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A two-stage calibration for detection of leakage hotspots in a real water distribution network

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Abstract

The paper presents a two-stage approach for solving a calibration-based problem for the ultimate purpose of detecting leakage hotspots. This is compared with a one-stage approach. A Genetic Algorithm is used to solve optimization problems of searching for calibration parameters values, while minimizing the differences between observations and model predictions. The approach takes into account suspect valves with unknown status, as well as pipes with incorrect roughness values and nodal leakage. The methodology also takes advantage of a new approach to reducing solution search space size for the optimisation problems. These problems are then solved for different leakage scenarios. Artificial calibration data are generated by means of hydraulic modelling employed to mimic planned hydrant discharges during a low demand period, combined with step tests. The case study demonstrates the improved leakage detection and model calibration of the two-stage calibration approach relative to the one-stage approach, which considers all calibration parameters together. This can result in a useful practical network operation tool.

Keywords: Calibration; Leakage Detection; Optimisation; Valve Status; Hydraulic Model

1. Introduction

Leakage from Water Distribution Networks (WDNs) is becoming a great concern for water utilities around the

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world. Quantifying and localizing leaks within WDNs is of significant importance to a water company. However, the whole leakage detection process may still have shortfalls in speed of detections with a significant volume of water being lost before the leak is found. To avoid these inconveniences, leakage detection based on mathematical models may be used by "comparing" and analysing the network monitoring data, with the network model simulated outputs.

Currently, the calibration of hydraulic models is based on trial-and-error adjustments for pipe friction factors and nodal demands, due to the lack of major advances from the practitioner's perspective. This is to simulate pressures within an accuracy of ±1 metre relative to observations [1], which is too coarse criterion for supporting operational work at the distribution mains level. This is a result of system and data anomalies associated with accidentally left closed (or open) valves, which are unreported in the Geographic Information Systems, incorrect pipe state information and undetected leaks, which cause a considerable effect on how accurately can the model simulate WDN hydraulics. Sophocleous et al. [2] suggested that a calibration process combining smarter field testing along with staged optimization analyses can provide a promising solution to solving such complex problems. Here, an improved two-stage optimisation-based calibration approach is applied to a real WDN for the ultimate purpose of detecting leakage hotspots, supported by improved reconciliation of observed pressure and flow data collected during night fire flow field tests. The staged approach is then compared to a one-stage calibration method. Both approaches take into account candidate unknown status valves, pipes with incorrect roughness values and suspect leakage nodes. Different leakage scenarios are tested for each of the two approaches to determine the number of leaks that best represents losses within the WDN. Using a preliminary topological analysis and sensitivity-based methods the search for leakage hotspots in the network is reduced, simplifying the calibration problem. Then, optimisation analyses are carried out. The paper is organized as follows: section 2 provides literature review on calibration-based leakage detection, section 3 describes the two-stage calibration approach and the search space reduction method, section 4 presents the case study, section 5 discusses the calibration results and compares between the one- and two- stage approaches, followed by conclusions.

2. Background

Model-based studies for the detection of leakage hotspots in WDNs have always attracted significant attention in water systems research. A variety of techniques, including inverse transient analysis, Bayesian identification method and belief-rule-based expert system have been applied to locate leaks with inverse transient modelling being the most attractive research area. More recent developments include non-transient model-based leakage detection techniques, which analyse the difference between measurements and estimated values from leaky scenarios to signal the probability of a zone to contain leakage. However, some of these model-based methodologies assume the hypothesis of a single leak in the network [3]. Calibration-based methods can leverage steady state hydraulic models and optimisation tool technology, such as Genetic Algorithms (GAs), to improve on the detection of leaks. Wu et al. [4] calibrated leakage as a pressure-driven demand using a competent GA. Similarly, Sage [5] carried out leakage hotspot optimization analyses in a real system using a pressure-dependent calibration-based method, suggesting that leakage detection accuracy was significantly affected by the sizes and ranges of the demand, pipe roughness and valve status groups. This comes into opposition with the current modelling assumptions with respect to valve location and status, which compromise existing calibration methods. Traditional calibration methods assume that the network topology associated with closed/open valves is perfectly known, but in reality this is uncertain. Wu et al., [6] highlighted the imperative need of determining the status and/or settings of valves, in order to adequately calibrate a WDN model, especially for those valves on critical flow paths. Walski et al., [7] recommended practical methods for field measurements collection, in order to improve model calibration by finding leaks and the correct status of valves in the network. Furthermore, additional errors in model calibration for leakage detection can result from incorrect pipe roughness values, as a result of custom-and-practice approaches that do not take uncertainty into consideration (Alvisi and Franchini [8]). Sophocleous et al. [2] implemented a two-stage calibration-based approach on a real WDN model, considering unknown valve status detection and leakage localization. The inclusion of field test planned hydrant discharges and concurrent tactical valve operations demonstrated an improved detection of unknown status valves and subsequently more accurate pipe roughness values and leakage hotspots.

3. Methodology

3.1. Optimization problem formulation

A MATLAB optimization code was developed for model calibration and was linked to the EPANET2 tool-kit [9]. The optimization process uses a non-dominated sorting genetic algorithm II (NSGA II) [10]. Valve status, pipe roughness, leakage location and leakage coefficients were considered as decision variables. The calibration was defined as a nonlinear optimization problem with the single objective to minimize the weighted sum of squared differences between the field observed and simulated values of nodal heads and pipe flows. The calibration problem was subject to two sets of constraints: (1) the set of implicit type constraints considering mass and energy balance equations; and (2) the set of explicit constraints used as bounds for the algorithm solution search space for each decision variable. The optimization problem is formulated as follows:

Search for: $\vec{X} = (s_{k,t}, LN_i^n, K_i^n, f_j^g)$ $\quad k = 1,..,NK; \quad LN_i^n \in J^n; \quad n = 1,..,Ngroup;$ *(1)*

$$i = 1,..,NLeak^n; \quad j = 1,..,NJ; \quad (1)$$

Minimize:

$$F(\vec{X}) = \sum_{t=1}^{T}(\sum_{nh=1}^{NH} W_{nh}\left(\frac{Hs_{nh}(t)-Ho_{nh}(t)}{Hpnt}\right)^2 + \sum_{nf=1}^{NF} W_{nf}\,(\frac{Qs_{nf}(t)-Qo_{nf}(t)}{Qpnt})) \quad (2)$$

Subject to: $s_{k,t} \in \{0,1\}$ *(3)* $\quad 0 \le K_i^n \le K_{max}^n$ *(4)* $\quad \overline{f_j^g} \le f_j^g \le \underline{f_j^g}$ *(5)*

Where $\vec{X}$ represents a set of model calibration parameters, $s_{k,t}$ is the status of a valve *k* at time step *t*, belonging to a vector with values 0 and 1, LN_i^n is the leakage node index for node *i* within demand group *n*, K_i^n is the emitter coefficient for the corresponding leakage location V for the number of possible leaks *i* from the vector of candidate nodes *n* with 0 and K_i^{max} being the minimum and maximum values the emitter coefficient for the group can take, J^n is the set of nodes within group *n*, *NGroup* is the number of node groups, $NLeak^n$ is the number of specified leakage nodes to be identified for the leakage group *n*, f_j^g is the roughness coefficient for pipe *j* in group *g* with $\overline{f_g}$ and $\underline{f_g}$ being the upper and lower limits a roughness coefficient, NK is the number of candidate valves to calibrate, NJ is the number of candidate roughness groups, $F(\vec{X})$ is the objective function to be minimized, corresponding to weighted (W_{nh}, W_{nf}) goodness-of-fit between the field observed and the model simulated values for heads ($Hs_{nh} - Ho_{nh}$) and flows ($Qs_{nf} - Qo_{nf}$), respectively.

3.2. Artificial field data generation using fire flow hydrants and step testing

A hydraulic simulation analysis was carried out in EPANET2 considering the "true" state of the network (Figure 1), i.e., the expected calibrated model. This created an artificial set of field pressure and flow measurements, without accounting for noise. The artificial data were generated to emulate situation when data are collected by means of planned hydrant discharges during night fire flow field tests (NFFFT). The hydrants are, opened to cause a controlled hydraulic stress to the system. Water discoloration risks were also taken into consideration with regards to maximum hydrant velocities (Boxall and Saul, [11]). Planned closures of valves near the hydrants were introduced while the hydrants were open, to cause a controlled alteration of flow direction in the network and variation in velocities of pipes adjacent to hydrants. A number of nodes and pipes of the network were selected as monitoring locations for pressure and flow, with the NFFFT observations being used in the calibration process.

3.3. Model pre-processing for solution search space reduction

A systematic preliminary analysis of the existing network topology was performed and was combined with sensitivity analysis, which provided insight to the topological observability of the different parts of the WDN according to the location of available measurements. This model pre-processing approach was carried out to have as few calibration model parameters as possible and avoid unnecessary simulation of solutions that do not cause any impact on model fitness. Based on this preliminary analysis of observability, the search space size for either unknown status valves, leakage hotspots and incorrect pipe roughness can be reduced significantly. Any pipe, or node that was monitored for flow or pressure, respectively, was assumed to have its state and status known and thus, was excluded from the search space. All valves that were step tested during NFFFT were also assumed to have a known status and no leakage, thus, were removed from the search space along with their upstream and downstream nodes. In addition, all hydrant nodes that were opened during NFFFT were assumed to have no leakage. Any branched component, where no pressure measurements at terminal nodes were available were classified as unobservable from the available measurements and, thus, were also excluded, as calibration cannot be actually performed. From the remaining valves, only those on loops were included in the search space. This is because, in reality, unknown fully closed valves on any branch of the network would be sensed by the customer. Moreover, from the remaining nodes, candidates for leakage were restricted to pipes longer than 20 metres. A sensitivity analysis was, then, performed to assess the effect of any change in topology (e.g., valve closure) or system state (e.g., nodal leakage, pipe roughness change) on the remaining parameters. The candidate valves and leakage nodes were restricted to pipes and nodes with large sensitivity. The remaining valves and nodes were considered as calibration parameters for the optimization problems.

3.4. Calibration Approach

Two calibration problems were solved for the ultimate purpose of leakage detection. One that considered all decision variables together, i.e., a one-stage calibration approach where valve status, leakage hotspot locations, emitters and pipe group roughness are calibrated together and a second one, that considered a staged approach. The second calibration problem involves two stages including two separate optimization problems. During the first stage of the approach only the candidate valves are calibrated for the detection of their initial status. The aim of the first stage is to determine the correct topology of the observable part of the WDN model by minimizing the differences between the observed and simulated heads and flows. Following the first optimization analysis it is expected that the model topology matches the true topology of that part of the WDN. The initial incorrect WDN model is, then, updated accordingly. A second stage optimization analysis follows, using the updated model, which is still uncalibrated for unknown leaks and incorrect pipe roughness. Calibration parameters for this stage involve the index and emitters for the candidate leakage nodes for each demand group and the roughness coefficient for the candidate pipes in each pipe group. Here, a single demand group was used, as the nodal demand mainly involves domestic consumption, along with a group of emitter coefficients. Pipes were grouped according to material with consequent *ks* coefficient ranges. This stage involves several optimization runs, where the number of leakage nodes to be identified by the GA, is specified. At each optimization run the number of leakage nodes to be identified increases and the change in the total objective error is compared with the previous analyses. The fittest scenario should best represent the system losses and locations. A similar approach was used for the one-stage calibration process. Five optimization problems were solved for both calibration problems. The first optimization analysis was undertaken for the identification of a single leak location and corresponding emitter in the WDN. Subsequent optimization runs were carried out to identify additional leaks up to a maximum of five. Following the second optimization stage it is expected that the simulated model predictions for pressure and flow match the field test data as closely as possible, while all leaks within the observable part of the network have been accurately detected and located.

4. Case Study

4.1. The "true" system state

The network layout of the system is shown in Figure 1. It involves a real-life District Metered Area (DMA). The WDN contains 460 junction nodes, 389 pipes, 104 valves and has one reservoir source with a head of 213.19 m. The total mains' length is 14.28 km. Flow from the source node varies between 12.16 l/s at Minimum Night Flow and 17.33 l/s at morning peak demand. Four leakage hotspots (Figure 1) were introduced at nodes j111, j142, j192, j203 (Table 1) leading to a global leakage of 9.89 l/s during minimum domestic demand. Moreover, two valves (T51 and T18) were closed and one (T73) was opened (Table 2). In addition, 21 pipes from the base model, associated with three different pipe material groups (e.g., 15 Cast Iron (CI) pipes, three Cast Iron Cement Lined (CICL) pipes and three Ductile Iron (DI) pipes) were considered for the calibration problem. The rest were assumed to have a known *ks* coefficient. The larger number of pipes chosen for the CI group was based on the fact that it is the dominant pipe material in the specific WDN. The selected pipes in each group were chosen to occur on major flow routes following the model hydraulic analysis, as well as on flow routes to the hydrants. Table 3 provides information for the pipe *ks* roughness values. The *ks* for each pipe group represents the roughness for the pipes considered and not all pipes in the network for that material. This was considered as the true system state for artificial field data generation. Six planned field tests, included in the EPANET model as nodal demands, were operated at nodes j60, j218, j416, j417, j438 and j457 between 00:30 – 07:30 and flows up to a maximum 8 l/s. Generated field test data was obtained from 16 locations recording pressures every 15 minutes, while flows from the inlet main, the pipes supplying the six hydrants and the pipe p375, supplying the upper right-hand corner part of the network were also obtained (Figure 1). A total of 96 data sets over 24 hrs, from midnight to midnight, have been used for the calibration process.

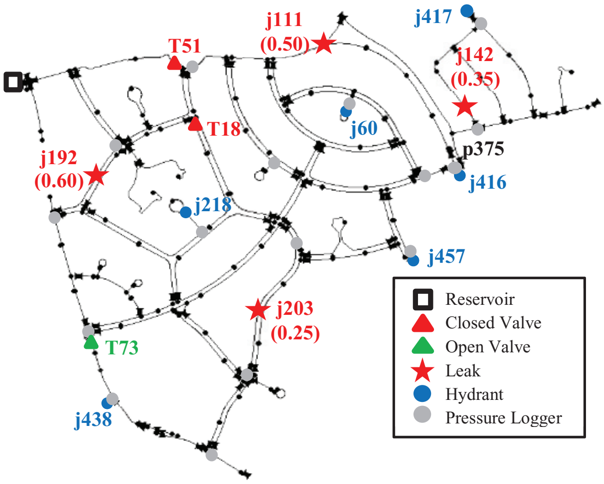

Figure 1. The true District Metered Area system

Table 1. Leakage hotspot information

Label	Emitter Coefficient	Pressure at 04:45 (m)	Leakage at 04:45 (l/s)	Pressure at 08:15 (m)	Leakage at 08:15 (l/s)
j111	0.50	42.86	3.27	32.37	2.84
j142	0.35	45.83	2.40	35.32	2.08
j192	0.60	22.02	2.82	13.55	2.21
j203	0.25	31.35	1.40	20.73	1.14
		Total	**9.89**	**Total**	**8.27**

4.2. The leakage detection model

The hydraulic model that was considered for leakage detection assumed all valves are open, except from known closed boundary valves (Table 2), and that no leaks exist in the network. Furthermore, the *ks* coefficients for each pipe group were set to the assumed "correct" pipe roughness (Table 3). Following model pre-processing using the topological and sensitivity analyses the population of candidate calibration parameters was reduced. Candidate valves were reduced by 71% (from 104 to 30), while candidate leakage nodes were reduced by 79% (from 460 to 97). The following GA parameters were determined experimentally and used for multiple optimisation runs: population size of 300, 1,000 generations, binary tournament selection operator, random-by-gene mutation with the probability of 0.25 and single-point crossover with the probability of 0.90.

Table 2. Valve Initial Status Information

Valve ID	True	Simulated
T18	0	1
T51	0	1
T73	1	0

Table 3. Pipe roughness Information

Pipe Material	Group	True Ks (mm)	Simulated Ks (mm)
CI	1	3.0	5
CICL	2	1.5	4
DI	3	1.5	3

5. Results

5.1. Number of leaks in the Water Distribution Network

Table 4 compares the outcome of the five leakage scenarios between the one-stage and two-stage approaches. The values involve the best objective function errors out of three 1,000 generation optimization runs for each leakage scenario for the task of calibrating for the correct leakage hotspot location and emitter coefficient with and without considering a staged approach to valve status detection. For both approaches a four-leak scenario attains the lowest objective error relative to the rest and, thus, can be considered the most likely, which also matches with the "real" number of leaks in the WDN. However, there is a large difference between the best optimization runs for each scenario between the two approaches. A staged approach for a four-leak scenario, resulted in a much improved objective error of $F = 2.4$, relative to the one stage approach where the best run lead to an error of $F = 475$. The four-leak scenarios for each approach are further analyzed and compared in the next section.

Table 4. Comparison of the best runs for each leakage scenario between the two calibration approaches

Approach used	One-stage					Two-Stage				
Leakage Scenario	1	2	3	**4**	5	1	2	3	**4**	5
Best run	116,146	56,408	12,939	**475**	27,070	35,988	1,486	181	**2.4**	4.3

5.2. One-stage calibration approach

Figure 2 illustrates the best optimization outcome for the four-leak scenario when considering all calibration parameters together. Following a 1,000 generation run the optimizer failed to sufficiently calibrate the model. Table 5 outlines the optimization results for the leakage hotspots. The location and emitters of leakage hotspots were incorrectly detected, while only two out of three unknown status valves were successfully identified. Valve T18 was falsely reported as open. Pipe roughness calibration was also generally unsuccessful (Table 6). CICL pipe material roughness was correctly calibrated and suggested *ks* values for CI pipes were reduced relative to the initial uncalibrated models with values very close to the true *ks* of the pipe groups. On the other hand, *ks* for DI was increased relative to the starting uncalibrated model. The suggested adjustments lead to a reasonable simulation of the global leakage in the WDN during minimum demand conditions of 9.84 l/s, compared to true water losses of 9.89 l/s, however, give a false sense of being correct.

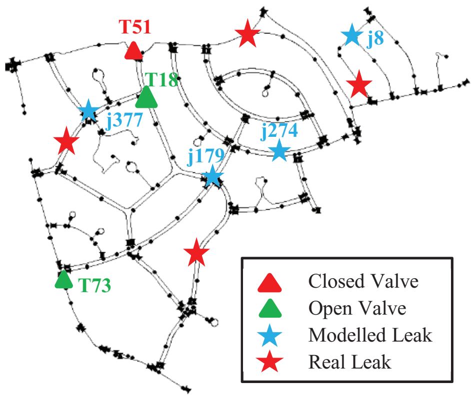

Figure 2. Visualization of the one-stage approach optimisation outcome

Table 5. One-stage optimization results for leakage

Reported leak location	Closest real leak (m)	Emitter Coefficient	Pressure at 04:45 (m)	Leakage at 04:45 (l/s)
j8	161	0.40	39.45	2.51
j179	235	0.45	31.11	2.51
j274	515	0.40	37.78	2.46
j377	100	0.50	22.35	2.36
			Total	**9.84**

Table 6. Roughness calibration result

Pipe Material	True Ks (mm)	Calibrated Ks (mm)
CI	3.0	2.0
CICL	1.5	1.5
DI	1.5	4.0

5.3. Two-stage calibration approach

Following the staged optimization, the calibration of the hydraulic model was improved. During the first stage of the optimization the two unknown closed valves and the open cross connection were successfully detected (Figure 3). This provided insight into the correct network topology. No false positives were detected by the optimizer. After successful detection of unknown status valves, the optimization outcome for the second stage lead to an objective error of $F = 2.4$. Two out of four leak locations were successfully detected on the spot, while the rest were reported within 150m distance away from the true leakage location (Table 7). The corresponding leakage emitter coefficients were simulated very close to the real values, which lead to a successful representation of the global leakage in the WDN. On the other hand, the optimization outcome for pipe *ks* coefficients did not lead on to correct calibration (Table 8). However, as in the one-stage calibration the suggested *ks* values for CI-based pipes were reduced relative to the initial uncalibrated model, while DI pipe material group roughness was further increased.

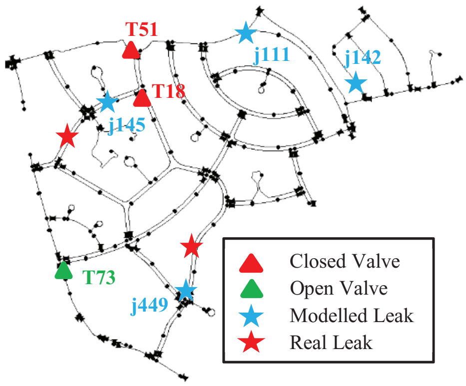

Figure 3. Visualization of the two-stage approach optimisation outcome

Table 7. Two-stage optimization results for leakage

Reported leak location	Closest real leak (m)	Emitter Coefficient	Pressure at 04:45 (m)	Leakage at 04:45 (l/s)
j111	0	0.60	42.83	3.93
j142	0	0.35	45.79	2.37
j145	149	0.50	21.08	2.30
j449	121	0.25	26.45	1.29
			Total	**9.89**

Table 8. Roughness calibration result

Pipe Material	True Ks (mm)	Calibrated Ks (mm)
CI	3.0	1.5
CICL	1.5	1.5
DI	1.5	6.0

6. Discussion

6.1. One-stage vs Two-stage approach

The inverse calibration problem is often under-determined in real-life conditions, due to a larger number of calibration parameters relative to the number of available measurements, which must be grouped to produce an even- or over- determined problem. This issue can often lead to non-uniqueness of the identified parameter values. Through topological and sensitivity-based analyses, important benefits were secured, as unobservable network components were removed from the search space causing a significant reduction to the number of calibration parameters and avoidance of unnecessary solution generations. In theory, an over-determined optimization problem including observable parts of the network as calibration parameters should be able to be solved with a reasonable accuracy.

Further improvements can be achieved by using a staged approach to solve the calibration problem, as demonstrated by the optimal solutions between the applied calibration methods. A first stage optimization analysis which only considered candidate valves, followed by second stage repeated analyses for different possible leak-scenarios and pipe *ks* calibration, achieved over-determined problems in both instances. This initially led to a successful topological calibration. Such step was essential for the improved detection of leakage hotspots. The two incorrectly detected leak locations lead to a compromised sub-optimal pipe *ks* calibration. The low flows in pipes leading to hydrant j457, where leak j203 is located, have impacted its correct localization, while the near-correct emitter detection of the leak close to j192, has also possibly caused its incorrect localization. However, when all calibration variables were considered together for the optimization analysis, the larger number of solution combinations lead to sub-optimal leakage detection. Only two out of three topological anomalies were detected. The incorrect network topology was compromised by incorrect assignment of leakage hotspot locations and emitters, as well as pipe *ks* coefficients.

This method is also applicable to larger WDNs, however, its accuracy depends on the number and locations of available measurements. It is expected that a staged calibration approach would perform better than a one-stage method, due to the optimization problem dimensionality. Nevertheless, a drawback of the presented method is that the possible number of leaks to be identified has to be specified a priori. The results suggest that multiple optimization runs for different leakage scenarios prove beneficial for getting a reasonable representation for the number of leaks in the network. This involved increasing the coded chromosome genes of the GA, each time by two, one representing an additional leakage location and one for the corresponding leakage emitter coefficient. However, running several optimization analyses for many leakage scenarios can be time consuming, especially for larger systems.

6.2. Improved calibration field test data using hydrants and step testing

Optimisation can be a powerful tool for leakage hotspot detection. Thus, systematic approaches that leverage hydraulic models along with optimization techniques can be beneficial for network operations, if accompanied by good quality field data. A large amount of accurate observation data is a necessary step for estimating calibration parameters with sufficient confidence [1]. However, this often comes to opposition with reality, because of financial and time constraints for field measurement collection. Apart from that, the impact caused by small unknown leaks, or the local effect caused by unknown closed/open valves can be often insufficient to allow detection due to the measurement noise levels compared to model accuracy. Current WDN models are calibrated to simulate observed pressures within ±1 metres, whereas field pressure transducer accuracy lies within an order of magnitude less (e.g., ±0.1m). Thus, hard-to-find leaks and topological anomalies can remain undetected due to small head losses. This can be improved by introducing known interventions during field tests, such as fire flow hydrant discharge during low demand periods, along with planned valve closures on pipes close to the hydrant locations. Taking into account discoloration risk, such approaches cause a controlled hydraulic stress on the WDN. As leakage is at its highest value during minimum domestic demand due to higher pressures in the WDN, opening of fire flow hydrants at key low-discoloration risk locations will increase head losses (or gains) arising from the topological and leakage-related errors, able to highlight the anomalies. This will lead to improved opportunities for more successful detection of those previously undetected model anomalies, in association with new optimisation-based modelling methods.

7. Conclusions

This paper presented an improved staged calibration approach that uses a WDN hydraulic model along with an optimization method to determine the location and flows of leaks which were modelled, as flow emitters. Moreover, discussions were made on how improved calibration can be achieved through the use of field data that involve controlled stress in the WDN from fire flow hydrant discharge and step testing. A desktop study of a real WDN was undertaken, where unknown status valves, leakage and incorrect pipe roughness were introduced. Artificial calibration data were generated by means of planned hydrant discharges during a low demand period, combined with step tests. Two calibration problems were solved, comparing a one-stage approach with a two-stage approach. Preliminary topological and sensitivity analyses of the hydraulic model lead to a reduced solution search space in excess of 70%.

Calibration parameters included unknown status valves, leakage location and emitter coefficients, as well as grouped pipe roughness coefficients. Several optimization analyses were implemented to determine the best leakage scenario.

The results obtained suggested that relative to a one-stage approach, a two-stage approach where the status of candidate valves is firstly detected to provide insight in WDN topology, can lead to an improved leakage detection. The staged approach has fulfilled the purpose of the paper, being successful detection of unknown valve statuses, leakage hotspot detection and pipe roughness calibration. In practice, the promising approach can be lead to a useful tool for network operations. Future work include the implementation of the approach using real field test data.

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