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Managing Nighttime Pressure for Background Leakage Control in Water Distribution Networks Using Simulated Annealing

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Abstract: In recent decades, the global imperative to address drinking water scarcity encourages initiatives that ensure a sustainable supply. In this context, this work presents a two-stage methodology designed to reduce background leakages in water distribution networks by controlling pressures during hours of lower water demand using pressure-reducing valves (PRVs). The first stage focuses on dividing the network into smaller structures, or modules, optimizing the topological modularity index. Here, conceptual cuts are determined at the boundaries between modules, identifying them as potential positions for the installation of PRVs. The second stage determines the quantity, optimal settings, and operational status of these valves. Focused on reducing elevated nighttime pressures, the strategy minimizes the network's nighttime resilience index using simulated annealing for optimization. The application of this methodology to two reference networks results in different levels of PRV activity, achieving a substantial decrease in pressure and nighttime background leakage volumes, without a negative impact on peak demand hours. **DOI: 10.1061/JWRMD5.WRENG-6454.** *This work is made available under the terms of the Creative Commons Attribution 4.0 International license, https://creativecommons.org/licenses/by/4.0/.*

Practical Applications: Water scarcity is a global challenge that requires innovative solutions to manage and conserve water resources. This study presents a two-stage method to reduce water leakages in distribution networks by managing pressure during off-peak hours, which are characterized by low demand and high system pressures. In the first stage, the network is divided into smaller sections using strategic cuts that identify optimal locations for interventions such as installing shut-off valves or pressure-reducing valves. In the second stage, the pressure-reducing valves are installed at these strategic points and initially set to be fully open. The optimization process, focused on nighttime hours, adjusts the settings to reduce excessive pressures, thus minimizing water leakages without affecting daytime water supply. Applying this methodology to reference networks has shown significant reductions in both pressure and nighttime water leaks. This approach provides practical guidelines for water utilities to improve the efficiency and sustainability of their distribution systems, addressing the broader goal of mitigating water scarcity.

Introduction

Water losses from pipes, joints, and accessories in water distribution networks (WDNs), commonly known as background leakages, pose a significant concern for stakeholders in both the private and public sectors. These losses not only impact consumers but also the companies providing the service and water reserves. The volume of this type of leakages is influenced by the pressure within the system and the duration until detection (Farley 2001; Sophocleous et al. 2019; Xu et al. 2020; Vrachimis et al. 2021). Effective reduction of these losses requires the implementation of appropriate strategies, such as pressure management, active leakage detection, or maintenance. The selection of the most suitable approach is contingent upon network characteristics and the social, technical, and economic evaluation carried out by the service provider. Infrastructure replacement poses significant challenges during implementation, primarily due to social and economic factors. However, leakages can still be reduced with existing infrastructure without significant investments. This can be achieved through minor enhancements, such as adding valves and optimizing the operation of the current network, including schedules and configurations for pumps and valves. Such strategies have been extensively documented in the literature for decades (Jowitt and Xu 1990; Araujo et al. 2006; Ali 2015; Creaco and Pezzinga 2018; Gupta and Kulat 2018; Cavazzini et al. 2020; Maskit and Ostfeld 2021). While a universal method applicable to any network type has not yet been established, studies often capitalize on the benefits of using specific devices such as flow control valves (FCVs), pumps as turbines (PATs), or pressure-reducing valves (PRVs) to reduce leaks in WDNs. This work proposes a two-stage methodology using PRVs for pressure management during off-peak hours, which are characterized by low demand and elevated system pressures. In the first stage, the aim is

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to divide the network into smaller structures that can function as possible pressure management zones (PMZs) through the optimal location of conceptual cuts. These cuts, introduced for the first time by Giustolisi and Ridolfi (2014), denote strategic points within the network where interventions, such as installing shut-off valves or PRVs, could facilitate optimal management of the hydraulic system. Since this study aims to initiate the search for potential solutions based solely on the network's topology, the objective at this stage is to maximize the modularity index, a metric used to identify modules (also known as communities) (Newman 2006; Berardi et al. 2019; Bianchotti et al. 2021). These terms describe groupings of nodes with significantly higher density of connections among themselves than with nodes outside the group. Thus, the modularity index quantifies the quality of partitioning a network into modules by assessing the density of connections within modules compared to connections between modules. A high modularity value signifies a more modular network structure, indicating a clear division into well-defined modules. In the second stage, PRVs are proposed to be installed at all conceptual cuts and at the reservoirs outlets. The settings of these valves are initially fixed to be fully open, with parameters set to the maximum system pressure for all hours of the day. After the optimization process, which is conducted solely for the nighttime period, many of these valves may end up either fully open or fully closed, in addition to being in the active state. This occurs because the operating parameters of the PRVs are optimized to reduce nodal pressures of the network during the night. To achieve a reduction in nodal pressures, this approach utilizes the resilience index as a key metric, which is closely related to the system's intrinsic capacity to withstand failures (Todini 2000). It is worth noting that the resilience index is a scalar value defined for a specific hour of the day, and it depends on the values of the required demand and minimum pressure for that particular hour. Therefore, in the second stage it is necessary to calculate this index for each hour of the night. The average of the resilience indices for the nighttime period is referred, in this work, to as the nighttime resilience index. Minimizing nighttime resilience entails reducing the disparity between the current and required minimal head within that average. This strategy contrasts with common practice, which aims to maximize resilience to increase the difference between the current and required head, thereby providing excess pressure that can be utilized in case of increased flow due to higher demand or pipe failures. However, during nighttime hours, when demands decrease to minimal levels, this excess pressure mainly leads to an increase in background leakage.

Both steps involve single-objective optimization problems that are mathematically classified as NP-hard (NP denotes nondeterministic polynomial time) combinatorial optimization problems. The first step, maximizing the modularity index, is addressed by applying a Louvain-type algorithm (Blondel et al. 2008). The second step, minimizing the nighttime resilience index, employs the simulated annealing algorithm (Kirkpatrick et al. 1983).

The methodology is illustrated using two benchmark networks: (1) 25 nodes (25N) is an academic water network comprising of 25 demand nodes, 42 pipes, and 2 reservoirs; and (2) modified large network (MLN) is a real system, which was investigated by Kang and Lansey (2012), composed of 935 demand nodes, 1,278 pipes, and 5 reservoirs. The hydraulic analysis is conducted over a 24-h period, with time steps of 1 h. However, the optimization process in this study is restricted to the first six hours of the day, specifically during the night. Indeed, since the valve settings are fixed to be fully open starting at 6:00 AM, simulations from that time onward are performed for illustrative and comparative purposes only.

The structure of this work is organized as follows: In the next section, a comprehensive literature review is provided, covering methods related to pressure management and leak control, and outlining the primary contributions of this study. The following section explains each stage of the methodology and presents the case studies. Then, the obtained results are examined, and the conclusions are provided in the final section.

Literature Overview and Contributions

Various methodologies have been utilized to manage leaks using alternative devices instead of PRVs. For example, Creaco and Haidar (2019) presented a method for reducing leakages in a network associated with the average operating conditions of the day of maximum demand. The methodology is based on the hybrid combination of three algorithms: a multiobjective genetic algorithm (MOGA) to find the optimal placement of FCVs, a fast and greedy partitioning algorithm to divide the WDN into district measurement areas (DMAs), and a linear programming algorithm to obtain the optimal configuration of the FCVs that connect the DMAs. Alternatively, Cimorelli et al. (2020) proposed a hybrid genetic algorithm to maximize energy savings and water volume by reducing pressure in a WDN. This technique provides the best number, position, and direction of the pump as turbine (PAT) units to achieve the stated objective. Maskit and Ostfeld (2021) poses a multiobjective optimization problem in which the leakage and the cost of additional energy needed to pump the lost water are simultaneously minimized using MOGA.

Several other studies have made valuable contributions to the field of leakage management by employing pressure control through PRVs. Thus, Brentan et al. (2017) seeks to minimize, in a period less than one time step, the costs linked to the operation of a single PRV and a single pump already installed in a DMA, to generate a pumping and pressure management schedule. In this work, posed as a single-objective optimization problem, the particle swarm optimization (PSO) algorithm is applied for the joint minimization of the energy cost of the pump and the relative difference between the minimum operating pressure required by the system and real operating pressure in a WDN. Berardi et al. (2019) propose to reduce leakage by initially using topological segmentation of the network followed by DMA hydraulic design and optimization of the operating parameter of a local PRV already included in a WDN. The work proposes to obtain the optimal configuration of the PRVs, actuated by local or remote controls in real time, to improve the reduction of leakages and the reliability of the final solution. Dai (2021) focuses on the optimal management of pressures in a WDN, converting this problem into a nonlinear programming (NLP) problem to be solved using a PRV model. The objective here is to determine the optimal configuration of the already installed PRVs in the network to achieve proper operation of the WDS and the quality of overall pressure control. Later, Alsaydalani (2024) proposed to reduce the leakage percentages of a calibrated model corresponding to a DMA by controlling the pressure. To do this, it incorporates a PRV downstream of a preset flowmeter and assigns it an arbitrary and constant operating parameter throughout the day, to reduce overpressure in the network. While the studies detailed above propose efficient algorithms to optimize the operational parameters of PRVs, they do so by working with existing valves in the network, which limits the space for searching for possible solutions to the problem of leak control. To avoid restricting the optimization process in this way, the methodology proposed in the current study, at an initial stage, uses the modularity index to determine the optimal positions of possible PRVs that regulate pressures within the hydraulic system. In addition, this stage incorporates the structural resolution parameter in the modularity index calculation, which allows controlling and limiting the maximum number of potential valves to be installed.

Numerous alternative methodologies found in the literature also seek to optimize the position and quantity of PRV to manage leakages in the hydraulic system. For example, Zhang et al. (2021) propose the reduction of preestablished leak volumes by partitioning the network into DMAs and controlling PRVs in the entries to the DMAs. To do this, their work initially uses a modified community detection algorithm and then determines the optimal connections between DMAs using NSGA-II. Finally, it optimizes the operation of PRVs installed in these connections to reduce background leakages using a single-objective genetic algorithm (GA). More recently, Huzsvár et al. (2023) introduced a two-stage procedure for leak simulation and minimization for a single period (snapshot) simulation. In a first stage, the number and location of PRVs are optimized from a clustering perspective with the Leiden algorithm. In a second stage, the optimal status and the settings of these valves, in the snapshot, are determined with a differential evolution algorithm that aims to minimize leakage volumes. While both works make great contributions to the network management process, they do not specifically address adjustments during periods of excess pressure or conduct analyses over extended periods. The present study seeks to specifically reduce pressures at night without compromising demands during peak hours of water consumption activity. To this end, the proposed methodology incorporates the minimization of the average network resilience index at night.

Sousa et al. (2015) present two optimization models using simulated annealing (SA). The models include a lower-cost design model to identify pipes requiring replacement and resizing, as well as an optimal model to determine pump control and PRV configuration. Sahu and Gupta (2020) present a methodology to minimize leakages through pressure management, but this work uses variable speed pumps and PRVs. Initially, the pump speed is modified according to the variation in demand. The optimal number and location of PRVs are then determined using a modified reference pressure algorithm. Once the PRV location operation has been carried out, the adjustment of each valve is optimized and leaks are sought to be minimized using MOGA. While these methodologies focus on optimal PRV placement, they overlook the benefits of segmenting the network into smaller structures that can later serve as PMZs. The present work uses a fast Louvain algorithm to detect communities and determine the network tubes where the potential PRVs should be installed. These communities allow the establishment of possible pressure management zones and the consequent reduction of leaks.

Mehdi and Asghar (2019) propose a methodology based on the PSO algorithm to reduce leakage by managing nodal pressures in the system. The pressure management problem involves the optimal location and configuration of PRVs maximizing the network pressure reliability index (NPRI) by applying a valve selection index. Price et al. (2022) use a graph theory-based algorithm for pressure reduction in WDNs as a means to reduce leakages indirectly (since their volumes are not modeled directly). The authors propose to manage the network pressure by detecting the position of PRV valves, sequentially, according to the maximum downstream pressure. These works focus on reducing pressure but do not emphasize the impact of this reduction on leakage volumes, nor do they incorporate leakage models in the network. The methodology proposed here provides the ability to quantify, hour by hour, both the initial volumes and those obtained after optimization. This is achieved by modeling losses by introducing new nodes that serve as senders to the output of each network demand node.

This study proposes an additional strategy, applied to the hydraulic model, which involves the simulation of two PRVs in parallel. This modeling technique is used because, for complex networks sectorized through an automated process, optimal flow directions are not predefined. Dual valve modeling therefore allows for changes in flow direction resulting from changes in valve parameters during the optimization process.

Methodology

Hydraulic Model

Water distribution systems can be characterized topologically as a graph $G(V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$ is the set of vertices and $E = \{e_1, e_2, \ldots, e_m\}$ is the set of edges. Demand nodes, reservoirs, and tanks are represented by vertices, and pipes, valves, and pumps are represented by edges. The behavior of this type of network can be evaluated by knowing the demands of its nodes and the pressure in the system. In this work, the hydraulic analysis is performed under a pressure-driven approach (PDA), which is represented by the following matrix equations:

$$\begin{aligned} &\mathbf{A}_{pp}\mathbf{Q}(s) + \mathbf{A}_{pn}\mathbf{H}(s) = -\mathbf{A}_{p0}\mathbf{H}_0(s) \\ &\mathbf{A}_{np}\mathbf{Q}(s) - \mathbf{q}(\mathbf{H}_n, s) = \mathbf{0} \end{aligned} \tag{1}$$

where $s = 1, \ldots, S_d$, and $S_d = 24$ is the number of hour of the hydraulic analysis. $\mathbf{A}_{pp}$ is the diagonal matrix of pipe resistance, $\mathbf{A}_{pn}$ is derived from the pipe-node topological matrix, $\mathbf{A}_{p0}$ is the matrix of static heads, $\mathbf{Q}$ is the vector of unknown flow rates, $\mathbf{H}$ is the vector of unknown nodal heads, $\mathbf{H}_0$ is the vector of known nodal heads, and $\mathbf{q}$ is the vector of water demand, which depend on time and current pressure [for detail on the hydraulic model see Giustolisi et al. (2008)]. Eq. (1) is completed with a model for the supplied demands (Wagner et al. 1988)

$$q_i^t = \begin{cases} q_i^{t^*} & P_i^t \geq P_i^{t\mathrm{req}} \\ q_i^{t^*}\left(\dfrac{P_i^t - P_i^{t^*}}{P_i^{t\mathrm{req}} - P_i^{t^*}}\right)^{1/2} & P_i^{t^*} \leq P_i^t < P_i^{t\mathrm{req}} \\ 0 & P_i^t < P_i^{t^*} \end{cases} \tag{2}$$

where P_i^t is the pressure at node i at hour t, $P_i^{t^*}$ is the minimum pressure, and $P_i^{t\mathrm{req}}$ is the required pressure for supplying the minimum required demand $q_i^{t^*}$.

In this work, the software EPANET 2.2 (Rossman et al. 2020) is used to solve the hydraulic system according to the previously detailed model.

Leakage Model

In the developed methodology, the optimization process begins with a network that includes background leakages. Since the networks under study do not have predefined leakage volumes, the approach involves modeling these losses by placing emitters at each demand node in the network. Emitters are devices that simulate flow through an orifice discharging to the atmosphere. They are commonly used to represent flow in sprinkler systems, irrigation networks, or leaks in pipes connected to junctions. While more detailed models exist for representing background leaks, such as those considering pipe length (Giustolisi et al. 2008), this work opts for a simpler approach using emitters given by the following expression:

$$L_i^t = C P_i^{t\beta} \tag{3}$$

where L_i^t is the background leakage flow rate of node i at hour t, C is the discharge coefficient, and β is the pressure exponent, usually equal to 0.5. Different values of C will signal an increase or decrease in the background leakage volumes under constant system boundary conditions. In this approach, each scenario defines a new WDN with its own background leakage rates, and each is referred to as a base case scenario (BCS).

Algorithm Stages

The flowchart in Fig. 1 outlines the two primary stages of the proposed methodology. In the first stage, the optimization problem focuses on sectorizing the network into smaller structures, achieved by minimizing the topological modularity index using a Louvain-type algorithm. This initial phase allows the identification of conceptual cuts at the boundaries between these structures, which then serve to determine the locations for potential PRVs that enable pressure reduction. Subsequently, in a second stage, PRVs are installed at these conceptual cuts, and their states and operating parameters are optimized during nighttime using the simulated annealing algorithm.

First Stage: Optimal Location of Conceptual Cuts

In the initial stage, treated as a single-objective optimization problem, the objective is to determine the optimal locations for conceptual cuts (Giustolisi and Ridolfi 2014; Berardi et al. 2019) [alternative partitioning approaches can be found in Khoa Bui et al. (2020) and Hernandez Hernandez and Ormsbee (2022)]. These cuts indicate potential intervention sites within the infrastructure for pressure management. To achieve this goal, the network is segmented into smaller structures, and the conceptual cuts are strategically placed at the boundaries of these structures. These smaller structures, referred to as *modules* or *communities* in the context of network science, are characterized by densely interconnected vertices that exhibit relatively weaker connections to vertices outside the structure. In this stage, based solely on the topological properties of the network, the hydraulic system is not solved (Bianchotti et al. 2021).

Detection of Communities

There are different approaches for the detection of communities in complex networks (Giustolisi and Ridolfi 2014; Zhang et al. 2017; Liu et al. 2018). This work uses a Louvain-type algorithm (Blondel et al. 2008), which is based on the maximization of a metric known as *modularity*. This metric is defined by Newman (2004, 2006) and extended by Reichardt and Bornholdt (2004) as

$$Q_T = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \gamma\frac{k_i k_j}{2m}\right)\delta(C_i, C_j) \tag{4}$$

where m is the total number of edges; A_{ij} are the elements of the adjacency matrix $\mathbf{A}_{nn}$; γ is the structural resolution parameter; k_i is the degree of the vertex i; δ is the Kronecker delta function, which is equal to one if vertex i and j belong to the same community ($C_i = C_j$), and zero otherwise and the sum runs over all pairs of vertex i, j, with $i \neq j$. The structural resolution parameter γ allows controlling the number and size of communities. Thus, the larger the value of γ, the greater the number, and the smaller the

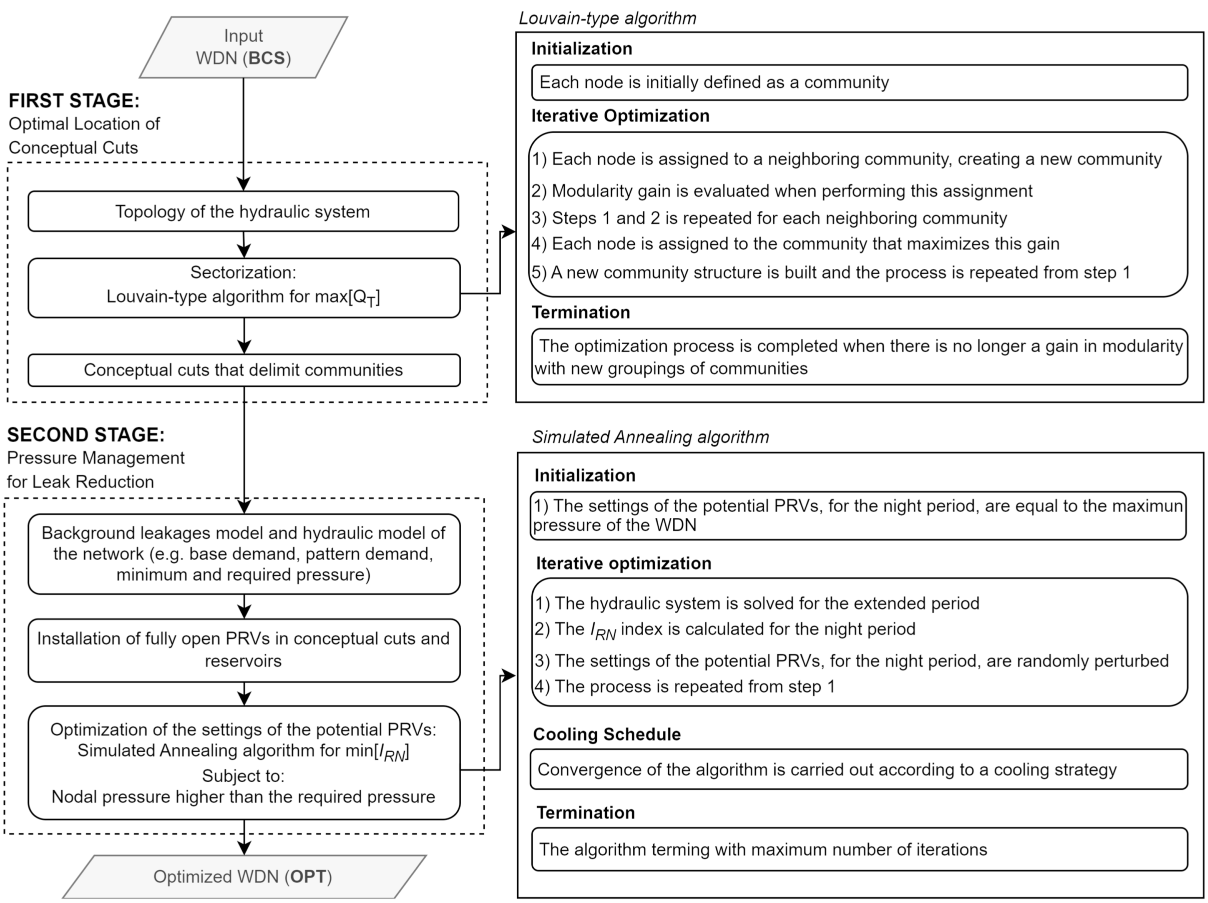

Fig. 1. Flowchart of methodology.

size, of the communities. Modularity index is a scalar that takes values between 0 and 1.

The Louvain algorithm consists of two iterative stages: in the first one, each node is initially assigned to a community. Then, the modularity gain is evaluated by moving nodes between communities, assigning each node to the community that maximizes this gain. In the second stage, a new network is constructed where the communities become nodes, and the process is repeated.

Problem Formulation

The optimization problem at this stage is formulated as follows:

$$F_1(\mathbf{X}) = \max[Q_T] \tag{5}$$

The maximization of Q_T yields a set of nodes constituting each module, and from these nodes, the edges that do not connect nodes within the modules themselves are identified. These edges, referred to as *conceptual cuts*, are denoted by the binary vector $\mathbf{X} = (x_1, x_2, \ldots, x_p)$, where p is the number of edges that are in the limits between modules. In the second stage, the edges will no longer be abstract entities but will instead represent the pipes of the water network. The installation of potential PRVs for pressure management is carried out at these conceptual cuts. Additionally, PRVs are installed in the pipes adjacent to the reservoirs to enable operational control of the water sources.

Second Stage: Pressure Management for Leak Reduction

In WDNs primarily serving domestic connections, water consumption levels typically reach a minimum during nighttime. This period is characterized by low demand, such as occasional toilet flushes, coinciding with elevated system pressures. Throughout the day, water pressures in WDNs fluctuate in response to changes in consumer demand. Peaks in demand lead to decreased pressures during midday, while minimal demand at night results in higher pressures. Despite limited control provided by pumps and tank operations, strategically placed PRVs within the network effectively manage excess pressures and enhance overall pressure control (Price et al. 2022). The second stage of the proposed methodology aims to reduce additional, nonessential pressure within the network to minimize background leakage volumes. This strategy involves installing PRVs in pipes delineating modules identified in the first stage, and optimizing their operating parameters during nighttime.

Considerations for PRV Modeling

EPANET 2.2 software models each PRV with unidirectional flow; that is, the downstream and upstream node of the device corresponds to the start node and end node initially assigned to the valve, respectively. In this way, the valve setting (maximum value that pressure can take at the node downstream) is always compared to the pressure at the end node of the device, to determine if PRV is open, closed, or active. Carrying out simulations of the hydraulic system with a model that contemplates the installation of a single valve would imply predefining the flow direction, which would strongly limit the search for possible solutions to the problem posed in the second stage. The method proposes to install in each conceptual cut a pair of PRVs [see modeling scheme in Fig. 2(a)]. These PRVs are arranged in such a way that the downstream node of one valve corresponds to the upstream node of the other, and vice versa. This structural modification of the hydraulic system avoids restricting the direction of water flow through the pipe to only that which has the valve. It is important to keep in mind that, in practice, it is only necessary to install one valve per pipe. Therefore, the recommendations to the utility will include installing just one valve according to the optimal solution's direction. The proposed valve duplication serves as a simulation strategy to model two opposing flow directions that occur during the optimization process.

Resilience Index

This stage involves the reduction of background leakage volumes by decreasing the pressure in the network during nighttime hours. To achieve this, the proposal is to minimize the average of a metric known as resilience index. This index was introduced by Todini (2000) and it is used to quantify the intrinsic capability of a network to cope with failures. For a network without pumps, is defined as $I_R = 1 - W^*_{\text{int}}/W^*_{\max}$, where $W^*_{\text{int}} = \gamma_w \sum_{k=1}^{r} Q_k H_k - \gamma_w \sum_{i=1}^{n} q^*_i h_i$ represents the power dissipated in the network to satisfy the total demand. $W^*_{\max} = \gamma_w \sum_{k=1}^{r} Q_k H_k - \gamma_w \sum_{i=1}^{n} q^*_i h^*_i$ represents the maximum power dissipated internally while satisfying the constraints in terms of required demand q^*_i and minimum head h^*_i at the node i, where γ_w is the specific weight of water; h_i is the head at node i; Q_k and H_k are, respectively, the discharge and head of reservoir k; and r is the number of reservoirs. With these definitions, and explicitly considering the temporal dependence of the terms involved, the resilience index can be expressed as

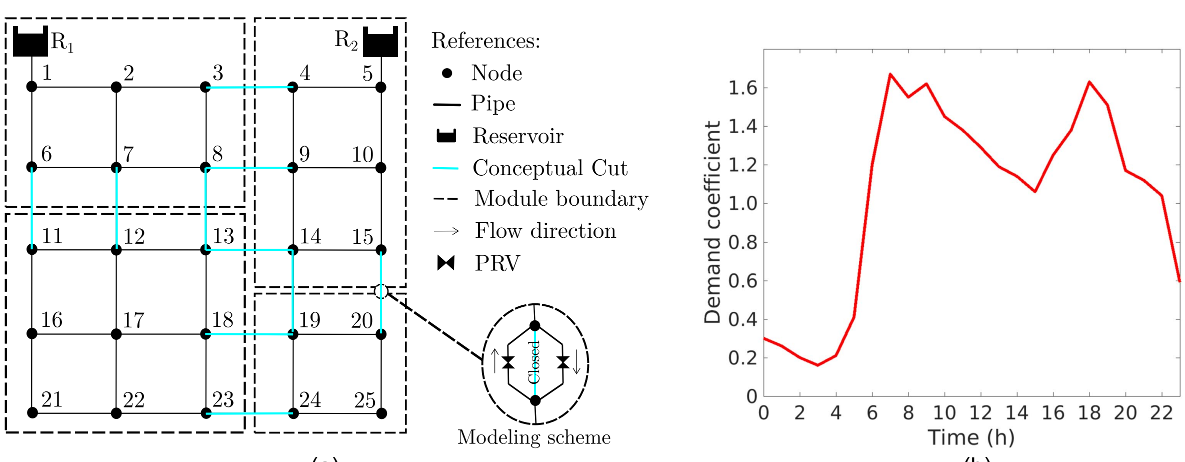

Fig. 2. Case study 25N: (a) arrangement of conceptual cuts in the network; and (b) demand pattern for an extended period.

$$I_R^t = \frac{\sum_{i=1}^n q_i^{t^*}(h_i^t - h_i^{t^*})}{\sum_{k=1}^r Q_k^t H_k^t - \sum_{i=1}^n q_i^{t^*} h_i^{t^*}}$$

It is important to emphasize that the nodal head h_i^t is the only variable subject to change during the optimization process. Furthermore, it is worth noting that the resilience index is defined for a specific hour t of the day with well-established required demand and minimum pressure. Accordingly, this index should be computed for every nighttime hour and then averaged over the number of hours to obtain a scalar index characterizing the network's resilience during the nighttime period; formally

$$I_{RN} = \frac{\sum_{t=1}^{S_n} I_R^t}{S_n} \tag{6}$$

where $S_n = 6$ is the number of hour of the night period.

Problem Formulation

In the second stage, the aim is to decrease background leakage volumes by restricting the available pressure in the network during nighttime hours. This work proposes to achieve this by minimizing the nighttime resilience index given by Eq. (6). Formally, the problem is formulated as a single-objective optimization:

$$F_2(\mathbf{Y}) = \min[I_{RN}] \tag{7}$$

subject to $P_i^s \geq P_i^{t\text{req}} \quad \forall\ i = 1, \ldots, n\ \wedge\ \forall\ s = 1, \ldots, S_d$.

Since the second stage seeks to reduce the nodal pressures when demands decrease, the design variables are the valve operating parameters, or the settings of PRVs, for each hour at night time. The setting of a PRV indicates the maximum value that pressure can take at the node downstream of the device. The design variable is denoted by the matrix $\mathbf{Y}$, with elements y_{ij} denoting the setting (i.e., downstream pressure) of valve j at time step i, with $1 \leq j \leq (2p + r)$ and $1 \leq i \leq S_n$, where S_n equals the last time step s of the night period, that is, at 05:00 AM. It should be noted that the dimension of $\mathbf{Y}$ is given by $S_n \times (2p + r)$, with $2p$ indicating the double number of valves than conceptual cuts and r indicating a valve for each reservoir. It should be noted that the optimization process aims to minimize the nighttime resilience index (I_{RN}) while ensuring the full satisfaction of demands at these hours. Upon completion of the optimization process, all PRV valves are adjusted to be fully open. This ensures that, starting from 6:00 AM, the network operates with the same performance as the original configuration (termed as BCS).

Simulated Annealing

The minimization problem stated in the second stage is a hard combinatorial optimization problem known as an NP-hard problem (NP denotes nondeterministic polynomial time). The present work proposes the implementation of simulated annealing (Kirkpatrick et al. 1983) algorithm to achieve of the minimization formulated in Eq. (7). The SA method was selected due to its proven effectiveness in handling complex optimization problems with discrete variables (Puccini et al. 2016; Sousa et al. 2015; Bianchotti et al. 2021). This algorithm is expected to deliver near-optimal solutions by efficiently exploring the solution space and effectively escaping local optima. Its stochastic nature allows for a comprehensive search for the best configuration of PRV settings, ensuring robustness and reliability in finding optimal solutions. For this specific problem, the algorithm is divided into the following phases:

1. *Initialization*. The algorithm initializes by setting an initial temperature T_0 and starting from a set of initial values for the design variables, $\mathbf{Y}_0^{\text{Cur}}$. A hydraulic analysis is conducted using the PDA approach to calculate the cost of the current solution, I_{RN}^{Cur}. Each element of $\mathbf{Y}_0^{\text{Cur}}$ is set to the maximum pressure in BCS.
2. *Parameterization for SA*. The algorithm iterates through a given number of iterations, generating new solutions by randomly perturbing the values within the current solution matrix $\mathbf{Y}^{\text{Cur}}$ to create $\mathbf{Y}^{\text{Per}}$. Each element of this matrix can take values between $P_{\min}$ and the maximum pressure of BCS. The hydraulic system is solved for the new solution, and the cost I_{RN}^{Per} is calculated. If $I_{RN}^{\text{Per}} < I_{RN}^{\text{Cur}}$, the new solution is accepted. Otherwise, acceptance is determined probabilistically using Boltzmann's probability, which depends on the actual temperature T_i. This allows the algorithm to escape local minima. If the current cost I_{RN}^{Cur} is lower than the best cost obtained so far, it updates the best cost and solution (I_{RN}^{Best}, $\mathbf{Y}^{\text{Best}}$).
3. *Cooling schedule*. The convergence of the algorithm relies on a fictitious parameter, the temperature T. Initially, the temperature is set high enough to accept approximately 80% of generated solutions. It is then decreased at each step according to a cooling strategy, typically $T_{t+1} = \alpha T_t$, where $0 < \alpha < 1$. This work uses $\alpha = 0.97$.
4. *Termination*. The algorithm terminates when the maximum number of iterations is reached. The water network obtained at this stage is referred to as the optimized network (OPT).

All the simulations for this study were conducted using MATLAB 2017a running on an Intel Core i7-9700k CPU @ 3.60 GHz × 8 processor.

Case Studies

The proposed methodology was implemented in two case studies. The first case, referred to as 25 nodes (25N), is an academic network designed by the authors, consisting of 25 demand nodes, 41 pipes, and 2 reservoirs [see Fig. 2(a)]. The topographic nodal heights vary according to the position of the node, being equal to 10 m (for node 13), 15 m (for nodes 7–9, 12, 14, 17–19), and 20 m (for nodes 1–6, 10, 11, 15, 16, 20–25). The total height of both reservoirs is equal to 50 m. The diameter of the pipes is 250 mm and the length is 1,000 m, except for the pipes that connect the reservoirs whose length is 2,000 m. The base demand of the nodes has a value of 2 L/s for nodes 1–3 and 6–8; 3 L/s for nodes 4, 5, 9, 10, 14, and 15; 4 L/s for nodes 11–13, 16–18, and 21–23; and 5 L/s for nodes 19, 20, 24, and 25. The second case study is the MLN, which was investigated by Kang and Lansey (2012). This network is composed of 5 reservoirs, 1,278 pipes, and 935 demand nodes [see Fig. 8(a)]. The pressures values adopted for the first case study are $P_i^* = 0$ m for the minimum pressure, $P_i^{\text{req}} = 7$ m for the required pressure (see Wagner et al. 1988), and, for the second case study, are $P_i^* = 5$ m and $P_i^{\text{req}} = 10$ m (all for 24 h).

For the first case study, the optimization process is applied to five scenarios characterized by different values of the discharge coefficient C, each with different outflow rates ranging from 16% to 31% during nighttime. The objective of diversifying scenarios is to analyze the sensitivity of the method to the changes that a variation in the volume of leakages. However, a deeper analysis is made for the coefficient $C = 0.25$. For the second case study, the optimization process is performed for a single value of $C = 0.30$. This coefficient was adjusted to achieve a daily leakage volume approximately equal to 20% of the total volume delivered to the network during the 24 h (Sousa et al. 2015; Creaco and Pezzinga 2018; Sahu and Gupta 2020).

For all scenarios and both case studies, $S_n = 6$; that is, the minimization of I_{RN} is planned for the first 6 h of the day, from 00:00 AM to 05:00 AM. This particular period is evaluated because it is considered to be the time with highest pressure available in the system given that consumer demands decrease.

Results

Case Study 1: 25 Nodes (25N)

The initial stage of our methodology, aimed at maximizing modularity with the Louvain algorithm, yields a modularity value of $Q_T = 0.49$ ($\gamma = 1.0$), identifying 10 conceptual cuts that divide the network into 4 distinct modules. These cuts and modules are visualized in Fig. 2(a). The location of the potential PRVs is carried out in these conceptual cuts and, additionally, in the adjacent pipes to reservoirs. As described in the previous section, every conceptual cut is substituted with a pair of PRVs, with only one PRV assigned for each reservoir. Hence, a total of 22 PRVs require to be modeled. For a visual representation of how the valves are positioned within each conceptual cut, refer to Fig. 2(a). The hydraulic analysis is conducted using a specific demand pattern, which is shown in Fig. 2(b) and represents a typical summer Monday.

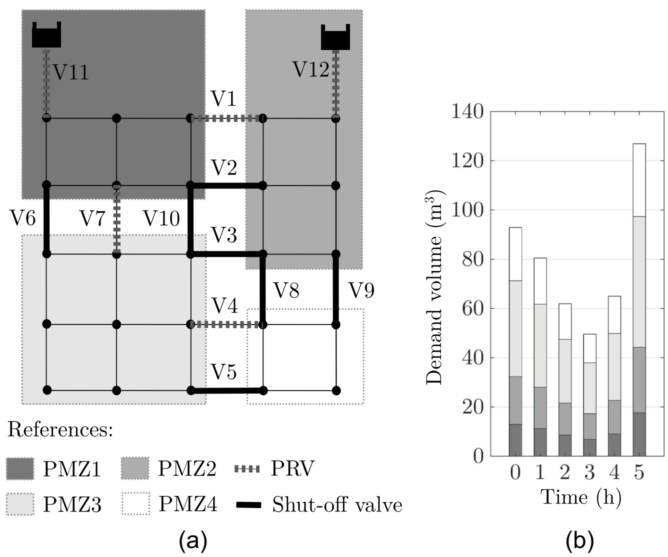

Fig. 3. Case study 25N—coefficient $C = 0.25$: (a) final valve configurations; and (b) demand by PMZ.

Initially, all valves in the BCS network are set to fully open. However, after optimization, new states emerge: fully closed and active. What each of these states indicates is detailed below:

- Fully closed (FC): The valve is closed at hour t, meaning it does not allow any flow of the fluid it controls.
- Fully open (FO): The valve remains open at hour t, allowing the maximum flow of the fluid it controls.
- Active (A): The valve is in an active state, meaning it regulates the pressure at the outlet of the device at hour t.

A combination of states of valve that only varies between FO and FC throughout the day turns the potential PRV into a shut-off valve. In such cases, the type of device installed in the OPT is replaced: the PRV is substituted with an shut-off valve. However, if a potential PRV remains FO throughout the day without any control, the valve is removed and this position is considered as a possible observation point, since the flow through the device is not restricted. The decision of whether or not to place a flow meter there is the responsibility of the service provider company to guarantee precise control of the flow that allows a mass balance of the network to be carried out. Conversely, valves that become active at any point during some time of the day are retained as PRVs.

Fig. 3 presents the result of the second stage for the emitter coefficient $C = 0.25$. In Fig. 3(a), the types of valves to be installed in each conceptual cut are distinguished by line style, such as dashed or solid, depending on whether the device corresponds to a PRV or a shut-off valve. The distribution of shut-off valves and PRVs in the network accounts for 60% and 40% of the total installed valves, respectively. Particularly, this new configuration of the valves divides the network into a number of PMZ equal to the number of modules obtained in the first stage; that is, the total of PMZ is equal to 4, which are represented by different grayscale shades in Fig. 3(a). Additionally, Fig. 3(b) presents a bar graph depicting the demands for each PMZ during each hour of the nighttime.

The flow directions through the valves in both the BCS and OPT networks during the first 7 h of the day are presented in Figs. 4 and 5, respectively. An additional hour, 06:00 AM, is included to indicate the variability that occurs after optimization since from that hour the valves are always open. In these figures, a center dash indicates that the valve is closed, while arrows indicate the direction of flow through the device (use Fig. 3 as a reference). The superscript denotes the PRV setting at that particular hour.

Valve ID	Hours						
	00:00	01:00	02:00	03:00	04:00	05:00	06:00
V1	←	←	←	←	←	←	←
V2	←	←	←	←	←	←	←
V3	←	←	←	←	←	←	←
V4	→	→	→	→	→	→	→
V5	→	→	→	→	→	→	→
V6	↓	↓	↓	↓	↓	↓	↓
V7	↓	↓	↓	↓	↓	↓	↓
V8	↓	↓	↓	↓	↓	↓	↓
V9	↓	↓	↓	↓	↓	↓	↓
V10	↓	↓	↓	↓	↓	↓	↓
V11	↓	↓	↓	↓	↓	↓	↓
V12	↓	↓	↓	↓	↓	↓	↓

Fig. 4. Case study 25N—coefficient $C = 0.25$. Direction of flow through valves in BCS.

Valve ID	Hours						
	00:00	01:00	02:00	03:00	04:00	05:00	06:00
V1	$\rightarrow$	-	$\rightarrow$	$\rightarrow$	$\leftarrow^{10}$	$\rightarrow$	$\leftarrow$
V2	$\rightarrow$	-	-	-	-	-	$\leftarrow$
V3	-	-	$\rightarrow$	-	-	-	$\leftarrow$
V4	-	$\leftarrow$	-	-	-	$\rightarrow$	$\rightarrow$
V5	$\leftarrow$	$\leftarrow$	-	$\leftarrow$	$\leftarrow$	$\rightarrow$	$\rightarrow$
V6	-	$\uparrow$	$\downarrow$	-	$\downarrow$	$\downarrow$	$\downarrow$
V7	$\downarrow$	-	-	-	$\downarrow$	-	$\downarrow$
V8	$\downarrow$	-	-	$\downarrow$	-	-	$\downarrow$
V9	$\downarrow$	$\downarrow$	$\downarrow^{10}$	$\downarrow$	$\downarrow^{10}$	-	$\downarrow$
V10	-	$\uparrow$	-	-	$\downarrow$	$\downarrow^{16}$	$\downarrow$
V11	$\downarrow^{10}$	-	$\downarrow^{12}$	$\downarrow^{10}$	$\downarrow^{10}$	$\downarrow^{10}$	$\downarrow$
V12	-	$\downarrow^{10}$	-	-	$\downarrow^{12}$	-	$\downarrow$

Note: The superscript of the arrow indicates the setting value of the active valve.

Fig. 5. Case study 25N—Coefficient $C = 0.25$. Direction of flow through valves in OPT.

Fig. 5 highlights the significant changes that occur in the dynamics of the hydraulic system when attempting to reduce nodal pressures. During the night period, the flow of water becomes intermittent as it passes through the valves. Notably, Valve V11, which is adjacent to one of the reservoirs, is the one that is activated most frequently, while the remaining four PRVs are only activated at limited times.

The pressure variation for the operational configuration schematized in Fig. 3(a) is shown using a violin diagram in Fig. 6. In this diagram, the nodal pressures for the first 6 h of both BCS and OPT networks are plotted in Figs. 6(a and b), respectively. Meanwhile, the nodal pressures for the remaining hours, during which the settings of potential PRVs are not optimized, are shown in Fig. 6(c). This figure illustrates that the optimized average nighttime pressures are similar to those during peak demand periods (7:00–8:00 AM and 6:00–7:00 PM). Additionally, it is conceptually significant to note that the average nighttime pressures without intervention are higher than the daytime average pressures. It should be emphasized that the PRV status from 6:00 onward is fixed to fully open, ensuring that the pressures in the OPT network are equal to those in the BCS network.

To illustrate the difference between the average nodal pressures per PMZ in BCS and OPT, the top graph in Fig. 7 showcases this comparison. The difference consistently falls within a positive range of approximately 17 to 21 m across all PMZs. Furthermore, the lower graph in Fig. 7 displays the leakage volume for each optimized hour, per PMZ. The graph reveals that higher demand in a particular module corresponds to a greater reduction in leakage volume, for similar values of pressure reduction. These results demonstrate the effectiveness of the optimization process in reducing leakage and achieving more uniform nodal pressures throughout the day, thereby enhancing the overall efficiency and performance of the hydraulic system.

Table 1 summarizes, for the OPT network, the number of valves classified into different classes based on its mode of operation, considering various scenarios of the emitter coefficient (from $C = 0.20$ to $C = 0.40$ in increments of 0.05). Table 2 details the results for second stage. Columns 2, 3, and 4 contain the percentages minimum (Min), average (Mean) and maximum (Max) of leakages, respectively. These percentages were calculated by considering the outflows of all emitters for the first 6 h of the day. Columns 5 and 6 show the values of nighttime resilience index, I_{RN}, obtained before and after of optimization, respectively: I_{RN} for the BCS decreases as the emitter coefficient C increases while for the OPT, the value of I_{RN} remains approximately constant within a range of 0.30 to 0.32. The daily leakage volumes (L_w) for BCS are shown in column 7, ranging from 200.6 m^3/day to 395.3 m^3/day for the first and last scenarios, respectively. For OPT, in column 8, the leakage volumes are reduced to 176.1 m^3/day and 349.7 m^3/day for the first and last scenarios, respectively. The difference between both volumes, expressed in m^3, varies as the coefficient increases. However, the quotient (L_{w_r}) between this difference and the volume of leakages from the BCS, expressed as a percentage in column 9, remains similar for all scenarios and ranges between 11% and 12%.

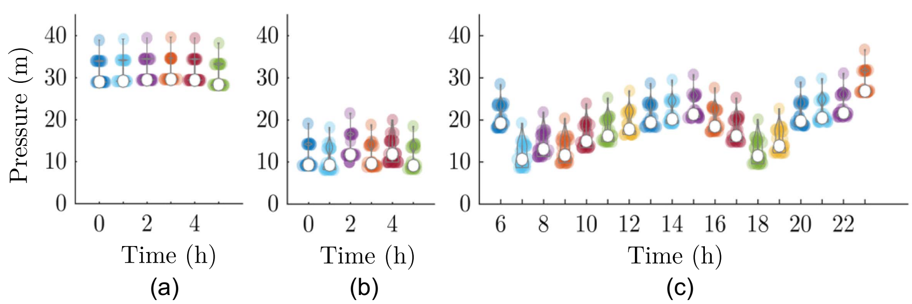

Fig. 6. Case study 25N—coefficient $C = 0.25$. Violin plot of nodal pressures for the extended period: (a) nighttime for BCS; (b) nighttime for OPT; and (c) rest of the day for BCS and OPT.

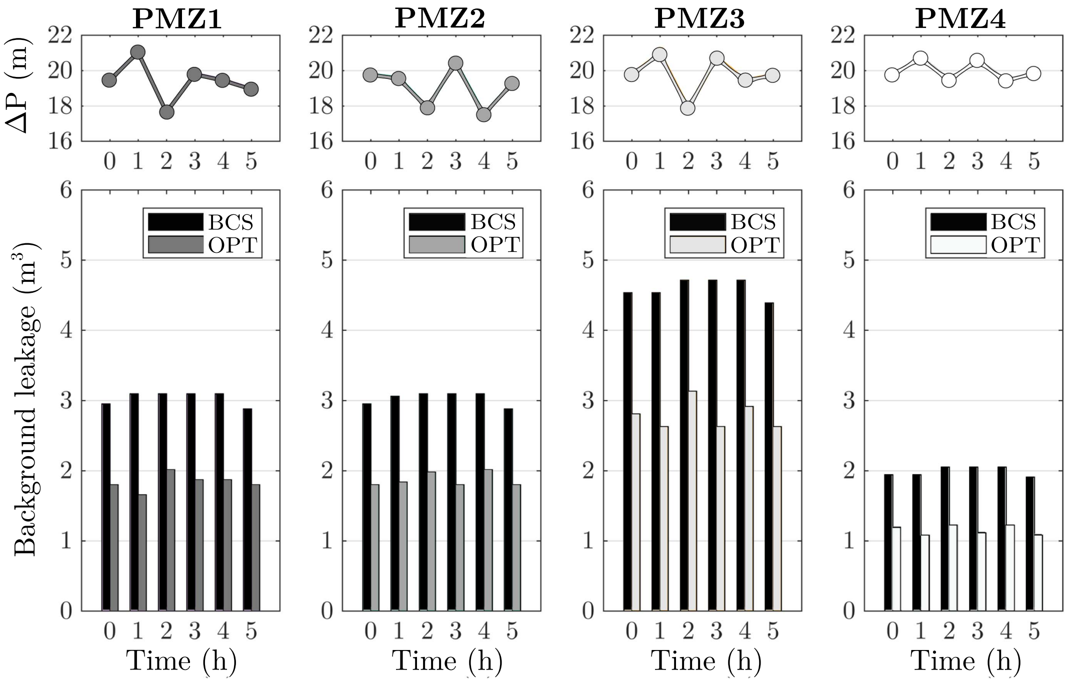

Fig. 7. Case study 25N—coefficient $C = 0.25$. Average pressure differences and leakage volumes for PMZ.

Table 1. Case study 25N: accounting of the number of devices belonging to each class of the proposed classification, for OPT

Emitter coefficient	Number of valves	
C	Shut-off valve	PRV
0.20	6	6
0.25	7	5
0.30	7	5
0.35	5	7
0.40	7	5

Table 2. Case study 25N: summary of optimization results for all scenarios

Emitter coefficient	Leakages percentage Min	Leakages percentage Mean	Leakages percentage Max	I_{RN} BCS	I_{RN} OPT	L_w BCS	L_w OPT	L_{w_r}
C	%	%	%	—	—	m^3/day	m^3/day	%
0.20	5	16	38	0.80	0.32	200.6	176.1	12
0.25	6	19	47	0.77	0.31	249.5	219.5	12
0.30	8	23	56	0.74	0.32	297.8	264.4	11
0.35	9	27	66	0.71	0.32	347.5	309.0	11
0.40	10	31	75	0.68	0.30	395.3	349.7	12

Case Study 2: Modified Large Network (MLN)

The first stage of the methodology yields a modularity index of $Q_T = 0.90$ ($\gamma = 1.0$) and divides the network into 24 modules through the optimal placement of 68 conceptual cuts [see Fig. 8(a)]. The sensitivity analysis for the γ parameter is presented in Appendix S1. The bar graph in Fig. 8(b) illustrates the total base nodal demand volumes of the network for each hour of the night.

The number of devices obtained after optimization process, according to the classification proposed for case study 25N, can be summarized as follows: 38 observation points, 19 shut-off valves, and 16 PRVs (i.e., 22% of the total conceptual cuts). The PMZs defined in the network and the final configuration of the devices is detailed in Fig. 9(a). Valves that ultimately function as PRVs are labeled with the number assigned to the device to facilitate reading Table 3. Fig. 9(b) shows, using a bar graph, the leakage volumes for the first 6 h of the day, for BCS and OPT. The volumes, per hour, corresponding to BCS are close to 6,000 m^3/h, while the leakage volumes for OPT are around 5,000 m^3/h. The difference of the total volumes covered within the night period, before and after the optimization, is 6,014 m^3; that is a reduction of, approximately, 16% with respect to the leakage volumes of the unoptimized network. This 16% represents 6% of the total base demand of the network during the night.

Table 3 details the variation of states experienced by these PRVs during nighttime hours, where the subscript that accompanies the status A indicates, again, the setting of the valve at the moment it is active. Table 3 shows, moreover, that three of the valves adjacent to the reservoirs (V70, V71, and V73) have greater activity than the rest. Despite the varied dynamics of the valves operation, the state that predominates in all the valves, throughout the night period, is the FO.

The nodal pressures of the first 6 h, for BCS and OPT, are plotted in Figs. 10(a and b), respectively. The nodal pressures for the rest of the day are shown in Fig. 10(c). The plots show that the median value decreased by approximately 15 m after optimization.

Figs. 11(a and b) represent the pressure contour map of the BCS and OPT networks, respectively, for the hour 00:00 AM. This time is used to show the change in the distribution and magnitude of the pressures in the network after optimization. For the rest of the hours of the night, the characteristics are similar. The figure on the left shows two large areas in the network: An area with pressures between 25 m and 40 m and another area with pressures between 40 m and 55 m. A zone of smaller extension, with pressures greater than 55 m, is displayed below on the lower left. On the contrary, in the network located to the right, pressures between 10 m and 25 m predominate, with sectors with pressures between 25 m and 40 m and a small one between 40 m and 55 m.

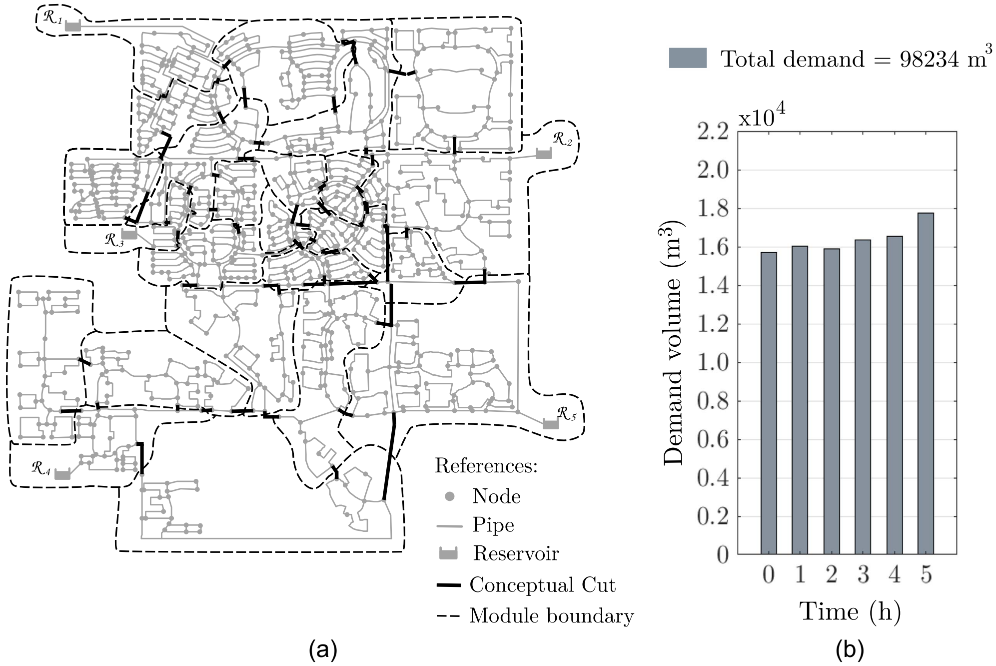

Fig. 8. Case study MLN—coefficient $C = 0.30$: (a) arrangement of conceptual cuts in the network; and (b) demand volumes for nighttime.

To evaluate the proposed methodology, it is useful to consider an alternative approach. This approach involves installing a PRV at each reservoir outlet and adjusting its settings to maintain pressure levels 10% above those required at the nodes immediately downstream from the reservoirs. While this alternative achieves the same levels of leak reduction, it fails to meet the required demands (see Appendix S2). Another approach to evaluating the methodology involves directly minimizing pressure values above a desired threshold rather than focusing on resilience. By using an optimization criterion that minimizes the difference between the pressure at each node and the required pressure averaged over nighttime, a leakage reduction of 4.4% is achieved with the activation of 22 PRVs. Additionally, this method does not exhibit the same uniformity as observed in the violin plot diagrams obtained using the resilience index (see Appendix S3).

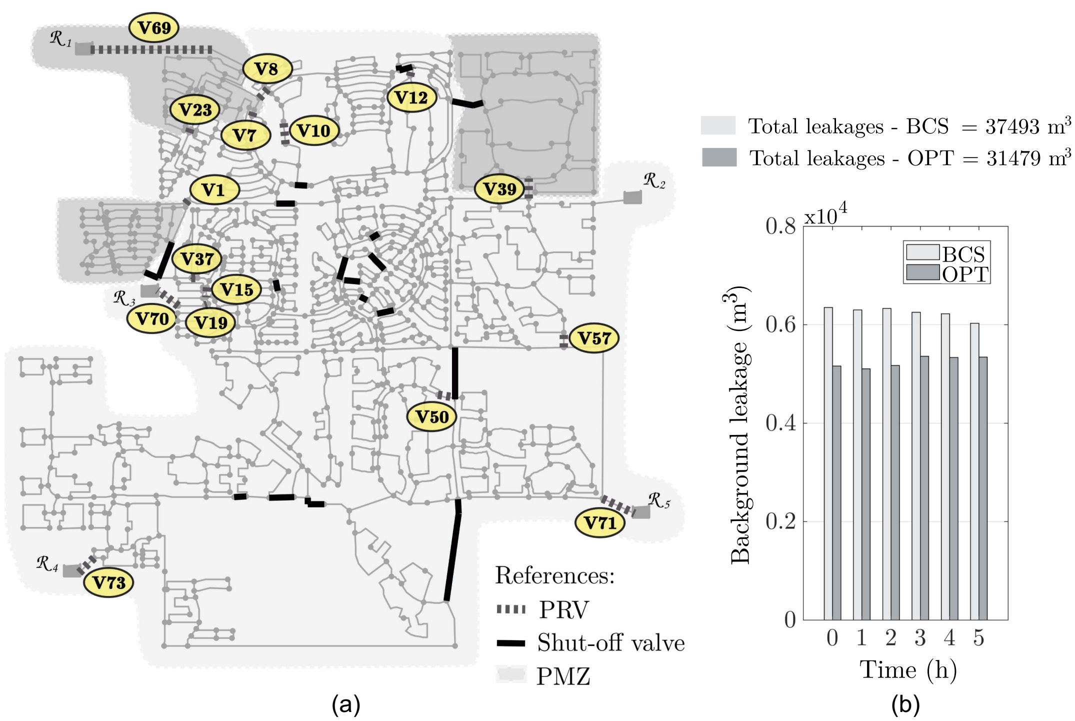

Fig. 9. Case study MLN—coefficient $C = 0.30$: (a) final valve configurations; and (b) leakage volumes for nighttime.

Table 3. Case study MLN—coefficient $C = 0.30$: valve operating parameters in OPT

	Hour					
Valve ID	00:00	01:00	02:00	03:00	04:00	05:00
V1	FO	FO	A^{25}	FO	FO	FO
V7	A^{29}	A^{25}	FO	FC	FO	FO
V8	FO	FO	FO	A^{25}	A^{29}	FO
V10	A^{29}	FO	FO	FO	A^{25}	FO
V12	FO	FO	FO	FO	A^{27}	FC
V15	A^{25}	FO	FO	FO	FO	FO
V19	FO	FO	A^{27}	FO	FO	FO
V23	FO	FO	FO	FO	A^{37}	A^{37}
V37	FO	FO	FO	FO	FO	A^{29}
V39	A^{37}	FO	FO	A^{33}	A^{31}	A^{33}
V50	FO	FO	FO	FO	A^{25}	FO
V57	FO	A^{29}	FO	FO	FO	A^{25}
V69	A^{33}	A^{27}	FO	FO	FO	FO
V70	A^{33}	A^{39}	FO	FO	A^{33}	A^{43}
V71	A^{43}	FO	A^{47}	FO	A^{55}	A^{53}
V73	A^{37}	A^{27}	A^{27}	A^{25}	A^{37}	A^{37}

Note: The superscript of status A indicates the current setting value of the valve that is active.

Conclusions

This study addressed pressure management at nighttime, specifically focusing on PRVs as a means to reduce background leaks. The proposed methodology consists of two stages aimed at improving the efficiency and overall performance of the network. In the first stage, the optimization process divides the network into communities by optimally identifying conceptual cuts in the network. In the second stage, the optimization process introduces new configurations for the potential PRV states that were incorporated into the conceptual cuts and at the outlet of the reservoirs.

The first stage of the methodology implicitly limits the number of valves through the structural resolution parameter γ, which controls the maximum number of conceptual cuts and thus the potential number of PRVs that can be installed. This parameter serves as a constraint to prevent an unlimited placement of valves. However, the final number of PRVs to be installed will be determined at the end of the complete optimization process.

The second stage aims to establish the optimal settings that minimize the averaged resilience during the nighttime period. In cases where the optimization results in FO or FC valves, PRVs will not be

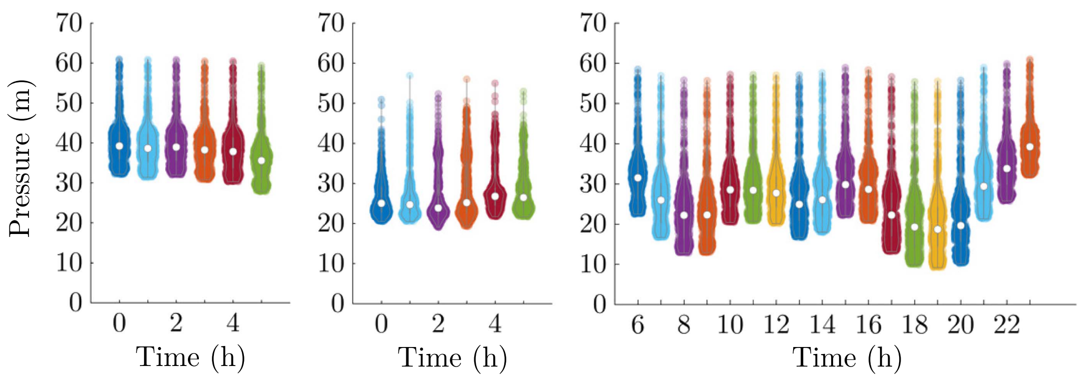

Fig. 10. Case study MLN—coefficient $C = 0.30$. Violin plot of nodal pressures for the extended period: (a) nighttime for BCS; (b) nighttime for OPT; and (c) rest of the day for BCS and OPT.

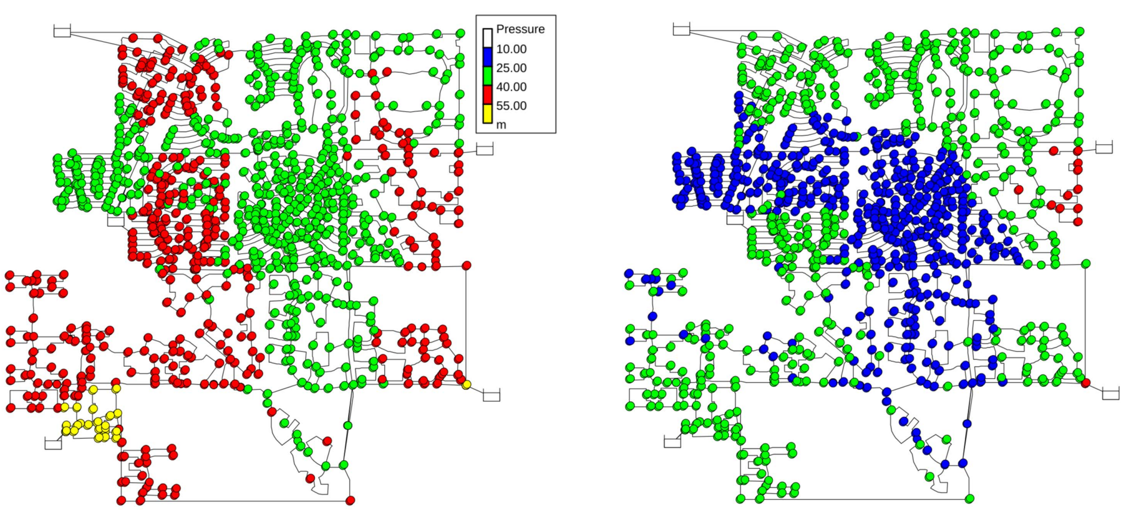

Fig. 11. Case study MLN—coefficient $C = 0.30$. Nodal pressures 00:00 AM: (a) BCS network; and (b) OPT network.

necessary. PRVs will only be installed in cases where some activity is observed, that is, when they limit the pressure at the downstream node. Therefore, although the method allows determining the maximum number of potential valves beforehand, which occurs at the end of the first stage, it does not predict the final number of valves of each type (PRVs, shut-off, etc.) until the end of the second stage. Consequently, if a different number of PRVs is desired at the end of the second stage, new simulations must be conducted by adjusting the resolution parameter to increase or decrease the initial maximum number of potential PRVs.

Comparing the BCS and OPT network configurations shows that nighttime optimization results in improved pressure distribution and reduces background leakage volumes. This optimization effectively regulates pressure and changes hydraulic dynamics without affecting peak demand periods during the day.

The study also highlights the effect of the developed methodology on different leakage scenarios simulated specifically for the 25N network, employing different values of the emitter coefficients. It was found that despite the fact that the volumes of leakage increase as the emitter coefficient increases, the percentage of around 12% of volume of water saved is similar for all the scenarios proposed in the 25N network. Furthermore, a comparative analysis between the OPT network and the BCS network demonstrates a significant reduction in leakages of approximately 16% for the MLN network. In particular, this research employed a leakage model based on emitters. It would be interesting to explore how the reduction of losses depends on the different leakage models.

Regarding the design of PMZs, in this study we consider PMZs as specific areas of the potable water distribution network delimited by PRVs or shut-off valves. While in the first case study PMZs align with the communities identified in the initial stage, in the second case study a notable disparity is observed in terms of the number of nodes encompassed by these zones. Although this methodology is effective for its primary goal of reducing leaks in the network, the observed disparity in PMZs presents practical challenges for zone pressure control. It would be desirable for the methodology to provide more precise control for PMZ design, considering factors such as the volume of water or pressure involved in each zone or the number of nodes covered. Future investigations will aim to address the limitations highlighted in this study.

Finally, the work presented highlights the effectiveness of simulated annealing as an optimization algorithm. This approach successfully reduces nighttime background leakages by strategically adjusting valve states by minimizing the averaged resilience index during off-peak hours.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available from the corresponding author by reasonable request. The 25N network is available in an archive online at https://github.com/gpuccini/25-Nodes.

Acknowledgments

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Supplemental Materials

Appendixes S1–S3, including Figs. S1–S3 are available online in the ASCE Library (www.ascelibrary.org).

References

Ali, M. E. 2015. "Knowledge-based optimization model for control valve locations in water distribution networks." *J. Water Resour. Plann. Manage.* 141 (1): 04014048. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000438.

Alsaydalani, M. O. 2024. "Hydraulic modelling for leakage reduction in water distribution systems through pressure control." *Open Civ. Eng. J.* 18 (Jun): 1874–1945. https://doi.org/10.2174/0118741495289971240112101323.

Araujo, L. S., H. Ramos, and S. T. Coelho. 2006. "Pressure control for leakage minimisation in water distribution systems management." *Water Resour. Manage.* 20 (1): 133–149. https://doi.org/10.1007/s11269-006-4635-3.

Berardi, L., D. Laucelli, A. Simone, G. Perrone, and O. Giustolisi. 2019. "Integrated pressure control strategies for sustainable management of water distribution networks." In Vol. 85 of *Proc., E3S Web of Conf. 06005*. Paris: EDP Sciences. https://doi.org/10.1051/e3sconf/20198506005.

Bianchotti, J. D., M. Denardi, M. Castro-Gama, and G. D. Puccini. 2021. "Sectorization for water distribution systems with multiple sources: A performance indices comparison." *Water* 13 (2): 131. https://doi.org/10.3390/w13020131.

Blondel, V. D., J. Guillaume, R. Lambiotte, and E. Lefebvre. 2008. "Fast unfolding of communities in large networks." *J. Stat. Mech.: Theor. Exp.* 2008 (10): P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008.

Brentan, B. M., E. Luvizotto Jr., I. Montalvo, J. Izquierdo, and R. Pérez-Garca. 2017. "Near real time pump optimization and pressure management." *Procedia Eng.* 186 (Jun): 666–675. https://doi.org/10.1016/j.proeng.2017.06.248.

Cavazzini, G., G. Pavesi, and G. Ardizzon. 2020. "Optimal assets management of a water distribution network for leakage minimization based on an innovative index." *Sustainable Cities Soc.* 54 (Aug): 101890. https://doi.org/10.1016/j.scs.2019.101890.

Cimorelli, L., A. D'Aniello, L. Cozzolino, and D. Pianese. 2020. "Leakage reduction in WDNs through optimal setting of pats with a derivative-free optimizer." *J. Hydroinf.* 22 (4): 713–724. https://doi.org/10.2166/hydro.2020.142.

Creaco, E., and H. Haidar. 2019. "Multi-objective optimization of control valve installation and DMA creation for reducing leakage in water distribution networks." *J. Water Resour. Plann. Manage.* 145 (10): 04019046. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001114.

Creaco, E., and G. Pezzinga. 2018. "Comparison of algorithms for the optimal location of control valves for leakage reduction in WDNs." *Water* 10 (4): 466. https://doi.org/10.3390/w10040466.

Dai, P. D. 2021. "Optimal pressure management in water distribution systems using an accurate pressure reducing valve model based complementarity constraints." *Water* 13 (6): 825. https://doi.org/10.3390/w13060825.

Farley, M. 2001. *Leakage management and control: A best practice training manual*. WHO/SDE/WSH/01.1. Geneva: World Health Organization.

Giustolisi, O., and L. Ridolfi. 2014. "New modularity-based approach to segmentation of water distribution networks." *J. Hydraul. Eng.* 140 (10): 04014049. https://doi.org/10.1061/(ASCE)HY.1943-7900.0000916.

Giustolisi, O., D. Savic, and Z. Kapelan. 2008. "Pressure-driven demand and leakage simulation for water distribution networks." *J. Hydraul. Eng.* 134 (Feb): 626–635. https://doi.org/10.1061/(ASCE)0733-9429(2008)134:5(626).

Gupta, A., and K. Kulat. 2018. "A selective literature review on leak management techniques for water distribution system." *Water Resour. Manage.* 32 (10): 3247–3269. https://doi.org/10.1007/s11269-018-1985-6.

Hernandez Hernandez, E., and L. Ormsbee. 2022. "A heuristic for strategic valve placement." *J. Water Resour. Plann. Manage.* 148 (2): 04021103. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001497.

Huzsvár, T., R. Wéber, M. Szabó, and C. Hös. 2023. "Optimal placement and settings of valves for leakage reduction in real life water distribution networks." *Water Resour. Manage.* 37 (12): 4949–4967. https://doi.org/10.1007/s11269-023-03590-1.

Jowitt, P. W., and C. Xu. 1990. "Optimal valve control in water-distribution networks." *J. Water Resour. Plann. Manage.* 116 (4): 455–472. https://doi.org/10.1061/(ASCE)0733-9496(1990)116:4(455).

Kang, D., and K. Lansey. 2012. "Revisiting optimal water-distribution system design: Issues and a heuristic hierarchical approach." *J. Water Resour. Plann. Manage.* 138 (3): 208–217. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000165.

Khoa Bui, X., M. S. Marlim, and D. Kang. 2020. "Water network partitioning into district metered areas: A state-of-the-art review." *Water* 12 (4): 1002. https://doi.org/10.3390/w12041002.

Kirkpatrick, S., C. D. Gelatt, and M. P. Vecchi. 1983. "Optimization by simulated annealing." *Science* 220 (4598): 671–680. https://doi.org/10.1126/science.220.4598.671.

Liu, H., M. Zhao, C. Zhang, and G. Fu. 2018. "Comparing topological partitioning methods for district metered areas in the water distribution network." *Water* 10 (4): 368. https://doi.org/10.3390/w10040368.

Maskit, M., and A. Ostfeld. 2021. "Multi-objective operation-leakage optimization and calibration of water distribution systems." *Water* 13 (11): 1606. https://doi.org/10.3390/w13111606.

Mehdi, D., and A. Asghar. 2019. "Pressure management of large-scale water distribution network using optimal location and valve setting." *Water Resour. Manage.* 33 (14): 4701–4713. https://doi.org/10.1007/s11269-019-02381-x.

Newman, M. E. 2004. "Analysis of weighted networks." *Phys. Rev. E* 70 (5): 056131. https://doi.org/10.1103/PhysRevE.70.056131.

Newman, M. E. J. 2006. "Modularity and community structure in networks." *Proc. Natl. Acad. Sci.* 103 (23): 8577–8582. https://doi.org/10.1073/pnas.0601602103.

Price, E., G. R. Abhijith, and A. Ostfeld. 2022. "Pressure management in water distribution systems through PRVs optimal placement and settings." *Water Res.* 226 (Jun): 119236. https://doi.org/10.1016/j.watres.2022.119236.

Puccini, G., L. Blaser, C. Bonetti, and A. Butarelli. 2016. "Robustness-based design of water distribution networks." *Water Util. J.* 13 (Jun): 13–28.

Reichardt, J., and S. Bornholdt. 2004. "Detecting fuzzy community structures in complex networks with a Potts model." *Phys. Rev. Lett.* 93 (21): 218701. https://doi.org/10.1103/PhysRevLett.93.218701.

Rossman, L. A., H. Woo, M. Tryby, F. Shang, R. Janke, and T. Haxton. 2020. *EPANET 2.2 User's manual, water infrastructure division, center for environmental solutions and emergency response*. Cincinnati: USEPA.

Sahu, R. C., and A. Gupta. 2020. "Genetic algorithm based pressure management technique for leakage reduction in the water distribution system." In *Proc., 2020 3rd Int. Conf. on Intelligent Sustainable Systems (ICISS)*, 1464–1470. New York: IEEE.

Sophocleous, S., D. Savić, and Z. Kapelan. 2019. "Leak localization in a real water distribution network based on search-space reduction." *J. Water Resour. Plann. Manage.* 145 (7): 04019024. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001079.

Sousa, J., J. Muranho, A. Sá Marques, and R. Gomes. 2015. "Optimal management of water distribution networks with simulated annealing: The C-Town problem." *J. Water Resour. Plann. Manage.* 142 (5): C4015010. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000604.

Todini, E. 2000. "Looped water distribution networks design using a resilience index based heuristic approach." *Urban Water* 2 (2): 115–122. https://doi.org/10.1016/S1462-0758(00)00049-2.

Vrachimis, S. G., S. Timotheou, D. G. Eliades, and M. M. Polycarpou. 2021. "Leakage detection and localization in water distribution systems: A model invalidation approach." *Control Eng. Pract.* 110 (Jun): 104755. https://doi.org/10.1016/j.conengprac.2021.104755.

Wagner, J., U. Shamir, and D. Marks. 1988. "Water distributions system reliability: Simulation methods." *J. Water Resour. Plann. Manage.* 114 (Sep): 276–294. https://doi.org/10.1061/(ASCE)0733-9496(1988)114:3(276).

Xu, W., X. Zhou, K. Xin, J. Boxall, H. Yan, and T. Tao. 2020. "Disturbance extraction for burst detection in water distribution networks using pressure measurements." *Water Resour. Res.* 56 (5): e2019WR025526. https://doi.org/10.1029/2019WR025526.

Zhang, Q., Z. Y. Wu, M. Zhao, J. Qi, Y. Huang, and H. Zhao. 2017. "Automatic partitioning of water distribution networks using multiscale community detection and multiobjective optimization." *J. Water Resour. Plann. Manage.* 143 (9): 04017057. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000819.

Zhang, T., H. Yao, S. Chu, T. Yu, and Y. Shao. 2021. "Optimized DMA partition to reduce background leakage rate in water distribution networks." *J. Water Resour. Plann. Manage.* 147 (10): 04021071. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001465.