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Review of Metaheuristic Methodologies for Leakage Reduction and Energy Saving in Water Distribution Networks

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Abstract

Metaheuristic methods have emerged as powerful tools for solving complex optimization problems in various domains, including the sustainability of water distribution systems. They provide efficient and effective solutions by mimicking natural processes and searching for the optimal option within a large solution space. Despite the existence of these methods in the water distribution field for several years, a direct comparison between the various proposed solutions often proves challenging, due to the different parameter definitions used by the authors. The present review presents the solutions proposed by a total of 36 research papers taken from the Web of Science, Scopus and Google Scholar databases focusing on the application of metaheuristic methods for leakage reduction and energy saving in water distribution networks. The review is intended to facilitate comparative analysis among the solutions proposed by authors concerning key aspects of the optimization process. These aspects include the definition of the algorithm, the specification of the objective function, and the strategies employed for reducing the search space. The characteristics of the networks used as case studies by the reviewed papers are also presented to allow the reader to evaluate the applicability of the solutions to specific networks.

Keywords Metaheuristic methods · Genetic algorithms · Water distribution network · Pressure management · Leakage reduction

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1 Introduction

Aging pipelines together with other stresses have rendered the water distribution networks (WDNs) vulnerable to leakage, creating one of the most significant challenges facing WDNs all over the world in recent decades. The effects of leakages could be mitigated in network management operations by adopting technological solutions to monitor and control more efficiently the WDN. For instance, installing pressure-reducing valves (PRVs) reduces excessive pressure in the network and consequently the amount of leakage. This approach for leakage reduction is widely used by water utility management because it has proved to be effective, inexpensive, and immediate.

Despite the theoretical simplicity of the solution, one of the main issues regarding its implementation is the need to identify an optimal location for PRV installation and its ideal setting, which is the pressure that the PRV must regulate downstream of the valve. Some researchers suggest the installation of devices for energy recovery in place of a simple PRV; this would combine the solution to leakage reduction with energy recovery, improving two aspects of water distribution sustainability: energy and water saving.

The problem of valve location is a non-linear non-convex problem. Assuming a network of 150 pipes, the placement of five PRVs entails the evaluation of over 591,600,030 possible combinations of positions without considering the evaluation of the best valve setting, which would add further combinations. This kind of large search space highlights the importance of a proper optimization methodology, such as the application of metaheuristic methods. The qualities of metaheuristic methods include the ability to explore efficiently large search spaces, find good solutions without strict assumptions, and adapt to different problems, making them valuable tools for solving real-world optimization problems in various fields. The interest of researchers in metaheuristic methods for leakage reduction and energy saving in water distribution networks (WDNs) spans several decades and has led to the development of several possible approaches.

Genetic Algorithms (GA), inspired by natural evolution, were among the first metaheuristic methods applied to WDNs (Cembrowicz and Krauter 1977). GA were mainly used to optimize pipe layouts and pressure management, aiming to mitigate leakage and energy consumption.

Over time, other metaheuristic methods based on different approaches have emerged (Samadi-Koucheksaraee et al. 2022). Simulated Annealing (SA), which simulates the annealing process in metallurgy to find near-optimal solutions, was firstly introduced by Sousa et al. (1970). Particle Swarm Optimization (PSO), inspired by the collective behaviour of bees in a swarm (Wegley et al. 2000), was first introduced to optimize pump scheduling and minimize leakages. Recently, Ant Colony Optimization (ACO) has gained attention for its ability to solve complex optimization problems (Maier Holger et al. 2003). ACO mimics the foraging behaviour of ants, allowing for the optimization of pipe layouts, valve location, and leakage detection in water distribution networks.

Only recently, thanks to the advent of new technologies, researchers have suggested to combine water leakage reduction solutions and energy recovery. Some authors, also considered in this review, suggested replacing simple PRVs with small turbines (Ferrarese and Malavasi 2020; Giudicianni et al. 2023), inverse pumps, cross flow turbines, and other alternative technologies able to recover energy and control the flow. It is evident that the deployment of sophisticated network management methodologies demands to rapidly develop hydraulic devices that meet new standards and requirements, such as remote control or increased frequency of variable monitoring (Ferrarese et al. 2022). Nowadays, the integration of machine learning is also gaining momentum, aiming at improving the capacity of predicting consumer behaviours so as to manage the network pressure accordingly (Shirvani-Hosseini et al. 2022).

This review aims to be a reference document for researchers and practitioners of the various metaheuristic methodologies mentioned above, which were developed by researchers to regulate the pressure in the network, limit leakage, and recover energy. Furthermore, the case studies used in various studies to validate optimization methodologies are analysed. Specifically, all the key features of the networks used as case studies are reported, allowing the reader to assess their applicability to the different specific cases.

Section 2 describes the reason for the review and methodology used for it. Section 3 presents the state of the art, highlighting the differences and similarities between the various approaches introduced by the works under review. Finally, Section 4 proposes conclusions and perspectives for future developments.

2 Reason and Motivation of the Review

Metaheuristic methods have been introduced in the field of water distribution network optimization for several years with the main but not sole purpose of improving network sustainability by reducing losses and recovering energy. Methods based on different algorithms, diverse objective functions, and various strategies for reducing the search space have been proposed. The proposed solutions are sometimes challenging to compare, also due to the different definitions used by the authors. This review systematically organizes the contributions of various authors, categorising them based on key aspects of the optimization process: algorithm design, objective function formulation, search space reduction, and the case studies used by authors to validate their methods. This structured approach facilitates reader comprehension, allows for a more effective comparison of proposed methodologies and helps selecting the most suitable approach for addressing specific problems of interest.

This review covers the papers published over the last three decades, from 1990 to May 2023, concerning the use of metaheuristic methods for valves location and settings in WDNs with objective leakage reduction and/or energy recovery. The keywords used to search for publications are: metaheuristic methods, genetic algorithms, water distribution network optimization, pressure management, leakage reduction. The databases queried are Web of Science, Scopus and Google Scholar.

The main section of the paper, “Current situation”, is organized in four sub-sections:

3.1 Algorithms: presentation of the main optimization approaches introduced in the reviewed papers.
3.2 Reduction of the search space: detailing techniques for search space reduction.
3.3 Objective functions: comparison of the various objectives and penalty functions and their corresponding equations.
3.4 Case studies: illustration of both real and theoretical networks used to validate and evaluate the performance of the different methodologies.

3 Current Situation

3.1 Algorithms

Typically, algorithms used for optimization in distribution networks fall into two fundamental categories: deterministic and stochastic. Each approach has its own set of advantages and disadvantages. The deterministic approach ensures that the solution found is the absolute optimum. This characteristic represents a fundamental difference with respect to stochastic methods, which instead are characterized by uncertainty in finding the absolute optimum in the search space.

The deterministic approach is suitable for problems characterized by continuous variables, linear objective functions and constraints. It can also be applied to nonlinear objectives and discrete variables such as the problem of locating valves in WDNs, but only in a restricted number of instances. For example, Jowitt and Xu (1990) used iterated linear programming to find optimal valve control, whereas Vairavamoorthyl and Lumbers (1998) used the sequential quadratic programming method. The authors were constrained to use a linearized model of the network to be able to evaluate the fitness function. Pezzinga and Gueli (1999) proposed a fully deterministic methodology based on sequential addition also used in comparison or coupled with other methodologies, as proposed in Creaco and Pezzinga (2018).

The main recognized issues with deterministic methodologies (Liberti and Kucherenko 2005) are their difficulty in dealing with problems where the simulation is required to evaluate objective function and constraints. They are also computationally expensive and slow convergent methods. For these reasons, the stochastic approaches have gained importance to solve valve location and pressure management issues.

The stochastic approach implies the use of randomness in finding the optimum solution and it consists of two classes of algorithms: specific heuristics and metaheuristics (Talbi 2009). The latter are problem-independent, much faster, and less expensive (Liberti and Kucherenko 2005). The metaheuristic approach suits well Non-deterministic Polynomial, Non-linear Non-convex combinatorial problems, to which many water resources field-related problems belong. Many metaheuristics methods have been applied to optimize numerous issues concerning not only the design of the water distribution network (WDN) (Sangroula et al. 2022) but also the rehabilitation planning (Elshaboury and Marzouk 2022), operation (Behandish and Wu 2014), water quality control and WDN security (Yudina et al. 2021).

In the following, the stochastic methodologies used in the reviewed papers for PRV or energy recovery device's location and setting are presented together with the methodologies used to reduce the search space and drive the evolution of the algorithms. Finally, hybrid methodologies (between deterministic and stochastic) are also presented.

3.1.1 Genetic Algorithms

One of the most prominent and established metaheuristic algorithm used for water distribution networks optimization is the genetic algorithm (GA). Araujo et al. (2006) used GA in a two-phase methodology, to find the optimal location in the first phase and the optimal setting of the PRV in the second phase. The simulation strategy is to assume a pseudo-valve on each pipe, considering an increased roughness 90% greater than the normal roughness as a potential location for a valve. They used the elitism technique and total replacement of parents by children. The total number of valves is a constraint of the problem. Making several repetitions, they found that installing 4 PRVs reduced leakage by 19% in the considered test case (see Table 3). The main drawback is that considering a pseudo-valve for each pipe, the computation cost for the real network rises considerably. Besides that, the method has some ambiguity about dealing with pressure violations, i.e., pressures under the limit for a sufficient service to water users.

Using real coded GA, Ali (2015) implemented tailored genetic operators of crossover and mutation (Gaussian mutation and an improved arithmetical crossover) appropriate for mixed integer variables, optimizing the location and average setting synchronously in one phase. It reduced leakage by 16% in the benchmark network considered (see Table 3). However, the application of this methodology requires the skeletonization of the network to only consider the most important pipes. In addition, when there are huge variations in demand, it entails a forecasting model, especially for real-time applications.

Using binary grey representation, exponential rank selection, uniform crossover, bitwise mutation and partial elitism, Covelli et al. (2016a, b) went a step further, also considering the direction of valve installation as a decision variable, and aiming to minimize the whole cost associated with installation and purchase of valves as well as the cost of water losses.

3.1.2 Other Metaheuristic Algorithms

Other studies opted for different metaheuristic algorithms, such as Scatter Search used by Liberatore and Sechi (2009) with a modest computation burden according to the authors, or De Paola et al. (2017a) who used Harmony Search (HS) with double harmonic components to optimize the valve location and setting in a single step. The obtained leakage reduction rate is almost similar to the one obtained by Araujo in a 24 h simulation on the same reference network (see Table 3), but the method showed less sensitivity to the selected parameters. Moreover, the small computational time required by the calculations suggests the suitability of HS for real-time optimization of the WDN.

Jafari-Asl et al. (2020) applied the PSO algorithm to minimize leakage through a two-step process for optimal location and then for a 24 h setting testing of three characteristic demand conditions. The method achieves a reduction of the losses by 19.5% maintaining the minimum pressure in the reference nodes.

Mehdi and Asghar (2019) used PSO to minimize leakage and maximize reliability via the network pressure reliability index (NPRI). The method reduced leakage by 19% considering the fuzzy logic for evaluating pressure in the WDN.

3.1.3 Multi-Objective Algorithms

When the problem to be solved requires to set more than one objective, and in order to give the decision maker various possibilities to choose among, a Pareto front needs to be generated, where the best solutions are represented on the closest curve to the origin. In recent years, many researchers (Gupta et al. 2017; Latifi et al. 2018; García et al. 2019) have adopted this method for reducing water leakages.

Nicolini and Zovatto (2009) applied the Non-Sorting Genetic Algorithm NSGAII to find a compromise between the minimization of the number of valves and the minimization of the total leakage in the system. This method uses a combination of non-dominated sorting and elitism to maintain a diverse and well-distributed population of solutions throughout the optimization process. NSGA-II introduces the concept of crowding distance to promote the spread of solutions along the Pareto front. The number of PRVs is used as a surrogate for installation costs. The method obtained a leakage reduction rate of 14.8% by installing three valves, while when installing five valves, it reached a leakage reduction rate of 16.5%. The study is applied to the reference network indicated in Table 3.

Saldarriaga and Salcedo (2015) also used NSGAII to trade off the unperceived financial cost of water loss against the annual cost of valve installation and maintenance. The results show that the valves should be installed in leakage-free areas to decrease the pressure's surface, thus reducing the leakages downstream the PRVs. However, the 15% reduction achieved is lower than the best solution (31%) found by (Giugni et al. 2014) on benchmark networks (see Table 3).

Nicolini et al. (2011) compared NSGAII and Epsilon Multi-Objective Evolutionary Algorithm (Epsilon-MOEA) in terms of minimization of the number of valves versus minimization of total leakage. The Epsilon-MOEA method extends the traditional non-dominated sorting approach by introducing an epsilon dominance concept. The "epsilon" parameter controls the level of convergence desired. By manipulating this parameter, users can obtain a diverse set of solutions along the Pareto front, striking a balance between convergence and diversity. The authors found that Epsilon-MOEA behaves in a better way than NSGA-II and it appears to be more robust to the variation of the initial seed.

3.1.4 Hybrid Algorithms

Taking advantage of the exploration capability of metaheuristics and the fast convergence of deterministic approach, some researchers tried to create a hybrid between the two methods. Reis et al. (1997) embedded linear programming in the genetic algorithm to find the optimal valve settings for each location of valves proposed as a solution by the genetic algorithm.

Creaco and Pezzinga (2018) tried to compare NSGAII and the sequential adding (SA) method, embedding linear programming to assess the fitness function in both algorithms. They found that GA outperforms SA when the number of valves exceeds 4, due to the non-linear effects of WDNs. SA needed less computation, whereas GA can account for other issues in the evaluation of the fitness.

Creaco and Haidar (2019) combined three algorithms: NSGAII for location, a Fast-Greedy partitioning algorithm to divide the network in DMAs, and iterated linear programming to optimize the setting of PRVs. They searched for a trade-off between minimizing daily leakage volume, installation cost and demand uniformity.

3.2 Reduction of the Search Space

Reducing the search space is paramount as it effectively reduces the computational cost and, as a consequence, the time needed to apply a methodology. For example, a 40% reduction in potential locations for valves may reduce by 88% the possibility of having to install a network of 100 pipes and 4 valves, which will accelerate the process consistently and reduce the computational cost. To reduce the search space, different criteria have been implemented based on hydraulic considerations. These criteria allow one to exclude less important pipes placing a valve on which has a negligible effect on the pressure in the rest of the network.

This criterion could be Pipe Index PI (Ali 2015), specific power SP (Saldarriaga and Salcedo 2015), Valves Selection Index VSI (Mehdi and Asghar 2019) or Pipe Closure Index PCI (Dini and Asadi 2020). Saldarriaga and Salcedo (2015) and Salcedo and Saldarriaga (2018) compared SP, PI and a sectorization criterion that measures the hydraulic impact of closing a pipe. The authors deduced that both the SP and the sectorization criterion could reach best solutions but the latter entails higher computational complexity. All the search space reduction methods mentioned so far aim to create a list of the pipes ordered according to their importance. In the following, the different indexes are specified:

- pipe index, PI, (Ali 2015) is defined as:

$$PI = \frac{Q \cdot L}{CHW \cdot D} \tag{1}$$

  where Q is the pipe flow; L and D are the pipe length and diameter, respectively; and CHW is the roughness coefficient of the pipe. Arulraj and Rao (1995) found that pipes that have the greatest impact on the whole network have higher values of this index.
- specific power, SP, (Saldarriaga and Salcedo 2015):

$$SP = Q\left(h_f + h_m\right) \tag{2}$$

  where: h_f is the friction loss and h_m is the minor loss
- valves selection index, VSI, (Mehdi and Asghar 2019):

$$VSI = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Q_k^t * \Delta P_{ij}^t}{CHW_k^t}\right| \tag{3}$$

  where Q_k^t is the flow of pipe k from node i to node j at time t; ΔP_{ij}^t is the pressure head difference between node i and j at time t; CHW_k^t is the roughness coefficient of pipe k at time t; and T is the simulation period time.
- pipe closure index, PCI, (Dini and Asadi 2020):

$$PCI_i = \left(1 - \frac{1}{T}\sum_{t=1}^{T}\frac{D_{io}^t}{D_i}\right) * \frac{\frac{1}{T}\sum_{t=1}^{T} Q_i^t}{\sum_{j=1}^{N} q_j^t} \tag{4}$$

  where D_{io}^t is the optimal diameter of pipe i at time t, which is calculated in the calibration process; D_i is the real diameter of each pipe; Q_i^t is the flow rate of pipe i at time t; q_j^t is the nodal demand of node j at time t; N is the number of nodes; and T is the simulation period time.

3.2.1 Penalty Functions

Penalty functions play a vital role in metaheuristic methods for handling constraints. These functions help transform constrained problems into unconstrained problems, allowing the efficient exploration of the search space. When a solution violates a constraint, a penalty value is added to the objective function, penalizing the infeasible solutions. This encourages the algorithm to avoid violating constraints during the search process. Choosing an appropriate penalty function is crucial as it directly influences the algorithm's convergence and the quality of the final solutions. Balancing the trade-off between exploration and exploitation is essential to ensure algorithm effectively navigate constraint-rich search spaces. In pressure management problems, penalty functions are usually used to guarantee that the pressure in the demand node satisfies the consumer expectations, hence equal or above the pressure of service p^{min} that usually ranges between 20 and 30 m of head. Considering a single time step and a node *j,* a penalty function used in several works can be generalized as follows:

$$f_p(p_j) = a \cdot \left[max(0, p^{min} - p_j)\right]^c + b \cdot sgn\left[max(0, p^{min} - p_j)\right] + d \cdot \left[max(0, p_j - p^{min})\right]^c \tag{5}$$

where p_j is the service pressure at node j; a, b, c, and d are coefficients that change depending on the authors as follow (Table 1).

Recently, Sangroula et al. (2022) suggested the introduction of a specific penalty function based on the target velocity in the pipe to be used together with the penalty based on pressure. Moreover, the pressure considered in Eq. 5 is a target pressure rather than a minimum pressure like the one used by other authors, giving penalties both when the pressure at the node is below and when it is above the target with different weights. The suggested penalty function on a single time step and link is as follows:

$$f_p(V_i) = V_{p2} \cdot \left[max(0, T_V - V_i)\right] + V_{p1} \cdot \left[max(0, V_i - T_V)\right] \tag{6}$$

where $f_p(V_i)$ is the velocity penalty at a given link i; V_i is the flow velocity at link i; T_V is the target velocity; V_{P1} is the velocity penalty coefficient if the velocity at a given link is above target velocity (equals to 0.3); and V_{P2} is the velocity penalty coefficient if the velocity at the link is below target velocity (equals to 0.06).

A penalty function that unifies penalties based on conditions on both the nodes and pipes can be written as follows:

$$OF_{pen} = \sum_{j=1}^{N_n} f_{p,j} + \sum_{i=1}^{N_L} f_{p,i} \tag{7}$$

where OF_{pen} is the penalty function that can be introduced in a general objective function; $f_{p,j}$ is a generic penalty function for nodes; and $f_{p,i}$ is a generic penalty function for links.

3.3 Objective Functions

An objective function is a function that is minimized or maximized through the search process. In the following, the main objective functions introduced by the authors are reported. Table 2 below lists all equations reported in the following section with cross

Table 1 Penalty function coefficients

Reference	a	b	c	d
(De Paola et al. 2017b)	10^3	10^4	2	0
(Jafari-Asl et al. 2020)	$10^5/p^{min}$	0	1	0
(Liberatore and Sechi 2009)	different for each node	0	2	0
(Covelli et al. 2016b)	10^{20}	0	1	0
(Giugni et al. 2014)	1	0	2	fairly high
(Sangroula et al. 2022)	1.9	0	1	0.02

Table 2 Reviewed papers

Reference	Subject	Optimization Methodology	Optimization algorithm	Decision variables / constraints	OF and other equations used
(Creaco and Pezzinga 2018)	Location & setting of Valves	Hybrid Meta & Deter	NSGAII, SA, LP	Max NV=10, VL (GA or SA), S (LP)	8/9/10/11
(Jowitt and Xu 1990)	Setting of Valves	Deter	Iterated LP		-
(Vairavamoorthyl and Lumbers 1998)	Setting of Valves	Deter	Sequential quadratic programming		-
(Reis et al. 1997)	Location & setting of Valves	Hybrid Meta & Deter	GA & LP	Pre NV=3, VL, S	8/9/10/11
(Ali 2015)	Location & setting of Valves	Meta	Real GA	Pre NV=3, VL, S	8/9/10/11
(Araujo et al. 2006)	Location & setting of Valves	Meta	Generational GA	Max NV=6, VL, S	8/9/10/11/19
(Covelli et al. 2016a)	Location & setting of Valves	Meta	Binary Gray GA	Max NV=5, VL, S	15/16/17/18
(Covelli et al. 2016b)	Location & setting of Valves	Meta	GA	Max NV=15, VL, S	15/16/17/18
(Liberatore and Sechi 2009)	Location & setting of Valves	Meta	Scatter search	NV, L, S	23/24
(De paola et al. 2017a)	Location & setting of Valves	Meta	HS	Pre NV=4, VL, S	-
(Jafari-Asl et al. 2020)	Location & setting of Valves	Meta	PSO	Pre NV=5, VL, S	12
(Pezzinga and Gueli 1999)	Location & setting of Valves	Hybrid Meta & Deter	GA, SA & LP	-	-
(Nicolini and Zovatto 2009)	Location & setting of Valves	Meta	Real NSGA-II	Max NV=5, VL, S	12
(Creaco and Pezzinga 2015)	Location & setting of Valves	Hybrid Meta & Deter	Hybrid NSGAII & iterated LP, NSGAII	NV, VL, S	8/9/10/11/14

Table 2 (continued)

Reference	Subject	Optimization Methodology	Optimization algorithm	Decision variables / constraints	OF and other equations used
(Saldarriaga and Salcedo 2015)	Location & setting of Valves	Meta	NSGAII	NV, VL, S	13/14
(Gençoğlu and Merzi 2017)	Location & setting of Valves	Meta	Binary GA	NV, VL, S	20/21/22
(Covelli et al. 2015)	Location & setting of Valves	Background leakage modelling	/		/
(Gupta et al. 2017)	Location & setting of Valves	Meta	NSGA-II	NV, VL, S	8/9/10/11
(Latifi et al. 2018)	Location & setting of Valves	Meta	NSGA-II	Max NV=5, VL, S	25/26/27/28/29/30/31/32
(Mehdi and Asghar 2019)	Location & setting of Valves	Meta	PSO	NV, VL, S	20/21/22
(Nicolini et al. 2011)	Location & setting of Valves	Meta	Real GA, (NSGAII, Epsilon-MOEA)	Max NV=10, VL, S (NM)	12
(Darvini and Soldini 2015)	PAT, Location &setting of Valves	No optimization Algorithm	-	Max NV= 9	-
(Wright et al. 2015)	Control of WDN with PRVs and Boundary valves	Deter	Sequential convex programming (SCP) null space algorithm	Pre NV = 3, S	-
(Samir et al. 2017)	Pressure control, PRVs location, Leakage reduction	No Optimization Algorithm	-	Max NV = 3, VL	8/9/10/11
(Creaco and Haidar 2019)	Location &setting of Valves	Hybrid, Meta & Deter	NSGAII (location) Fast-Greedy partitioning algorithm (DMAs) The iterated linear programming(setting)	NV, VL, S	8/9/10/11/18/34

Table 2 (continued)

Reference	Subject	Optimization Methodology	Optimization algorithm	Decision variables / constraints	OF and other equations used
(Do et al. 2018)	Partially closed valves location and setting	Meta	GA, the Levenberg-Marquardt Algorithm	VL, S	-
(García et al. 2019)	Location and setting of valves and optimal location PAT	Meta	Strength Pareto Evolutionary Algorithm 2 (SPEA2), NSGAII	NV, VL	13/14/35
(Salcedo and Saldarriaga 2018)	Reducing the search space, location of valves	Meta	NSGAII	VL	-
(Dini and Asadi 2020)	Calibration & setting of valves	Meta	PSO, ACO	Calibration, S	12/13/14
(Paola et al. 2017b)	Location and setting of valves	Meta	HS	Pre NV, VL, S,	-
(Bonthuys et al. 2020a)	Optimization of energy recovery device sizes and locations	Meta	GA, PERRL2.0	Size of device (hydro-turbines) and location	36/37/38
(Shao et al. 2019)	The cost savings contributed by leakage reduction and energy consumption savings	Meta	GA	PRVL, S, variable speed	12/39
(Giugni et al. 2014)	Maximizing the hydropower generation	Meta	PIKAIA GA & NITSOL library (hydraulic solver)	Max NV=3, PRVL, turbine L, S	40
(Bonthuys et al. 2020b)	Maximizing recovered energy and reduced water losses	Meta	GA (with Elitism) , PERRL	Turbine L, S	35

Table 2 (continued)

Reference	Subject	Optimization Methodology	Optimization algorithm	Decision variables / constraints	OF and other equations used
(Galdiero et al. 2016)	Sectorization, pressure management, cost, resilience	Meta	NSGA-II, graph theory	DMA	12/13/14/33
(Karakatsanis and Theodossiou 2022)	Installing small hydraulic turbines, energy recovery	Meta	AI, graph theory (for sensors location), , HS	PATL, S	35

NV number of valves; *max NV* maximum number of valves; *pre NV* predetermined number of valves; *VL* valve location; *S* valve setting; *PATL* Pump As Turbine location; *DMA* district metered areas; *Meta* metaheuristic; *Deter* deterministic; *LP* linear programming; *SA* sequential addition; *NSGAII* non sorting genetic algorithm II; *PSO* particle swarm optimization; *ACO* ants colony optimization; *GA* genetic algorithm; *HS* harmony search; *PERRL* Program for Energy Recovery and the Reduction of Leakage; *MOEA* multi-objective evolutionary algorithm

Table 3 Principal information about the case study networks

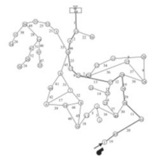
Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
Santa Maria di Licodia; Sicily, Italy	32	41	2R	-	Real. 6,700 inhabitants, Skeletonized network	(Creaco and Pezzinga 2018)	4	40% LR	
							10	47% LR (using SA), 52% LR (using GA)	
						(Creaco and Pezzinga 2015)	5	40% LR	
							10	44% LR	
							15	46% LR	
Benchmark WDSA 2014	46	52	1R	1P	Synthetic	(Creaco and Pezzinga 2018)	4	13% LR	
							10	22% LR (using SA), 25% LR (using GA)	
						(Creaco and Pezzinga 2015)	5	25% LR	
							10	28% LR	
						(Covelli et al. 2016b)	5	5% LR	
							15	11% LR	

Table 3 (continued)

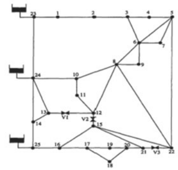
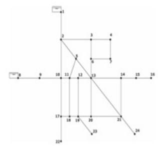
Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
Jowitt & Xu Network 1990,	22	37	3R	-	Synthetic. Based on part of the Yorkshire water Authority network. Introduced firstly by (Coulbeck and Sterling 1978)	(Reis et al. 1997)	3	-	
						(Ali 2015)	3	16% LR	
						(Araujo et al. 2006)	4	18.7% LR	
						(Liberatore and Sechi 2009)	4	-	
						(De Paola et al. 2017a)	4	18% LR	
						(Jafari-Asl et al. 2020)	5	23% LR	
						(Nicolini and Zovatto 2009)	5	16.1% LR	
						(Saldarriaga and Salcedo 2015)	2	15% LR	
						(Gupta et al. 2017)	4	20.64% LR	
						(Mehdi and Asghar 2019)	4	19% LR	
						(García et al. 2019)	2	-	
						(Dini and Asadi 2020)	6	22.5% LR	
						(De Paola et al. 2017b)	4	-	
						(Bonthuys et al. 2020a)	3	-	
						(Giugni et al. 2014)	3	31% LR	
						(Bonthuys et al. 2020b)	3	24% LR	
						(Galdiero et al. 2016)	-	DMA	
						(Karakatsanis and Theodossiou 2022)	-	PAT	
Pi.Co.Sa	24	32	2T	-	Real. 31500 inhabitants Cast iron mains	(Covelli et al. 2016a)	5	25% LR	
						(Covelli et al. 2016b)	5	23% LR	

Table 3 (continued)

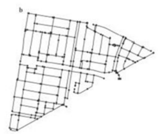
Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
Burcei Distribution Network; Sardinia, Italy	72	98	1R	-	3000 inhabitants	(Liberatore and Sechi 2009)	9	-	
Balerma Network; Almeria, Spain	443	454	4R	-	Real. Irrigation system, 8 loops	(De Paola et al. 2017a)	1	19% PR	
Bogotá, Colombia	378	432	1R	-	Synthetic. Based on Subsection 8-04 of WDS in Bogotà, Colombia	(Saldarriaga and Salcedo 2015)	3	10% LR	
Yayla, Ankara DMA; Ankara, Turkey	89	107	-	-	Real. District metered area	(Gençoğlu and Merzi 2017)	17	20.72% PR	/
							27	21.38% PR	
							50	15.5% PR	

Table 3 (continued)

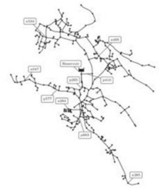
Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
Damavand Network; Iran	51	70	1R	-	Real. 3.62 km^2, diameters [63–400 mm], 19.5 km long	(Latifi et al. 2018)	3	14% LR	
WDS of Buja; Udine, Italy	338	367	1R	-	Real. 3500 inhabitants, 35.5 km long.	(Nicolini et al. 2011)	4	15.76% PR	
Saadnayel WDN; Lebanon	152	186	1R	-	Real. Nominal diameters and within the ranges [50-350]	(Creaco and Haidar 2019)	4	63.7% LR	
							9	65.7% LR	
Ahar WDN; East Azerbaijan Province, Iran	169	192	1R 5T	4Ps	Real	(Mehdi and Asghar 2019)	4	15% LR	

Table 3 (continued)

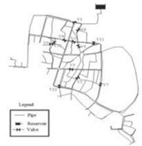
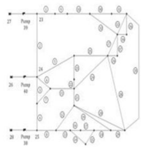
Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
third zone of Maragheh Network; East Azerbaijan Province, Iran	168	263	1R	-	Real. Large number of parallel pipes in any path,	(Dini and Asadi 2020)	12	31.7% LR	
Napoli Est; Naples, italy	259	358	1R 6T	-	Real. 65÷70.000 Inhabitants. Heavy looped network, DN [40-1000]	(De Paola et al. 2017b)	3	30% LR	
							6	45% LR	
Polokwane Central DMA; Limpopo, South Africa	6225	7133	13R	2Ps	Real. 592 km long	(Bonthuys et al. 2020a)	3	ER 942 KWH/day	
						(Bonthuys et al. 2020b)	3	ER 763 KWH/day	
Jowitt & Xu Network 1990, modified	22	37	3R	3 Ps	Synthetic. Based on Jowitt and Xu in 1990, with 3 speed variable pumps SVPs added.	(Shao et al. 2019)	4	34.4% LR (25.4% energy consumption reduction 33.1% total cost reduction)	

Table 3 (continued)

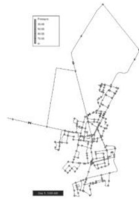
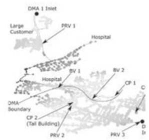
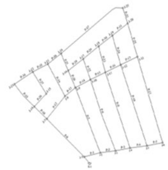
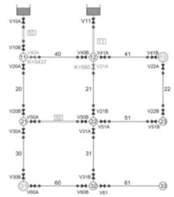
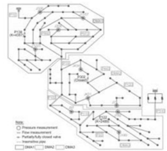
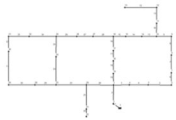
Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
Town of Chiaravalle, in the central part of Italy	-	-	1R	-	Real. 15000 inhabitants, 53.6 km , mixed materials	(Darvini and Soldini 2015)	4	(calibration)	
Experimental programme WDN, UK	2,374	2,434	-	-	Real. 8,000 properties	(Wright et al. 2015)	3	3.7% PR	
Arama DMA, Alexandria, Egypt	25	37	1R	-	Real. 4800 inhabitants	(Samir et al. 2017)	2	37% LR	
(Do et al. 2018) first case study	9	13	2R	-	Synthetic. 24 valves	(Do et al. 2018)	2 partially closed valves	-	

Table 3 (continued)

Net. Name Place	Nn	Nl	Sources		Notes	Reference	Nv	Result obtained	Network sketch
(Do et al. 2018) second case study,	135	147	1R 1T	1Ps 3P	Synthetic. Part of the C-town network	(Do et al. 2018)	3	-	
Hanoi	31	34	1R	-	Synthetic	(Salcedo and Saldarriaga 2018)	-	-	

Nn Node number; *Nl* Link number; *R* Reservoir; *T* Tank; *Ps* Pump station; *P* Pump. *LR* Leakage reduction; *PR* Pressure reduction; *ER* Energy recovery reference to their authors, also specifying the main objective of the papers, the optimization algorithm, the optimization methodology, and the constraints of the problem. The last column of the table indicates the equations used to define the objective function of the problem. All the equations reported have been adapted is such a way as to always use the same symbols for their parameters, to help the reader comparing the different approaches.

3.3.1 Leakage Reduction

The most adopted objective for valve placement problems is the minimization of leakage volume. Leakage volume can be modelled considering the following equations:

$$W_L = \sum_{\Delta t=1}^{N_{\Delta t}} W_{L,\Delta t} \tag{8}$$

$$W_{L,\Delta t} = \sum_{j=1}^{Nn} \widetilde{Q}_{j,\Delta t} \Delta t. \tag{9}$$

$$\widetilde{Q}_{j,\Delta t} = K_j p_{j,\Delta t}^{\beta} \tag{10}$$

$$K_j = \sum_{i=1}^{M} c_i 0.5 L_{ij} \tag{11}$$

where W_L is the total period leakage volume; $W_{L,\Delta t}$ is the cumulated leakage volume from all nodes N_n at each time step (or load condition); Δt is the time step of the problem; $N_{\Delta t}$ is the number of time steps; $\widetilde{Q}_j$ is the leakage flow at node j; $p_{j,\Delta t}^{\beta}$ is the service pressure at node j at time step Δt; K_j is a fixed leakage coefficient for the node j and β equals 1.18 in several papers. In Eq. 11, c_i is the discharge coefficient of the orifice, which depends on several characteristics such as shape, diameter, material, and age, whereas L_{ij} is the pipe length between nodes i and j, and M is the number of pipes connected to the node j.

Considering a specific K_j coefficient for each node, the Objective Function (OF) devoted to the minimization of the leakage volume (W_L) can be summarized as follows:

$$OF = W_L = \sum_{\Delta t=1}^{N_{\Delta t}} \sum_{j=1}^{Nn} K_j p_{j,\Delta t}^{\beta} \Delta t \tag{12}$$

Coefficients K_j and β are not always specifically defined by authors.

3.3.2 Costs Minimization

Many researchers based the search of the optimal solution on cost minimization. This is often used as a surrogate of minimization of the number of valves to be installed in the network.

The costs considered by most Authors are:

1. the cost of water not sold due to leakage $C_{tot,L}$; this amount can be calculated as:

$$C_{tot,L} = U_{NP} \cdot W_L \tag{13}$$

   where U_{NP} represents the unperceived profit per lost unit of water.
2. the cost composed by the purchase, installation and maintenance cost of the valves $C_{tot,v}$; it can be defined as:

$$C_{tot,v} = \sum_{1}^{N_{valve}} C_{cv} d_i^k \tag{14}$$

where C_{cv} and k are the parameters of a potential regression that represents the increasing capital cost of valves according to their diameter, and d_i stands for the diameter of the *i-th* valve.

The total amount of costs can be expressed as:

$$OF = C_{tot,v} + C_{tot,L} + OF_{pen} \tag{15}$$

where a penalty function OF_{pen} is added to consider penalties caused by problem constraints related to special features of the network.

To extend the cost analysis and also consider the sustainability of investment, Covelli et al. (2016a) valuated the cost of the intervention during the lifetime of the installed valve (N_{EWT}):

The total cost of the investment is then calculated as:

$$C_{tot}^{inv} = C_{tot,v}^{inv} + C_{tot,L}^{inv} \tag{16}$$

$$C_{tot,L}^{inv} = c_{\mathrm{CM}} \cdot W_{\mathrm{lost}} \sum_{n=1}^{N_{EWT}} \left(1 + r_{WL}\right)^{n-1} \tag{17}$$

$$C_{tot,v}^{inv} = \sum_{v=1}^{N_{valve}} \left(C_{maint,\mathrm{v}} + C_{Inst,\mathrm{v}}\right) \tag{18}$$

where N_{EWT} is the Expected Working Time of the valves before their replacement (years); W_{lost} is the expected volume of water lost over 1 year; c_{CM} is the initial cost for a single unit of water lost; r_{WL} is the rate at which the price of the volume of water that could be delivered to users if no longer dispersed in the subsurface would grow annually; ν and N_{valve} are the generic PRV and the whole number of PRVs considered in the simulation, respectively ($\nu = 1,2, \ldots, N_{valve}$); $C_{maint,\mathrm{v}}$. are the costs sustained for the maintenance of both the PRV and manhole; $C_{Inst,\mathrm{v}}$ are the costs sustained for purchasing the PRV, the construction of the related manhole, and the installation of the PRV in the manhole, evaluated at the end of the expected PRV working time.

3.3.3 Pressure Management

A widely shared objective in the literature is pressure management; the discrepancy between the actual pressure and the target or minimum pressure of service in each demand node is usually minimised to reduce leakage by considering the following objective function:

$$OF = f(p_j, N_{valve})\Big|_{\Delta t=1}^{N_{\Delta t}} = \frac{N_{valve,\Delta t}}{\left\{\sum_{j=1}^{Nn}\left[\left(P_{j,\Delta t} - P^{min}\right)/P^{min}\right]^2 N_{valve,\Delta t} + N_{valve,\Delta t}\right\}^2\Big|_{\Delta t=1}^{N_{\Delta t}}} \tag{19}$$

where $N_{\Delta t}$ is the number of simulation period time Δt; $P_{j,\Delta t}$ is the pressure calculated in the node j for the instant Δt; P^{min} is the minimum pressure of service, pre-established by the user, for any node of the network; and $N_{valve,\Delta t}$ is the number of valves calculated at instant Δt.

3.3.4 Minimization of Excess Nodal Pressure

In this case, the objective is to reduce the nodal pressure when it overcomes a threshold value, in order to protect the pipes and equipment in the network. The suggested definition of the objective function to be minimized is as follows:

$$\mathrm{OF} = \sum_{j=1}^{N_n} Pe_j \tag{20}$$

where

$$Pe_j = \begin{bmatrix} 0 & \text{if } P_{j,\Delta t} \leq P^{max} \\ \left(P_{j,\Delta t} - P^{max}\right) \times C_{\mathrm{ep}} & \text{if } P^{max} < P_{j,\Delta t} \end{bmatrix} \tag{21}$$

where N_n is the number of demand nodes; Pe_j is the excess pressure at node j; $P_{j,\Delta t}$ is the pressure of node j at time Δt; P^{max} is the maximum node pressure limit; and C_{ep} is the excess node pressure penalty constant, with the following constraints:

$$P_{j,\Delta t} \geq P^{min} \tag{22}$$

3.3.5 Maximization of the Reliability

Some authors suggest optimizing pressure distribution in the WDN on the basis of a reliability index, specifically the Nodal Pressure Reliability Index (NPRI). The index can be defined as follows:

$$NPRI_{j,\Delta t} = \begin{cases} 0 & P_{j,\Delta t} < 10\,m \\ \frac{1}{32}\left(P_{j,\Delta t} - 10\right) & 10\,m < P_{j,\Delta t} < 26\,m \\ \frac{1}{10}\left(P_{j,\Delta t} - 26\right) + 0.5 & 26\,m < P_{j,\Delta t} < 31\,m \\ 1 - \frac{1}{38}\left(P_{j,\Delta t} - 31\right) + 1.0 & 31\,m < P_{j,\Delta t} < 50\,m \\ -\frac{1}{40}\left(P_{j,\Delta t} - 50\right) + 0.5 & 50\,m < P_{j,\Delta t} < 60\,m \\ 0.25 & 60\,m < P_{j,\Delta t} \\ 1 & P_{j,\Delta t} = 31 \end{cases} \tag{23}$$

$$OF = NPRI = \frac{\sum_{j=1}^{Nn} Q_{j,\Delta t}^{req}\left(NPRI_{j,\Delta t}\right)}{\sum_{j=1}^{Nn} Q_{j,\Delta t}^{req}} \tag{24}$$

where $NPRI$ is the nodal pressure reliability of the network; $NPRI_{j,\Delta t}$ is the nodal pressure reliability index of node j at time Δt; $P_{j,\Delta t}$ is the nodal pressure at time Δt in meter, Nn is the number of nodes; and $Q_{j,\Delta t}^{req}$ is the demand of node j at time Δt. Another interpretation of the use of the reliability index for optimizing water network pressures is the Fuzzy Reliability Index (FRI), defined as follows:

$$OF = FRI = \begin{cases} FRI_{\mathrm{node}} \times FRI_{\mathrm{pipe}} & \text{if } Nn_{35} < \frac{Nn}{2} \\ \sqrt{FRI_{\mathrm{node}} \times FRI_{\mathrm{pipe}}} & \text{if } Nn_{35} \geq \frac{Nn}{2} \end{cases} \tag{25}$$

$$\mathrm{FRI}_{\mathrm{node}} = \frac{\sum_{j=1}^{Nn}\left(MemF_{\mathrm{Node}\,j} \times Q_j^{req}\right)}{\sum_{j=1}^{NJ} Q_j^{req}} \tag{26}$$

$$\mathrm{FRI}_{\mathrm{pipe}} = \frac{\sum_{i=1}^{NL}\left(MemF_{\mathrm{Pipel}} \times L_i\right)}{\sum_{i=1}^{NL} L_i} \tag{27}$$

$$\mathrm{Mem}\ F_{\mathrm{Node,j}} = \begin{cases} 0 & \text{if } P_j \le 5 \\ \left(\frac{P_j - 5}{30}\right)^{0.51} & \text{if } 5 < P_j \le 35 \\ 1 - \frac{P_j - 35}{30} & \text{if } 35 < P_j \le 50 \\ 0.25 & \text{if } P_j > 50 \end{cases} \tag{28}$$

$$\mathrm{Mem}\ F_{\mathrm{Pipe,i}} = \begin{cases} h_{fi} & \text{if } h_{fi} < 1 \\ 1 & \text{if } 1 < h_{fi} \le 5 \\ \left(\frac{30 - \frac{h_f \times L_i}{1000}}{30}\right)^{0.51} & \text{if } 5 < h_{fi} \le \frac{30000}{L_i} \\ 0 & \text{if } \frac{30000}{L_i} > h_{fi} \end{cases} \tag{29}$$

$$h_{fi} = \frac{10680 \times Q_i^{1.852}}{D_i^{4.87} \times CHW_i^{1.852}} \tag{30}$$

where *FRI* is the fuzzy reliability index of the water distribution network; FRI_{Node} is the total nodal fuzzy reliability; FRI_{Pipe} is the total fuzzy reliability of the pipes; Nn_{35} is the number of nodes with pressure higher than 35 m; *i* and *j* are counters for pipes and nodes, respectively; *NL* and *Nn* are the total number of pipes and nodes, respectively; $Q^{req}{}_j$ is the demand at node *j;* L_i is the length of *i-th* pipe; $MemF_{pipe,i}$ is the membership function of pipe *i* to the pipe fuzzy reliability function; $\mathrm{MemF}_{\mathrm{Node,j}}$ is the membership function of the node *j* to the nodal fuzzy reliability function; P_j is the pressure head at node *j;* h_{fi} is the head loss per 1 km length of pipe, as computed by the Hazen-Williams equation; Q_i discharge in pipe *i;* D_i is the diameter of pipe *i;* and CHW_i is the Hazen Williams coefficient of pipe *i*. In this case, the OF is subjected to the following constraints:

$$P^{set,min} < P_{valve}^{set} < P^{set,max} \tag{31}$$

$$\mathrm{NPRV} \in \{1, \ldots, \text{ Maximum number of PRV }\} \tag{32}$$

$P^{set,min}$ and $P^{set,max}$ are the minimum and maximum possible PRV set pressures, P_{valve}^{set} is the set pressure of each valve, and *NPRV* is the number of PRV.

3.3.6 Maximization of the Resilience

This is an objective function that can be used for networks partitioned into districts. The index used as an objective function is the resilience deviation index I_{RD}, which compares pressures before and after the network partitioning operation, i.e., after the installation of a control valve. It is defined as:

$$OF = I_{RD} = \frac{\sum_{j=1}^{N_n} Q_j \left(P_{j,nd} - P_j\right)}{\sum_{j=1}^{N_n} Q_j \left(P_{j,nd} - P^{min}\right)} \tag{33}$$

where Q_j is the total water demand at node j, including the pressure-dependent leakage flow; P^{min} is the minimum pressure required for proper supply; $P_{j,nd}$ and P_j are the total heads detected at the same node in the starting configuration of the WDN and in the partitioned one, respectively.

3.3.7 Maximizing the Demand Uniformity throughout the Network

This objective function is used when valves are placed in order to create a District Metered Area (DMA). The objective is to obtain a DMA where the demand has the highest possible uniformity. The uniformity is evaluated using the coefficient of variation Cu. The lower Cu is, the more uniform is the demand across the DMAs:

$$OF = Cu = \sum_{j=1}^{Nn} \frac{std(Q_j^{req})}{average(Q_j^{req})} \tag{34}$$

where $std(Q_j^{req})$ is the standard deviation of the demands in the area considered, and $average(Q_j^{req})$ is the average of the demands in the area considered.

3.3.8 Maximization of Energy Recovery

Energy recovery and saving are strongly connected to valve placement in the WDN. In fact, every time a control valve is installed in a WDN, a minor loss is introduced in the pipeline. Where this loss is particularly intense, some researchers suggest to install energy recovery devices in place of simple pressure reducing valves. Among the devices most commonly proposed in place of PRVs for energy recovery purposes are Pumps As Turbines (PATs) (See Table 2 for reference details). In these cases, the objective function is devoted to the optimization of the recovered energy. The energy recovered can be translated into a revenue introducing an electrical energy tariff t_e:

$$OF = \sum_{\Delta t=1}^{N_{\Delta t}} \sum_{k=1}^{N_{PAT}} t_e \rho g Q_k^* H_k \eta_k \tag{35}$$

where ρ is the water density; g is the gravitational acceleration; Q_k^* is the flow at *k-th* PAT at timestep Δt; H_k is the head available for recovery at *k-th* PAT at timestep Δt; η_k is the efficiency of the *k-th* PAT; and N_{PAT} is the number of PATs installed in the water network.

An alternative solution is to introduce an objective function that also considers the volume of water saved thanks to the regulation of pressure made possible by the PATs introduced in the networks. This alternative solutions ranks the solutions based on the most cost-effective combination of energy recovery (based on total daily energy recovered) and leakage reduction (average percentage leakage reduction), according to the following equation:

$$\mathrm{OF} = \sum_{\Delta t=1}^{N_{\Delta t}} \left[\left(365 W_{ER} \times t_e \times ER_{\Delta t} + \frac{W_L}{365} \times W_{LR} \times c_{\mathrm{CM}} \times LR_{\Delta t} \right)^{(1-OF_{pen})} + \left(\frac{26.317 \times ER_{\max}{}^2 - 50948 \times ER_{\max} - 79324}{24} + 2.473 \times 10^7 \right) \times 10^{-6} \right] \quad (36)$$

where W_{ER} is the energy recovery weight; t_e is the energy cost; $ER_{\Delta t}$ is the energy recovery per timestep; W_L is the current annual real losses; W_{LR} is the leakage reduction weight; c_{CM} is the water cost per unit; LR_i is the leakage reduction per timestep; ER_{max} is the energy recovery installation capacity; and OF_{pen} is the solution penalty defined as follows:

$$OF_{pen} = \frac{\sum_{\Delta t=1}^{24} \left[\frac{p_j - p^{min}}{30 + (p_j - p^{min})} \right]^{0.5}}{24} \quad (37)$$

An alternative version of the equation is given by the same authors as follows:

$$OF = \sum_{\Delta t=1}^{N_{\Delta t}} \left[\frac{\left(ER_{\Delta t} \times LR_{\Delta t} \right)^{(1-OF_{pen})}}{\left(-26.317 \times ER_{\max}{}^2 + 50948 \times ER_{\max} + 79324 \right) / \left(130245.7 \times ER_{\max} \right)} \right] \quad (38)$$

Another issue concerning energy saving is the optimization of pump scheduling, which is not strictly related with valve installation and setting but involves pressure regulation. Researchers applied metaheuristic algorithms also for optimizing pump scheduling. Usually, the objective functions used in these cases are based on the cost, because it is a simple way to put together the water saved from pressure regulation and the energy saved by pump scheduling, which can both be considered as a cost for the utility. An example of this application is represented with the following objective function:

$$OF = \sum_{t=1}^{T} \omega (W_t - W_t') + F_{before} - \sum_{t=1}^{T} \sum_{m=1}^{p} \sum_{n=1}^{q} \Psi_m (Q_{mnt} H_{mnt} / \eta_{mnt}) \quad (39)$$

where ω is the water price coefficient, equal to the water price multiplied by the conversion factor. W_t' and W_t are the leakage amount of the Δt period before and after scheduling, respectively. T is the number of time steps. Q_{mnt} is the quantity of the n pump in the m pump station in period Δt. H_{mnt} is the corresponding head. η_{mnt} is the efficiency coefficient, which includes pump efficiency, motor efficiency, etc. ψ_m is the electric price coefficient of the m pump station. p and q are the total number of pump stations and the total number of pumps in the m pump station. F_{before} is the total electric consumption before scheduling. Including energy recovery and pressure regulation in the same OF brings to:

$$OF = \sum_{k=1}^{N_{PAT}} Q_k \cdot \Delta H_k - \sum_{j=1}^{Nn} a \cdot \left[max(0, p^{min} - p_j) \right]^2 \quad (40)$$

where flow discharge Q_k by the pressure drop ΔH_k caused by the *k-th* device, and a is a penalty coefficient defined in Table 1.

3.4 Case Studies

To test and validate the optimization methodologies developed in their research, the authors introduced several benchmark networks. Some networks are real whereas others are synthetic and specifically designed to the benchmarking scope. An issue that often limits the possible use of the same network by other researchers is the lack of information about the network characteristics. This is the main reason why methods are not applied to the same network as first benchmark, which is a major obstacle to a structured comparison among the different methodologies. An effort in this direction has been made by Creaco and Pezzinga (2018) and by Ormsbee et al. (2022): the former compared different optimization methodologies using the same reference network; the latter created an organized database of several networks that can be used for water distribution research activities. A repository is accessible and can be freely used by researchers (University of Kentucky 2022).

Table 3 summarizes the different networks used as a case study in the papers considered in this review, illustrating the characteristics of each network along with a sketch of its layout. The initial point to consider is that various networks exhibit distinct characteristics, such as varying numbers of nodes and links, as well as the presence of reservoirs or pumps. This diversity prevents straightforward comparison between the methodologies. The network most used as benchmark case (21 of the total number of paper reviewed) is the one firstly introduced by Coulbeck and Sterling (1978), inspired from the Yorkshire Water Authority's network. It is composed by 22 nodes and 37 links highly interconnected and by three reservoirs. The network has been used for the application of several optimization methodologies, in particular GA, PSO, ACO, and, lastly, also AI. Comparing the results obtained by the different methodologies in terms of percentage reduction of leakage, the highest performance solution was found by (Giugni et al. 2014), with a reduction of 31% of losses, obtained by installing 3 control valves and using several insulation valves in the network. The methodology is based on a hybrid multi-objective algorithm that composes GA and LP respectively for valve placement and valve setting.

4 Concluding Remarks and Future Directions

Over the last three decades, various research teams have developed their own approaches, algorithms, test networks and optimization variables. Research groups in Italy, the UK, and Iran have been particularly productive on these areas with a particular focus on leakage reduction for Italy and Iran and on energy saving for UK. The results obtained by researchers are promising with respect to the use of metaheuristics as an optimization method for reducing water loss in WDNs and recovering dissipated energy. Despite the proven validity and functionality of all the presented methodologies, at least on the network used as a case study, none has emerged as the final reference method. Nevertheless, there is still much research to be done on reducing computational burdens and integrating prediction models.

The current research trend on metaheuristic methods, highlighted in the most recent publications, such as Karakatsanis and Theodossiou (2022) and Samadi-Koucheksaraee et al. (2022), suggests a focus on hybridization, integrating multiple metaheuristic methods to leverage their strengths and overcome their weaknesses. Hybrid algorithms combine the exploration capabilities of Genetic Algorithms with the exploitation abilities of other metaheuristic methods, or combine Machine Learning with different metaheuristic algorithms (Sangroula et al. 2022). The development of these methods is linked to the recent high availability of data that can be used in the learning process by Artificial Intelligence methods. In this context, the recent momentum in technology development should also be considered for the development of new technologies for the control and monitoring of networks. These technologies, capable of providing remote control, reliable data, and high-frequency updates, can enable the implementation of new strategies for optimizing loss reduction and energy recovery in water distribution networks.

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Data Availability Materials and data used in the present paper are available under request to the corresponding author.

Declarations

Competing Interests The authors have no relevant financial to disclose.

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