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LEAKAGE LOCALIZATION IN VIRTUAL DISTRICT METERED AREAS WITH DIFFERENTIAL EVOLUTION

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Leakages in water distribution systems (WDS) can lead to supply interruptions, contaminations and economic losses. Hence finding leaks before they cause severe problems is a crucial task for water utilities. To identify the existence of leaks, night flow measurements in district-metered areas (DMA) are common practice. Therefore, the entire system has to be structured in hydraulically separated partial networks. However, many utilities do not want to lose the hydraulic redundancy of their system and hence search for other solutions to identify and allocate leaks. In our research, the effects of leakages on the hydraulic behavior of WDS are utilized to find the optimal solution for placing hydraulic sensors. From the discrepancy of the unperturbed and the perturbed WDS due to the occurrence of leakage, a methodology is developed which enables an efficient placement of flow meters and pressure sensors. A Fault Sensitivity Matrix (FSM) achieves this. A specific Genetic Algorithm (GA) called Differential Evolution (DE) to save significantly on computation time in large WDS carries out finding the optimal position of a minimum number of sensors. DE is chosen due to its good rate of convergence. Once an optimal sensor placement is obtained, DE is also used for leakage localization. The methodology has been applied and tested in two different WDS. The first WDS was a model network, which was previously used by other authors. The second was the distribution network of the city of Linz. Here the task was to place as few sensors as possible concerning economical costs while guaranteeing leakage localization to an area of a predefined size. In this paper it is shown that DE performs well, both on sensor placement and leakage localization, for the two investigated systems. Additionally the implementation of demand and measurement uncertainties is outlined.

INTRODUCTION

Leakages in WDS can cause crucial damage on surrounding infrastructure. Furthermore they increase the risk of contamination of the delicate resource water. That is the reason, why finding leaks in WDS as soon as possible is of great importance.
There exist various technologies for leakage detection based on different physical effects caused by water loss in the system, e.g. acoustic noise logging, ground penetrating radar, transient analysis, step testing, etc. The method presented in this paper is solving a so-called inverse problem. Therefore, measurements of flow and pressure during the period of minimum

night flow are compared with the outcome of a hydraulic simulation. The measurement period at the minimum night flow is chosen, because at this time the demand is at its minimum resulting in a higher pressure in the system that in turn influences leakage outflow. The leakage parameters in the simulated hydraulic model are adjusted in such a way, that the simulation reproduces the measured values as good as possible. The optimization task then is, to find the ideal parameter set that describes the leakage in the system reproducing the measured flows and pressures the best. The problem is solved with the help of GAs (Goldberg [1]). In the last decades, GAs became more and more used in water related work (Nicklow et al. [2]). For this problem a special GA called DE, invented by Storn and Price [3], is used due to its good rate of convergence. In the past, Marchi et al. [4] already showed that DE performed best for WDS optimization.

Furthermore, for leakage localization the choice of the measurement positions in the WDS is also of great importance. Finding the best sensor positions in a WDS is achieved by a method called Fault Detection and Isolation (FDI) (Pérez *et al.* [5]). This leads once more to an optimization problem that is again solved by DE.

Both methods, the leakage localization and the sensor placement, were applied to two different WDS. The first WDS is a model system from literature introduced by Poulakis *et al.* [6]. The second WDS is a sub network of the city of Linz in Austria. The application of the sensor placement and the leakage localization with DE performed excellent in both investigated WDS. Finally, we discuss a method how to incorporate demand uncertainty propagations, causing noise at the measurement locations, into the computations. This can be achieved by Monte Carlo analysis, which would lead to high computational effort. On the other hand by linearizing the hydraulic system in a working point with a hydraulic small signal model (HSSM) is pointed out as well.

METHODS

In the approach presented in this paper finding leakages in WDS is achieved by solving an inverse problem. For that reason, pressure and flow is measured at N selected sensor positions in the WDS. Simultaneously, a calibrated hydraulic model of the investigated WDS is simulated with EPANET (Rossman [7]). The input parameters $\vec{x}$ of the hydraulic model, in this case parameters describing the leakage (in EPANET the emitter coefficient $\boldsymbol{c_e}$ and the emitter exponent $\boldsymbol{e_e}$), are tuned in such a way, that the discrepancy of the real world measurements m and the resulting pressures and flows obtained from the simulated model $\tilde{m}$ is minimized. Mathematically, this is described by the following equation

$$f(\vec{x}) = \frac{1}{N}\sum_{i=1}^{N}\left(m_i - \tilde{m}_i(\vec{x})\right)^2 \quad \rightarrow \quad \min \tag{1}$$

The challenge is to find the ideal parameter set $\vec{x}$ that minimizes the quadratic distance between the model output and the data. We consider this vector to be the best representation of the state of the real system.

Leakage Localization with DE

The problem described by Eq. (1) forms a non-linear quadratic optimization problem, which is challenging to solve. The non-linear nature is caused by the hydraulic model. Further the problem formulation offers a discontinuous objective function due to numerical inaccuracies and the discrete representation of leakages by the parameter vector.

These two features of the problem statement make GAs the method of choice for solving Eq. (1). Due to its good rate of convergence, a special GA, called DE is chosen. For the fitness function for the DE algorithm Eq. (1) can be used. The assumption of the genome of the candidate solution is more complex. To describe leakages as pressure dependent demands in EPANET, the emitter exponent e_e and the emitter coefficient c_e to model a leakage outflow Q has to be adjusted. The mathematical relationship between Q and the pressure p obeys the power law behavior

$$Q = c_e \, p^{e_e} \quad . \tag{2}$$

If focusing just one time step instead of a whole time series, a fixed value for e_e, e.g. $e_e = 1$, can be chosen and the leakage outflow is then represented through c_e parameter. Due to the fact that we are just interested in measurements during the night minimum, since at this time step the demand uncertainties have a minimum. Thus, the effect of the leakage on the system is at its maximum, so this approach is valid. Besides the size of the leakage, the leakage position L_P is also important. Therefore, the genome of one candidate solution consists of the 2-tuple $\vec{x} = (c_e, L_P)$ for a single leakage. This genome is easily extendable for multiple leakages, e.g. the 2n-tuple describes a fixed number of n leakages in the system $\vec{x} = (c_{e1}, L_{P1}, c_{e2}, L_{P2}, \ldots, c_{en}, L_{Pn})$. For a variable number of leakages DE is not capable. Consequently, one has to switch to another class of GAs, called messy GA (mGA) (Goldberg *et al.* [8]) that can handle variable genome lengths.

One main difference between normal GAs and DE is the crossover operator. In the DE algorithm the crossover needs three input candidate solutions, instead of two in a normal GA. The procedure of generating a new candidate solution in DE is depicted in Figure 1.

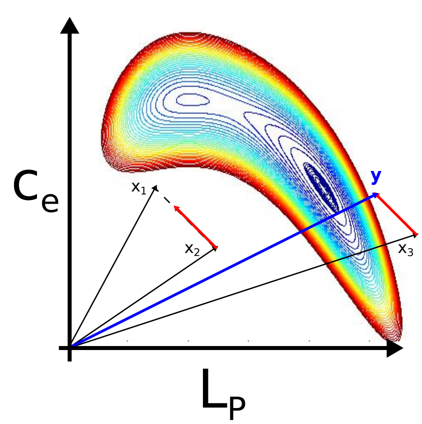

Figure 1. Example of the generation of a new candidate solution y from three parent candidate solutions x_i in the parameter space (c_e, L_P) for the DE algorithm. The distance between two solutions (x_1 and x_2) is calculated and weighted with the differential weight F (red arrow) and added to a third individual x_3 to obtain the new candidate solution. The fitness function is adumbrated as contour plot.

Sensor Placement

Another important task is the ideal placement of the sensors in the system. This is achieved by FDI by deploying a FSM (Pérez *et al.* [5]). DE is used for the search for the optimal combination of columns in the FSM. The genome of a candidate solution consists of the indices of the columns. The fitness function of the problem consists of two criteria, namely detectability of all possible leakage positions and isolation of single leakage positions. Additionally, the sensitivity of a measurement point due to uncertain demands can be incorporated. The fitness function then schematically reads as

$$f = detectability + isolability + sensitivity \tag{3}$$

DE is sufficient for a fixed number of sensors. Finding the ideal number of sensors due to actual sensor costs and detectability constraints, one can again use mGA with genomes of variable length.

RESULTS

In this section, we introduce the case study areas and the results achieved. First, an artificial hydraulic model network used by Poulakis *et al.* [6] is investigated. Second, a sub-network of a real world WDS provided by the Austrian City of Linz.

Sensor placement for both WDS is carried out by finding the ideal combination of columns in a FSM obtained by FDI. This problem is solved with DE.

Basic information for both, the artificial hydraulic model introduced by Poulakis and the sub-network of the city of Linz is given as follows. Poulakis net consists of 30 nodes and 50 pipes with a total length of approximately 71 km. The pipe diameters used in this network range from 300 mm up to 600 mm.

Using the described sensor placement methodology, two flow and two pressure measurement devices are positioned in Poulakis net. As seen in figure 2, the black cross marks the chosen leakage position, black triangles symbolize flow meters whereas blue triangles pose the pressure transducer position. Filled red circles with various degree of severity show, how often this pipe was detected as a potential leakage position in 100 simulation runs. The bar plot in Figure 2 on the right side shows the amount of correctly hit pipe sections (H), pipes hit correctly or nearest neighbors to the actual leakage position (NN). NNN stands for possible leakage positions being either correctly hit, at nearest neighboring pipes or at next nearest neighboring pipes (NNN).

To simulate leakage, values for the parameters $\boldsymbol{c_e}$ and $\boldsymbol{e_e}$ were set to $\boldsymbol{c_e = 0.025}$ respectively $\boldsymbol{e_e = 1}$ according to Eq. (2). At the leakage position there is a pressure head of approximately 12 m. The outcome of calculating leakage outflow for the mentioned set of parameters results in about $\boldsymbol{Q}$ **= 0.3 l/s** leakage outflow. To evaluate the leakage localization performance, a larger number of simulations were carried out using various parameter values for $\boldsymbol{c_e}$ and $\boldsymbol{e_e}$ respectively leakage outflow and leakage positions. Excellent performance was observed in leakage localization for many different positions within this WDS. Due to shortage of space, only the outcome of one specific leakage localization run is shown in Figure 2. The actual leakage is found in over 50 % of the simulations and in 98 % percent of the simulations the leakage was found in an area containing the actual leakage position, the nearest neighboring and the next nearest neighboring pipes.

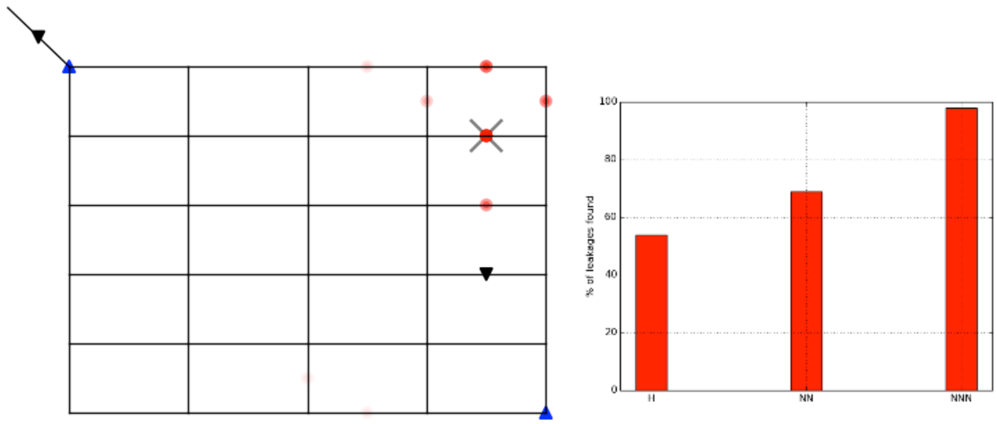

Figure 2: The left side of the figure shows the model network introduced by Poulakis with two flow meters (black triangles) and two pressure measurement devices (blue triangle). The grey cross marks the actual leakage position. Red circles correspond to possible leakage positions found in 100 simulation runs with DE. The opacity shows, how often the leakage was found at that position. The right side of the figure shows a bar plot containing information, how often the leakage was found at the actual leakage position (H), the actual leakage position plus all nearest neighboring pipes (NN) and additionally all next nearest neighboring pipes (NNN).

The same procedure was applied to the real world WDS in Linz. In contrast to Poulakis net, the hydraulic model of Linz has one inflow and an additional pipe section where the discharge in the next sub-network is measured. Thus, we assume that pressure is also known at the in- and outflow position. In addition to this two measurement sites, three pressure transducers were positioned. This Linz WDS consists of 392 nodes and 452 links with approximately 37 km in length. Pipe diameters vary from 70 mm up to 400 mm.

The simulation results are depicted in Figure 3. The symbols for pressure and flow measurement, leakage position and determined leakage position are the same as in Figure 2. The emitter parameters for the simulated leakage were expected to be $\boldsymbol{c_e}$ **= 0.00835** and $\mathbf{e_e}$ **= 1**. The outcome of the leakage outflow calculation at the leaky pipe #9078 results in about

$\boldsymbol{Q}$ **= 3.2 l/s** with an average pressure head of 40 m.

In contrast to Poulakis net, the WDS of Linz is more complex. Thus, it can be found that there is a bigger range of pipes detected as potential leakage hotspot. However, the applied DE algorithm performs well in leakage localization. The findings for 100 simulation runs were as follows. 20 % of conducted simulations hit the correct leakage pipe section. 62 % of all simulations detect the leakage location at pipes next to the assumed leakage spot respectively 99 % at pipes being in the area containing the next nearest neighbor of the actual leakage.

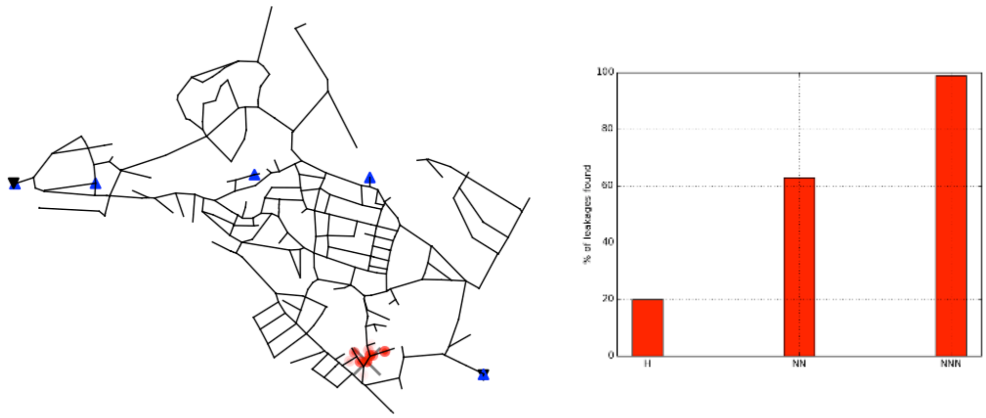

Figure 3: The left side of the figure depicts a part of the real world network of Linz with three pressure measurement devices (blue triangle). Additionally, flow and pressure are known at the in- and the outflow of the system. The grey cross marks the actual leakage position. Red circles correspond to possible leakage positions found in 100 simulation runs with DE. The opacity shows, how often the leakage was found at that position. The right side of the figure shows a bar plot containing information, how often the leakage was found at the actual leakage position (H), the actual leakage position plus all nearest neighboring pipes (NN) and additionally all next nearest neighboring pipes (NNN).

CONCLUSION

In this paper we presented an approach for sensor placement and leakage localization that performed well and is efficient in terms of computation time. Sensor placement has been conducted with FDI solved by DE. For Leakage localization, also DE was chosen and we observed excellent performance in determining the proper leakage position. Based on the presented approach, we are working on an extension to consider measurement uncertainties as well as uncertainties in customer demand. One opportunity to incorporate demand uncertainties in calculations is a Monte Carlo analysis. Unfortunately, this goes in hand with high computational effort. The auspicious work of Neumayer et al. [9] presents an effective approach to solve such problems with a hydraulic small signal model (HSSM) to calculate fast hydraulics. This is achieved by linearizing the hydraulic model in a working point. Although, this results in a slight imprecision, the necessary calculations can be performed in a few simulation runs. Further on, first promising trials have shown that this attempt could also be incorporated into the FSM for sensor placement tasks.

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