van Thienen, Peter; Keedwell, Edward; Farmani, Raziyeh; Vertommen, Ina

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Hydrolink

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By Peter van Thienen, Edward Keedwell, Raziyeh Farmani and Ina Vertommen

Even though formal optimization techniques have been applied to several types of problems in the water industry, the vast majority of examples from the literature is based on (meta)heuristics, and in particular those inspired on nature. Their application has been shown quite successful and has allowed significant boosts in performance while reducing costs. This article provides an overview of nature-inspired optimization techniques, and briefly discusses a number of case studies in which they have been applied.

There is already a long history of numerical optimization in the water industry[1]. Many advances have been made regarding the solution methods from linear and non-linear programming[2] to nature-based optimization techniques, like genetic algorithms, simulated annealing, particle swarm[3], ant colony and many others. Besides the optimization methods, the design problems have evolved from single to multiobjective, and from deterministic to stochastic[2] and robust approaches. For a thorough overview of the optimal design of water distribution networks and the applied evolutionary algorithms and metaheuristics, the reader is referred to[4,5]. The application of the methods has been shown quite successful and has allowed significant boosts in performance of many aspects of systems while reducing costs. In this article, we present an overview of nature-inspired optimization techniques, and briefly discuss a number of case studies where they have been applied.

Nature-inspired optimization techniques

Nature-based or nature-inspired optimization techniques have been in existence since the work of Rechenberg and Schwefel in the early 60s on evolutionary strategies[6]. Since then, thousands of approaches have been developed based on a wide variety of natural systems. A complete taxonomy of these approaches would be much too large for this article, but generally speaking these methods fall into the following categories:

- Evolutionary based approaches:[4] where the underlying iterative process includes perturbation by crossover and/or random mutation and variously selection and replacement of individuals. Methods here include evolutionary strategies, genetic algorithms, multi and many objective evolutionary algorithms, genetic programming and differential evolution.
- Swarm intelligence based approaches:[3] where the underlying iterative process is based on the movement and interaction of individual agents working as part of a collective (e.g. a herd, a flock or a swarm). Methods here include particle swarm optimization, ant colony optimization, artificial bee colony and many other approaches based on a diverse array of organisms including fireflies, wolves, herons, fish schools and whales.

- Other approaches:[7] other sets of metaheuristic optimization methods exist that are perhaps more distantly related to their natural inspiration but are nonetheless nature-inspired. Methods such as simulated annealing (inspired by the cooling of metal), chemical reaction optimization and gravity search are examples of these. Other methods that have a related mode of operation but are not naturally inspired in the conventional sense include methods such as tabu search and many variants of local search.

Although each of the above approaches is inspired by a different natural system, it is an open question as to whether they all represent distinctly separate methods in the exploration of the search space. However, each method has to balance the trade-off between exploration and exploitation of the space of possible solutions, which for most problems in the water industry is very large indeed. Methods that solely exploit (e.g. hillclimbing) will find mediocre solutions quickly, whereas those that solely explore (e.g. random search) will eventually find good solutions, but over huge timescales. Nature-inspired algorithms typically embed exploration through the use of a random or probabilistic operation (e.g. mutation in evolutionary algorithms, probabilistic path selection in ant colony optimization) and exploitation by conferring some preference on solutions that perform well at the optimization task. A further feature that characterizes these nature-inspired methods is that they are general-purpose optimization algorithms that can be applied to many different problems. For most algorithms application to new problems requires the specification of three elements:

- Representation/encoding: this is the mapping between the features of the problem being solved and the numeric decision variables that will be optimized by the algorithm. Although some representations will be straightforward, there are often choices to be made that will determine the efficacy of the search.
- Fitness or objective function(s): provides an assessment of solution quality in terms of one or more objectives of the problem being solved. Objectives in water industry network problems usually include calculations of CAPEX, OPEX, hydraulic constraints such as pressures, velocities and tank penalties, the coverage or detection likelihood for sensor networks, etc.
- Parameter settings: most algorithms have parameter settings that can affect the efficacy of the algorithm and can vary on different problems. Common parameter settings include population sizes, number of iterations, perturbation operator selections and application rates (evolutionary approaches) and various momentum, velocity and pheromone evaporation terms (swarm intelligence). These are usually set by rule of thumb or through prior experimentation, although adaptive methods that set these parameters automatically through the search are becoming increasingly popular.

The choice of algorithm is often dictated by the number and complexity of the decision variables and constraints, the computational complexity of the objective function and the number of objectives to be optimized. Often the computational complexity can be the largest factor and if the problem is particularly time consuming to solve, on the optimization run may require access to high performance or cloud computing resources, although many problems can be optimized with modern desktop equipment.

Nature-inspired optimization algorithms are among the best-known approaches for discovering good solutions to highly complex large-scale problems in reasonable time and have the potential to transform the design and operation of the complex assets and systems that characterize the water industry. This is particularly the case when these methods are combined with other popular AI methods such as machine learning, where the predictive power of these methods can be coupled with optimization to yield asset and operations upgrade programmes designed for future system demands. AI is revolutionizing many sectors and as such, it offers great potential for the water industry as well.

Applications in the drinking water industry

A wide range of problems exists in the water industry for which nature-based optimization algorithms can provide valuable solutions. We give a generic overview here and discuss a number of case studies for different fields of application and/or geographies in the following paragraphs. For water resource management, areas of application include model calibration, choosing sampling locations for monitoring, and risk-based water supply portfolio planning, the optimization of reservoir operation, and regulation of the abstraction from different sources for scarcity management. Water pipe networks, both drinking water distribution and wastewater collection networks have also been subjected to numerical optimization in numerous cases. Not only their layout and sizing, but also their subdivision into functional sections and the optimal placement of different types of sensors, including water quality sensors for contami-nation detection and pressure sensors for leak detection have been explored.

Network design with multiple planning horizons

Climate change, population mobility and urban development in cities necessitates the planning of major distribution network upgrades and requires a phased approach where changes to population and demand increase over time. Work in 2007[8] brought together researchers, consultants and city planners to develop the water distribution system master plan for the City of Ottawa. This phased expansion reflected expected population and demand increases over a 25-year planning horizon, optimized by using an evolutionary algorithm. When the work was carried out, the population of Ottawa was about 800,000 which has risen to almost one million at the time of writing, highlighting the extent of the planned urban growth and underlining the accuracy of the projections which anticipated 1.07 million by 2021. The city's demand is fed by two water

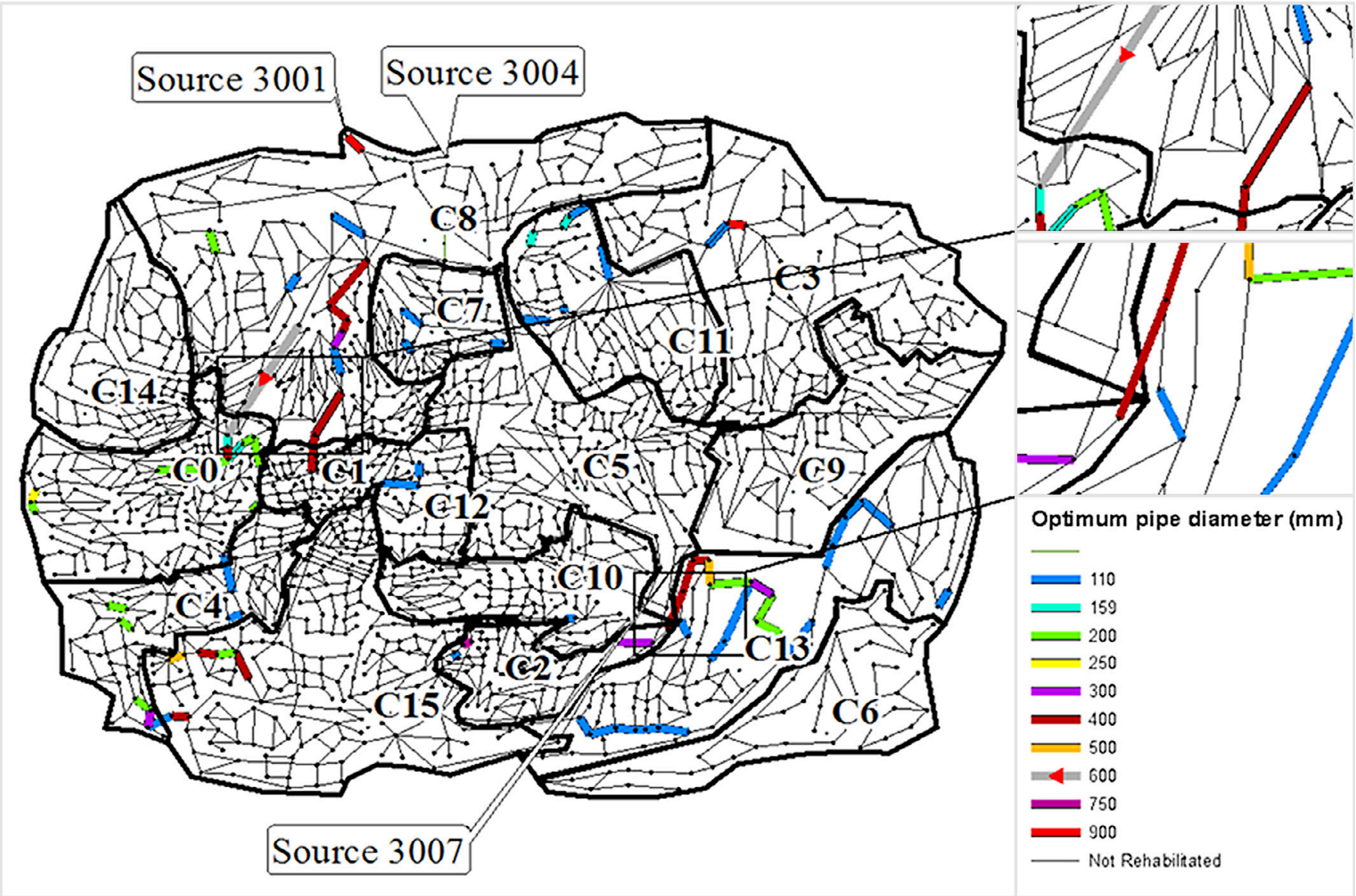

Figure 1 | Layout of proposed pipes for rehabilitation in different clusters for solution with no deficiency.

purification plants, Britannia and Lemieux, located along the Ottawa River, with a combined capacity of 640 Millions of Liters per Day (MLD) and the East and West Urban Communities are fed by a 1,200 mm transmission feed. A 1,220 mm main also feeds the west portion of the South Urban Community and a 762 mm main feeds a small area on the east side of the river. There are two major storage reservoirs, one located in the center of the city and the other in the East Urban Community with storage capacity of 108 ML and 82 ML respectively. There are also two smaller reservoirs in the West and South with storage capacity of 34 ML and 18 ML respectively, and additional elevated storage in the communities.

As with many evolutionary optimization applications, the majority of the work was involved in the development of representation and objective (fitness) function formulations to enable the evolutionary algorithm to effectively solve the problem. The representation establishing the link between the algorithm and problem, provided the options to introduce new infrastructure and upgrade existing assets. A key element here was the introduction of single variables that combined logical sets of infrastructure upgrades. An example of this is in the introduction of a new tank; this must be accompanied by the pipework necessary to connect the tank to the network and so was established as a single 'decision' for the algorithm to take. The introduction of these variables had the dual effect of increasing the engineering feasibility of the developed solutions and reducing the search space for the evolutionary algorithm. A single objective function minimized costs (CAPEX and OPEX) and hydraulic penalties under demand scenarios in 2011, 2021 and the final planning horizon in 2031. The single objective function required a coefficient to balance the cost and individual hydraulic components, which allowed the optimization to be tailored towards end-user requirements, although it would also suit a multi-objective approach. Extensive optimization runs were conducted, and a final 2031 solution was developed at an estimated CAD 402M, including CAD 205M for plant expansions, CAD 110M for new water mains, CAD 45M for pumping stations and CAD 24M and CAD 17M for reservoir expansions and elevated tanks respectively. However, the optimization was able to show only CAD 79M was required to satisfy 2011 demands and a further CAD 152M was required between 2011 and 2021, demonstrating the benefit of using multiple planning horizons within the project.

Optimum rehabilitation schemes

The water sector is under growing pressure to deliver service that satisfies customer expectations and regulatory requirements. Urbanization and growing water demand are putting great stress on ageing or inadequate infrastructure in many countries. This example[9] demonstrates how existing scientific and engineering knowledge benefited from advances in soft computing analytics to address deficiencies in a water distribution networks. This network is part of a water distribution network of a city in the UK. The network has grown over years from a small network to a system that serves 400,000 customers.

The network has two reservoirs, 5 connections that import water from adjacent systems, 1,891 nodes and 2,462 pipes. The pipes have small to moderate diameter sizes with no major transmission mains due to the way the system evolved in the past. The existing network is unable to satisfy the recent growth and projected future demands with adequate pressure. The problem was set as a multi-objective optimization problem in order to generate a set of optimum rehabilitation schemes that trade-off between capital investment and system performance. A two-stage methodology was proposed. In the first stage, using network connectivity and topology, the system was divided into a number of clusters with stronger internal than external connectivity. In the second stage, three different problem setting strategies, for optimal rehabilitation, were considered including: 1 | rehabilitation of pipes within clusters 2 | rehabilitation of feed pipelines, pipes that connect the clusters with deficiency to other clusters or to the sources, and 3 | rehabilitation of pipes within clusters and feed pipelines.

Using an undirected graph algorithm of the Gephi tool[10], 16 clusters with different degrees of pressure deficiency were identified for this network. The pipes in the clusters that have no performance issues and do not participate in water transmission to other areas of the network will have no contribution towards reducing deficiency in the system. Therefore, they were not considered as candidate pipes for rehabilitation of the system. A total of 248, 149 and 349 pipes were considered for rehabilitation (as decision variables) for strategies 1, 2, and 3 respectively. The non-dominated sorting genetic algorithm II (NSGA-II) was used to generate optimum Pareto-front between total cost and number of nodes with pressure deficiency for different strategies.

The generated results (**Figure 1**) based on strategy 3 dominated the results generated by both strategies 1 and 2. The results of strategy 2 were also compared with those generated based on considering i) all the pipes as design variables and ii) a subset of pipes (567 pipes) based on the engineering judgment (water company). The optimum Pareto front generated by strategy 3, again dominated the results generated based on these two problem settings. The optimum solution with no pressure deficiency generated by strategy 3, has a total cost of GBP 3.05 million. A solution, with total cost of GBP 4.15 million with 195 nodes with pressure deficiency, was generated independently by the water company by trial and error. A solution, with a similar number of deficient nodes, on Pareto-front of strategy 3 has a cost of GBP 1.5 million which is 65% cheaper than the solution generated manually.

Network design and transition optimization

Different challenges arise when applying optimization techniques to larger real-world networks: the computational effort involved in applying numerical optimization techniques to such large networks and being able to translate practical challenges and constraints to formal problem formulations with clear objectives, constraints and decision variables. To tackle the first challenge, one might think of high-performance computing and problem-specific variators. Regarding the second one, we have learned that these types of problems are best solved in an iterative process between researchers and practitioners, wherein each result is assessed, and the optimization problem is adjusted accordingly to the gained insights. This approach leads to results that are a perfect fit for what water utilities are looking for and has the added bonus of providing them with new insights into their own water supply systems.

An optimization tool has been applied to the rehabilitation of real-life networks in the Netherlands. It uses (modified) genetic algorithms and NSGAII as optimization methods. Network rehabilitation is approached as a two-phased problem: (1) the optimal design of the network (so called blueprint or master plan) and (2) the optimal transition between the currently existing network and the blueprint, i.e., the rehabilitation timeline. The design of the network blueprint considers the minimization of costs (a function of the diameter and length of the new pipes), constrained by minimum pressure requirements and commercially available pipe diameters and materials. For the rehabilitation timeline both hydraulic (improvement of current pressure deficiencies) and risk based (reduction of pipe failures, which are a function of pipe diameter, material and age) objectives have been considered, in combination with a practical aspect regarding the number of construction sites in each rehabilitation step. A construction site is a cluster of valve sections where old pipes are replaced by new ones. Water utilities prefer to concentrate rehabilitation works in a few sites, instead of working in a very disperse manner.

This approach was applied to the water distribution network serving the area of Helmond-Mierlo, with 105,000 inhabitants in the Netherlands[11]. The network model has about 12,000 pipes. Adding to that 32 commercially available pipe diameters, it is clear how large the solution space for this problem is. By starting the optimization problem from the current pipe diameter values and using problem specific variators in the GA, it was possible to effectively explore the solution space.

Figure 2 illustrates the obtained results. The costs for rebuilding entirely the network currently in the ground would be EUR 41.1M. At the peak demand conditions (maximum demand in the past 10 years) the 30 m pressure requirement is not met at several nodes of the network. The costs of the optimized blueprint are significantly lower, at EUR 26.4M. At the same time, the hydraulic performance is significantly improved: the total pressure deficiency in the network (sum of all pressures below the required 30 m) is reduced by 97%. Regarding the rehabilitation timeline two Pareto fronts were obtained: (1) trade-off between maximization of hydraulic performance and number of construction sites, and (2) trade-off between the minimization of pipe failures and the number of construction sites. **Figure 2** (b) illustrates one of the identified solutions.

Network rehabilitation is an opportunity for re-designing, an often organically grown network. The achieved results prove that numerical optimization techniques can be used in this context. Moreover, the achieved amount of savings allows the

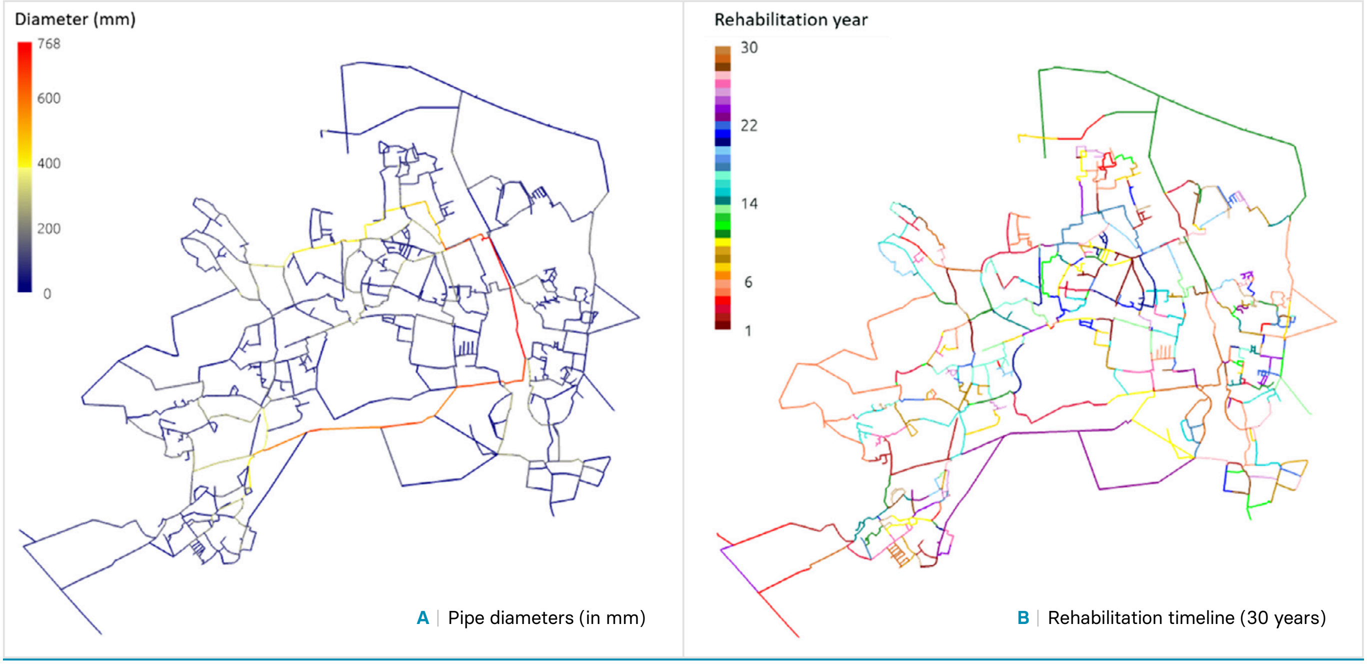

Figure 2 | Optimized solution for (A) pipe diameters to minimize costs while guaranteeing adequate network performance given by different colors, and (B) rehabilitation timeline that maximizes the reduction of pipe failures with a maximum of 10 rehabilitation sites per year (the colors and numbers indicate the year in which the pipes should be rehabilitated, pipes with the same color are rehabilitated in the same year).

water utility to rehabilitate their networks at a higher rate. Proactively replacing old and fragile pipes with new ones reduces the risk of pipe failure and thus, water losses due to leakage.

Moreover, having the initial optimization problem defined and all relevant data organized, it makes it easy to accommodate different objectives, constraints, and scenarios. In this way, the optimization problem can be re-run when new information, such as changes in urban development or water demand, becomes available, making it a very flexible approach.

Optimal water quality sensor placement

Both societal events and technological advances have pushed the development of techniques for online water quality monitoring in drinking water distribution systems since the beginning of this century. Their purpose is generally to protect customers from incidental and/or intentional drinking water contamination. The number of online monitoring sensors that can be placed in any system is always constrained by budgetary limitations. Therefore, methods have been developed to determine optimal sensor placement [12,13] within a drinking water distribution network. Optimality is, however, a matter of definitions and requirements. The objectives that have been presented in the literature can be classified roughly into three categories[14], aimed at obtaining information, facilitating utility response, and mitigating the effects of contamination (Table 1).

Of the three classes of sensor placement optimization objectives, those that are information-oriented are the simplest to compute[12], requiring only a network model (hydraulics and material transport). The more complex effect-oriented approach has been implemented in the Threat Ensemble Vulnerability Assessment and Sensor Placement Optimization Tool (TEVA-SPOT)[13]; here we present some results of its application to a network model of part of the network of Vitens, the largest water utility in the Netherlands. Many simulations were performed

Objective class	Orientation of optimization strategy towards...		
	Information	Utility response	Effect mitigation
Examples	Detection likelihood, time to first detection, network/customer coverage	Redundant detection, identifiability of contamination source	Population affected, ingested volume, numbers of people above does threshold
(Dis) advantages	Simple, but several steps from information to actual customer protection	Close to operational practice	Objective matches final objective of utility, but the latter is complex to compute and the results show a strong dependence of utility response (time)

Table 1 | Rate of increase of potential energy as a function of the lake trophic state with Po = 395,343 W

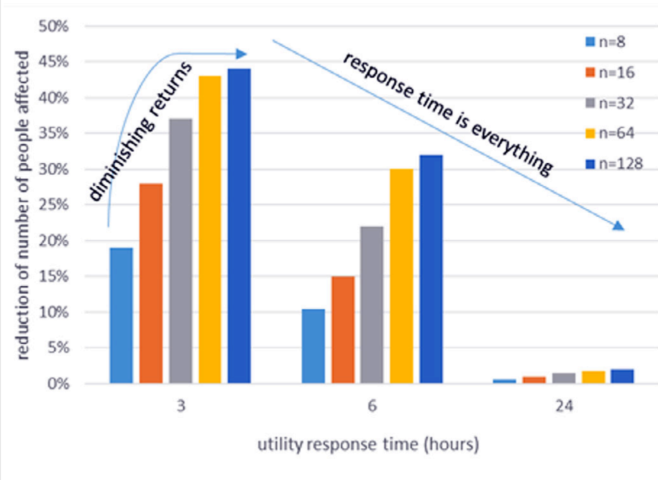

Figure 3 | Performance of optimized water quality sensor networks as a function of number of sensors (n) and utility response times. Results from[14].

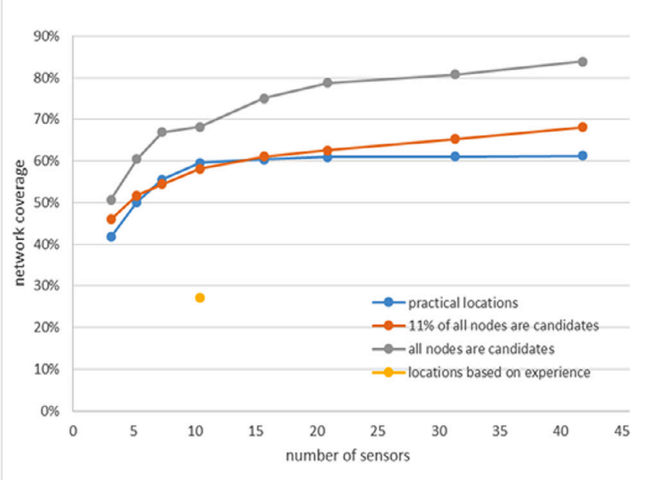

Figure 4 | Water quality sensor network performance for ideal and practically feasible locations. Results from[14].

to study the relationship between the assumed and actual response times of the utility (after which water consumption is assumed to cease), on the one hand, and the performance of the sensor network (reduction in the number of people affected) on the other. In all cases, the sensor locations were optimized using a genetic algorithm. Some results are shown in Figure 3. Two important observations can be made: Sensors are useless for event detection if the utility's response time is too long and Every additional sensor contributes less to the objective than its predecessors (the law of diminishing returns).

When the water utility elects to consider only practically suitable locations for sensor placement, this may have a significant effect on the network's performance as shown in a different study presented in Figure 4 which presents a comparison between the performance of optimizations (again using a genetic algorithm) for different sets of uniformly distributed nodes used as potential locations (300, and all 2,700, respectively). In some cases, the network based on the practical set of potential locations performs better than one based on a larger number of uniformly distributed nodes. The practical set may include, by chance, suitable locations that are absent from the uniformly distributed sets. The best performance is seen when all network nodes are considered as candidate locations (grey curve in Figure 4). But the main conclusion must be that even though optimizing a sensor network configuration based on practically available locations results in some performance loss compared to networks in which sensor placement is not restricted, performing an optimization is still worthwhile.

Conclusions

Several decades of development of ideas, methods and applications have resulted in a myriad of cases which demonstrate the added value of applying numerical optimization techniques to water industry problems. Nature-based metaheuristic methods have been and continue to be particularly popular and successful because of their ability to deal with the scale and complexity that are typical in this field of application. Nevertheless, the vast majority of system design projects in practice continues to rely on human designs and expert judgment. This is not to say that the human factor should be taken out of the equation, rather the opposite: the application of numerical optimization techniques taking into account the deep domain knowledge of the water industry's experts holds the potential for performance increase and cost reduction (both monetary and in terms of environmental impact) in all these projects. The primary gains for the industry from numerical optimization will come from taking the step to actually more or less universally applying these methods.

Ongoing development in this area is focused on the development of new and faster formulations of algorithms, often through the combination of one or more techniques and in the development of methods that can take advantage of modern CPU and GPU (graphical processing unit architectures). Other areas of development are learning optimization (hyperheuristic) methods[15] and multi-method[16] search which combine machine learning and optimization components to create methods that can adapt to new search space domains on the fly. Real-world applications are being addressed through the development of many-objective[17] and human-in-the-loop[18] algorithms that aim to consider the large number of objectives that characterize real world problems and leverage the domain expertise of experienced staff. In this way, the people that have always been responsible for the design of systems and their operation continue to be so, but with a new and very powerful tool in their toolbox.

We are becoming more aware of the uncertainties that exist in the models and data that we are applying optimization to. In addition to this we observe that the world is changing at an ever quicker pace, and progressing climate change can be expected to have more changes and con-sequences in store for us for the rest of the century, both in terms of water availability and demand. Considering these uncertainties in the present state and future conditions and requirements (discussed in[19]), it becomes urgent to start taking these uncertainties into account in the formulation of our optimization problems. Academic work on robust and resilient optimization has been presented in the past decades[2, 20] this should become the standard in real world applications as well.

Peter van Thienen
Peter van Thienen is a senior researcher and chief information officer of KWR. He holds a PhD in geophysics and has over 10 years of experience in the water industry. At KWR, Peter works with a number of colleagues on research and development questions with respect to the drinking water distribution network, from a quantitative and modelling point of view. Examples include the analysis of flow data for the understanding of the network and the detection of leaks (including the development of the CFPD method); the numerical optimization of the design of sensor and pipe networks (development of the Contamination Source Toolkit and the Gondwana platform); and the development of an inspection robot for drinking water pipes.

Ed Keedwell
Ed Keedwell is a Professor of Artificial Intelligence at the University of Exeter and has 20 years of experience in the research and development of novel optimization techniques for application in the water industry. He is currently Director of Research for Computer Science and has research interests in optimization (e.g. genetic algorithms, swarm intelligence, hyperheuristics) machine learning and AI-based simulation and their application to a variety of difficult problems in engineering and bioinformatics that has led to over 150 journal and conference publications. Particular areas of current interest are the optimization of transportation systems, the development of sequence-based hyperheuristics and human-in-the-loop optimization methods for applications in engineering.

Raziyeh Farmani
Raziyeh Farmani is an associate professor of Water Engineering and industrial fellow of Royal Academy of Engineering at Centre for Water Systems, University of Exeter, UK. She is the Chair of IWA's Intermittent Water Supply Specialist Group and associate editor of Journal of Hydroinformatics. She specialises in urban water systems modelling, asset management, water resources management, many-objective optimization, uncertainty and risk assessment, and decision aid. Her research interests cover interdisciplinary field of Hydroinformatics including Artificial Intelligence, data mining and optimization techniques and their application for real-time control for smart water systems.

Ina Vertommen
Ina Vertommen is a scientific researcher in the Water Infrastructure team at KWR. She works with her colleagues on the development of the Gondwana optimization platform and translates water-practice problems, such as the design of network masterplans and sensor networks (for instance for sectorization or leak detection), into mathematical optimization problems. Ina also researches the impact of the weather, holidays and vacation periods on water consumption, and has experienced in the detection of leakages and changes in consumption patterns based on the CFPD method. Moreover, Ina contributes to the monitoring and investigation of trends in lead in drinking water in the Netherlands.

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