Fire and drinking water capacity enhancement in water distribution networks

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ABSTRACT

The purpose of the present study is to introduce a newly developed capacity increment (also pressure sensitivity reduction) technique in the case of drinking water distribution systems (WDS). The main novelty of this method is based on a correlation between two parameters of the water distribution network – one characterises its robustness in a topology-specific way, the other can be calculated with only one hydraulic simulation. With the help of connection the topology optimisation – the identification of the optimal place for installing a new pipe – can be determined within a short processing time, and without the implementation of a stochastic optimiser algorithm. The first part of the paper presents problems caused by high pressure sensitivity and introduces the mathematical background of the method, besides which it discusses the details of the algorithm. After that, the second part presents the results gained by the implementation of the method in two case studies: real-life water distribution systems of a small and a medium-sized town. For the small town, verification is possible by comparing the result of our method with the total hydraulic evaluation of the WDS.

Key words | capacity increment, pressure sensitivity, topology optimisation, water distribution systems

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INTRODUCTION

Water distribution systems (WDS) are crucially important infrastructural elements of every settlement (from small villages to large cities). Therefore, pressure fluctuations originating mostly from unpredictable consumption variation inflict significant financial loss to the provider and discomfort to the inhabitants. As Ghorbanian *et al.* (2016) found, this problem has two main aspects. On the one hand, if the pressure of the water distribution system decreases below a critical level, the consumers experience demand fulfilment injury as a consequence of the low outflow. Due to this phenomenon the providers of this area experience a growth in both the number of customer complaints and profit loss. On the other hand, the water distribution systems supply water for fire hydrants. If the system pressure falls below the minimal pressure requirement of the hydrants, the discharge rate of the hydrant is not adequate, and thus it raises disaster management concerns and can lead to a significant fine for the provider, as is mentioned by Snyder *et al.* (2002). Addressing these issues, our goal is to identify the minimal topological modification (adding a single pipeline to the system) which leads to the largest increment in the pressure robustness of the network.

These pressure and demand uncertainties, as House-Peters & Chang (2011) review, originate from almost unpredictably complex human and natural processes, uncertainty and resilience across spatial and temporal scales. As a result, many researchers focus their effort on the pressure robustness increment of the WDS, like Diao *et al.* (2016), who developed a technique to characterise network robustness from the viewpoint of pipe bursts. As Mala-Jetmarova *et al.* (2018) summarises this, the commonly used method for WDS topology optimisation is the implementation of a stochastic global optimiser algorithm

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(e.g. genetic algorithm as in Saldarriaga et al. (2015) or self-adaptive differential evolution as in Zheng et al. (2013)) and forming one (or many different) objective function(s) (e.g. as in Babayan et al. (2007)). In contrast, Pudar & Liggett (1992) were the first to use a fully analytical optimisation technique where they used the nodal pressure sensitivity as a robustness property of a WDS for the identification of the unreported pipe bursts. Based on this work, Izquierdo et al. (2008) used this method for the recognition of the sundry and relative importance of different pipes in a water distribution network, and to help in assessing their impact on the hydraulic performance of the network. Lastly, Fiorini Morosini et al. (2014) extended this technique for the optimal measuring point determination in the case of network model calibrations.

As was analysed by the many cited researchers, if one would like to design a new water distribution system – or to extend a system with a large new segment – genetic algorithms (GAs) or other stochastic global optimising algorithms are the most efficient tools for this purpose. But in this case, when our focus is to upgrade an already operating system by adding one single pipeline, the optimising algorithm would face many challenging aspects from the viewpoint of the fitness function. As was analysed by Maier et al. (2014), if the number of possible solutions is too large – which is called combinatorial explosion – the convergence robustness of GAs strongly decreases. Cui & Kuczera (2005) identified the same effect in the case when the topology of the fitness function is completely unordered. In this case, the fitness function of the optimisation is the following:

$$f(ID_1, ID_2) = \max(F) \tag{1}$$

where ID_1 and ID_2 mark the start and end node identification number of the new pipeline, F is the selected fitness function, and max means that the algorithm searches for the maximum of the function. The identification numbers given by the distributors are completely unordered in terms of optimisation, resulting in a stochastically generated discrete fitness function, meaning that one step forward or backward in the ID list could result in a huge change in the fitness function. On the other hand, the fitness function has only two parameters – ID_1 and ID_2, meaning the GA's genetic operators only have two input variables for inheriting the information and the essence of the evolutionary optimisation is not utilised. These factors imply that the reliability of the global stochastic optimisation algorithms decreases considerably, as was analysed by Fan et al. (2004) and López-Pujalte et al. (2002, 2003). To overcome these issues, we are introducing a significantly different approach in this paper.

APPROACH

To determine the location where the installation of a new pipeline eventuates the largest pressure sensitivity decrement, and through that the largest capacity increment in the water distribution network, a new method was defined based on the sensitivity matrix defined by Pudar & Liggett (1992). The implementation of this method is done using the Staci one-dimensional hydraulic modelling software developed by Selek et al. (2012).

The objective function of the sensitivity analysis

As is suggested by Pudar & Liggett (1992) we take the linear equation system describing a WDS in the following form:

$$\underline{F}(\underline{p}(d), d) = \underline{0}, \tag{2}$$

where p is the vector of the nodal pressures, and d is the nodal demands. The calculation of the derivative of this equation with respect to the demands results in:

$$\frac{\partial \underline{F}}{\partial \underline{x}}\frac{\partial \underline{x}}{\partial d} + \frac{\partial \underline{F}}{\partial d} = \underline{0}, \tag{3}$$

where $\partial \underline{F}/\partial \underline{x}$ is the Jacobian matrix, and $\partial \underline{x}/\partial d$ is the sensitivity matrix. The sensitivity matrix holds the derivatives of the nodal pressures with respect to the demands, in the following form:

$$S_d^p = \left[\frac{\partial p_i}{\partial d_j}\right] = \begin{pmatrix} \frac{\partial p_1}{\partial d_1} & \cdots & \frac{\partial p_1}{\partial d_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial p_n}{\partial d_1} & \cdots & \frac{\partial p_n}{\partial d_n} \end{pmatrix} \tag{4}$$

where n is the number of nodes in the WDS. Based on the sensitivity matrix, three new parameters, namely local, average and peak sensitivity, are introduced. If the demand increases in a node, the pressure of the system changes. To characterise the pressure robustness of a node, the local pressure sensitivity (S^i_{local}) is introduced, which is the row-wide summation of the elements of the pressure sensitivity matrix. The peak sensitivity (S_{peak}) is the pressure sensitivity of the node which has the highest local sensitivity, while the average sensitivity ($\bar{S}$) describes the whole system through the average value of the local sensitivities.

We can extend these parameters between two topological states of the WDS as the following:

$$\Delta S_{\mathrm{peak}} = \left(1 - \frac{S^{\mathrm{new}}_{\mathrm{peak}}}{S^{\mathrm{old}}_{\mathrm{peak}}}\right) \cdot 100\ [\%] \tag{5}$$

where 'new' superscript means the topology after, and 'old' superscript means the topology before connecting a new pipeline in the system. We can define a new parameter which characterises the effect of a topological modification, the peak sensitivity difference. If we do the same with average sensitivity value, we get the average sensitivity difference:

$$\Delta \bar{S} = \left(1 - \frac{\bar{S}^{\mathrm{new}}}{\bar{S}^{\mathrm{old}}}\right) \cdot 100\ [\%] \tag{6}$$

We found that $\Delta \bar{S}$ and ΔS_{peak} parameters are topology-specific values, as the calculation of these parameters before and after the virtual installation of a new pipeline describes its effect on the pressure robustness of the system.

The implementation of the method

With the help of the $\Delta \bar{S}$ and ΔS_{peak} parameters, we define the following fitness function:

$$f(ID_1, ID_2) = \max(\Delta \bar{S}) \tag{7}$$

where (ID_1) and (ID_2) mean the identification number of the connected nodes. If we are not limited by the calculation time – because of the exponential growth of the possibilities as a function of the system's size – we could use a trial-and-error method for all of the possibilities, but for industrial use and real-life water distribution analysis a faster technique is needed. At the beginning, we used the genetic algorithm toolbox published and developed by Wall (1996). Later the differential evolution algorithm was implemented following the work of Storn & Price (1995). But in all cases, we experienced convergence problems with these fitness functions, which originated from the randomness of the identification numbers, and through that the non-smoothness of the fitness function.

To solve this problem, we searched for new variables that can be used for the refinement of the fitness function. First, fully synthetic networks are created where the optimal pipeline connection is known. As we analysed the parameters of these synthetic networks we found that the local pressure sensitivity difference, described as:

$$\Delta S_{\mathrm{local}} = \left(\frac{|S^i_{\mathrm{local}} - S^j_{\mathrm{local}}|}{\max(\Delta S_{\mathrm{local}})}\right) \tag{8}$$

shows strong correlation with the optimal pipeline connection. Namely, where the local pressure sensitivity difference is maximal – where we connect a very robust node to one very poorly conditioned – the optimal pipeline connection is found. This phenomenon can be explained with the following considerations; if we analyse a network from the viewpoint of pressure sensitivity it can be seen – e.g. the deep blue nodes in Figure 1 – that the nodes with the lowest pressure sensitivity are always close to the source point, and the most robust one is the source itself (its pressure will not change regardless of the parameters). As the average path length between the source and a node increases, more and more, consumer demand has an effect on the nodal pressure. As a result, the nodal pressure sensitivity increases as the distance from the source increases. Based on the pressure sensitivity map, our technique is able to identify the shortcut which decreases the path length of the water, along with increasing the robustness of the critical area.

The main novelty in our method is in finding that the local pressure sensitivity difference between two nodes (without a pipe connection between them) predicts the

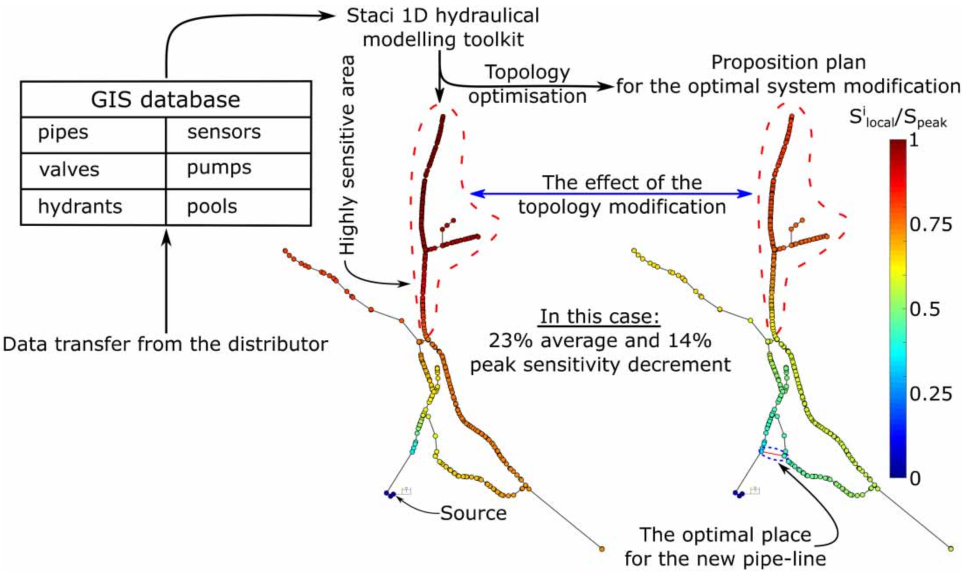

Figure 1 | The effect of the determined pipe connection. The two sensitivity maps have the same colour scale. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/ws.2020.037.

possible achievable average and peak robustness growth, resulting from the pipeline connection. With the help of this connection, the identification of the pipeline which maximises the pressure robustness of the system can be determined with only one hydraulic simulation. In the case of a real WDS, the steps of the method are the following:

- First, based on the GIS (geographic information system) database of the distributor, a one-dimensional hydraulic simulation model is built in the Staci modelling toolbox.
- After that, a hydraulic and sensitivity calculation is performed and all of the possible node connections – within an economic limit (maximalised pipeline-length) – are organised as pairs.
- At the end, for all of the node pairs the local pressure sensitivity difference is determined and the pairs with the ten highest values are chosen and hydraulically simulated for the evaluation of the peak and average sensitivity difference between the topologically extended – when the new pipeline has been implemented – and original state of the WDS.
- In order to reach a common optimum between the investment cost and robustness growth, out of the ten solutions the cheapest build-highest robustness gain construction can be chosen by the provider.

DISCUSSION

The described method was tested on the simulation model of real-life water distribution networks, which was built using the provider's GIS data. We found that the method only needs a few seconds runtime even in the case of a large network (more than 6,000 nodes).

Case study 1

The first analysed real-life network was the WDS of a small western Hungarian town, which has 400 nodes and distributes water for 1,000 inhabitants. As the results show, this small town has a large, highly sensitive area near its upper end.

With the help of the described method, we found a solution – within the economic limit of 120 m maximal pipe length – which reduces the average sensitivity by 23% and the peak sensitivity by 14%, while a 102.5-metre-long pipeline is connected (see the pipe marked by the blue dashed line in Figure 1).

The smallness of this network makes it possible to verify the results of our method with the complete evaluation of the possible pipe connections. With the help of 79,800 hydraulical simulations, the robustness map of the network is calculated, as can be seen in Figure 2. As is clearly seen, the result of the complete evaluation and the result of our method give exactly the same result (102.5 m long pipe, 23% average sensitivity decrement). The hydraulic simulation cost of the total evaluation scaled exponentially with the size of the network, until our method, which needs just a few simulations even in the case of the largest networks, to reach the same result.

The determination of the Pareto optimality

As the envelope curve of Figure 2 indicates, if the implementation of a very long (near 1.2 km long) pipeline is possible, we are able to reach the global optimum of pressure robustness increment, but in a real-life scenario, the project budget might prevent the realisation of the solution. With the help of the identified connection between the local sensitivity difference and average robustness it is possible to determine the Pareto-optimal solutions which connect the cost function – in this case it is the pipe length – with the reachable average robustness growth as can be seen in Figure 3.

With the help of the identified connection of the parameters it is possible to calculate the Pareto front of the optimal solutions partially – or even the full Pareto front under a few hundred hydraulic simulations. As is clearly seen for these case studies, the economically optimal pipe length was selected as the first large step of the Pareto-optimal solutions.

Case study 2

After the verification of the method, a larger network was analysed. The network presented below is also located in western Hungary, and provides water for 3,500 people and has 2,700 nodes. The figure below shows its pressure sensitivity map, on left without, and on the right with the proposed new pipe connection. The economically optimal pipe length was fixed as 120 metres again. As is seen in Figure 4, the algorithm found a pipeline which causes 15% decrease on average and 28% reduction in peak sensitivity, with only a 94.5-metre-long pipe connection.

At last, the extended system was analysed from a new aspect. Consultation with the operating company of the WDS revealed capacity problems in the critically sensitive region of the second network (see the red-coloured region in the left panel of Figure 4). To analyse the results from the aspect of the maximal reachable demand, a hydrant model was created. Most of the hydrants are passive hose connections for the fire service, and as a result, the fire extinguisher capacity is deeply based on the pressure stability of

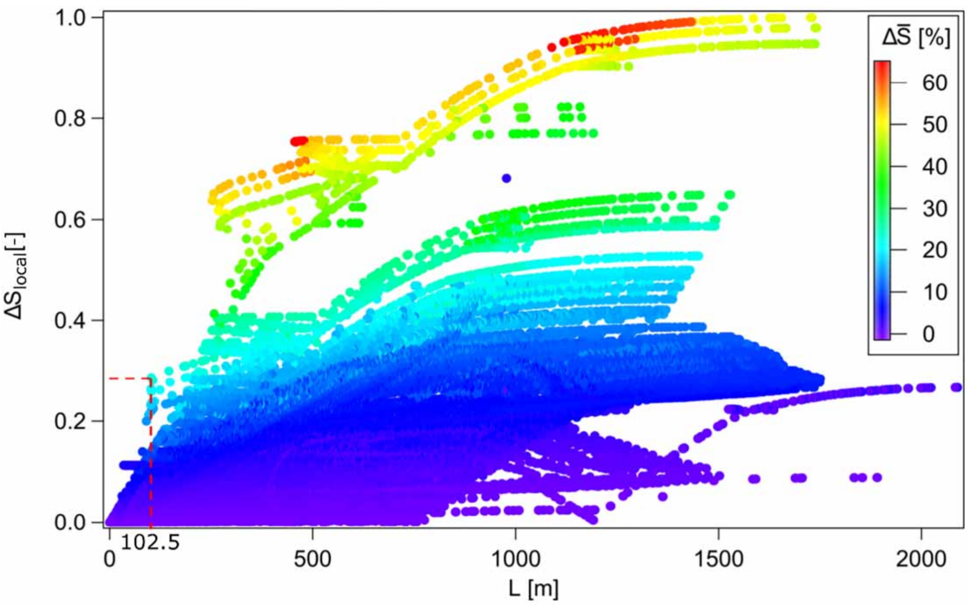

Figure 2 | The complete sensitivity map of the smallest analysed WDS. The red dashed line indicates the optimal solution within the 120 m pipeline-length economical limit. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/ws.2020.037.

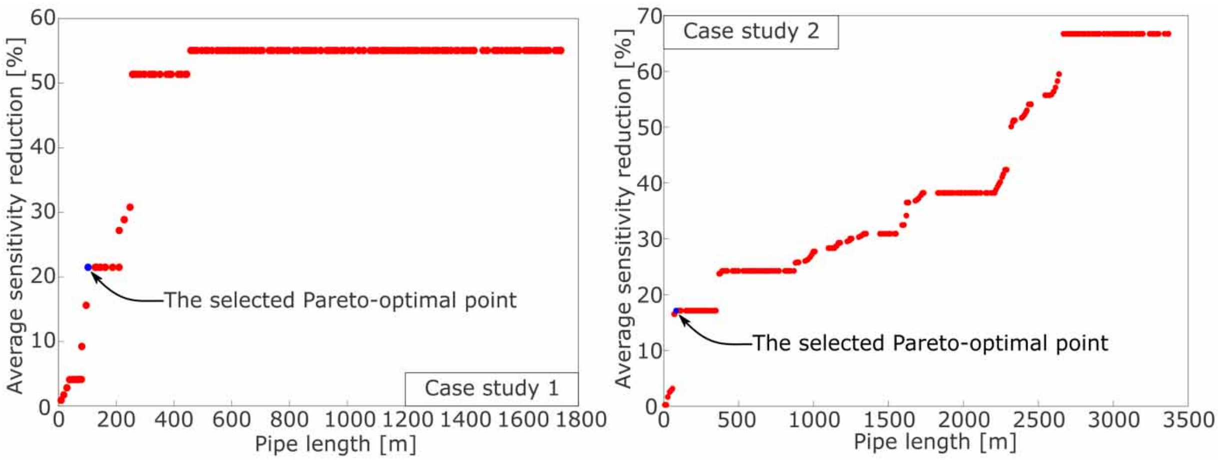

Figure 3 | The Pareto front of the pipe length and average sensitivity decrement for the two case studies.

the system, and it is a good indicator for the local outflow capacity of a network segment. Thus, if a hydrant is opened, a new large demand is applied for one specific node of the WDS. In the case of such a highly sensitive area, this size of demand increment decreases the pressure and through that the hydrant outflow capacity. The hydrant model was a simple choked outflow for the atmosphere. The choked opening for the atmosphere – the hydrant model – was connected only for one node at a time, and for every case a new simulation was calculated to gain the output volume of the system before and after the optimised pipe connection. To obtain detailed information about the firewater capacity of the system, 672 different nodes from the highly sensitive area were used for the histogram creation. As Figure 5 clearly indicates, the average firewater capacity of the critical area is increased by 20%. Besides that, some of the hydrants gain extremely high capacity. While the hydrants in the unmodified case have maximally 140% of the average firewater flowrate, in the modified case, a few hydrants can produce 200% of the original average flowrate. The impact of the modification was analysed from the aspect of the pump operation point and the results of the simulations verified its equality with the pre-modification state. As a result, it can be said that this method is able to reduce the WDS's pressure fluctuation and firewater

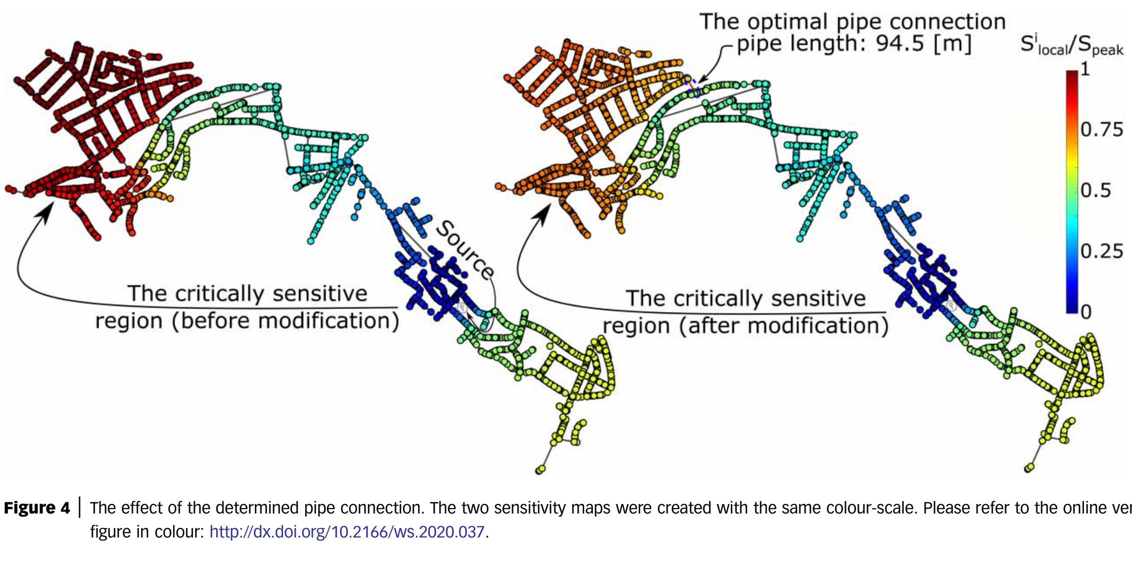

Figure 4 | The effect of the determined pipe connection. The two sensitivity maps were created with the same colour-scale. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/ws.2020.037.

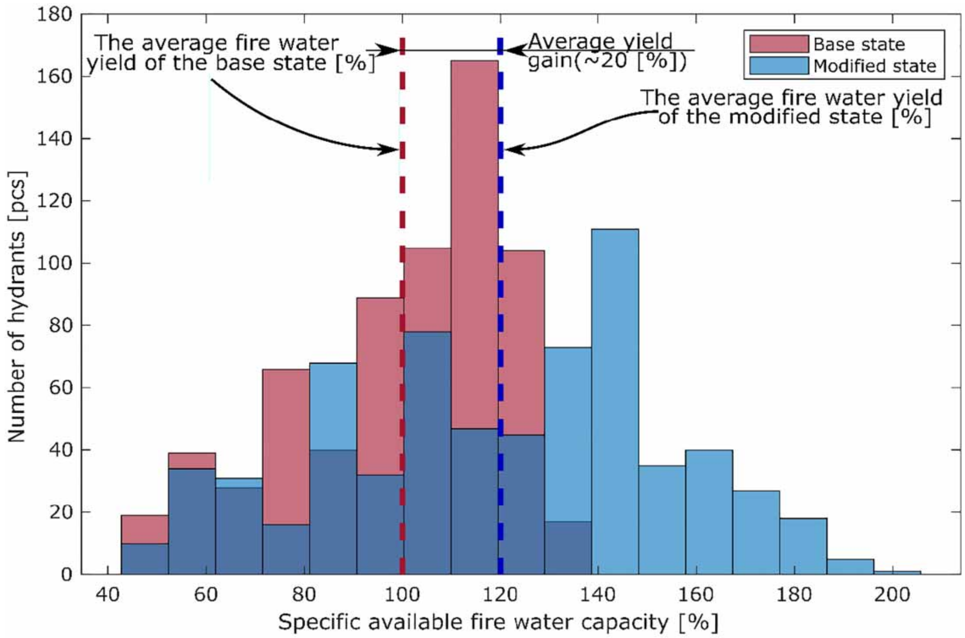

Figure 5 | The capacity histogram of the critically sensitive area. The original state is marked with red, the results of the modification are marked with blue colour. Please refer to the online version of this paper to see this figure in colour: http://dx.doi.org/10.2166/ws.2020.037.

capacity problems with the lowest possible investment cost and without increasing the operating cost of the system.

SUMMARY

In this paper, we introduced a highly computational time-efficient method for the identification of the optimal location for a new pipeline from the viewpoint of the pressure robustness and capacity increment of the network. The mathematical and physical background of this method and the algorithm itself were presented in the first part, while the second part introduced two case studies where the method was implemented on two real-life WDS. The validity of the method was verified through comparison with the results of the evaluation of all possible pipe connections, in the case of the smallest test network. After the verification of the method, the second case study presented the effect of the topology optimisation from the viewpoint of the firewater capacity increment. As a result, we found that the reachable firewater capacity in the highly pressure-sensitive city district showed a large increment, as shown in Figure 5. Lastly, the effect of the topology was considered in the aspect of the operating cost, and the simulation results suggested that the operating point of the system does not change due to the modification of the topology, thus it can be said that the operating cost remains on the original level.

In this paper, we worked out and verified a new method which can be utilised to increase the sustainability and cost-efficiency of WDS. The method relies on increasing the pressure robustness of the system through the optimisation of the network topology. A new connection was found between the local pressure sensitivity difference and the topology-dependent average pressure sensitivity. Thus, it takes only a few simulations to reach the same result as the evaluation of all possible connections.

REFERENCES

Babayan, A. V., Savic, D. A. & Walters, G. A. 2007 Multiobjective optimization of water distribution system design under uncertain demands. In: *Topics on System Analysis and Integrated Water Resources Management* (A. Castelletti & R. S. Sessa, eds), Elsevier, Amsterdam, The Netherlands, pp. 161–172.

Cui, L. & Kuczera, G. 2005 Optimizing water supply headworks operating rules under stochastic inputs: assessment of genetic algorithm performance. *Water Resources Research* **41** (5), W05016. doi:10.1029/2004WR003517.

Diao, K., Sweetapple, C., Farmani, R., Fu, G., Ward, S. & Butler, D. 2016 Global resilience analysis of water distribution systems. *Water Research* **106**, 383–393.

Fan, W., Fox, E. A., Pathak, P. & Wu, H. 2004 The effects of fitness functions on genetic programming-based ranking discovery for web search. *Journal of the American Society for Information Science and Technology* **55** (7), 628–636. doi:10.1002/asi.20009.

Fiorini Morosini, A., Costanzo, F., Veltri, P. & Savić, D. 2014 Identification of measurement points for calibration of water distribution network models. *Procedia Engineering* **89**, 693–701.

Ghorbanian, V., Karney, B. & Guo, Y. 2016 Pressure standards in water distribution systems: reflection on current practice with consideration of some unresolved issues. *Journal of Water Resources Planning and Management* **142** (8), 04016023.

House-Peters, L. A. & Chang, H. 2011 Urban water demand modeling: review of concepts, methods, and organizing principles. *Water Resources Research* **47** (5), W05401.

Izquierdo, J., Montalvo, I., Pérez, R. & Herrera, M. 2008 Sensitivity analysis to assess the relative importance of pipes in water distribution networks. *Mathematical and Computer Modelling* **48**, 268–278. doi:10.1016/j.mcm.2007.10.010.

López-Pujalte, C., Guerrero Bote, V. P. & de Moya Anegón, F. 2002 A test of genetic algorithms in relevance feedback. *Information Processing and Management* **38** (6), 793–805. doi:10.1016/S0306-4573(01)00061-9.

López-Pujalte, C., Guerrero-Bote, V. P. & de Moya-Anegón, F. 2003 Genetic algorithms in relevance feedback: a second test and new contributions. *Information Processing and Management* **39** (5), 669–687. doi:10.1016/S0306-4573(02)00044-4.

Maier, H. R., Kapelan, Z., Kasprzyk, J., Kollat, J., Matott, L. S., Cunha, M. C., Dandy, G. C., Gibbs, M. S., Keedwell, E., Marchi, A., Ostfeld, A., Savic, D., Solomatine, D. P., Vrugt, J. A., Zecchin, A. C., Minsker, B. S., Barbour, E. J., Kuczera, G., Pasha, F., Castelletti, A., Giuliani, M. & Reed, P. M. 2014 Evolutionary algorithms and other metaheuristics in water resources: current status, research challenges and future directions. *Environmental Modelling and Software* **62**, 271–299. doi:10.1016/j.envsoft.2014.09.013.

Mala-Jetmarova, H., Sultanova, N. & Savic, D. 2018 Lost in optimisation of water distribution systems? A literature review of system design. *Water* **10** (3), 307.

Pudar, R. S. & Liggett, J. A. 1992 Leaks in pipe networks. *ASCE Journal of Hydraulic Engineering* **118**, 1031–1046. doi:10.1061/(ASCE)0733-9429(1992)118:7(1031).

Saldarriaga, J., Páez, D., León, N., López, L. & Cuero, P. 2015 Power use methods for optimal design of WDS: history and their use as post-optimization warm starts. *Journal of Hydroinformatics* **17** (3), 404–421.

Selek, I., Gergely Bene, J. & Hős, C. 2012 Optimal (short-term) pump schedule detection for water distribution systems by neutral evolutionary search. *Applied Soft Computing* **12**, 2336–2351.

Snyder, K., Deb, A. K., Grablutz, F. M., McCammon, S. B., Grayman, W. M., Clark, R. M., Okun, D. A., Tyler, S. M. & Savic, D. 2002 *Impacts of Fire Flow on Distribution System Water Quality, Design and Operation*. AWWA, Denver, CO, USA.

Storn, R. & Price, K. 1995 *Differential Evolution – A Simple and Efficient Adaptive Scheme for Global Optimization over Continuous Spaces*. Technical Report TR-95-012.

Wall, M. 1996 *GAlib: A C++ Library of Genetic Algorithm Components*. Mechanical Engineering Department, Massachusetts Institute of Technology, Boston, MA, USA.

Zheng, F., Zecchin, A. C. & Simpson, A. R. 2013 Self-adaptive differential evolution algorithm applied to water distribution system optimization. *Journal of Computing in Civil Engineering* **27** (2), 148–158.

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