WDSA CCWI 2022

2nd International Joint Conference on Water Distribution
Systems Analysis & Computing and Control in the Water Industry
Valencia (Spain), 18-22 July 2022
doi: https://doi.org/10.4995/WDSA-CCWI2022.2022.*****

OPTIMIZING THE PERFORMANCE OF WATER DISTRIBUTION SYSTEM UNDER INTERMITTENT SUPPLY CONDITIONS USING A HEURISTIC TECHNIQUE

Gal Perelman[1], Lu Xing[2], Mashor Housh[3], Venu Kandiah[4], Barak Fishbain[5], and Ehsan Shafiee[6]

[1,5] Faculty of Civil and Environmental Engineering, Technion – Israel Institute of Technology, Haifa, Israel
[2,4,6] Xylem Inc., 1 International Drive, Rye Brook, NY 10573, United States
[3] Department of Natural Resources and Environmental Management, University of Haifa, Haifa, Israel

[1] *0000-0003-0345-4051, gal-p@campus.technion.ac.il,*
[2] *0000-0002-8881-5487, lu.xing@xylem.com ,*
[3] *0000-0003-4924-2636, mhoush@univ.haifa.ac.il ,*
[4] *venu.kandiah@xylem.com ,*
[5] *0000-0003-4211-7445, fishbain@tx.technion.ac.il,*
[6] *0000-0002-5568-146X, ehsan.shafiee@xylem.com,*

,

Abstract

This work describes an approach to developing rehabilitation and operation strategies for the challenge proposed in the Battle of Intermittent Water Supply (BIWS), 2022. Intermittent water supply is caused by deteriorating conditions within Water Distribution Systems (WDS). These conditions result in a loss of the network's pressure, thus affecting the ability to continuously supply water to all consumers throughout the day. The deterioration of water systems is an outcome of several strains which are common mostly in developing countries. Examples of such strains are water demand larger than the network's capacity, water losses due to inappropriate network development and lack of maintenance, inefficient pumps' operation, drop in underground water levels, and more. A common solution is to adopt an intermittent water supply policy that has huge disadvantages as it enforces the consumers to store water on their own and creates a feedback loop of worse pressure drops in the network. The approach proposed in this paper aims at restoring the network performance toward a pressurized system with continuous water supply. The challenge requires improving the network performance according to multiple objectives, including maintaining service pressure continuity, reducing water leakage, matching supply and demand, reducing negative pressure pipes, reducing energy consumption, and providing equity of supply for all users. The approach presented here decomposes the network into smaller subnetworks, based on the network configuration and its hydraulics, such that each subnetwork can be optimized separately. Then heuristics are applied for each subnetwork's design and operation optimization. The heuristic algorithm uses a greedy-based mechanism to search design options, including repairing leakages, replacing pipes, and improving pumps. The results of each local search are then combined to find a global optimal solution. While the principles presented here address the specific network of the battle, they can be applied in any water network that requires various design and operation modifications.

Keywords: Greedy optimization, Skeletonization, District meter area (DMA), Intermittent water supply, Network rehabilitation

1 INTRODUCTION

Water distribution networks (WDN) are designed and built to be able to provide demands at continuous service pressure. As the water network ages, the different elements of the network suffer from deterioration, which in return might lead to leaks development, insufficient pumping capacity, and suboptimal operational conditions. If these are not addressed in a timely fashion, the problems put even a higher toll on the network performance. Thus, poor maintenance, including a lack of proactive maintenance and failure to repair faulty network elements in a timely manner, can result in a larger loss of water, higher energy consumption, and failure to supply water with appropriate pressure. As a result, the task of delivering continuous service pressure becomes a relentless challenge [1]. Under such conditions, utilities sometimes use an intermittent water supply strategy to deliver water to end users. This strategy is not sustainable and is labor-intensive [2].

The battle of intermittent water supply (BIWS) explores how to overcome water supply issues in a WDN that has faulty elements and over-capacity demands up to the point that the network fails to maintain pressurized conditions and continuous supply for the consumers. The problem includes both design and operation aspects. While similar problems were investigated in the past, they focused on standard objectives in the field of water supply systems optimization, as minimum of total design and operational costs [3], [4], and as reliability [5]. Here a challenge is presented to create a five-year strategy to recover the network functionality and service level, using nine service indicators, which measure the maintenance of service pressure, the reduction of water leakage, balancing supply with demand, the reduction of negative pressure pipes and energy consumption, and the provision of equity of supply to all users.

Other aspects of the BIWS challenge are the pressure-dependent simulation and the poor hydraulic state of the network. In a pressure-driven simulation, the junctions' demands are the results of the consumer demands over time and the pressure at the junctions. This is a more complicated task than, the typically used, demand-driven simulation, where demands are known functions in the time domain [6]. Applying pressure-driven simulation in intermittent water supply conditions usually involves negative pressures and adds another dimension to the problem complexity [7]. Moreover, the BIWS network contains more than 3,000 leaks, and a 2odelling solution is required to prevent water flow into the network under negative pressure conditions. Combining all the above, with limited water sources causing pipes and tank to drain frequently, result in fragile hydraulic conditions, which significantly increase computational resources and make it difficult to find a feasible stable solution, not to mention an optimal one.

A new approach proposed in this paper is to restore the network performance toward a pressurized system and continuous water supply with the consideration of the aforementioned indicators. The new approach starts with decomposing the network into smaller subnetworks such that each subnetwork can be optimized separately. The decomposed subnetworks are then optimized to enhance one or several indicators altogether. The decomposition process considers the layout and the hydraulic pressure zones of the network. Each subnetwork's design and operation are optimized using a heuristics algorithm. The heuristic algorithm uses a greedy-based mechanism to search design options, including repairing leakages, replacing pipes, and improving pumps. For each subnetwork, a set of engineering features that can be used to improve operation is identified, and a brute force approach is used to exhaust all variations of these features. Furthermore, the hydraulic barrier between each subnetwork creates an opportunity to apply a local search and combine the result of each local search to find the global optimal operation solution.

In the following, a brief explanation of the methodology is provided. Then, a summary of the battle problem is presented, and finally, the submitted solution for the BIWS network is discussed.

2 METHODOLOGY

A new hierarchical methodology is developed here to find the optimal design and operation using greedy and local search algorithms. The proposed methodology uses mathematical optimization modeling to improve the performance of overall water networks with fewer fitness evaluations. The methodology is based on the principle that a hydraulic model can be decomposed into sub-models by synchronizing the flow and pressure at the boundaries of each sub-model. Therefore, the global performance of the model can be optimized by optimizing the performance of each sub-model individually while accounting for the boundary conditions between the sub-zones and global constraints ties to the decomposed problem if such constraint exists. Using the decomposition technique, optimization of subnetworks is less computationaly intense as the size of the subnetwork is significantly smaller than the entire network. Thus, less decision variables and constraints to evaluate. The solution evaluation is a common step in classical and advanced search algorithms such as the genetic algorithm. The computation time required for solution evaluation is the main burden for optimizing over multi-objective space. Figure. 1 recapitulates these notions. The Water Distribution System hydraulic scheme is fed into the decomposition block. In this block two cuts to subnetworks are performed: Subnetworks which are connected to the rest of the network through a single node, and thus cutting this node would separate the subnetwork from the net itself; and subnetwork which are connected with more than one node, but hydraulic dicatates it that they can be regarded as a separate network. This is leabotrated on in the methodology section.

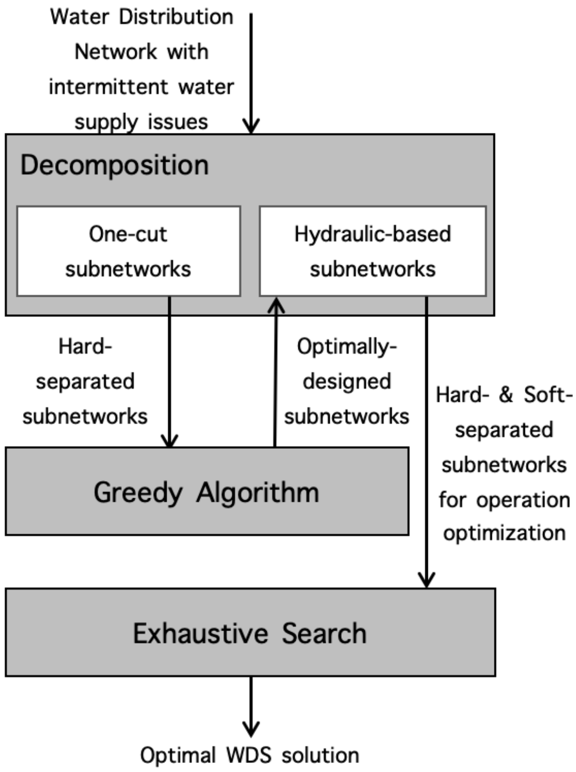

Figure 1. The framework for finding the optimal solution that includes asset design, asset rehabilitation, and operation design.

In addition to the problem simplification, a greedy algorithm is introduced here. The greedy algorithm for the problem is inspired by Dantzig's greedy approximation algorithm [8] for the knapsack problem. The knapsack problem in our context is stated as follows: Given a set of options, each with a cost and a benefit, one needs to select a subset of options so that the total cost is less than or equal to a given budget and the total benefit is as large as possible. Dantzig proposed to sort the options in decreasing order of benefit per cost (e.g., marginal benefit), one then proceeds by selecting options accordingly until the budget is met. While this algorithm is straightforward for the original knapsack problem, in which the benefit and the cost of each option are constants, its implementation for the nonlinear case is challenging [9]. In the nonlinear case, such as the one considered herein, the benefit from each option is not constant since the objective values will change when some of the options are implemented. Thus, the algorithm should be used iteratively, wherein each iteration, the benefits from all options should be re-evaluated while taking into account the already implemented options from previous iterations. This implies that each iteration requires many (order of the number of options) function evaluations. To handle this challenge, we employ two heuristics. First, we select more than a single option at each iteration before we re-evaluate the benefit values. For example, to limit the number of iterations, we can have an iteration-budget by taking the overall budget and dividing it by a predetermined number of iterations, such that at each iteration, we take all options within the iteration-budget simultaneously. Here the iteration-budget is defined as a threshold according to the percentage of the best action marginal benefit, thus, the number of actions to take is dynamically changing through the run. In the second heuristic, we use a change detection mechanism, so that we monitor the components of the network that have not been influenced by the selected options of the previous iteration. For example, if we fix a leak at zone A, then zone B, which is far away from zone A, will not be influenced by the selected option. As such, the benefits from options in the vicinity of zone B can be maintained as in the previous iteration without re-evaluating them. The monitoring is based on the change of average flow for each element as a result of the previous iteration. Only actions with the largest change in flow value will be re-evaluated. The number of actions is determined according to a parameter as a percentage of the total possible actions. Finally, a required total run time can be set. With a known run time for a single iteration, the total number of iterations is set to match the total time. In light of the above, the presented greedy algorithm allows the user to control the level of greediness with the tradeoff of computation time and suboptimality. In the presented case study, the greedy algorithm uses approximately 10% of the computational resources required for a genetic-algorithm-based methodology with a population size of 200 and 100 generations.

The proposed methodology starts with creating subnetworks. The subnetwork is either a hard decomposition by separating the subnetwork from the main network or a soft decomposition based on the hydraulic barrier. A hydraulic barrier is created in the network due to the balance of water columns generated from two different pressure heads. The soft decomposition creates subnetworks that are hard to physically separate from the main network because of the number of cuts (two or more cuts) that are required. The hard decomposition only considers one-cut subnetworks, that is, they can be separated from the main network by cutting only one pipe. To hydraulically model the boundary conditions between the subnetworks and the main network, General Purpose Valves (GPVs) are used to simulate the pressure-flow relationship in the cut edge. Each GPV is accompanied by a set of rules in the model to regulate the valve operation to mimic the original behavior in the network. Similarly, the produced pressure head in the main network is used as a head input in the subnetwork.

Once the network is decomposed, the greedy search algorithm is used to prioritize the leakage fixes and pipe replacements for the duration of maintenance planning (five years in the BIWS definition). The greedy algorithm uses a uniformly weighted summation of normalized objectives to rank and prioritizes the design actions. To run the greedy algorithm for each subnetwork, the available budget, which is typically a global constraint, needs to be allocated between subnetworks based on their characteristics. However, since the greedy algorithm is computationally efficient and the hard-separated subnetworks increase the computation time due to valve operation rules, the main intact network is used in this paper.

Once an optimal design is found, the next step is to search for a mode of operation that optimizes the system performance as measured by the objectives. We first identified that valve status during daytime and nighttime can have a significant impact on the system performance. Hence, we focus on searching for a combination of time-based valve controls to optimize the system operation. However, an exhaustive brute-force search on the valve status is computationally expensive considering the exponential complexity. For example, the brute-force search on the daytime and nighttime status of the 27 valves requires $2^{27\times2} \approx 1.8 \times 10^{16}$ evaluations. We proposed to group the valves into classes from each soft-separated subnetwork based on their hydraulic independency. The assumption is that valves in the same class act together to control the performance of the area where they are located, while valves in different classes are independent. Based on this assumption, 7 valve classes are identified, each of which contains 3-4 valves. The number of evaluations is then successfully reduced to $6 \times 2^{4\times2} + 2^{3\times2} = 1600$. The local search explores all combinations of these variables and chooses the best solution using the uniformly weighted summation of normalized objectives. The greedy and local search algorithms use a single-objective formulation, and the search can be directed to optimize certain objectives by adjusting weights.

3 PROBLEM STATEMENT

The BIWS network is outlined in Figure. 2. The network is mainly a gravity-fed network, which consists of 2859 nodes and 3231 pipes before adding the leaks. The battle rules allow adding the leaks in various ways, here the leaks were modeled by splitting pipes in the exact leaks' location and adding a check valve between the split node and the leak node to prevent water flow into the network in negative pressure conditions. The main transmission line feeds two tanks that create water columns for the lower elevated part of the network. As the water reaches the lower elevation, the network is unable to supply water because of numerous leakages in the network. This causes the middle tank to empty and prevents its functionality of regulating demands. Five wells are used to provide water to parts of the network that suffer from water shortages, these wells use as complementary sources to the main gravity-based source, and they require energy to be operated.

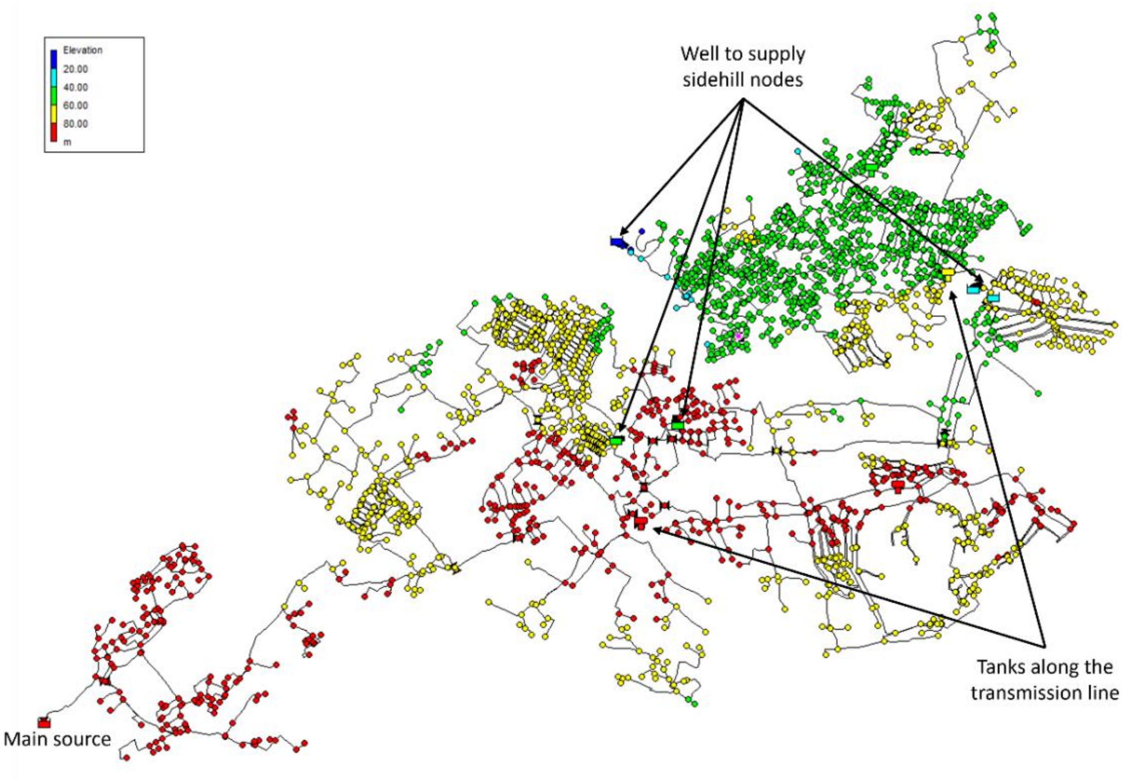

Figure 2. The layout of the network and the elevation of nodes.

The network suffers from background leakages, which withdraw water from every part of it. One of the wells suffers from a water level drop such that the existing pump cannot lift the water into the network. Most of the other pumps also cannot be operated due to the low pressures in the network that causes the wells' flow to exceed the BIWS limitations. The battle participants are tasked to improve system performance through nine indicators, as shown in Table 1:

Table 1 – Optimization objectives

Description	Type	Formula
Proportion of the number of effective hours a subscriber is served	Max	$I_1 = \frac{\sum_{j=1}^{6}\sum_{i=1}^{N} n_{i,j}}{N \cdot 24 \cdot 364 \cdot 6}$
Proportion of subscribers with continuous service	Max	$I_2 = \frac{\sum_{j=1}^{6}\sum_{i=1}^{N} w_{i,j}}{N \cdot 6}$
Volume of water leakage	Min	$I_3 = \frac{\sum_{j=1}^{6}\sum_{l=1}^{L_j} V_{l,j}}{\sum_{j=1}^{6}\sum_{s=1}^{S_j} V_{s,j}}$
Proportion of volume of water supplied to users	Max	$I_4 = \frac{\sum_{j=1}^{6}\sum_{p=1}^{N} V_{i,j}^{s}}{\sum_{j=1}^{6}\sum_{d=1}^{N} V_{i,j}^{d}}$
Level of pressures at consumption nodes	Max	$I_5 = \frac{\sum_{j=1}^{6}\sum_{h=1}^{168}\sum_{i=1}^{N} \max\,(0, \min\,(p_{i,h,j}, p_{ref})}{168 \cdot N \cdot 6 \cdot p_{ref}}$
Percentage of users supplied continuously	Max	$I_6 = \frac{\sum_{j=1}^{6}\sum_{i=1}^{N} \delta_{i,j}}{N \cdot 6}$

Pipe length with negative pressures	Min	$I_7 = \frac{\sum_{j=1}^{6}\sum_{m=1}^{M} L_{m,j}}{6}$
Energy consumption of pumps in operation over the whole period	Min	$I_8 = \sum_{j=1}^{6}\sum_{p=1}^{P} E_{p,j}$
Level of equity in supply	Max	$SR_{i,j} = \frac{V_{i,j}^{s}}{V_{i,j}^{d}}$ $ASR = \frac{\sum_{j=1}^{6}\sum_{i=1}^{N} SR_{i,j}}{N \cdot 6}$ $ADEV = \frac{\sum_{j=1}^{6}\sum_{i=1}^{N}\left\|SR_{i,j} - ASR\right\|}{N \cdot 6}$ $I_9 = 1 - \frac{ADEV}{ASR}$

j – Years index

i – Nodes index

N – Total number of demand nodes

$w_{i,j}$ – 1 if consumer i as continuous service pressure in year j

$V_{l,j}$ – Volume lost by leakage l in year j

$V_{s,j}$ – Volume supplied by source s in year j

$V_{i,j}^{s}$ – Volume actually supplied to consumer i in year j

$V_{i,j}^{d}$ – Volume demanded by user i in year j

Pi,h,j – Pressure at node I and hour h of year j

P_{ref} – Min acceptable pressure for quality supply by local municipality laws (P_{ref}=20m)

$\delta_{i,j}$ – 1 if the pressure at node i is larger than P_f for all hours of year j

P_f - min pressure for supplying all the demand, P_f=10m

$L_{m,j}$ – Longest negative pressure length of pipe m in year j (max length between all time steps)

$E_{p,j}$ – Energy consumption of pump p over year j

4 RESULTS

By utilizing the described heuristics and greedy approach, an optimal solution is obtained. The solution is composed of two parts, the design actions portfolio, which determines how the five years budget is allocated, and operation controls which determine the status of valves and pumps along the simulation period. Next, we provide a general description of the proposed rehabilitation strategy and the main insights from this strategy. The complete solution is detailed in the supplementary data of this paper.

Most of the budget was used for fixing leaks and replacing pipes with larger diameter pipes. Among the pipes that were replaced in the early years are pipes that have a significant contribution to the rehabilitation of the network services level, some examples are: L1156 and L1130, which connect the discharge of B_PT pumps to the northern part of the network.

Furthermore, short links that connect separate sections of the network and constitute bottlenecks were also replaced early in the planning horizon. For example, pipes like L1544 connect disconnected parts of the network and enables supply from a second direction to some consumers. A salient example is the case of pipes L2041, L2042, and L2043. These pipes create an extreme bottleneck narrowing between two 250 mm pipes connected with only 20 mm pipes for a short section (Figure 3). Here significant benefit can be achieved by utilizing very little budget. While manually finding this kind of configuration is almost impossible, the greedy algorithm is able to find it due to the high marginal benefit opportunity.

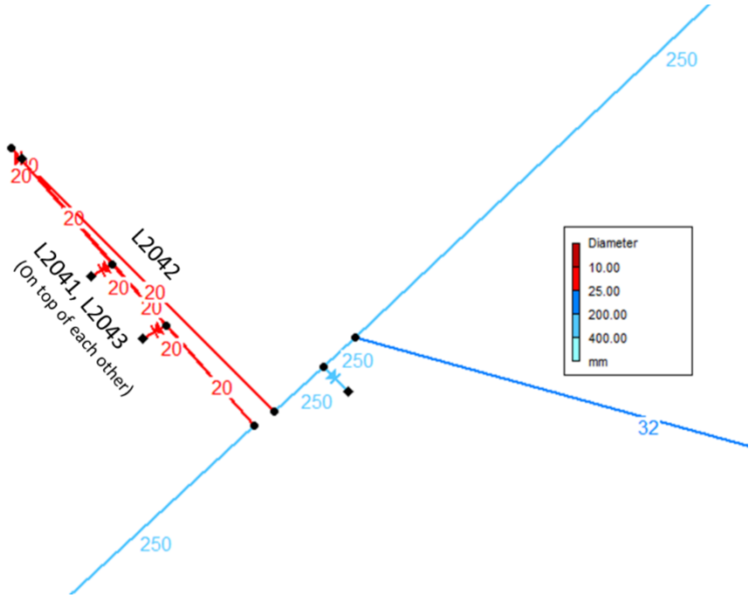

Figure 3. – Extreme bottleneck of pipes diameter

Generally, the greedy algorithm prioritized fixing leaks in the first years where the urgency is a result of large emitter coefficients and high pressure. Figure 4 shows the leaks in the network, where each point represents a leak in the water loss volume vs. repair cost domain. The vertical axis is the total weekly water loss in year 0 (before any changes were done in the network), the horizontal axis is the leak's repair cost, and the color represents the year in which the leak was fixed. We can see that the cheapest actions with large water loss are fixed first, then smaller leaks with higher repair costs are repaired gradually. Note that the red circles represent leaks that have not been fixed, and it can be seen that these are the ones with the smallest water loss volume which fixing them will contribute to the objectives the least.

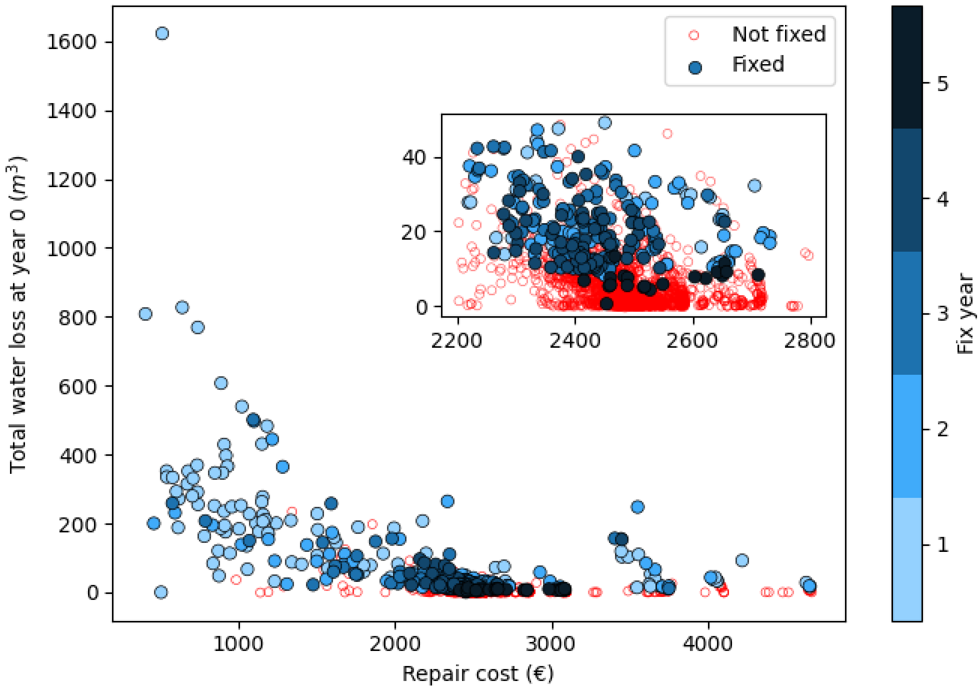

Figure 4. – Network leaks by water loss volume, repair cost, and fixing year

The greedy algorithm approach ignores large actions such as replacing pumps. These actions' cost is much higher than leak fixing and pipes replacement, as such, the immediate benefit is not enough to prioritize them when we consider a short planning horizon. This is a classic obstacle for greedy algorithms that miss the long-term cumulative benefits of large investments. To deal with this challenge, the pumps are replaced outside the greedy algorithm, where the combination of new pumps is selected using brute force search over all five years.

As expected, the solution obtained by the greedy approach prioritizes actions that bring the immediate best marginal benefit to the system. Nonetheless, we observe that some budgets are spent on counterintuitive actions. One example of such a case is a leak fixed in an early year while in a later year, the entire pipe of the same leak is replaced. Another example is the case where several leaks on the same pipe are fixed in different years despite that the total cost of the leak fixing is higher than the pipe replacement cost. To further examine this phenomenon, a post-process of rearranging the design actions was performed. In this post-processing, we permutated the design actions such that single action was applied instead of a set of actions that can be combined into one. The action was taken the earliest in time between the combined actions.

As a result of the permutation, some of the previously used budgets is saved and therefore used for more actions. The additional actions were taken from the last greedy algorithm iteration as if another iteration would be computed. The results of the Greedy and Permuted Greedy are shown in Table 2 below.

Table 2 – Optimization objectives

Indicator	1	2	3	4	5	6	7	8	9
Objective type	max	max	min	max	max	max	min	min	max
Greedy	**0.878**	0.513	0.351	**0.696**	**0.675**	**0.175**	**176,852**	98,946	**0.713**
Permuted Greedy	0.875	**0.514**	**0.347**	0.689	0.671	**0.175**	176,862	**98,806**	0.705

Comparing the two solutions according to the BIWS evaluation criteria, we conclude that the greedy solution obtained a better score, it outperformed the permuted greedy in 5 out of the nine indicators and was in a tie in another indicator. Although the Permuted Greedy enables to take more actions (e.g. fix more leaks) by reproitroizing actions. Some actions that are prioritized by the Permutaed Greedy logically make sense to be implemented in later years from the operation perspective. This illustrates the importance of considering not just which actions need to be taken but also the order of actions when rehabilitating a network with strive to reclaim the pressure conditions as fast as possible.

5 CONCLUSIONS

A hierarchal optimization method was presented here for the rehabilitation of water supply systems under intermittent supply conditions. The rehabilitation was done by design actions (pipes and pumps replacement, leaks fixing, and adding valves) and by operational controls (pumps and valves status) to reclaim pressure conditions in the network. To find the optimal rehabilitation strategy a heuristic method was developed based on the decomposition of the network to smaller subnetworks and optimizing each of them separately with a greedy algorithm (design) and exhaustive search (operation). The obtained results are consistent with engineering logic as fixing the largest leaks first, increasing diameter at bottleneck points, and improving the connectivity of different sections in the network. Some of the difficulties of the presented challenge are the computational burden required for a single objective function evaluation, the high dimensionality of the problem, and the non-elementary objective functions such count function. These properties of the problem make the use of classic mathematical optimization techniques to be very complicated and maybe not possible. The proposed solution can overcome these obstacles such that it constantly progresses toward a better solution thus not exposed to not converging or stuck in a local minimum.

6 REFERENCE

[1] K. Simukonda, R. Farmani, and D. Butler, "Intermittent water supply systems: causal factors, problems and solution options," *https://doi-org.ezlibrary.technion.ac.il/10.1080/1573062X.2018.1483522*, vol. 15, no. 5, pp. 488–500, May 2018, doi: 10.1080/1573062X.2018.1483522.

[2] E. E. Ameyaw, F. A. Memon, and J. Bicik, "Improving equity in intermittent water supply systems," *Journal of Water Supply: Research and Technology - AQUA*, vol. 62, no. 8, pp. 552–562, 2013, doi: 10.2166/AQUA.2013.065.

[3] A. Ostfeld, "Optimal Design and Operation of Multiquality Networks under Unsteady Conditions," *Journal of Water Resources Planning and Management*, vol. 131, no. 2, pp. 116–124, Mar. 2005, doi: 10.1061/(ASCE)0733-9496(2005)131:2(116).

[4] M. Moradi-Jalal, ; Sergey, I. Rodin, M. A. Mariño, and H. M. Asce, "Use of Genetic Algorithm in Optimization of Irrigation Pumping Stations," *Journal of Irrigation and Drainage Engineering*, vol. 130, no. 5, pp. 357–365, Oct. 2004, doi: 10.1061/(ASCE)0733-9437(2004)130:5(357).

[5] S. Beygi, M. Tabesh, and S. Liu, "Multi-Objective Optimization Model for Design and Operation of Water Transmission Systems Using a Power Resilience Index for Assessing Hydraulic Reliability," *Water Resources Management*, vol. 33, no. 10, pp. 3433–3447, Aug. 2019, doi: 10.1007/S11269-019-02311-X/TABLES/3.

[6] P. B. Cheung, J. E. van Zyl, and L. F. R. Reis, "EXTENSION OF EPANET FOR PRESSURE DRIVEN DEMAND MODELING IN WATER DISTRIBUTION SYSTEM".

[7] P. Ingeduld, A. Pradhan, Z. Svitak, and A. Terrai, “Modelling Intermittent Water Supply Systems with EPANET,” *8th Annual Water Distribution Systems Analysis Symposium 2006*, pp. 1–8, 2007, doi: 10.1061/40941(247)37.

[8] G. B. Dantzig, “Discrete-Variable Extremum Problems,” *https://doi.org/10.1287/opre.5.2.266*, vol. 5, no. 2, pp. 266–288, Apr. 1957, doi: 10.1287/OPRE.5.2.266.

[9] T. Ibaraki and N. Katoh, *Resource allocation problems: algorithmic approaches*. 1988. Accessed: May 13, 2022. [Online]. Available: https://dl.acm.org/doi/abs/10.5555/49354