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Gondwana: a generic optimization tool for drinking water distribution systems design and operation

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Abstract

Optimization of drinking water distribution systems has received considerable attention in the past decades, with an increasing use of supporting numerical methods. These have either remained in the academic domain, or found applications in practice for a limited number of specific optimization objectives.

With the aim of supporting the Dutch drinking water companies in optimizing their network design, management and operation, we have developed the generic software platform Gondwana for the optimization of drinking water distribution networks. It targets a broad spectrum of single and multiobjective problems in the topics of design, network blueprints, water quality, (virtual) DMA design and location of water quality sensors, among several others. The platform aims to bring optimization techniques within reach of non-specialists with knowledge of the practical problem at hand and also provide expert users with flexibility and freedom.

In this contribution, we present Gondwana and demonstrate its performance on well-known benchmark problems.

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Keywords: Optimization; DWDS; design; software

1. Introduction

Optimization of drinking water distribution systems has received considerable attention in the past decades, with an increasing use of numerical methods to support the optimization process. KWR has invested in developing a generic software platform for the optimization of Drinking Water Distribution Systems (DWDS). The aim of this platform is to provide (KWR) researchers with a tool which supports them in the multiobjective optimization of drinking water distribution networks for application in research and consultancy projects. The platform is designed to support its user in 1) solving optimization problems with respect to many aspects of design, operations and maintenance, and 2) answering research and design questions in the context of scenario studies and model fitting (data inversion).

It is recognized that this aim is ambitious, and that not all problems which can conceivably be addressed by such a platform will result in equally optimal or usable solutions, considering the limited set of optimization approaches

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which can practically be implemented in a single project. That is why the setup of the platform allows for easy expansion at a later stage. Nevertheless, the generic approach shows to be quite usable for many relevant single and multiobjective optimization problems. The platform has been named Gondwana, which stands for Generic Optimization tool for Network Design ANd operation.

To some degree, the aims and approach are similar to those of GAnet [7] and GANetXL [8], which are software tools for network optimization developed and maintained at the Centre for Water Studies at the University of Exeter. The Gondwana platform is different in the sense that it is designed to form a perfect match to KWRs needs in terms of flexibility, expansibility and connectivity to its end users with varying needs and levels of expertise.

2. DWDS optimization in the scientific literature

Computerized optimization of several aspects of drinking water distribution has received much attention in the scientific literature in the past two decades, though many papers are published outside of the literature that focuses on drinking water (distribution) per se. This section is not intended to provide an exhaustive overview of methods and approaches, but rather to give an overview of general directions, which puts our later choice of approach in context. Bieupoude et al. [1] and De Corte and Sörensen [2] give nice overviews of optimization method categories applied to the design of DWDSs. The most relevant of these, with a focus on methods which are readily available in software libraries, are listed in Table 1.

Table 1. Non-exhaustive overview of general optimization approaches applied to drinking water distribution systems in the scientific literature.

Class	Algorithm	Description
Local search meta-heuristics	Simulated Annealing	This method compares candidates resulting from a random move with the current solution. Some applications are presented in the literature.
Population-based meta-heuristics	Genetic Algorithms	These have been widely and successfully applied [e.g5]. They generally perform well [see the benchmark results in2] but may be computationally more expensive than other methods and may find different solutions depending on the starting point of the optimization process.
	Memetic Algorithms	MAs combine the evolutionary framework of a GA with individual learning procedures. Their application to DWDSs is a recent innovation with reportedly good performance in comparison with other methods [6].
Constructive meta-heuristics	Ant colony optimization	This approach mimics the use of pheromone trails by ants to minimize path lengths to food. A few applications to DWDSs have been reported in the literature.
	Particle Swarm optimization	PSO mimics the behaviour of a flock of birds in parameter space, moving towards better solutions. A single application to DWDSs was reported in the literature.

Note that many more approaches have been tried, mainly with specific applications in mind. Bieupoude et al. [1] and De Corte and Sörensen [2] also give an overview of and references to these more specialized approaches.

3. Design of the platform

The core idea of the optimization platform is that any parameter describing part of a hydraulic network model or its operation which is marked by the user as a degree of freedom can be automatically changed by the software. After this, an evaluation of the resulting network design is performed in the context of the prescribed objective(s). In order for any algorithm to update a network design towards an optimum, it requires several inputs and components. The required inputs are the hydraulic model itself, a list of decision variables, one or more objectives, and boundary conditions. The required components are a hydraulic simulation function or program, an optimization algorithm, and a function which evaluates the performance of the design in terms of the optimization objective(s). This set is shown in Figure 1.

The hydraulic simulation software used in the platform is EPANET2 [3]. The Inspyred library [4] provides metaheuristic optimization methods (see section 4).

Table 2 gives an overview of all sections of the EPANET2 input file format, which together describe a hydraulic model and its operation. The sections relevant for optimization are marked with an asterisk.

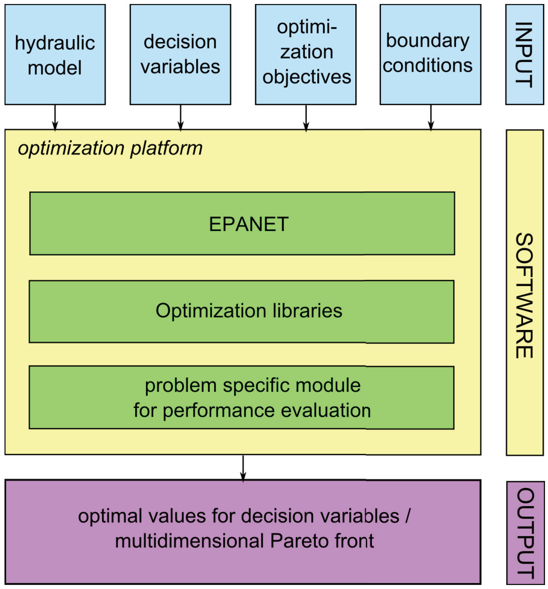

Fig. 1. Process overview.

Optimization objectives can encompass anything from minimal energy consumption to minimal build cost or minimal mean residence time. Energy consumption and residence time are parameters which can be computed by the hydraulic software for individual simulations or nodes in a simulation. Combining many scenarios, time steps or nodes in a single mean performance parameter requires additional computations outside the hydraulic simulation by the problem specific module indicated in Figure 1. Other performance parameters may be derived from the design (e.g. build cost) or operation [e.g. water temperature computed by a coupled thermal interaction model14]. Obviously these objectives also require boundary conditions, since for example the network which consumes the least energy is a network which supplies no water.

Table 2. All sections in the EPANET input file format which combined describe a hydraulic model and its operation [3]. Sections marked with an asterisk are relevant for automated optimization.

Components	Operation	Quality	Model run	Network
TITLE	CURVES*	QUALITY*	OPTIONS	COORDINATES*
JUNCTIONS*	PATTERNS*	REACTIONS*	TIMES	VERTICES*
RESERVOIRS*	ENERGY	SOURCES*	REPORT	LABELS
TANKS*	STATUS*	MIXING		BACKDROP
PIPES*	CONTROLS*			TAGS
PUMPS*	RULES*			
VALVES*	DEMANDS*			
EMITTERS*				

In addition to modification of the marked aspects in the definition of a hydraulic network and its operation, it is also possible to find a subset of elements (nodes, links) which optimizes a user defined performance for this subset of elements or derived entities. Examples include the selection of a limited number of optimal locations for water quality or pressure sensors from all network nodes, or an optimal subdivision of a network into a number of DMAs.

4. Optimization approach

Genetic algorithms are an obvious choice for the range and variety of optimization problems envisaged for the platform for the following reasons:

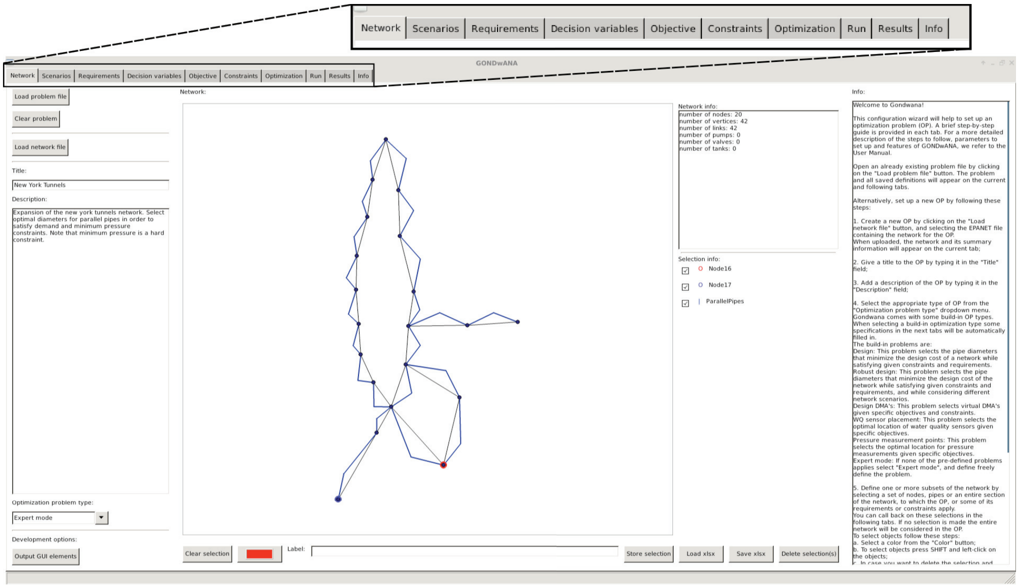

Fig. 2. Gondwana main window.

- good performance on large/complex problems [see also the benchmark results listed in 2];
- applicable to non-convex and nonlinear problems;
- applicable to both continuous and discrete problems;
- simplicity of implementation of objective specific strategies for moving towards an optimum.

In addition to these, a very important practical reason for choosing genetic algorithms is the experience that was gained within KWR with these algorithms and their application.

For single objective optimizations, a canonical genetic algorithm is applied; for multiobjective problems, NSGA-II [9] is used.

5. Software

Gondwana has been developed as a combined command line/GUI application written in Python (Figure 2). It runs on multiple platforms (Linux, Windows). The GUI provides functionality for defining optimization problems, scheduling and performing the calculations and finally analyzing the results (see Figure 2 and Table 3).

Internally, optimization problems are scripted. The GUI generates optimization problem scripts based on user settings. The command line version can read a script from file. This provides a useful mechanism for automated test suites to ensure continuing correctness of functioning during further development.

Computations are performed in one or more separate, parallel processes. This allows the user to analyze the results of a first optimization and define a third as a second optimization problem is running. Parallel computations up to 32 cores have been performed. This is, however, especially useful for optimization problems with a computationally expensive performance calculation, as the overhead of starting new processes can be significant.

Figures 3-6 show the controls for defining several aspects of optimization problems as an example. As indicated in Table 3, the tabs are interlinked and elements defined in one tab can be selected in other tabs.

Both single and multiobjective problems can be adressed with Gondwana (see Figure 7). Multiobjective optimization can be performed implicitly, prescribing weight factors to combine multiple parameters into a single performance parameter, or explicitly using NSGA-II.

In order to support users who have experience with hydraulic modelling but less so with optimization problems, a number of predefined problems is included in Gondwana. By selecting one of these, a number of definitions for

Table 3. Overview of Gondwana tab pages and their functionality

Tab	Description	Functionalities
Network	Initiation of optimization problem definition	loading initial EPANET file definition of node selections definition of link selections initiation of problem definition wizard for predefined problems
Scenarios	Definition of multiple types of scenarios	network modification scenarios demand scenarios contamination scenarios
Requirements	Definition/import/export of additional data, such as cost of pipes	
Decision variables	Selection of single or multiple decision variables	available sections and parameters from Table 2 application to node/link selections defined on the network tab
Objectives	Definition of single or multiple optimization objectives	application to node/link selections defined on the network tab inclusion of data from the requirements tab application of demand scenarios from scenarios tab
Constraints	Definition of contraints which apply to the optimization problem	application to node/link selections defined on the network tab inclusion of data from the requirements tab constraints can be enforced (violation not acceptable) or penalized application of demand and/or network modification scenarios from scenarios tab linking of individual constraints to individual objectives defined on the objectives tab
Optimization	Selection of optimization process parameters	
Run	Scheduling and running of optimization problems	interactivity during computations parallel processing visualizating of convergence curves or evolving Pareto front
Results	Analysis, visualization and export of optimization results	

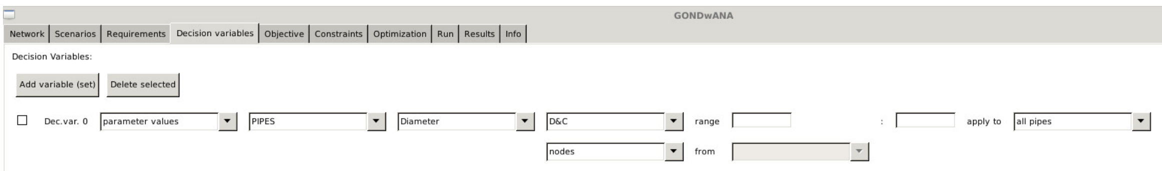

Fig. 3. Problem definition fields for selected aspects of the optimization problem: decision variables.

different aspects of the problem are set for the user (marked as such). For aspects which cannot be set automatically, the user is presented with additional text widgets describing what to do with each input element (see Figure 8).

Although Gondwana can already be applied to a range of problems, development is ongoing to include more problem types and performance computations. Table 4 gives an overview of the problem classes which were chosen to, together, define the initial functionality of Gondwana. The current status of development of each of these classes within the software is also indicated.

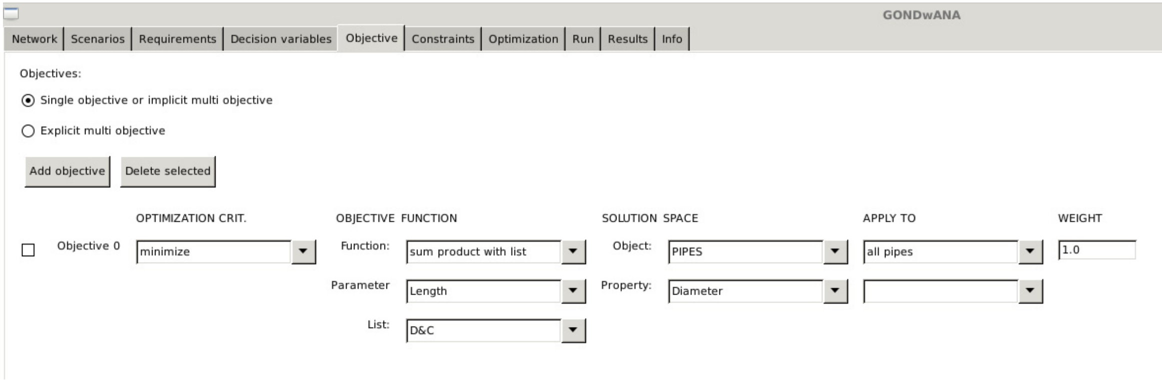

Fig. 4. Problem definition fields for selected aspects of the optimization problem: objectives.

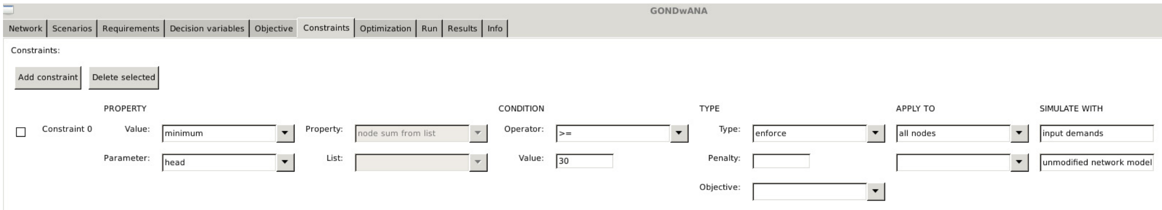

Fig. 5. Problem definition fields for selected aspects of the optimization problem: constraints.

Table 4. Range defining problem classes for Gondwana and their current state of implementation

	Class	status
1.	network design (diameter optimization)	implemented
2.	robust design (diameter optimization considering different working conditions or scenarios)	implemented
3.	water quality sensor placement optimization	development in progress
4.	hydraulic sensor placement optimization	implemented
5.	optimization of operation/energy	to be done
6.	design of network blueprints	implemented
7.	(virtual) DMA subdivision	implemented

6. Benchmark problems

6.1. Introduction

In order to test the performance of Gondwana, it has been applied to two well-known literature benchmark problems. In the following sections, the results are described and compared to results reported in the literature.

6.2. New York Tunnels

The New York Tunnels problem [13] concerns the expansion of an existing gravity driven network. Parallel links are defined for all existing links in the network model. The aim of the optimization is to minimize the cost for these parallel links whilst supplying a minimum head at all nodes. Pipe diameters for the parallel links can be chosen from commercially available diameters and 0 (no parallel pipe).

The resulting costs are compared to literature values in Table 5 and the resulting pipe diameters and corresponding nodal heads are shown in Figure 9. Note that some authors use slighly different values for the hydraulic coefficient.

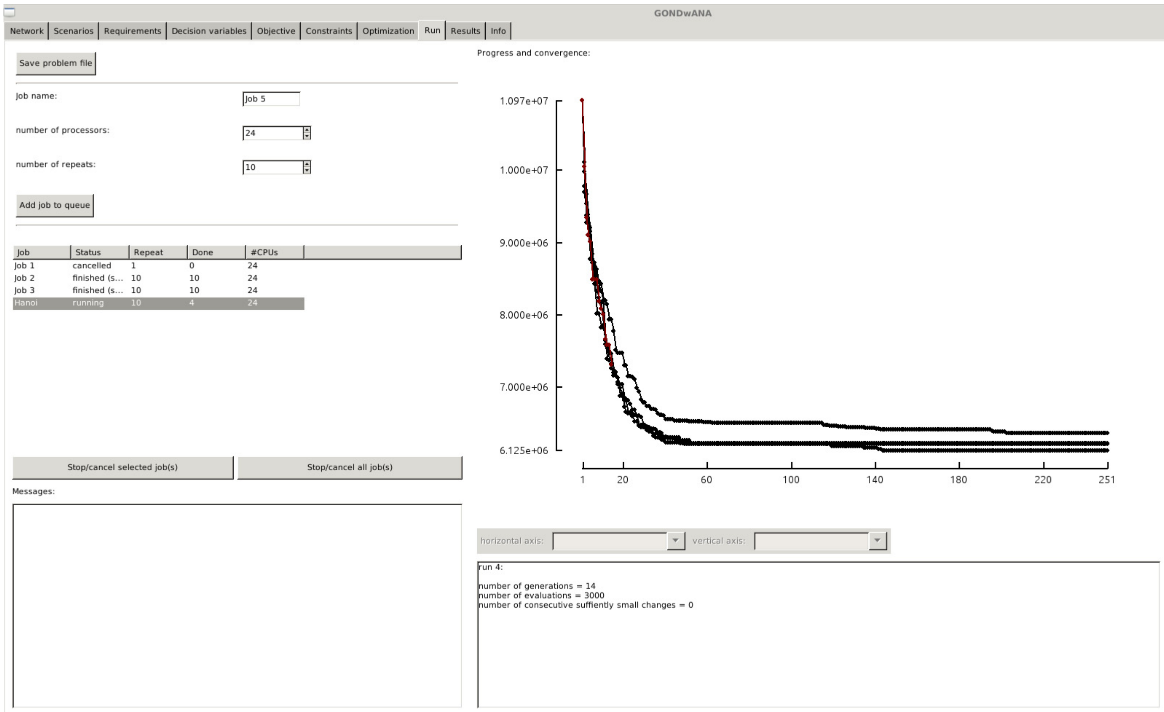

Fig. 6. Problem definition fields for selected aspects of the optimization problem: problem scheduling and execution.

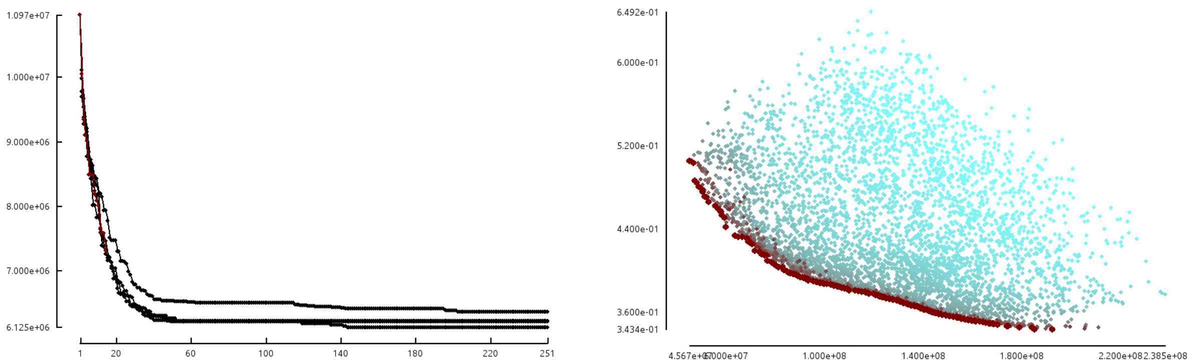

Fig. 7. Monitoring of progress during the optimization process: a) convergence curves for single or implicit multiobjective problems, b) Pareto front for explicit multiobjective problems.

Table 5. Performance of Gondwana in comparison to results reported in the literature for the New York Tunnels benchmark. Numbers represent costs. Used abbreviations: GA genetic algorithm, SA simulated annealing, w hydraulic coefficient. GA Optimization parameters: population 168, 42,000 function evaluations, mutation rate 0.5, crossover rate 0.95, elitism rate 0.10.

Gondwana GA w=10.6792	[11] GA w=10.5088	[11] GA w=10.9031	[10] SA w=10.6792	Common results in the literature (several algorithms) w≈10.7
3.85E+07	3.71E+07	4.04E+07	3.88E+07	3.86E+07

6.3. Hanoi

The Hanoi problem [12] aims to optimize the design of the distribution network of the city by minimizing the construction costs and meeting nodal head requirements at all nodes. Again, pipe diameters are selected by the optimization algorithm from commercially available values.

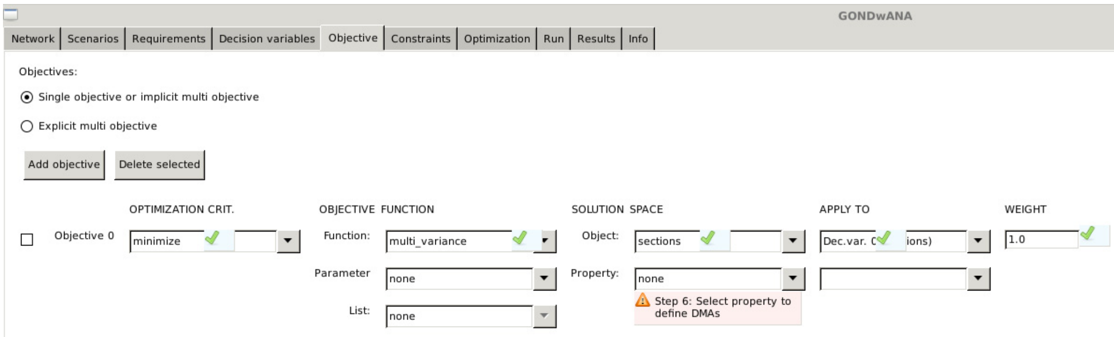

Fig. 8. Example of set values (check marks) and user support widget (pink) for a default problem, in this case DMA optimization.

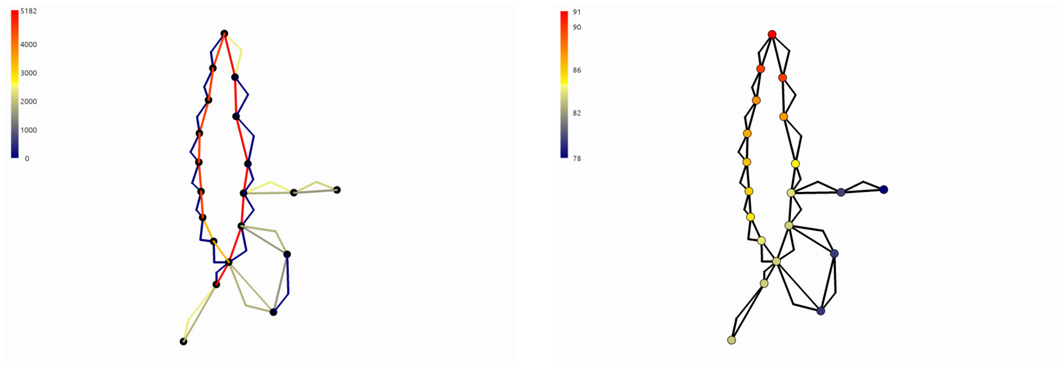

Fig. 9. a) Optimized diameters for the New York Tunnels benchmark. b) Corresponding nodal heads.

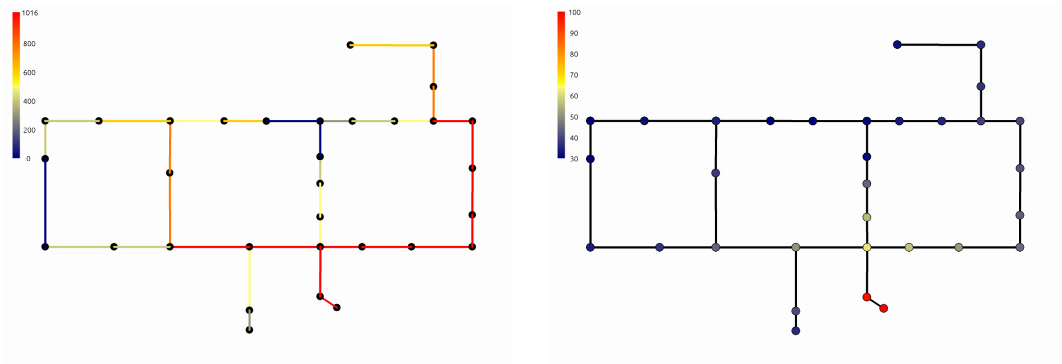

Fig. 10. a) Optimized diameters for the Hanoi benchmark. b) Corresponding nodal heads.

The resulting costs are compared to literature values in Table 6 and the resulting pipe diameters and corresponding nodal heads are shown in Figure 10. Note again that some authors use slightly different values of the hydraulic coefficient.

7. Conclusions and outlook

In its current state of development, Gondwana is sufficiently advanced to allow users experienced in hydraulic modelling with a short training in how to use the software to set up a relevant optimization problem within 5-10 minutes. As shown by the benchmarks, the numerical performance of Gondwana is quite good.

Table 6. Performance of Gondwana in comparison to results reported in the literature for the Hanoi benchmark. Numbers represent costs. Used abbreviations: GA genetic algorithm, SA simulated annealing, w hydraulic coefficient. GA Optimization parameters: population 204, 102,000 function evaluations, mutation rate 0.5, crossover rate 0.95, elitism rate 0.10.

Gondwana GA w=10.6792	[11] GA w=10.5088	[11] GA w=10.9031	[10] SA w=10.6792	Common results in the literature (several algorithms) w≈10.7
5.95E+06	6.07E+06	6.20E+06	6.09E+06	6.08E+06

Application of Gondwana by KWR within its research projects is starting this year. This is expected to contribute to the further development of Gondwana, as more specific problems are conceived and implemented, and included in the list of standard problems.

In addition to finalizing the functionality listed in Table 4, some more additions are foreseen for the near future:

- optimization of transitions (in time) from current to optimized networks;
- autonomous pipe pathfinding based on shape files for allowable pipe locations, to be used in automated network design.

With the flexibility and expandability of Gondwana, more additions are sure to be implemented in the near future.

For the next 2-3 years, KWR plans to employ Gondwana in its research projects for the Dutch drinking water companies, gaining experience and allowing Gondwana to mature. After that, a wider application by external parties such as the drinking water companies themselves will be considered.

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