously undetected model anomalies and leakage



hotspots means that the risks of double jeopardy unplanned events is reduced and that more previously ‘hard-to-find’ leaks can be repaired, should it be economic to do so.

An important custom-and-practice calibration assumption, also considered here, was that pipe ks and diameter values are known correctly. Xu and Goulter [13] showed that such parameters, which are traditionally estimated by modelers through an approach of adjusting pipe hydraulic ks coefficients to calibrate the model, comprise a lot of uncertainty that can deflect the calibration accuracy. It should be also noted that even following pipe ks calibration it is unlikely to accurately know the correct ks values, except from taking the pipe off the ground.

Albeit the presented case study involves a perfect model with assumptions that are not representative of a real-world system, several conclusions can be deduced from this analysis, which can contribute in tackling the unknown closed valves problem and improve the location of leakage hotspots within WMNM optimization analyses. Even though only three valves with unknown status were introduced within the model, the presented results uncover the effect and the anomaly caused by just a few unknown closed valves and open cross connections. The big scope for error in detecting the hotspots locations was demonstrated in the first instance when the optimization calibration for the model was undertaken “blind” of the existence of valves with incorrect status and over-roughened pipes. This led to failure in identifying the correct hotspots locations, while indicating falsely elevated total leakage.

## 6.2 New calibration approach

With the aim of matching simulated pressures and flows as closely as possible with those values collected from the field test, the traditional methods of calibration (adjusting pipe ks coefficients and nodal demands to find agreement with observed measurements) can be shown to have a low chance of meeting the even stricter calibration criterion now required for operational WMNMs. The new generation of network models, which aim to optimize valve status in order to fine tune leakage hotspot detection, will be able to accommodate the existing accuracy available for the high quality pressure transducers already in use for network modelling field tests that is reduced by an order of magnitude for traditional modelling calibration. It would be unfortunate to forego the opportunity to move from a calibration criteria of  $\pm 1.0\text{m}$  to  $\pm 0.1\text{m}$ , the latter being similar to the specified 0.1% full scale deflection for the 10bar transducers often used in the field work. By grasping this opportunity, the way will be open for the new generation modelling tools to provide far superior model calibration with new ways to detect unknown closed valves.

Fortunately, an alternative to traditional WMNM calibration is taking shape. Sage et al. [4] attempted an optimization-based approach for leakage hotspot detection in a pilot study District Meter Area (DMA) with two Pressure Managed Areas (PMAs). Significant hydrant discharges were introduced to the field test work at night. In order to confirm that leakage hotspots could be detected in a PMA downstream of a PRV a fabricated leak was set up by making use of a cracked open hydrant that operated for about 1 hour in the night. A valve was also closed prior to the test to provide an unknown closed valve. At first, the fabricated leak could not be detected but closer examination of the already reconciled field data indicated uncharacteristically high ks values on a key main in the upstream DMA that supplied both the PMA and a downstream DMA. It was not until the optimiser search fields had been expanded to test for short lengths of pipe that had been identified from a pipe tree analysis and that may have been acting as surrogate valves that a 9” valve on the key main was detected and subsequently verified as closed, and that the optimiser was able to start detecting the fabricated leak.

Fabricated leaks have found to be a useful feature of the NFFFT and the calibration process. They provide artificial ‘known’ leaks that can run for a set period and thus provides a valuable sense check on the optimiser’s capability to detect such leaks and, in doing so, help build confidence in the new method, such that the other detected leaks are representative of leaks in the real network, near or at the model’s detected leak nodes. Moreover, additional flow data from key mains in the study area helps improve the accuracy of the detected leakage hotspots. Subsequent verification of these model detected leaks in the field methods has been reasonably successful.

There are further significant points to consider with regard to the modified NFFFT where the controlled hydrant discharges at night replace the preferred custom-and-practice snapshots at peak hour demand associated with weekday breakfast times or early evening mealtimes. This may seem counter intuitive to 30 years of modelling practice but domestic demands within service pipes and small mains are known to be highly variable. So for

optimization-based calibration the need for calibration using the traditional peak hour snapshots recedes if it can be replaced by conditions with generally lower domestic demands accompanied by larger known demands at the hydrant discharge points. This means that the NFFFT should begin at midnight with sufficient observations for calibration being captured before the start of the next working day. Then, after the first night's NFFFT, the working day should be used for the first pass optimisation to seek out possible unknown closed valves. When identified in the model, these should be verified in the field on the same day (and presumably set to their correct working status). This will impact on the pressures and flows within the network on the second night. But there is no reason why additional observational data should not be collected from the second night, along with possible new hydrant tests and this extended set of observations, with control rules, used in a second pass optimisation, now with valve status verified, to obtain improved detection of any leakage hotspots and pipe roughness values. There will be also opportunities to gain even more measurements for calibration prior to the NFFFT, during the applied PODDS theory for mitigating discolored water.

## 7. Conclusions

Traditional modelling calibration methods are too coarse to routinely provide models for reliable leakage hotspot detection and the scope for error due to system and data anomalies has been demonstrated in a simple desktop study. The paper discussed how NFFFT field data investigation can help determine valves of unknown status and pipes with incorrect roughness coefficients, prior to leakage hotspot optimization. But more project work is required to provide the new generation model tools suitable for general use. The desktop model has been successfully used to test for the detection of unknown valve statuses. This has been found to be an essential step for subsequent detection of the leakage hotspots but, in practice, should lead to a useful support tool for network operations.

## 8. Acknowledgements

This work is part of the first author's STREAM EngD project, based at the University of Exeter and sponsored by the UK Engineering and Physical Science Research Council, Severn Trent Water Ltd and WITSConsult Ltd.

## 9. References

- [1] Savic, D.A., Kapelan, Z.S., Jonkergouw, P.M.R. Quo vadis water distribution model calibration? *Urb W J*, 2009, 6, 1, 3-22.
- [2] Sage, P.V. Practical methods to obtain improved outputs from Water Network Modelling Optimization, 12th International Conference on Computing and Control for the Water Industry, *Procedia Engineering*, 2014, 70, 1450-1499.
- [3] Wu, Z.Y. and Sage, P.V. Water loss detection via Genetic Algorithm Optimisation-based Model Calibration, *ASCE*, 8<sup>th</sup> Annual International Symposium on Water Distribution System Analysis, Aug. 27-30, 2006, Cincinnati, Ohio
- [4] Sage, P.V., Wu, Z.Y. and Croxton, N. Recent Developments in Leak Hotspot Detection Using Network Model Optimisation, CCWI 2011, *Urban Water Management: Challenges and Opportunities*, Exeter, Centre for Water Systems, 2011, 2, 509-514.
- [5] Wu, Z.Y., Song, Y., and Syed, J.L. Optimization model for identifying unknown valve statuses and settings, WDSA 2012, Sept. 22-27, 2012, Adelaide, Australia.
- [6] Walski, T., Sage, P., Wu, Z.Y. What does it take to make automated calibration find closed valves and leaks?. *Proc., Environment and Water Resources Institute (EWRI) Conf., ASCE*, 2014, Reston, VA.
- [7] Alvisi, S., and Franchini, M. Calibration and sensitivity analysis of the C-Town pipe network model." *Proc., 12th Water Distribution Systems Analysis Symp.*, K. Lansey, C. Choi, A. Ostfeld, and I. Pepper, eds., *ASCE*, 2010, Reston, VA.
- [8] STREAM IDC. The EPSRC STREAM Industrial Doctoral Centre (IDC) for the Water Sector, 2014, [<http://www.stream-idc.net/>].
- [9] Savic, D.A., Bicik, J., Morley, M.S. A DSS generator for multi-objective optimisation of spreadsheet-based models, *Env Mod & Soft*, 2011, 26, 551-56.
- [10] Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., A fast and Elitist Multiobjective Genetic Algorithm: NSGA-II, *IEEE, Trans Evol Comp*, 2002, 6, 2, 182-197.
- [11] Rossman, L.A. EPANET2 users' manual, Drinking Water Research Division, Risk Reduction Engineering Laboratory Office of Research and Development U.S. Environmental Protection Agency, 2000, Cincinnati.
- [12] Boxall, J.B. and Saul, A.J. Modelling discoloration in potable water distribution systems, *J Env Eng ASCE*, 2005, 131, 5.
- [13] Xu, C. and Goulter, I.C. Probabilistic Model for Water Distribution Reliability, *J Hyd Eng, ASCE*, 1998, 124, 4, 218-228.