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Review

Lost in Optimisation of Water Distribution Systems? A Literature Review of System Design

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Abstract: Optimisation of water distribution system design is a well-established research field, which has been extremely productive since the end of the 1980s. Its primary focus is to minimise the cost of a proposed pipe network infrastructure. This paper reviews in a systematic manner articles published over the past three decades, which are relevant to the design of new water distribution systems, and the strengthening, expansion and rehabilitation of existing water distribution systems, inclusive of design timing, parameter uncertainty, water quality, and operational considerations. It identifies trends and limits in the field, and provides future research directions. Exclusively, this review paper also contains comprehensive information from over one hundred and twenty publications in a tabular form, including optimisation model formulations, solution methodologies used, and other important details.

Keywords: water distribution systems; optimisation; literature review; design; rehabilitation; algorithms

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1. Introduction

Water distribution systems (WDSs) are one of the major infrastructure assets of the society, with new systems being continually developed reflecting the population growth, and existing systems being upgraded and extended due to raising water demands. Designing economically effective WDSs is a complex task, which involves solving a large number of simultaneous nonlinear network equations, and at the same time, optimising sizes, locations, and operational statuses of network components such as pipes, pumps, tanks and valves [1]. This task becomes even more complex when the optimisation problem involves a larger number of requirements for the designed system to comply with (e.g., water quality), includes additional objectives beside a least-cost economic measure (e.g., potential fire damage) and incorporates more real-life aspects (e.g., uncertainty, staging of construction).

The early research related to the design optimisation of WDSs can be dated from the 1890s to 1950s. It was based on the principle of economic velocity [2–4], which was gradually reviewed and replaced by establishing the minimum (annual) costs of the system (i.e., least-cost design) [5–7]. Due to lack of computational technology in that period, those previous studies involved manual calculations combined with graphical methods, often resulting in practical charts to derive economic pipe diameters. The development of the optimisation of WDS design, therefore, had been an incremental process over time and may have appeared to be "only too true that the design of the transmission and distribution system receives [at that period] little attention in spite of the great sums of money invested in such installations" [8].

A successive period from the 1960s to 1980s displays a more rapid progression, which was initiated by the introduction of digital computers to network analysis in 1957 [9]. The introduction of computers was subsequently followed by the development of iterative methods [10,11] and simulation packages [12,13] to solve simultaneous nonlinear network equations, and eventuated in the application of mathematical deterministic methods to solve WDS design optimisation problems. These methods, including linear programming (LP) [14], nonlinear programming (NLP) [15,16], and others [17], typically minimised the design or capital (and operational) costs of the system, which were combined into one economic measure.

Another significant advancement in the optimisation of WDSs represented an introduction of stochastic methods using principles of biological evolution [18] and natural genetics [19]. Nonetheless, it was not until the 1990s when these methods became more popular [20] due to their ability to solve complex, real-world problems for which deterministic methods incured difficulty or failed to tackle them at all [21,22], and to also control multiple objectives. The popularity of metaheuristics has resulted in a dramatic increase in the application [21,23] to optimal design of WDSs, with "the several hundred research papers written on the subject" by 2001 [24]. Optimisation of WDS design has also progressed from a cost-driven single-objective framework to multi-objective models, when various objectives that continually gain importance (e.g., environmental objectives, community objectives reflecting the level of service provided to customers) can be evaluated on more equal basis [25]. Some of the most recent developments include the use of an engineered (as opposed to a random) initial population to improve the algorithm convergence [26], application of online artificial neural networks (ANNs) to replace network simulations [27], analysis of the algorithm search behaviour [28] in relation to the WDS design problem features [29], and reduction of the search space [30] to increase computational efficiency.

2. Aim, Scope and Structure of the Paper

This paper aims to provide a comprehensive and systematic review of publications since the end of the 1980s to nowadays, which are relevant to the optimisation of WDS design, strengthening (i.e., pipe paralleling), expansion and rehabilitation. The purpose of the review is to enable one's speedy familiarisation with the scope of the field, insight in the overwhelming amount of publications available and realisation of the future research directions. This paper contributes to and goes beyond the existing review literature for the optimisation of WDS design and rehabilitation [20,21,31–39] by not only identifying trends and limitations in the field, but also by providing comprehensive information from over one hundred and twenty publications in a tabular form, including optimisation model formulations, solution methodologies used, and other important details.

The paper consists of two parts: (i) the main review and (ii) an appendix in a tabular form (further referred to as the table), each having a different structure and purpose. The main review is structured according to publications' design problems and general classification. The design problems cover application areas, such as new system design, existing system strengthening, expansion and rehabilitation, and time, uncertainty and performance considerations. The general classification captures all the main aspects of a design optimisation problem answering the questions: what is optimised (Section 4.1), how is the problem defined (Section 4.2), how is the problem solved (Section 4.3) and what is the application (Section 4.4)? The purpose of the main review is to provide the current status, analysis and synthesis of the current literature, and to suggest future research directions.

A significant portion of this review paper is represented by the table, which refers to over one hundred and twenty publications in a chronological order. Each paper is classified according to an optimisation model (i.e., objective functions, constraints, decision variables), water quality parameter(s), network analysis, optimisation method and test network(s) used. Obtained results as well as other relevant information are also included. The purpose of the table is to provide a representative list of publications on the topic detailing comprehensive information, so that it could be used as a primary reference point to identify one's papers of interest in a timely manner. Hence, it presents a unique and integral contribution of this review.

The structure of the paper is as follows:

- The main review: Design problems (Section 3), General classification of reviewed publications (Section 4), Future research (Section 5), Summary and conclusion (Section 6), List of terms (Section 7), List of abbreviations.
- The table: Appendix A.

3. Design Problems

Two types of a design problem have been identified based on the field progression as follows: (i) a traditional design (i.e., theoretical or static design) of a WDS with a single construction phase for an entire expected life cycle of the system usually considering fixed loading conditions reflecting maximum (and other) future demands (Section 3.1); (ii) an advanced design (i.e., real-life or dynamic design) of a WDS capturing the system modifications and growth (due to the development of the populated area) over multiple construction phases, including future uncertainties (e.g., in demands, pipe deterioration) and other performance considerations (Section 3.2).

3.1. Application Areas

3.1.1. New Systems: Design

Critical infrastructure, including water, energy and transport systems, is essential in ensuring the survival and wellbeing of populations worldwide. Since the ancient Greek civilisations, WDSs have been an important part of making human settlements sustainable, thus optimising these systems to meet various requirements has over time gained interest of researchers and practitioners alike. Generally, optimisation of WDS design involves determining sizes, locations and operational statuses of network components such as pipes, pumps, tanks and valves, while keeping the system design or capital (and operational) costs at their minimum. The problem scope is primarily dependent on a type of a WDS under consideration, which is either a branched or looped and gravity or pumped system.

A network topology, branched or looped, represents a fundamental distinction in the problem complexity at the network analysis stage due to a way of determining flows in pipes. In branched networks there is a unique flow distribution calculated directly using nodal demands, while in looped systems flows can undertake multiple and alternative paths from a source to a customer [40]. This possible variability results in iterative methods being required to solve pipe flows in looped networks, such as that described in [41].

Regarding gravity WDSs, a basic optimisation model minimises the design cost of the network subject to the nodal pressure requirements, with pipe sizes or diameters being the only decision variables [42–48]. Popular test networks used to solve such a problem are the two-loop network [14], Hanoi network [49] and Balerma irrigation network [50]. As far as pumped WDSs are concerned, the optimisation problem becomes more complex than in the case of gravity WDSs, because of the presence of pumps and tanks (see Section 3.1.3), which require selecting not only their sizes and locations [14,26,51,52], but also their operational statuses [14,29,53,54], as well as often running an extended period simulation (EPS) for multiple loading conditions. Unlike for gravity WDSs, there does not seem to be any test network that is frequently used by multiple authors for pumped WDSs.

Regarding test networks, nevertheless, study [26] comments that they are limited, in general, to simple transmission networks, so-called benchmark systems, excluding local distribution lines. This exclusion is mainly due to a dramatic increase in the problem dimension, thus computational time, if local pipes were included. A problem of excluding smaller distribution pipes from the optimisation is in oversizing the transmission mains, as local distribution networks provide alternative pathways and display significant capacity to carry when the transmission lines are out of service [26]. The lack of large and complex test networks has recently been addressed by a number of researchers [55–57] who developed methodologies for generating synthetic networks of varying sizes and complexity levels. Furthermore, several real-world networks have been used for the design competitions by international research teams working in the area of WDS design, including those that are described by [58,59].

The problem complexity further increases by considering multiple simultaneous objectives. Initially, single-objective optimisation models were used to formulate WDS design problems, in which all objectives are combined into one economic (i.e., least-cost) measure (see, for example, [14,51,60–62]). A multi-objective optimisation approach was possibly first applied in the late 1990s (Figure 1), maximising the network benefit on one hand and minimising the system cost (of network rehabilitation) on the other hand [63]. In studies of newly designed WDSs, in addition to the economic measure, the other objectives considered were the pressure deficit [30,62,64–67] or excess [68,69] at network nodes, the penalty cost for violating the pressure constraint [70], greenhouse gas (GHG) emissions [71–76] or emission cost [77], water discolouration risk [68] and water quality [78]. A multi-objective optimisation approach is considered "very appealing for engineers as it provides a tool to investigate interesting trade-offs", for example, a marginal pressure deficit can be outweighed by a considerable cost reduction [67].

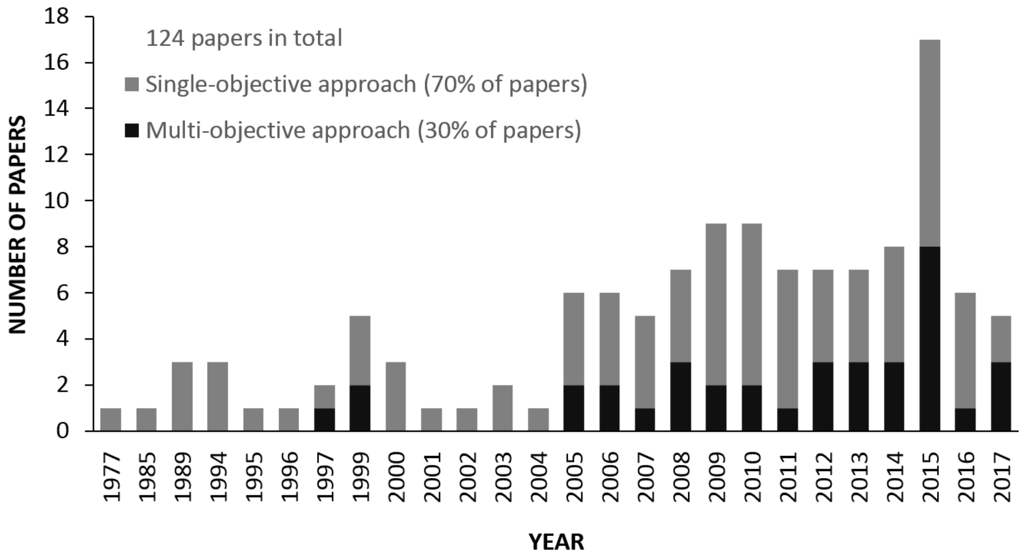

Figure 1. Papers (from Appendix A Table A1) by year and optimisation approach.

The single-objective approach benefits from being able to identify one best solution, which is then easy to analyse and implement. Multi-objective methods, on the other hand, result in a set of tradeoff (Pareto, non-dominated) solutions, which requires an additional step to select only one or a limited number of the promising solutions. Choosing such a reduced number of solutions from a potentially large (or even infinite) non-dominated set is likely to be difficult for any decision maker. This task makes the multi-objective approach less desirable as there is often a requirement to make a clear decision to be implemented. The research question resulting from this challenge is how to select the best solution(s) from the Pareto set, which may involve providing the decision makers with a practical and representative subset of the non-dominated set that is sufficiently small to be tractable [22]. For example, study [79] introduced game-theoretic bargaining models to take into account conflicting requirements and managed to reduce the solution sets to a reasonable size. Further investigation of the methodologies for identifying a handful of useful solutions, such as those where a small improvement in one objective would lead to a large deterioration in at least one other objective, is thus warranted. In addition to game-theoretic models, the approaches that are based on identifying 'knees' of the Pareto front or expected marginal utility, maximum convex bulge/distance from hyperplane, hypervolume contribution and local curvature [80] are all promising methods that require a thorough analysis on WDS problems.

3.1.2. Existing Systems

As a consequence of the development/growth and population density increase within urban areas, existing WDSs require to be upgraded to satisfy raising water demands. These upgrades involve system strengthening (i.e., pipe paralleling), rehabilitation (e.g., pipe cleaning and relining) and expansion. Even though these processes often take place within one WDS thus some of the research articles fall under all system strengthening, rehabilitation and expansion, they are divided into separate subsections in order to provide a systematic overview.

Strengthening

System strengthening represents a reinforcement of an existing WDS to meet future demands, through lying duplicated pipes in parallel to the existing water mains. It is also sometimes referred to as parallel network expansion [42] or pipe paralleling. The main objective and decision variables are, similar to the design of new WDSs, the minimisation of the design (or capital) cost and pipe diameters of duplicated pipes, respectively. Publically available test networks involving purely system strengthening include the New York City tunnels [81] and EXNET [82]. In addition, there are test networks considering system strengthening together with other design strategies (e.g., system expansion, rehabilitation), which include the 14-pipe network with two supply sources [20,83] and Anytown network [84]. Of those publically available test networks, the most frequently applied is the New York City tunnels, which was often the only network used to test the proposed methodology. These studies used genetic algorithm (GA) [85,86], combined with ANNs [87], fast messy GA (fmGA) [88] and non-dominated sorting genetic algorithm II (NSGA-II) [89] as a solution algorithm.

The complexity of an optimisation problem involving exclusively system strengthening as a design strategy can be substantially increased by incorporating water quality considerations. Such applications include, apart from pipe sizes as decision variables, also water quality decision variables that can be in a form of disinfectant (i.e., chlorine) dosage rates [27,87]. In order to reduce computational effort of those problems, ANNs were implemented to replace network simulations to a large extent. Further increase in the complexity presents the use of a multi-objective approach, with additional objectives being system robustness [89] (uncertainty and system robustness are contained in Section 3.2.3), the pressure deficit at network nodes [62,65], and the number of demand nodes with pressure deficit [65,90]. In those studies, a conflicting relationship was identified between the economic (i.e., least-cost) objective and pressure deficit/the number of nodes with pressure deficit. Based on such information, the decision maker is able to "quantitatively evaluate the cost of pressure constraints attenuation which implies a reduction in the system service to its consumers." Optimisation methods used in those studies were NSGA-II [65,89,90], strength Pareto evolutionary algorithm 2 (SPEA2) [65] and cross entropy (CE) [62].

Rehabilitation

Due to aging water infrastructure, which causes a decreased level of service in terms of water quantity as well as quality for customers, increased operation costs and leakage, pipe breaks and other issues, existing WDSs require rehabilitation in a timely manner. Large investments are and will be needed in the future to rehabilitate ever deteriorating pipe networks [91] reaching the end of their lifecycle. Network rehabilitation consists of the replacement of pipes with the same or larger diameter, cleaning, or cleaning and lining of existing pipes; with the main objective to minimise the pipe rehabilitation cost. Within an optimisation model, pipe replacement options can be represented by binary [17] or integer [92] decision variables to identify the pipes selected for replacement, and continuous [17] or integer [92] diameters, respectively, of the replaced pipes. Pipe rehabilitation options are often binary decision variables (i.e., 1 = cleaning/lining, 0 = no action) [17,93]. If a pipe is not scheduled for rehabilitation, it is expected to be subject of break repair over a longer planning horizon. Hence, study [17] added the expected pipe repair costs to the rehabilitation cost of the network. Because a network rehabilitation strategy also has a direct impact on pump operating costs and GHG emissions due to pumping (i.e., they are reduced with an increased quantity of rehabilitated pipes) [94], pump energy costs have been added to the total least-cost objective [17,95].

Some studies consider only a single economic objective to formulate a network rehabilitation problem [17], while other investigations apply a multi-objective optimisation framework in order to incorporate measures affecting the level of service provided to customers (i.e., 'community objectives'). Accordingly, additional objectives considered, beside the economic measure, include the network benefit [63], pressure violations at network nodes [68,95], velocity violations in pipes [95] causing potential sedimentation problems and subsequent water discolouration, water quality (i.e., disinfectant) deficiencies at network nodes [92], and potential fire damage expressed as lack of available fire flows [92]. To generate multi-objective optimal solutions, those studies use mainly metaheuristics or hyperheuristics, such as structured messy GA (SMGA) [63], NSGA-II [95], non-dominated sorting evolution strategy (NSES) [92], and evolution strategy (ES)/SPEA2 in a hyperheuristic framework with evolved mutation operators [68]. The resulting Pareto fronts can then serve decision makers in selecting a rehabilitation strategy that balances community objectives with a capital expenditure.

Note that publications included in this section belong to the category of static design, which involves a single network rehabilitation intervention for a near planning period, designed based on the current network status. Publications, which are concerned with staged rehabilitation interventions involving their timing over an extended planning horizon, are reviewed in Section 3.2.1.

Expansion

An expansion of a WDS means developing or expanding the existing system beyond its current boundary, with the main objective to minimise the total design (or capital) and operation cost. System expansion can be thought of as the following two interdependent design problems: (i) developing a new network that is connected to the existing one, and simultaneously (ii) strengthening, rehabilitating and upgrading the existing system in order to convey increased water demands. Hence, system expansion is the most complex WDS design problem as it can ultimately contain all aspects of designing new as well as existing systems. A typical example of the optimal network expansion is the Anytown network problem [84]. Essentially, the objective is to determine least-cost design and operation, using locations and sizes of new pipes (including duplicated pipes), pumps and tanks, as well as pipe rehabilitation options (i.e., cleaning and lining) as decision variables. Such extensive problems are often solved by combining a power of optimisation algorithms with "manual calculations and a good deal of engineering judgement" [84].

Although some studies solved the Anytown network problem as initially formulated [84], for example, study [83] by enumeration and [96] using GA, others included new aspects to the (original or modified) problem. Those aspects represent, for example, water quality [97] inclusive of the construction and operation costs of treatment facilities [53], new tank sizing approach (further discussed in Section 3.1.3) [93,98], and additional objectives, such as the network benefit incorporating multiple system performance criteria [93,99] or the hydraulic failure, fire flow deficit, leakage and water age with visual analytics used to explore the tradeoffs between numerous objectives [97]. These studies used SMGA [99], GA [53,93], and ε-NSGA-II [97] to solve the problem. Study [93] combined GA with fuzzy reasoning, where system performance criteria are individually assessed by fuzzy membership functions and combined using fuzzy aggregation operators.

An example of large system expansion represents the battle of the water networks II (BWN-II) optimisation problem, which involves the addition of new and parallel pipes, storage, operational controls for pumps and valves, and sizing of backup power supply, and includes the capital and operational costs, water quality, reliability and environmental considerations as performance measures [58]. This problem was solved by multiple authors within the Water Distribution Systems Analysis (WDSA) conference series [58]. Another example of large and real-world system expansion is presented in [100]. Apart from the decision variables for the BWN-II, it also includes selections of pipe routes, expansions of water treatment plants (WTPs) and configurations of pressure zones. The common approach that is applied to solve both of those optimisation problems was the use of engineering judgement, which led to a reduction in the number and type of decision variables. In the case of the study of [100], some eliminated variables were included in separate optimisation problems. Study [58] demonstrates that "different combinations of engineering experience, computational power and problem formulation can give similar results".

Despite the advances in optimisation methods developed for new system design, rehabilitation and/or expansion of WDS, most notably over the last three decades, the large, complex systems still represent a significant challenge to solve using a fully automated optimisation procedure. There are several reasons for that, including: (i) complexity resulting from a mixed-discrete, nonlinear optimisation problem with often conflicting and difficult to assess objectives and performance measures; (ii) the large network sizes normally encountered in practice, which translates into large search spaces where a global optimum is almost impossible to find; (iii) the so called No-Free-Lunch theorem [101], which says that not all of the optimisers are well suited to solving all problems, in other words, slow convergence of general population-based optimisation methodologies that do not utilise some form of traditional engineering experience/heuristics; and (iv) the lack of computational efficiency of network simulators required by modern population-based optimisation methods. A number of approaches have been developed to deal with these challenges, mainly aimed at increasing the computational efficiency of the optimisation process. Those improvements often include the division of a design problem into multiple phases [58] that can be solved separately, the involvement of engineering expertise and manual interventions [59] to reduce the search space, or the use of surrogate and meta-modelling to speed up the simulation process [27]. The work that is still needed in the WDS design optimisation area is to understand the link between the performance of an algorithm (and its operators) and certain topological features of a WDS (e.g., existence of pumps/tanks, loops), as indicated in [29].

3.1.3. Problem Elements

Pipes

Unlike other network elements (e.g., pumps, tanks, valves), pipes are always included in the optimisation of WDS design, as the basic model is to determine such pipe sizes (or diameters) for which the design cost of the network is minimal, subject to the nodal pressure requirement. Even though pipe decision variables are incorporated in every optimisation model, they do not seem to have been unified. Assuming a given layout of the pipe network, there are two types of a decision variable, pipe sizes/diameters, and pipe segment lengths of a constant (known) diameter. Pipe sizes/diameters are discrete by nature of the problem, because they are to be selected from a set of commercially available sizes, however both discrete and continuous values are used mainly depending on the optimisation method. Discrete sizes are used mostly for stochastic algorithms (i.e., metaheuristics) [42,70,85,88,102–109], whereas continuous sizes for deterministic methods [16,110,111]. In regards to continuous sizes, the final solution can be modified by splitting a link into two pipes of closest upper- and lower-sized commercially available discrete diameter [16].

WDS design optimisation problems, which use pipe sizes/diameters as decision variables, can be referred to as a single-pipe design [112,113], while problems with pipe segment lengths of a constant (known) diameter as a split-pipe design [112,113]. Pipe segment lengths of a constant (known) diameter are predominantly used in conjunction with deterministic algorithms [14,114,115] or hybrid methods (i.e., combined deterministic and stochastic methods) [113,116,117]. Single-pipe design with discrete decision variables can provide, compared to split-pipe design and continuous diameters solutions, high quality [102], or good quality results without unnecessary restrictions imposed by split-pipe design [42]. Even if only pipe diameters are optimised, the design of WDS is a complex problem that requires a careful selection of decision variables as to minimise the search space. The choice between direct representation of discrete pipe diameters and split-pipe solutions has largely been resolved in favour of the former, but further improvements in decision variable coding might be possible.

In cases of an unspecified network layout (e.g., when designing a new or extending an existing WDS), additional decision variables are required in order to determine or select pipe routes [52,100]. These variables can be formulated, for example, as binary selecting a link which should be included into the pipe route [52]. Pipe routes can also be considered when strengthening an existing WDS, as "parallel pipes do not necessarily have to be laid in the same street", they "may be laid in a parallel street or right-of-way that may not have existed at previous construction times" [118]. Another possible type of a pipe decision variable are pipe closures/openings to adjust a pressure zone boundary within a WDS [100].

Pumps

There are two main aspects of including pumps into the optimisation of WDS design. First, the pump design or capital cost and second, the pump operating cost due to electricity consumption. Typically, electricity consumption is one of the largest marginal costs for water utilities, with the price of electricity rising globally making it a dominant cost in managing WDSs. Therefore, "the presence of pumps requires that both the design and the operation of the network should be considered in the optimisation" [99]. Accordingly, the minimisation of the pump design or capital cost as well as the pump operating cost to achieve minimal amount of electricity consumed by pumps ought to be included in an optimisation model. Pump operating cost is usually calculated on annual basis using the typical daily demand patterns (i.e., EPS), but a longer period can be considered depending on the planning horizon of a case study, for example, 20 years [17,119], 100 years [72,76,77]. Because this cost occurs at different times in the future, its present value is required to be included in the objective function. This conversion of future economic effects into the current time is undertaken via a present value analysis (PVA), described in detail in [71,72,77], using zero, constant or time varying discount rates.

In the model, pumps are controlled by three types of a decision variable. Firstly, a pump location, which are used when designing a new or extending and upgrading an existing WDS. Possible options to consider are, for example, to predetermine a limited number of potential pump locations [93,120], to evaluate network nodes as potential pump locations (yes/no) via binary variables [52] or to upgrade the current pump stations where new pumps are to be installed in parallel to existing ones [99]. Secondly, a pump size, which can be included as a pump capacity [14,121], pump type [75,76], pumping power [17], pump head/height [52,122], pump operation curve/head-flow [93] or pump size in a combination with the number of pumps [26]. Thirdly, a pump schedule, which describes when the pump is on and off during a scheduling period (e.g., 24 h). It can be specified by a pumping power [53,54] or pump head [123] at each time step, the number of pumps in operation during 24 h [97], binary pump statuses [29], continuous options representing on/off times with a limit imposed on the number of pump switches [76], discrete options representing the time at which a pump is turned on/off using a predefined time step (e.g., 30 min) [75]. All of these decisions impact on the size of the search space and eventually on the computational efficiency of the optimisation algorithm used. A comparative study of various approaches would be useful to help determine what their advantages and disadvantages are and which one to use for a particular situation.

In terms of the model objectives, the pump design or capital and/or operating costs were mostly incorporated together with the costs of other network elements (e.g., pipes, tanks, valves) into one economic function (see, for example, [17,26,51,60,93,95,96,119]). Although a few studies, which considered the design and operating costs as part of separate objectives (e.g., [124]), reported on their conflicting tradeoff, this relationship was not confirmed for a higher-dimensional space when required to balance numerous objectives [97]. Additionally, the pump maintenance cost (see, for example, [61,62,121]) as well as the pump replacement and refurbishment cost [71,72,77] were accounted for. More recently, GHG emission cost or GHG emissions due to the electricity that is consumed by pumps [71–77] were introduced as an environmental objective. Similar to the pump operating cost, a PVA can be used for the pump maintenance, replacement and refurbishment costs, as well as GHG emissions/cost. Even though there is a significant tradeoff between economic and environmental objectives (i.e., GHG emissions decrease with the increasing costs and vice versa), GHG emissions can be considerably reduced by a reasonable increase in the costs [71,72]. Additional results indicate that the price of carbon has no effect on the tradeoff [77], whereas the discount rates do [72], the use of variable speed pumps (VSPs) (rather than fixed speed pumps (FSPs)) leads to significant savings in both total costs and GHG emissions [74].

The mixed-integer nature of pumps as decision variables and their often significant impact in terms of hydraulic behaviour of the entire system, makes them a difficult element to include and control its impact during an optimisation run. Furthermore, the increased complexity of modelling VSPs and their incorporation into the optimisation problem pose another difficulty that has to be tackled by modern optimisation algorithms. Finally, the formulation of various objectives, including maintenance requirements (i.e., often surrogated by the number of times a pump is switched on during the optimisation period), represents another challenge for including pumps into overall WDS design studies.

Tanks

In spite of having a valuable role in WDSs contributing to their reliability and efficiency [125], storage tanks (further in the text referred simply to as tanks) are not often included in WDS design optimisation problems. Several types of a decision variable have been used in the literature to control tanks in the model, and a few objectives (or objective functions) have been developed to mainly evaluate tank performance. However, the use of those variables as well as objectives seems to vary across studies with no general framework on how to model tanks available. As far as decision variables are concerned, they include tank locations [71,72,96–99,120], tank volumes [16,53,93,96,98,99], minimum (and maximum) operational levels [93,96,98,99], tank heads [78], tank elevations [14], ratio between diameter and height [98], ratio between emergency volume and total volume [98]. Study [99] compared two approaches to model tanks in terms of operational levels, first of which calculates tank levels analytically during the network analysis, and second of which includes tank levels as independent variables. Although they yielded similar results, the former approach obtained more robust solutions.

In regard to objectives, the most frequently used account for the tank design or capital cost, which is normally part of the total system costs (i.e., pipes, pumps, etc.) [16,53,76,93,96–99,120]. Furthermore, additional objectives have been introduced evaluating, along with others, the tank performance. These objectives are the network benefit, including storage capacity difference [99], safety and operational volume capacities, and the filling capacity of the tank [93], and system hydraulic failure including tank failure index [97]. A positive relationship was identified between the total cost of the system and network benefit [93,99], whereas a negative relationship exists between the cost and failure index [97]. The effect of changing the tank balancing volume, so called tank reserve size (TRS), on the minimisation of system cost and GHG emissions was also investigated [76]. It was identified that a larger TRS could assist in reducing GHG emissions with no additional cost by modifying pumping schedules.

In addition to pumps, the presence or absence of a tank can also play a significant role in changing hydraulic behaviour of a WDS. This presents a large challenge for any optimisation approach as it creates a discontinuity (i.e., a large change in behaviour with or without a tank at a particular location), which has to be properly managed by the algorithm. Additionally, the setup of the tank (i.e., the link to the system, overflow valve operation, consideration of upper/lower level limits) within a simulation model can also play a significant role in the efficiency of the optimisation run.

Valves

The inclusion of valves in WDS design optimisation problems appears to be rather sporadic and descriptions related to their implementation are often very brief with not many details provided. Studies [14,26] accounted for valves in the overall costs of the system, based on optimal valve locations. The optimisation of a real-life scale WDS incorporating not only transmission pipelines, but also local distribution pipelines, concluded that optimal valve locations are to be affected by the presence of local lines which "provide alternative pathways when the main lines are out of service" [26]. As shutdown of valves used to isolate a portion of the WDS during an emergency (e.g., pipe break or a water quality incident) creates a change in hydraulic behaviour, the valve numbers and locations play part in the overall system design, particularly when the reliability or resilience of the system is considered. For example, study [126] presented a methodology for optimal system design accounting for valve shutdowns. Another application of valves is using their settings to influence the pressure distribution in the network (via pressure reducing valves (PRVs)) [16], or to determine timing of flows and flow rate values (either via flow control valves (FCVs) or PRVs) [127].

Valves were also used to incorporate a simpler model of VSPs into the multi-objective optimisation of WDS design including total economic cost of the system (i.e., design and operation) and GHG emissions [74]. In such an application, a pump power estimation method uses a FCV combined with an upstream reservoir to represent a pump in the system, with the aim to maintain the flows via the FCV into the downstream tanks as close as possible to the required flows. Hence, the determination of the most appropriate FCV setting for calculating pump power is formulated as a single-objective minimisation problem that is subject to multiple flow constraints, which is implemented within a multi-objective GA (MOGA) framework [74].

A combined design of the isolating valve system and the pipe network presents a considerable challenge to optimisation methods. Not only that the number of decisions increases exponentially with the addition of valves, but also the consequences of various valve system designs can only be evaluated by investigating a large number of (probabilistic) scenarios making the whole process computationally inefficient. Furthermore, the location and status of isolating valves can form decision variables also when a WDS is to be divided into manageable subsystems. This is the case with the so-called district metering areas (DMAs), which have been first implemented in the UK primarily for leakage management purposes [128]. Due to the fact that the DMA optimal design is normally performed after a system has been constructed, this problem was deemed beyond the scope of this review paper.

3.2. Time, Uncertainty and Performance Considerations

3.2.1. Staged Design

A staged design represents an optimisation of a WDS over a long planning horizon divided into several construction phases, without considering future uncertainties (e.g., in demands, pipe deterioration). In other words, it is a deterministic dynamic design either over several prefixed time intervals or with timing decisions (i.e., year of action execution). The planning horizon can spread across a number of years to an expected life cycle of the system.

Initial work in the staged design is related to the development of multiquality water resources systems using a single-objective approach, which minimised the costs of water allocation, facilities expansion, water transportation, and losses caused by insufficient supply [129]. It was formulated as a LP optimisation problem, into which nonlinear water quality equations were incorporated using a successive linear approximation iterative scheme. An advantage of using a staged design was demonstrated by realising linkages between certain management processes and variables, and a particular planning period (prefixed time interval).

Concerning WDSs, the staged design is often applied to rehabilitate an existing system as this problem inherently involves the timing of ongoing works over an extended planning horizon. Both single- and multi-objective optimisation models were proposed to solve such problems. Single-objective models included beside the network rehabilitation [130], also network strengthening [131] and expansion [124,132] combined into one least-cost objective, while multi-objective models incorporated the network benefit [131] or the system operating costs [124,132] as additional objectives. Optimisation methods used were GA [130], SMGA [131] and NSGA-II [124,132]. As opposed to the study of [129], these models do not define prefixed time intervals, but include timing decision variables to schedule works, also referred to as event-based coding [124,132]. This coding dramatically reduces the search space, thus the computing and memory requirements, because it eliminates unnecessary zero values of a traditional coding based on a time-interval (e.g., yearly) basis [124]. A further search space reduction can be achieved by so called limited pipe representation introduced by [130], which involves placing an upper bound on the number of pipes considered for rehabilitation. These reductions in the search space and computing requirements are especially important for large size WDSs.

Moreover, the staged design was applied to extend and strengthen existing wastewater, recycled and drinking water systems applying an integrated optimisation scheme within a single-objective framework using GA [127], and to plan a new WDS considering two objectives, the construction costs and network reliability, using NSGA-II [118]. Both of these studies used prefixed time intervals to schedule the construction. In addition, study [118] analysed the effect of the scheduled construction on the network design using a set of scenarios reflecting different lengths of planning horizons (25–100 years), time intervals (25–100 years) and the number of construction phases (1–4). Both studies [118,127] confirmed that for long planning horizons, the staged design is cost effective. The system upgrades guarantee a predefined reliability and there is always opportunity to modify or redesign subsequent upgrades at the later stage, based on new up-to-date predictions of potential future development [118].

By introducing staged design to WDSs, it is obvious that the search space increases almost exponentially to accommodate decisions at various times in the planning horizon. This is one of the key challenges for deterministic staged design, as computational efficiency of optimisation algorithms plays even more significant role than with static design. Another difficulty for achieving the optimised staged design is that even if an optimal solution can be found for each of the intermediate time steps, the algorithm has to ensure that contiguity among the staged decision is maintained, i.e., that the decisions selected in the previous stages are retained in the subsequent ones. An approach by [133] presents one way of obtaining that contiguity of decisions, starting from the solution at one extreme of the Pareto front. However, this issue is still an under-researched area, which requires more investigation. All of the above challenges apply even when the future is assumed to be perfectly known, which is unfortunately not the case.

3.2.2. Flexible Design

A flexible design represents one of the most recent developments in the design optimisation of WDSs. Similar to a staged design, a flexible design represents an optimisation of a WDS over a long planning horizon divided into several construction phases, but with the consideration of future uncertainties (e.g., in demands, pipe deterioration, urban expansion scenarios). Specifically, it is a probabilistic dynamic design over several prefixed time intervals and with the planning horizon ranging from a number of years to an expected life cycle of the system. Such a design allows for flexible and adaptive planning, which is favoured by water organisations that are often encouraged to include risk and uncertainty in their long term plans.

Uncertainties included in the flexible design are related to future demands [122,134–136] and future network expansions [137]. They are implemented using either a probabilistic demand assessment [135] or scenario-based approach via demand/expansion scenarios [122,134,136,137]. A decision tree has been introduced to combine the uncertain demands and intervention measures into optional decision paths [135]. Analogously, studies [122,137] have proposed the use of real options

(ROs) approach, which is also based on decision trees that reflect future uncertainties. In ROs approach, a decision tree is formed by independent decision paths with assigned probabilities to each of the scenarios. This approach enables flexibility to be incorporated into the decision making process and to subsequently change the investment plan based on new circumstances [122].

The majority of the above studies apply multi-objective optimisation approach, including, besides an economic (least-cost) objective, the system resilience [135], reliability [136] or total pressure violations [137] as another objective. Stochastic optimisation algorithms, such as NSGA-II [135,136], simulated annealing (SA), and multi-objective SA [122,137] have been employed to solve flexible design problems, except for [134] who applied integer LP (ILP) combined with preprocessing methods to reduce the dimensionality of the problem. These preprocessing methods included separating the (branched) network into subnetworks, reducing the number of decision variables (e.g., velocity constraints were used to eliminate unsuitable pipe diameters) and solving each subnetwork separately. As a consequence, the quality of the solution was improved and the proposed methodology [134] can be applied to large size WDSs.

While comparing to a traditional deterministic design, the results indicate that a flexible design has a higher initial cost (i.e., in the first construction phases) [122,136], which enables the system to adapt to various future conditions. However, it outperforms a traditional design in terms of the total cost over the entire planning horizon [122,135].

The application of flexible optimisation methodologies in WDS design that consider long-term uncertainty and management options, is yet to be explored to a larger extent in the literature. One of the key reasons is that it is not clear how various types of uncertainties, i.e., stochastic vs. deep uncertainty or aleatoric vs. epistemic uncertainty, are best represented in the optimisation process. The other possible reason is that the flexible design incurs additional computational costs that affects the overall computational efficiency of the optimisation algorithm. However, as the planning and design exercises are done sporadically, the additional computational burden and costs are often justified. Future uncertainties that might have an impact on WDS design, including climate change, population movements and economic development, make flexible design probably the most promising area of research over the next few decades.

3.2.3. Resilient, Reliable and Robust Design

System resilience, reliability and robustness present performance characteristics of a WDS in relation to current and most importantly future uncertain conditions. Although there is no universally agreed definition of any of these measures, the resilience can be defined in broadest terms as the ability of a WDS to adapt to or recover from a significant disturbance, which can be internal (e.g., pipe failure) or external (e.g., natural disaster) (adapted from [138]). Similarly, the reliability can be defined as the ability of a WDS to provide expected service, and can be expressed as the probability that the system will be in service over a specific period of time (adapted from [139]). The robustness represents the ability of a WDS to maintain its functionality under all circumstances (adapted from [138]), or over everyday fluctuations that have the potential to cause low to moderate (i.e., not catastrophic) loss of performance [89].

A robust design problem of a WDS is primarily concerned with uncertainties in model parameters. These uncertainties are related mainly to future demands [89,110,121,123,140,141], but can also consider pipe roughnesses [89,110,140,141], minimum nodal pressure requirements [110], network expansions [137] and others [142]. Study [89] states that "neglecting uncertainty in the design process may lead to serious underdesign of water distribution networks".

Several approaches have been proposed in the literature to formulate a robust design problem for WDSs. Firstly, a redundant design approach which adds redundancy to the system to account for the uncertain parameters by assuming that those parameters are larger than expected [140]. Secondly, an integration approach where uncertainties are incorporated into the model formulation via either objective function [89] or constraints [140] sometimes referred to as a chance-constrained model [110]. Both of those approaches assume a probabilistic distribution of uncertain parameters and convert an original stochastic optimisation problem into a deterministic one. Thirdly, a two-phase optimisation approach that initially solves an optimisation problem with deterministic parameters (i.e., no uncertainties), and subsequently uses those obtained solutions as an initial population for a stochastic problem where future demands and pipe roughnesses are considered uncertain variables following a probability density function [141]. Fourthly, a scenario-based approach where the uncertainty is implemented via a set of scenarios, each assigned a probability [121]. Lastly and most recently, a robust counterpart (RC) approach which is non-probabilistic and incorporates the uncertainty through an ellipsoidal uncertainty set constructed according to the user-defined protection level [123].

Despite a number of approaches to incorporate robustness into the design of WDSs, the measure has been defined fairly well and consistently in the literature, and consequently it has been used in optimisation studies. This may be due to the advances in robust optimisation in other fields and/or due to the focus on non-catastrophic loss of performance that is associated with robust operation. However, the other two measures, reliability and most notably resilience, have not been defined consistently in the WDS literature or have been considered seriously only fairly recently. Therefore, this section focuses on robust design of WDSs, with resilience and reliability being outside of the scope of this review paper. This also indicates that future research efforts could be directed toward a consistent and agreed definition of reliability and resilience, with optimisation methods being capable of solving WDS design considering them as objectives/performance measures.

Robust design optimisation problems are mainly solved using stochastic methods, such as GA [140], NSGA-II [89,121], optimised multi-objective GA (OPTIMOGA) [141], PSO [142] and CE [123], except for [110], who solves it as a NLP problem.

3.2.4. Design for Water Quality

In the literature, water quality is incorporated into the WDS design optimisation problems in various ways concerning both an optimisation model and water quality measure used. In terms of optimisation models, single-objective as well as multi-objective exist which include water quality considerations. In the former, water quality related expenditures, such as the cost of disinfection [27,120], cost of water treatment [53] or cost of losses incurred by insufficient quality [129], are combined with the system design/capital (and operation) costs into one objective. Alternatively, water quality is included as a constraint to a single-objective model in a form of minimum (and maximum) disinfectant concentrations at the network nodes [87,143]. In the latter, water quality presents a sole objective, which is either water quality benefit (being maximised) [63,131], water quality deficiencies (being minimised) [92,97,144] or water quality reliability (being maximised) [78]. Regardless of an optimisation model used, study [120] highlighted an importance of incorporating water quality considerations with system design and operation in one optimisation framework, which enables promoting water quality in the design stage, rather than leaving potential water quality issues to be resolved during the system's operational phase. Indeed, study [78] reports a significant tradeoff between water quality objective based on disinfectant residual and the system capital costs (i.e., the best quality solutions correspond to higher costs and vice versa), and demonstrates the sensitivity of the obtained solutions to a disinfectant dosage rate. Interestingly, there was not tradeoff found between water quality objective based on water age and the cost.

Regarding the water quality measure, it is dependent on the system specifics, its requirements, and also the optimisation model advancements progressively implementing water quality objectives useful to system operators. Basic water quality parameters that are used in optimisation models of drinking WDSs are chlorine [27,87,120,143] and chloramine [120], modelled as non-conservative applying first order decay kinetics, adjusted by a higher decay rate in parts of the system when needed [120]. In contrast, conservative water quality parameters are typically important for regional multiquality WDSs. These parameters are either specified within an optimisation model, such as salinity [129] or unspecified being modelled in conjunction with the operation of treatment facilities [53]. In multi-objective optimisation models, both specific parameters and surrogate measures are used to quantify water quality objectives. Water quality benefit is expressed as a function of the length of renewed and/or lined old pipes, as aged pipes are considered to cause the development of microorganisms and water discolouration [63,131]. Water quality deficiencies can be represented by a performance function on disinfectant residual reflecting governmental regulations [92], water age [97], or the risk of water discolouration due to the potential material after daily conditioning shear stress [144]. Water quality reliability is based on disinfectant residual [145] and/or water age [78].

Optimisation methods used to solve WDS design problems including water quality considerations were LP [129], GA [53,87,100,120,143] and differential evolution (DE) [27] for single-objective models, and SMGA [63,131], NSES [92], ε-NSGA-II [97], NSGA-II and SPEA2 integrated with a heuristic Markov-chain hyper-heuristic (MCHH) [144] and ant colony optimisation (ACO) [78] for multi-objective models. These algorithms were mainly linked with a network simulator EPANET to solve network equations. Because these EPANET simulations, in particular water quality analyses, are very computationally demanding, they were replaced by ANNs [27,87,143] to reduce computational effort.

Unsurprisingly, introduction of water quality considerations increases the complexity of the quest for the optimal design considerably. This increased complexity is caused not only by the more complex simulations required to predict the temporal and spatial distribution of a variety of constituents within a distribution system, but also by the requirement to run shorter time step water quality computations [22]. Furthermore, computational efficiency is affected by the ability to model multiple constituents throughout the WDS via the EPANET Multi-Species Extension, EPANET-MSX [146].

4. General Classification of Reviewed Publications

Based on the selected literature analysis, the following are the four main criteria for the classification of design optimisation for WDSs: application area (Section 4.1), optimisation model (Section 4.2), solution methodology (Section 4.3) and test network (Section 4.4).

4.1. Application Area

As outlined in Section 3, there are four application areas: design of new systems (Section 3.1.1), strengthening, expansion and rehabilitation of existing systems (Section 3.1.2). Numerous publications do not deal only with those design optimisation problems, but also with the operational optimisation (see, for example, [14,26,53,71,120,135]), which is an equally important area if the total cost (i.e., including capital and operation expenditure) is considered. Hence, the system operation has been added to the following analysis. It represents papers optimising (mainly) the pump operation together with the system design, strengthening, expansion and/or rehabilitation. Figure 2 displays distribution of the application areas across the papers analysed and listed in Appendix A Table A1 as follows:

- Design of new systems is an application area with the highest representation (41%). Interestingly, an almost identical percentage (43%) totals applications for existing systems (i.e., strengthening, expansion and rehabilitation).
- An application area with the second highest representation (25%) is strengthening of existing systems.
- Expansion and rehabilitation of existing systems are both represented evenly by 9% of applications each.
- Optimisation of the system operation is represented by 16% of applications.

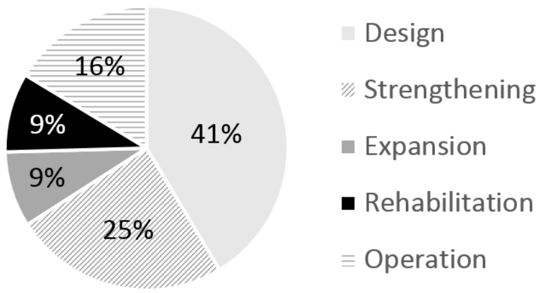

Figure 2. Application areas (of papers from Appendix A Table A1).

It is not surprising that design (and mostly using pipe diameters as decision variables) dominates the literature, which occurs mostly due to historical reasons. Namely, the sizing of pipes was addressed first in the literature, even before WDS simulation was possible. Other design variants, such as strengthening, expansion and rehabilitation, followed on, but use the same or quite similar performance measures and optimisation tools. The introduction of other network elements, such as pumps, tanks and valves, as well as various performance criteria, including water quality and operational considerations, appeared much later in the literature. Lately, more emphasis was put on robustness, reliability and resilience assessment of WDS design and operation, which seems to be the trend for the future.

4.2. Optimisation Model

An optimisation model is mathematically defined by three key components: objectives, constraints and decision variables. Figure 3 shows how many of these components are included in the optimisation models (of papers analysed in Appendix A Table A1), which indicates the degree of complexity of the formulation. Note that not all of the reviewed papers include mathematical formulations of an optimisation model used. Therefore, our assessment is limited to our interpretation of the provided information in the publications, where explicit formulation was partially presented or missing altogether.

- The number of objectives included in optimisation models ranges from one to six. The majority of models (69%) are single-objective, determining the least-cost design. The second largest proportion (27%) represents two-objective optimisation models. Multi-objective models including more than two objectives (i.e., 3–6 objectives) are very sparse as they represent only 4% of all formulations.
- The number of constraints incorporated in optimisation models ranges from zero to ten. Hydraulic constraints (such as conservation of mass of flow, conservation of energy and conservation of mass of constituent) are normally included as implicit constraints and are forced to be satisfied by a WDS modelling tool, such as EPANET, and thus are not included in these statistics. There are 5% of models with no constraints, which are mainly multi-objective optimisation models where the pressure requirement is defined as an objective rather than a constraint. Almost half models (48%) include only one constraint (mostly the minimum pressure requirement). A quarter of models (25%) incorporate two constraints. The proportion of optimisation models with exactly three or more (i.e., 4–10) constraints is 13% and 9%, respectively.
- The number of types of a decision (i.e., control) variable included in optimisation models ranges from one to 13. The majority of optimisation models (60%) uses one type of a decision variable, being a pipe diameter/size or pipe segment length of a constant (known) diameter. The use of more than one type of a decision variable is considerably less frequent and is represented by 16%, 11% and 13%, respectively, for two, three and more (i.e., 4–13) types of a decision variable.

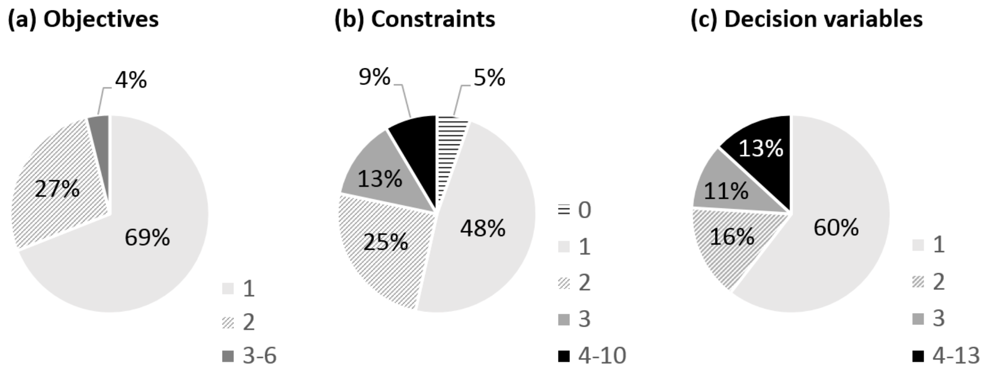

Figure 3. Optimisation models (of papers from Appendix A Table A1) by: (**a**) number of objectives, (**b**) number of constraints, (**c**) number of types of a decision variable, in an optimisation model.

Inspecting Figure 3, the question arises as to how many optimisation models there are, which include only one objective, one constraint and one type of a decision variable? There are, in total, 129 optimisation models formulated and solved in 124 papers listed in Appendix A Table A1. From those optimisation models, 30% (i.e., 39 models) consist of one objective (mostly design costs), one constraint (mostly the minimum pressure at nodes) and one type of a decision variable (mostly pipe diameters).

As indicated, the prevailing use of single-objective optimisation is probably caused by the preference to arrive at a single solution, which can be implemented by decision makers. On the other hand, the preference for one constraint seems surprising as the number of constraints of the problem depends on the complexity of the system and the number of criteria expressed as constraints rather than objectives. Finally, the number and types of decision variables appearing in the literature is a function of historical developments in the field and the increasing trend is expected in the future. Research questions still remain as how to best formulate the optimisation model for a particular case, and what effect the model formulation has on obtained solution(s) [22,23].

4.2.1. General Optimisation Model

A general multi-objective optimisation model for optimal design of a WDS can be formulated as:

$$\text{Minimise/maximise } (f_1(x),\ f_2(x),\ \ldots,\ f_n(x)) \tag{1}$$

subject to:

$$a_i(x) = 0, \quad i \in I = \{1, \ldots, m\}, \quad m \geq 0 \tag{2}$$

$$b_j(x) \leq 0, \quad j \in J = \{1, \ldots, n\}, \quad n \geq 0 \tag{3}$$

$$c_k(x) \leq 0, \quad k \in K = \{1, \ldots, p\}, \quad p \geq 0 \tag{4}$$

where Equation (1) represents objective functions to be minimised (e.g., system capital costs) or maximised (e.g., system reliability), Equations (2)–(4) present three types of a constraint, with x representing decision variables.

Objectives

Objectives of a general optimisation model of WDS design are listed in Table 1. They can be divided into four distinct groups according to their type. The first group represents *economic objectives* such as capital and rehabilitation costs, and expected operation and maintenance costs of the system. The second group are *community objectives*, which report on the level of service provided to WDS customers, and which, if inadequate, could eventuate in water supply related issues for those customers. Those objectives include, for example, a benefit function (using various performance criteria), water quality deficiencies, pressure deficit at demand nodes, hydraulic failure of the system and potential fire damages. The third group presents *performance objectives*, reflecting the operation of a WDS, specifically system robustness, reliability and resilience. These objectives, although ultimately indicating the level of service for WDS customers, have separate classification, due to their primary purpose to report on the performance in relation to a WDS rather than to customers. The fourth group represents *environmental objectives*, namely GHG emissions, consisting of capital emissions due to manufacturing and installation of network components applicable at the WDS construction phase, and operating emissions due to electricity consumption occurring during the WDS life cycle.

Table 1. Objectives of a general optimisation model.

Objective Type	Objectives	Reference (An Example)
Economic	*Capital costs* of the system, including purchase, installation and construction of network components (pipes, pumps, tanks, treatment plants, valves, etc.)	[53,74,121]
	Rehabilitation costs of the system, including pipe/pump replacement, pipe cleaning/lining, pipe break repair	[17,124] (pipes), [77] (pumps)
	Expected operation costs of the system, including pump stations, treatment plants and disinfectant dosage	[53] (pump stations and treatment plants), [27] (disinfectant dosage)
	Expected maintenance costs of the system	[121]
Community	*Benefit/benefit of the solution* (i.e., rehabilitation, expansion and strengthening) using various performance criteria by authors	[131] (welfare index to place greater importance on early improvements), [99] (quantity shortfalls as criteria), [93] (e.g., safety volumes and operational capacities as criteria)
	Water quality (e.g., disinfectant, sedimentation, discolouration) deficiencies or water age at customer demand nodes, water discolouration risk, velocity violations (causing sedimentation/discolouration)	[92,120] (water quality deficiencies), [97] (water age), [144] (water discolouration), [95] (velocity violations)
	Pressure deficit at customer demand nodes (maximum individual or total), or the number of demand nodes with the pressure deficit	[65] (maximum individual deficit), [66,68] (total deficit), [90] (the number of demand nodes)
	Hydraulic failure of the system expressed by the failure index	[97]
	Potential fire damages using either expected conditional fire damages or fire flow deficit	[142] (expected conditional fire damages), [92] (fire flow deficit)
Performance	*System robustness* using either a redundant design approach, integration approach (via objective function or constraints), two-phase optimisation approach, scenario-based approach or RC approach	[140] (redundant design), [89] (integration via objective function), [110,140] (integration via constraints), [141] (two-phase optimisation), [121] (scenario-based), [123] (RC)
	System reliability	[118]
	System resilience	[135]
Environmental	*GHG emissions* or emission costs consisting of capital emissions (due to manufacturing and installation of network components) and operating emissions (due to electricity consumption)	[77] (capital and operating GHG emission costs), [73,75] (capital and operating GHG emissions), [132] (operating GHG emission cost)

Constraints

Constraints of a general optimisation model of WDS design are described in Table 2 and divided into three groups as follows. *Hydraulic constraints* are given by physical laws governing the fluid flow in a pipe network. These constraints are incorporated in an optimisation model either explicitly often in conjunction with deterministic [147] and hybrid optimisation techniques [116,117], or implicitly by a

WDS modelling tool (e.g., EPANET) [26] and/or ANNs [27,87] normally in combination with stochastic optimisation algorithms. *System constraints* arise from limitations and operational requirements of a WDS, and include tank water level bounds, pressure/water quality requirements at demand nodes, etc. The ways to manage these constraints include an integration of EPANET (e.g., tank water levels), the augmented Lagrangian penalty method [17], a penalty function [26], a penalty function with a self-adaptive penalty multiplier [45,88], or a (modified) constraint tournament selection [148–150]. *Constraints on decision variables*, such as pipe diameters being limited to commercially available sizes and others, are handled explicitly by an optimisation algorithm.

Table 2. Constraints of a general optimisation model.

Constraints	Reference (An Example)
Hydraulic constraints given by physical laws of fluid flow in a pipe network: (i) conservation of mass of flow, (ii) conservation of energy, (iii) conservation of mass of constituent	[41]
System constraints given by limitations and operational requirements of a WDS, for example, minimum/maximum pressure at (demand) nodes and flow velocity in pipes, water deficit/surplus at storage tanks at the end of the simulation period, maximum water withdrawals from sources	[54] (limits on nodal pressure, storage tank deficit and water withdrawals from sources), [127] (limits on pipe velocity)
Constraints on decision variables x, for example, limits on pipe diameters, pipe segment lengths (so called split-pipe design), pump station capacities	[92] (limits on pipe diameters), [117] (limits on pipe segments), [121] (limits on pump stations)

Decision Variables

Decision variables of a general optimisation model of WDS design are listed in Table 3. They are grouped according to an element or aspect that drives the optimisation (i.e., pipes, pumps, tanks, valves, nodes, water quality and timing). In general, a pipe diameter/size is often the main (or the only) decision variable used in design optimisation of WDSs. Accordingly, a total of 60% optimisation models (of papers listed in Appendix A Table A1) use only one type of a decision variable (see Figure 3c), which is either a pipe diameter/size or the pipe segment length of a constant (known) diameter. As the complexity of an optimisation model increases, so does the number of types of a decision variable. An example of such an optimisation model could be an expansion and rehabilitation of an existing WDS with pumps, tanks and a treatment plant to meet future demands and water quality requirements.

Table 3. Decision variables of a general optimisation model.

Decision Variables	Reference (An Example)
Pipes: pipe diameters/sizes, pipe duplications, pipe rehabilitation options (pipe replacement, pipe cleaning/lining), pipe break repair, pipe segment lengths (so called split-pipe design), future pipe roughnesses, pipe routes, pipe closures/openings (to adjust a pressure zone boundary)	[75] (diameters), [132] (duplications, replacement, lining and break repair), [117] (segments), [141] (roughnesses), [52] (routes), [100] (routes and closures/openings)
Pumps: pump locations, pump sizes (pump capacities, pump types, pumping power, pump head/height or head-flow), the number of pumps, pump schedules (pumping power or pump head at each time step, the number of pumps in operation during 24 h, binary statuses at time steps, on/off times)	[52,99] (locations), [14] (locations and capacities), [75] (types), [17] (power), [52,122] (head/height), [93] (head-flow), [26] (sizes and the number of pumps), [53,123] (power or head at each time step), [97] (the number of pumps in operation), [29] (binary statuses), [75] (on/off times)
Tanks: tank locations, tank sizes/volumes, minimum operational level, ratio between diameter and height, ratio between emergency volume and total volume, tank heads	[98] (locations, sizes/volumes, minimum operational level, ratios), [78] (heads)
Valves: valve locations, valve settings (headlosses or flows)	[14] (locations), [16] (headlosses via a roughness coefficient), [127] (headlosses and flows)

Table 3. *Cont.*

Decision Variables	Reference (An Example)
Nodes: flowrates from sources, future nodal demands, threshold demands, hydraulic heads at junctions	[127] (flowrates), [135,141] (demands), [147] (heads)
Water quality: disinfectant dosage rates (at the sources, at the treatment plants, in the tanks), treatment removal ratios, treatment plant capacities	[143] (dosage at the sources), [27] (dosage at the treatment plants), [78] (dosage in the tanks), [53] (removal ratios), [121] (capacities)
Timing: year of action (e.g., network expansion, rehabilitation, pipe replacements) execution	[131] (network expansion and rehabilitation), [130] (pipe replacements)

Tables 1–3 provide a generic set of components used for formulating an optimisation problem involving initial design with subsequent operational management of a WDS. Particular circumstances being considered in different case studies may warrant only a portion of those components to be used.

4.3. Solution Methodology

An enormous effort has been dedicated to the application and development of optimisation methods to solve WDS design optimisation problems since the 1970s. Initially, deterministic methods namely LP [14,114,129], NLP [16,110] and mixed-integer NLP (MINLP) [17,115] were used. In the mid 1990s, after the first popular applications of a GA [20,151], there was a swing towards stochastic methods and they dominate the field since (see Figure 4). A great range of those methods has been applied to optimise design of WDSs to date, inclusive of (but not limited to) a GA [42,45,50,85,86,152–154], fmGA [88], non-crossover dither creeping mutation-based GA (CMBGA) [149], adaptive locally constrained GA (ALCO-GA) [155], SA [60], shuffled frog leaping algorithm (SFLA) [103], ACO [104,156], shuffled complex evolution (SCE) [157], harmony search (HS) [105,158,159], particle swarm HS (PSHS) [160], parameter setting free HS (PSF HS) [161], combined cuckoo-HS algorithm (CSHS) [162], particle swarm optimisation (PSO) [106,153,154], improved PSO (IPSO) [163], accelerated momentum PSO (AMPSO) [164], integer discrete PSO (IDPSO) [165], newly developed swarm-based optimisation (DSO) algorithm [150], scatter search (SS) [166], CE [61,62], immune algorithm (IA) [167], heuristic-based algorithm (HBA) [168], memetic algorithm (MA) [107], genetic heritage evolution by stochastic transmission (GHEST) [169], honey bee mating optimisation (HBMO) [170], DE [46,153,154,171], combined PSO and DE method (PSO-DE) [172], self-adaptive DE method (SADE) [173], NSGA-II [70], ES [68], NSES [92], cost gradient-based heuristic method [119], improved mine blast algorithm (IMBA) [174], discrete state transition algorithm (STA) [175], evolutionary algorithm (EA) [109], and convergence-trajectory controlled ACO (ACO_{CTC}) [176]. The vast majority of those studies solely solve a basic single-objective least-cost design problem (i.e., pipe cost minimisation constrained by the nodal pressure requirement) and use a small number of available benchmark networks (e.g., Hanoi network [49], New York City tunnels [81], two-loop network [14]) to test the proposed optimisation method. The usual result obtained was a better or comparable optimal solution reached more efficiently than by algorithms previously used in the literature, without providing an explanation as to why the selected algorithm performed better for a particular test network. It seems, therefore, that research have been trapped, to some extent, in applying new metaheuristic optimisation methods to relatively simple (from an engineering perspective) design problems, without understanding the underlying principles behind algorithm performance. Moreover, study [177] stresses that there has been "little focus on understanding why certain algorithm variants perform better for certain case studies than others".

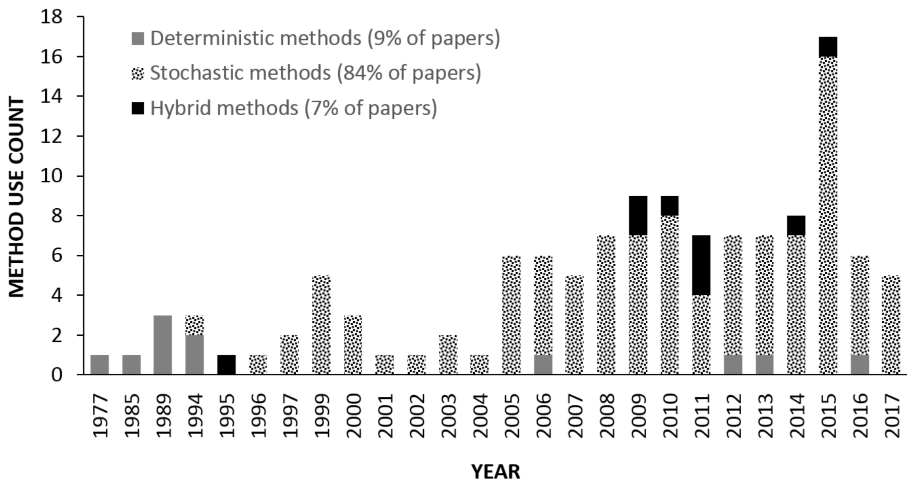

Figure 4. Optimisation methods (of papers from Appendix A Table A1) by year.

Over the past decade, an increase in the use of deterministic and hybrid methods (i.e., a combined deterministic and stochastic method) can be observed from Figure 4. These methods, which are computationally more efficient when comparing to stochastic methods, thus more suitable for large real-world applications, include ILP [51,134], MINLP [147], a combined GA and LP method (GA-LP/GALP) [113,117], combined GA and ILP method (GA-ILP) [178], combined binary LP and DE method (BLP-DE) [179], combined NLP and DE method (NLP-DE) [111], hybrid discrete dynamically dimensioned search (HD-DDS) [180], decomposition-based heuristic [52], optimal power use surface (OPUS) method paired with metaheuristic algorithms [47], and modified central force optimisation algorithm (CFOnet) [181]. However, WDS simulations may still be computationally prohibitive even with more efficient deterministic or hybrid optimisation methods, especially as the fidelity of the model and the number of decision variables increase [22].

The choice of the solution methodology depends on the type of problem being considered, the level of expertise of the analyst and the familiarity with the particular method/tool. Nonetheless, there is often no clear justification provided as to why a particular methodology has been selected over another and/or why an alternative methodology has not been tested. Quite often, this choice is based on the analyst's preference, level of familiarity, and software availability, rather than on a comparison of the tests performed using two or more solution methodologies. This practice makes it difficult to progress towards the development of meaningful guidelines for the application of different optimisation methods [177]. An interesting research question for further studies would be how to characterise and select the best optimisation method for a particular WDS design problem.

However, that being stated, several attempts have been made to compare or evaluate algorithm performance for both single- and multi-objective WDS design problems, but with an absence of a universally adopted method to date. A methodology for comparing the performance of various single-objective algorithms involves assessing the best solution obtained (which is straightforward contrary to multi-objective optimisation), the convergence speed, and the spread and consistency of the solutions using a number of random starting seeds and evaluations [153,154]. A methodology has also been developed to evaluate the performance of a particular algorithm by assessing the effectiveness of its parameters (such as crossover and mutation) applying their different values [182]. In multi-objective optimisation, in general, performance metrics were proposed and are commonly used to compare performance of various algorithms in terms of the quality of the Pareto fronts obtained (see, for example, [183–185]). A comparison of solutions is substantially more complex than in single-objective optimisation as there is no single performance metric both compatible and complete [186]. Possibly for that reason, some WDS design studies have limited their analysis to a visual comparison of solutions only (i.e., two-objective Pareto fronts), which was criticised by [187].

Most recent research, progressively, evaluates the performance and search behaviour of multi-objective algorithms in relation to their parameters and/or WDS features [28] (more such studies are listed in Section 4.3.2).

4.3.1. Computational Efficiency

Numerous advancements have been reported in the literature to improve the computational efficiency of both optimisation algorithms and network simulators. These developments include methods for search space reduction [45,63,88,95,99,120,131,188,189], parallel programming techniques [109], hybridisation of the evolutionary search with machine learning techniques to limit the number of function evaluations [67], surrogate models (metamodels) to replace network simulations [27,43,67,87,143], approximation of the objective function by shortening the EPS [119], and enhanced methods for speedy network simulations for large size WDSs [190].

Various techniques for search space reduction have been proposed, which can be broadly classified as algorithm-based and network-based methods. The algorithm-based techniques include the method for more efficient encoding of decision variables [63,99,131], a self-adaptive boundary search strategy for selection of the penalty factor within the optimisation algorithm to guide the search towards constraint boundaries [88], and the application of an artificial inducement mutation (AIM) to acceleratingly direct the search to the feasible region [95]. The network-based techniques analyse either the network as a whole or individual pipes. The former include a network stratification into upper, middle and lower diameter sets using engineering judgment [188], and the critical path method [45,191]. The latter involve the elimination of certain pipes from the optimisation based on their preliminary capacity assessment [120], application of a pipe index vector (PIV), a measure of the relative importance of pipes regarding their hydraulic performance in the network, which assists in exclusion of impractical and infeasible regions from the search space [189], and introduction of upper/lower bounds on pipe diameters based on the initial analysis [30].

In terms of replacing time consuming network simulations with faster means, three types of a surrogate model have been applied to the design optimisation of WDSs to date. These models include a linear transfer function (LTF) [43], Kriging [67] and ANNs [27,87,143], which are used more frequently than two previous ones. The purpose of a surrogate model is to approximate network simulations (hydraulics and/or water quality), hence reduce the calls of the simulation model during the optimisation. Kriging uses solutions visited during the search to model the search landscape [192]. ANNs can be divided into two groups, offline ANNs, which are trained only once at the beginning of the optimisation, and recently proposed online ANNs, which are "retrained periodically during the optimisation in order to improve their approximation to the appropriate portion of the search space" [27]. ANN metamodels are often used in conjunction with water quality simulations [27,87,143].

All of those methods have shown promise on a limited number of test cases or a specific case study. It would be interesting to conduct a thorough comparison of all of those on a selection of benchmark cases of various sizes and complexity.

4.3.2. Recent Developments

More recently, a number of advancements, such as improving and understanding the algorithm performance and others, have been proposed in the literature indicating potential directions for future research. Some of those developments are a consequence of an appeal of [23,177] "to counteract potential repetition and stagnation in this field" to continually produce too many papers using "an ever increasing number of EA variants" and "theoretical or very simplistic case studies".

Firstly, to improve the algorithm performance regarding the solution quality, an engineered initial population has been suggested [26,30,44,66,108]. Traditionally, a random (or naïve) initial population of solutions (expressed as pipe sizes) is used as a starting point for algorithms. An engineered initial population, in contrast, is created by taking into account the rules and hydraulics principles of water flow in a pipe network, or by performing pre-optimisation runs under various parameter scenarios (e.g., [30]). Another way to achieve better algorithm convergence, particularly for design problems incorporating water quality, is to run the algorithm with hydraulic analysis only for several first generations, and subsequently add water quality analysis [120]. Furthermore, a postoptimisation technique can be used to refine the solutions that are found by an optimisation algorithm to get closer to the global optimum [193]. Secondly, a range of strategies have been introduced to eliminate the tedious and time demanding process of calibrating algorithm parameters (i.e., selecting the best performing combination of parameter values) for a particular test problem. These strategies involve the use of a statistical analysis [158], evolved heuristics (i.e., hyper-heuristic approach) [68,144,194], and convergence trajectories [176]. Thirdly, several studies focused on analysing algorithm performance [195] and search behaviour [28,48,196] in relation to the WDS design problem features [29]. Lastly, methodological improvements using existing methods have been proposed rather than applying/developing new algorithms, with the aim to improve computational efficiency. Those improvements represent multiple-phase optimisation concepts [30], which can be combined with graph decomposition [46,69] or clustering [90] techniques.

4.4. Test Network

An enormous diversity exists among test networks used in optimisation of WDS design. These networks vary in size, complexity, and the types of network components that they contain (i.e., nodes, pipes, pumps, tanks, reservoirs/sources and/or valves). The simplest networks are small gravity WDSs with one source, a few nodes and pipes (see, for example, [14,60]), or simplified pumped WDSs including only one source, one pump, one pipe and one tank (see, for example, [71]). An example of a large network represents EXNET [82], which is a realistic WDS comprising two sources, control valves and almost 2500 pipes. Figure 5 categorises test networks that are used (in the papers listed in Appendix A Table A1) by network size. In order to be consistent with the previous review [22], network size is expressed by the number of nodes within a network. Networks, for which the number of nodes cannot be identified from the reviewed paper or the references provided, are excluded from the analysis. Figure 5 reveals that nearly a half of the networks (49%) is limited in size to 20 nodes and the majority of the test networks (84%) contains up to 100 nodes. This finding is analogous to operational optimisation of WDSs, where networks with up to 100 nodes represent 80% of applications [22].

Figure 5 illustrates that in the large body of literature, various WDS design formulations and optimisation methods have usually been tested using small, computationally cheap networks. This prevalent usage of small networks is in contrast to the requirement to optimise design of real-world systems that contain hundreds of thousand elements (including pumping stations, tanks and valves) causing a single EPS simulation to take minutes or even hours to execute even on powerful desktop computers. Consequently, large networks are not often considered by optimal design studies. This situation can be remedied by using latest developments in methods capable of generating realistic WDS networks by [55–57], who have each developed their own automatic network generation software.

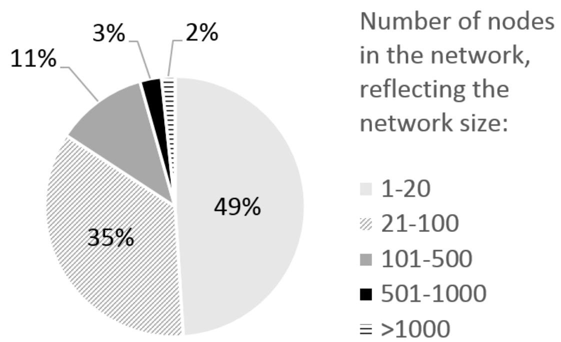

Figure 5. Test networks (of papers from Appendix A Table A1) by network size.

Real-world WDS design optimisation problems normally involve large size, complex-topology networks, comprising a number of elements of various types. Such a problem is often solved by combining a sophisticated simulation model (to potentially analyse both hydraulics and water quality) with a non-trivial optimisation method. The approach ought to satisfy the requirements of a water utility and other stakeholders for objectives, constraints, decision variables, as well as model assumptions. Although studies exist that report on successful solutions to such problems [100,127,197–199], they are limited possibly due to the complexity associated with mathematically formulating objectives and constraints and/or finding the best solution. Study [200] even speculates that the real-world considerations need to be explicitly quantified, "if it is possible to do so at all", otherwise the water industry will apply engineering judgment instead of any optimisation method to design WDSs.

Similar to network size, the frequency of use of test networks varies considerably, as some networks have been used only once, while others have been used repeatedly and by multiple authors. In particular, the prevalence of some networks attributes to their use as benchmark problems to test optimisation algorithms. These benchmark networks, all of which have been used (in the papers listed in Appendix A Table A1) 10 or more times, are listed in Table 4 in order of their usage count. They are, except for the Anytown network, gravity-fed WDSs with the common objective to determine the most economical pipe design. The popularity of those benchmark networks contributed to high percentages of the first two categories in Figure 5, because the majority of them are limited in size to 20 and 100 nodes, respectively.

Table 4. Frequently used test networks.

Test Network Name	No. of Nodes	Network Description	Optimisation Problem	Network Modified Versions	Network Usage Count *
Hanoi network ++ [49]	32	Network organised in three loops supplied by gravity from a single source	New system design (pipes)	Double Hanoi network, triple Hanoi network (both [113])	55
New York City tunnels ++ [81]	20	Tunnel system supplied by gravity from a single source, constituting the primary WDS of the New York city	Existing system strengthening (i.e., pipe paralleling) to meet projected demands	Double New York City tunnels [201]	42
Two-loop network ++ [14]	7	Small network with two loops supplied by gravity from a single source	New system design (pipes)	Adapted to system strengthening and expansion over a planning horizon [118]	40
Balerma irrigation network ++ [50]	447	Large looped network supplied by gravity from four sources, adapted from the existing irrigation network in Balerma, Spain	New system design (pipes)	N/A	20
Anytown network [84]	19	Hypothetical looped system supplied by three parallel pumps from a single source	Existing system strengthening, expansion and rehabilitation (pipes, pumps, tanks) to meet projected demands	** With additional source and tank [53], with additional tank [119] proposed by [83]	15

5. Future Research

Future research challenges for the optimisation of WDS design are illustrated in Figure 6 and divided into the following four groups: (i) model inputs, (ii) algorithm and solution methodology, (iii) search space and computational efficiency, and (iv) solution postprocessing. As far as model inputs are concerned, there is a requirement to explore how to best represent various types of uncertainties, i.e., stochastic vs. deep uncertainty or aleatoric vs. epistemic uncertainty, in the optimisation process. Additional future uncertainties, for example, climate change, population movements and economic development, might affect planning for optimal WDSs, and make flexible design one of the promising research areas over the next few decades. Another research challenge in regards to model inputs is to compare various approaches to pump decision variables, including VSPs and their coding, in order to determine their advantages, disadvantages and suitability for a particular case. Furthermore and overall, a research question remains how to best formulate the optimisation model for a particular case [22,23].

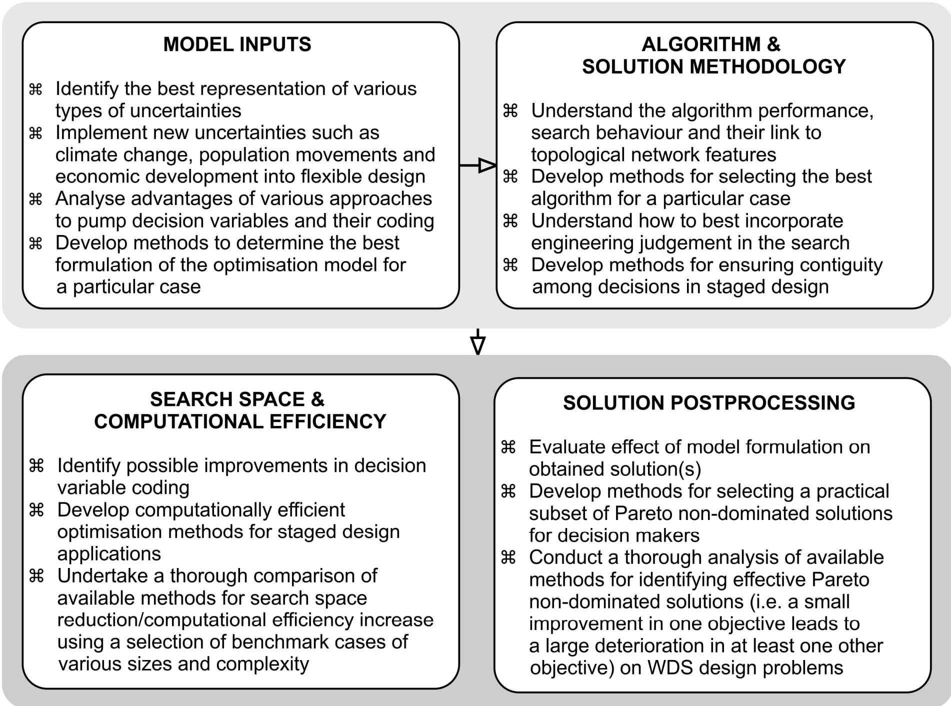

Figure 6. Future research challenges.

Concerning algorithm and solution methodology, a vast research area represents a progression towards better understanding of algorithm performance and its search behaviour. These aspects need to be further linked to the WDS design problem features including system topology (e.g., existence of pumps/tanks, loops) and initial population used. A related challenge is to eliminate a time consuming process of calibrating algorithm parameters to achieve a satisfactory performance, hence there is a question how to select the best performing combination of parameter values. Moreover, it is important to develop understanding related to the suitability of various optimisation methods for particular design problems and the incorporation of engineering judgement in the search. In relation to staged design, methods for ensuring contiguity among decisions, i.e., that the decisions selected in the previous stages are retained in the subsequent ones, are required.

Recently, there has been an observed increased interest in aspects of the search space and computational efficiency. Indeed, the reduction of the search space and an increase in the computational efficiency are significant particularly for real-world WDS optimisation problems as well as dynamic (i.e., staged and flexible) design, so they are expected to remain important and promising research areas into the future. The research community would benefit from a thorough comparison of existing methods for search space reduction and computational efficiency increase, which could use a selection of benchmark cases of various sizes and complexity. In addition to currently available methods for search space reduction, it might be possible to further improve decision variable coding.

Regarding solution postprocessing, an open question is how sensitive the obtained solution(s) is to the optimisation model used [22,23]. When multi-objective optimisation approach is used, a remaining challenge is to select a practical and representative subset of the non-dominated solutions, which could be useful for the decision makers. Accordingly, there is a need for methods to identify a handful of effective solutions, such as those where a small improvement in one objective leads to a large deterioration in at least one other objective. The existing approaches, including maximum convex bulge/distance from hyperplane, hypervolume contribution, and local curvature [80] are all promising and require a thorough analysis on WDS design problems.

6. Summary and Conclusion

A systematic literature review of optimisation of water distribution system (WDS) design since the end of the 1980s to nowadays has been presented. The publications included in this review are relevant to the design of new WDSs, strengthening, expansion and rehabilitation of existing WDSs, and also consider design timing, parameter uncertainty, water quality and operational aspects. The value of this review paper is that it brings together a large number of publications for design optimisation of WDSs, just under three hundred in total, which have been published over the past three decades. Therefore, it may enable researchers to identify one's articles of interest in a timely manner. The review analyses the current status, identifies trends and limits in the field, describes a general optimisation model, suggests future research directions. Exclusively, this review paper also contains comprehensive information for over one hundred and twenty publications in a tabular form, including optimisation model formulations (i.e., objectives, constraints, decision variables), solution methodologies used and other important details.

This review has identified the following main limits in the field and future research directions. It was demonstrated that there is still no agreement among researchers and practitioners on how to best formulate a WDS design optimisation model, how to include all relevant objectives and constraints, and whether and how to take into account various sources of uncertainty, while still allowing for an efficient search for the best solution to be achieved. Although a plethora of generic and problem-specific optimisation methods have been developed and applied over the years, there is no consensus on what optimisation method is best for a particular design problem, whether a single or multiple-phase optimisation concept is to be used, and how engineering judgement can best be incorporated in the search. Therefore, a concerted effort by the research community is required to develop methods for objective comparison and validation of various optimisation algorithms and concepts on large, real-world problems. In addition, an analysis of available methods for reducing the search space, increasing computational efficiency, as well as selecting effective Pareto non-dominated solutions representing a practical subset for decision makers, is needed using WDS design problems of various sizes and complexity. In spite of the overwhelming amount of literature that has been published over the past three decades, design optimisation of WDSs faces considerable research challenges in the years to come.

7. List of Terms

- Deterministic dynamic design = staged design over a long planning horizon divided into several construction phases, without considering future uncertainties.
- Deterministic static design = traditional design with a single construction phase for an entire expected life cycle of the system, without considering future uncertainties.
- Dynamic design = staged (i.e., real-life) design capturing the system modifications/growth over a long planning horizon divided into several construction phases (adopted from [118]).
- Hydraulic constraints = constraints arising from physical laws of fluid flow in a pipe network, such as conservation of mass of flow, conservation of energy, conservation of mass of constituent.
- Optimisation approach = single-objective approach or multi-objective approach.
- Optimisation method = method, either deterministic or stochastic, used to solve an optimisation problem.

- Optimisation model = mathematical formulation of an optimisation problem inclusive of objective functions, constraints and decision variables.
- Probabilistic dynamic design = flexible design over a long planning horizon divided into several construction phases, with considering future uncertainties.
- Probabilistic static design = traditional design with a single construction phase for an entire expected life cycle of the system, with considering future uncertainties.
- Simulation model = mathematical model or software used to solve hydraulics and water quality network equations.
- Single pipe design = design which uses pipe sizes/diameters as decision variables (either discrete or continuous).
- Solution = result of optimisation, either from feasible or infeasible domain, so we refer to a 'feasible solution' or 'infeasible solution', respectively. In mathematical terms though an 'infeasible solution' is not classified as a solution.
- Split-pipe design = design which uses pipe segment lengths of a constant (known) diameter as decision variables.
- Static design = traditional (i.e., theoretical) design with a single construction phase for an entire expected life cycle of the system (adopted from [118]).
- System constraints = constraints arising from the limitations of a WDS or its operational requirements, such as water level limits at storage tanks, limits for nodal pressures or constituent concentrations, tank volume deficit etc.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ACO	ant colony optimisation
ACO_{CTC}	convergence-trajectory controlled ant colony optimisation
ACS	ant colony system
AEF	average emissions factor
AIM	artificial inducement mutation
ALCO-GA	adaptive locally constrained genetic algorithm
AMPSO	accelerated momentum particle swarm optimisation
ANN	artificial neural network
AS	ant system
AS_{elite}	elitist ant system
AS_{rank}	elitist rank ant system
BB	branch and bound
BB-BC	big bang-big crunch
BLIP	binary linear integer programming
BLP-DE	combined binary linear programming and differential evolution
BWN-II	battle of the water networks II (optimisation problem)
CA	cellular automaton
CAMOGA	cellular automaton and genetic approach to multi-objective optimisation
CANDA	cellular automaton for network design algorithm
CC	chance constraints
CDGA	crossover dither creeping mutation genetic algorithm
CE	cross entropy
CFO	central force optimisation
CGA	crossover-based genetic algorithm with creeping mutation
CMBGA	non-crossover dither creeping mutation-based genetic algorithm
CR	crossover probability (parameter)
CS	cuckoo search

CSHS	combined cuckoo-harmony search
CTM	cohesive transport model
D	design
dDE	dither differential evolution
DDSM	demand-driven simulation method
DE	differential evolution
DMA	district metering area
DPM	discoloration propensity model
DSO	newly developed swarm-based optimisation algorithm
EA	evolutionary algorithm
EA-WDND	evolutionary algorithm for solving water distribution network design
EEA	embodied energy analysis
EEF	estimated (24-h) emissions factor (curve)
EF	emissions factor
EPANETpdd	pressure-driven demand extension of EPANET
EPS	extended period simulation
ES	evolution strategy
F	mutation weighting factor (parameter)
FCV	flow control valve
fmGA	fast messy genetic algorithm
FSP	fixed speed pump
GA	genetic algorithm
GA-ILP	combined genetic algorithm and integer linear programming
GA-LP/GALP	combined genetic algorithm and linear programming
GANEO	genetic algorithm network optimisation (program)
GENOME	genetic algorithm pipe network optimisation model
GHEST	genetic heritage evolution by stochastic transmission
GHG	greenhouse gas (emissions)
GOF	gradient of the objective function
GP	genetic programming
GRG2	generalised reduced gradient (solver)
GUI	graphical user interface
HBA	heuristic-based algorithm
HBMO	honey bee mating optimisation
HD-DDS	hybrid discrete dynamically dimensioned search
HDSM	head-driven simulation method
HMCR	harmony memory considering rate (parameter)
HMS	harmony memory size (parameter)
HS	harmony search
IA	immune algorithm
IDPSO	integer discrete particle swarm optimisation
ILP	integer linear programming
IMBA	improved mine blast algorithm
IPSO	improved particle swarm optimisation
KLSM	Kang and Lansey's sampling method [26]
LCA	life cycle analysis
LHS	Latin hypercube sampling
LINDO	linear interactive discrete optimiser
LM	Lagrange's method
LP	linear programming
LTF	linear transfer function
MA	memetic algorithm
MBA	mine blast algorithm

MBLP	mixed binary linear problem
MCHH	Markov-chain hyper-heuristic
MdDE	modified dither differential evolution
MENOME	metaheuristic pipe network optimisation model
mIA	modified immune algorithm
MILP	mixed integer linear programming
MINLP	mixed integer nonlinear programming
MMAS	max-min ant system
MO	multi-objective
MODE	multi-objective differential evolution
MOEA	multi-objective evolutionary algorithm
MOGA	multi-objective genetic algorithm
MSATS	mixed simulated annealing and tabu search
NBGA	non-crossover genetic algorithm with traditional bitwise mutation
NFF	needed fire flow
NLP	nonlinear programming
NLP-DE	combined nonlinear programming and differential evolution
NSES	non-dominated sorting evolution strategy
NSGA-II	non-dominated sorting genetic algorithm II
OP	operation
OPTIMOGA	optimised multi-objective genetic algorithm
OPUS	optimal power use surface
PAR	pitch adjustment rate (parameter)
PESA-II	Pareto envelope-based selection algorithm II
PHSM	prescreened heuristic sampling method
PIV	pipe index vector
PRV	pressure reducing valve
PSF HS	parameter setting free harmony search
PSHS	particle swarm harmony search
PSO	particle swarm optimisation
PSO-DE	combined particle swarm optimisation and differential evolution
PVA	present value analysis
RC	robust counterpart (approach)
ROs	real options (approach)
RS	random sampling
RST	random search technique
SA	simulated annealing
SADE	self-adaptive differential evolution
SAMODE	self-adaptive multi-objective differential evolution
SCA	shuffled complex algorithm
SCE	shuffled complex evolution
SDE	standard differential evolution
SE	search enforcement
SFLA	shuffled frog leaping algorithm
SGA	crossover-based genetic algorithm with bitwise mutation
SMGA	structured messy genetic algorithm
SMODE	standard multi-objective differential evolution (i.e., optimising the whole network directly without decomposition into subnetworks)
SMORO	scenario-based multi-objective robust optimisation
SO	single-objective
SPEA2	strength Pareto evolutionary algorithm 2

SS	scatter search
SSSA	scatter search using simulated annealing as a local searcher
STA	state transition algorithm
TC	time cycle
TRS	tank reserve size
TS	tabu search
VSP	variable speed pump
WCEN	water distribution cost-emission nexus
WDS	water distribution system
WDSA	water distribution systems analysis (conference)
WPP	water purification plant
WSMGA	water system multi-objective genetic algorithm
WTP	water treatment plant

Appendix A

Table A1. Papers reviewed in a chronological order.

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
1. Alperovits and Shamir (1977) [14] SO Optimal water distribution system (WDS) design and operation with split pipes considering multiple loading conditions using linear programming (LP) with a two-phase procedure.	Objective (1): Minimise (a) the overall capital cost of the network including pipes, pumps, reservoirs and valves, (b) present value of operating costs (pumps, penalties on operating the dummy valves). Constraints: (1) Min/max pressure limits, (2) sum of lengths of pipe segments within an arc equals to the length of this arc, (3) non-negativity requirement for the length of pipe segments. Decision variables: (1) Flows in pipes as primary variables, (2) length of pipe segments of constant pipe diameter (so called split-pipe decision variables), (3) dummy valve variables to represent multiple loadings (demands), (4) pump locations and capacities, (5) valve locations, (6) reservoir elevations, (7) pump operation statuses, (8) valve settings.	Water quality: N/A. Network analysis: Initial flow distribution is to be specified, flows are then redistributed using a gradient method within an optimisation process. Optimisation method: LP gradient method.	• A looped network is used. • A nonlinear problem is replaced by a linear problem. Hierarchical decomposition is iteratively applied as follows. In the first phase, LP solves the problem for the given flow distribution. In in the second phase, flows in the network are updated and so on. • The method considers multiple loading conditions (i.e., peak and low demands) simultaneously, and is applicable for real complex systems. • The method gives only a local optimum. • Results: The optimal solutions represent a decrease in the total cost of 3-9% for the test networks, comparing to the costs for the initial flow distributions. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes), (2) two-loop network with a pump and balancing reservoir (incl. 8 nodes), (3) real network with 65 pipes and 2 pumps (incl. 52 nodes).
2. Schwarz et al. (1985) [129] SO Optimal development of a regional multiquality water resources system over a planning horizon (e.g., several years) using LP.	Objective (1): Minimise the costs of (a) water supply (water), (b) temporary curtailment of water supply, (c) network expansion, (d) conveying water, (e) excess salination. Major constraints: (1) Water quantity bounds, (2) water quality bounds, (3) regional water balance (quantity), (4) capacity expansion of the network, (5) annual source water balance (quantity), (6) annual source mass balance (salinity), (7) node mass balance (salinity). Decision variables: (1) Target water supply (m^3/year), (2) temporary curtailment of water supply (m^3/year), (3) capacity expansion (m^3/day), (4) conveyance of water (m^3/day), (5) amount of water used from storage (m^3/day), (6) salinity (mg/L).	Water quality: Salinity. Network analysis: TEKUMA model [202,203]. Optimisation method: TEKUMA model [202,203] using LP.	• Seasonal variations and probabilities of climatic states are included. • Constituent (i.e., salinity) mass balance equations make the model nonlinear. These nonlinear equations are incorporated into the LP model by using a successive linear approximation iterative scheme. • The TEKUMA model was developed to determine "the plan of allocation, capacity expansion, production, transportation and operation that maximises the net benefit - the sum of all water-related values minus the sum of all investment and operating costs and losses incurred by insufficient supply". • Results: Some of the typical quality management processes are demonstrated, such as that the source salinity increases steadily as a result of saline return flows, desalination is economically justified after the third period, etc. • Test networks: (1) Simplified system with one source and one customer (incl. 3 nodes), (2) real-world regional water supply system in Southern Arava, Israel, consisting of 59 consumer groups in 9 regions, 31 water sources, 77 links, considering 3 planning horizons, 3 climatic zones and 3 seasons.

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
3. Kessler and Shamir (1989) [114] SO Optimal WDS design with split pipes using LP with a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Pressure limitations at selected nodes, (2) sum of lengths of pipe segments within an arc equals to the length of this arc. Decision variables: (1) Lengths of pipe segments of constant (all available) pipe diameters (so called split-pipe decision variables), (2) flows in pipes.	Water quality: N/A. Network analysis: Flow in pipes is calculated using projected gradient method within an optimisation process. Optimisation method: LP gradient method.	• A looped network is used, assuming that flow distribution is known. In the first phase, the pipeline cost for a known flow distribution is minimised using LP. In the second phase, flows are redistributed based on the gradient of the objective function (GOF). These steps repeat iteratively converging to a local optimum. • In contrast to [204], it is proved that the mathematical expression of the GOF is independent of the initial choice of the sets of loops and paths, which are used for formulation of the head constraints (conservation of energy). • Results: The optimal solution obtained is comparable to the best known solution [205] with the flows distributed more evenly. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14].
4. Lansey and Mays (1989) [16] SO Optimal WDS design, rehabilitation and operation considering multiple loading conditions using nonlinear programming (NLP) with a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network including pipes, pumps and tanks, (b) penalty cost for violating nodal pressure heads. Constraints: (1) Lower and upper pressure bounds at nodes, (2) design constraints (i.e., storage requirements), (3) general constraints. Decision variables: (1) Pipe diameters (continuous), (2) pump sizes (horsepower or head-flow), (3) valve settings, (4) tank volumes.	Water quality: N/A. Network analysis: KYPIPE [12]. Optimisation method: NLP solver generalised reduced gradient (GRG2) [206].	• The solution algorithm consists of an inner and outer loop, where the inner loop links KYPIPE with GRG2 and the outer loop updates penalty parameters. The augmented Lagrangian penalty method is used to incorporate nodal pressure head constraints in the objective function. • The final solution is modified, so that a pipe within a link is split into two pipes of upper- and lower-sized commercially available (discrete) diameters closest to the obtained optimal (continuous) diameter. • Multiple demand loads are analysed (i.e., combination of instantaneous peak, daily peak and fire demands at the selected nodes). • Results: The method determines optimal sizes/settings of all network components with the limitation of continues (rather than discrete) values for pipes and pumps. • Test networks: (1) Anytown network [84] with modifications (incl. 16 nodes), (2) network example 5A (incl. 13 nodes) from KYPIPE [12].
5. Lansey et al. (1989) [110] SO Optimal WDS design including uncertainties in demands, minimum pressure requirements and pipe roughnesses using NLP.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Conservation of mass of flow and energy, (2) min pressure at the nodes, (3) pipe diameter bigger than or equal to zero. Decision variables: (1) Pipe diameters (continuous), (2) pressure head at nodes.	Water quality: N/A. Network analysis: Network hydraulics is included as a constraint to the optimisation model. Optimisation method: NLP solver GRG2 [206].	• The model includes uncertainties in (i) demands, (ii) minimum pressure head requirements and (iii) pipe roughnesses, they are included as chance constraints (CC). • Constraints (1) and (2), initially expressed as probabilities, are transformed into a deterministic form using the concept of the cumulative probability distribution, where model uncertainties are assumed to be normal random variables. The final chance-constrained optimisation model represents a NLP problem. • Results: A more reliable WDS design is obtained when including uncertainties. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes), (2) more realistic size network with 33 pipes (incl. 16 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
6. Eiger et al. (1994) [115] SO Optimal WDS design with split pipes using mixed-integer NLP (MINLP) with a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Pressure limitations at selected nodes, (2) sum of lengths of pipe segments within an arc equals to the length of this arc. Decision variables: (1) Lengths of pipe segments of constant (all available) pipe diameters (so called split-pipe decision variables), (2) flows in pipes. Note: Same formulation as in Kessler and Shamir (1989).	Water quality: N/A. Network analysis: Flow in pipes is calculated using projected gradient method within an optimisation process. Optimisation method: Branch and bound (BB) method.	• The optimisation model is decomposed into two models, inner (linear) and outer (nonsmooth and nonconvex) problems, which are solved by the LP solver CPLEX [207] and bundle trust region method, respectively. The dimension of the outer problem is significantly reduced by an affine transformation. This process is further referred to as primal. • Using the duality theory, a dual problem paired with the original problem is formulated and solved by CPLEX to estimate a global lower bound of the solution. This process is further referred to as dual. • Both of these processes, primal and dual, are combined in a BB type algorithm. • Results: The proposed method produces better (and feasible) solutions than previously used methods [14,49]. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) complex two-loop network (incl. 8 nodes) [14], (4) real network (incl. 52 nodes) [14].
7. Kim and Mays (1994) [17] SO Optimal WDS rehabilitation and operation over a planning horizon (e.g., 20 years) using MINLP with a two-phase procedure.	Objective (1): Minimise the sum of the present value of the (a) pipe replacement cost, (b) pipe rehabilitation cost, (c) expected pipe repair (i.e., break repair) cost, (d) pump energy cost. Constraints: (1) Demand supplied to each node should be greater or equal to the required demand, (2) min/max pressures at demand nodes, (3) constraints on binary decision variables representing pipe replacement and rehabilitation options, (4) constraints on continuous decision variables representing the diameter of the replaced pipe and pump horsepower. Decision variables: (1) Pipe replacement option (binary), (2) pipe rehabilitation option (binary), (3) pipe diameters of the replaced pipes (continuous), (4) pump horsepower (continuous).	Water quality: N/A. Network analysis: KYPIPE [12]. Optimisation method: BB method combined with GRG2 [206].	• The optimisation problem is formulated as a MINLP problem. This problem is divided into the following two phases within an optimisation procedure. • The NLP subproblem, which involves continuous decision variables, such as pipe diameters and pumping powers, is solved by GRG2 linked with KYPIPE. Nodal pressure head constraints are implemented using the augmented Lagrangian penalty method. • The master problem, which involves binary decision variables, such as pipe replacement and rehabilitation options, is solved by a BB implicit enumeration procedure. • The global optimum cannot be guaranteed. • Results: The method is able to find optimal solutions, which is supported by the comparison with the minimum cost obtained from the 1000 random system configurations. • Test networks: (1) Simple network with 4 pipes and 1 pump (incl. 3 nodes), (2) network with 17 pipes and 1 pump (incl. 12 nodes), (3) network with 43 pipes and 1 pump (incl. 27 nodes).
8. Murphy et al. (1994) [96] SO Optimal WDS strengthening, expansion, rehabilitation and operation considering multiple loading conditions using genetic algorithm (GA).	Objective (1): Minimise the design cost of the network including (a) pipes, (b) pumps, (c) tanks, and (d) the pump energy costs. Constraints: (1) Limits for nodal pressure heads, (2) limits for tank water levels. Decision variables: Options for (1) new pipes, (2) duplicated pipes, (3) cleaned/lined pipes, (4) pumps, (5) tanks.	Water quality: N/A. Network analysis: Unspecified steady state hydraulic solver. Optimisation method: GA.	• Pipe costs are calculated for the lengths of new pipes (i.e., network expansion), pipes laid in parallel to the existing pipes as duplications (i.e., network strengthening), and existing pipes cleaned and lined (i.e., network rehabilitation). • Four demand loadings are considered, these include instantaneous peak flow and three fire flow conditions at various nodes around the network. • Results: The obtained solution compares favourably with the previous designs presented in [84]. • Test networks: (1) Anytown network (incl. 19 nodes) [84].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
9. Loganathan et al. (1995) [116] SO Optimal WDS design and strengthening with split pipes using a combination of LP, mutlistart local search and simulated annealing (SA) in a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes, (2) sum of pipe segment lengths must be equal to the link length, (3) nonnegativity of segment lengths. Decision variables: (1) Lengths of pipe segments of known diameters (so called split-pipe decision variables).	Water quality: N/A. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Combined LP, mutlistart local search and SA.	• The problem is solved by using an inner-outer optimisation procedure as follows. • Inner: for a fixed set of flows, a LP problem is solved to obtain (least-cost) pipe diameters and heads. • Outer: the flows are altered (optimised) using two global optimisation techniques, multistart local search and SA. Initially, a set of flows corresponding to a near optimal spanning tree of the network is found. The flows in the looped network are then taken as the perturbed tree link flows. • Results: The proposed optimisation method yields better least-cost designs than those previously reported in the literature. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) New York City tunnels (incl. 20 nodes) [81].
10. Dandy et al. (1996) [85] SO Optimal WDS strengthening using GA.	Objective (1): Minimise (a) the sum of material and construction costs of pipes, (b) the penalty cost for violating the pressure constraints. Constraints: (1) Min/max pressure limits at certain network nodes, (2) min diameters for certain pipes in the network. Decision variables: (1) Pipe diameters (discrete diameters are coded using binary substrings).	Water quality: N/A. Network analysis: KYPIPE [12] and another hydraulic solver developed for the paper. Optimisation method: GA.	• Improved GA is used incorporating: (i) variable power scaling of the fitness function using a new variable exponent, which is initially kept low to preserve population diversity and allow global exploration, and gradually increases to emphasise fitter strings; (ii) adjacency or creeping mutation operator, which allows local exploration; (iii) Gray codes instead of binary codes representing decision variables to ensure that nearby designs are coded similarly. • Results: A solution found by the improved GA for the New York tunnels problem is the lowest-cost feasible discrete solution yet published. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81].
11. Halhal et al. (1997) [63] MO Optimal WDS rehabilitation and strengthening over a planning horizon (e.g., several years) using structured messy GA (SMGA).	Objective (1): Maximise the weighted sum of the following benefits of the network: (a) hydraulic performance, (b) physical integrity of the pipes, (c) system flexibility, (d) water quality. Objective (2): Minimise the cost (supply and installation) of the network including (a) new parallel pipes (i.e., duplication), (b) cleaning and lining existing pipes, (c) replacing existing pipes. Constraints: (1) Costs cannot exceed the available budget. Decision variables: String comprising 2 substrings: (1) substring consisting of pipe numbers, (2) substring consisting of decisions associated with those pipes (8 possible decisions). Note: One MO model including both objectives.	Water quality: A general water quality consideration. Network analysis: EPANET. Optimisation method: SMGA.	• Hydraulic performance benefit is quantified as the difference between the pressure deficiencies in the initial network and in the solution found. Physical integrity benefit is quantified using break repair costs for the renewed pipes. System flexibility and water quality benefits are quantified using the total diameter for the parallel pipes and the total length of renewed or relined pipes. Regarding water quality, old pipes usually create sites for the development of microorganisms and/or discoloured water. • A SMGA is introduced. It starts by evaluating all possible single variable decisions, the best of which are kept for the initial population. As the algorithm progresses, the short strings are concatenated to form longer strings. This enables to start with cheaper solutions which stay under budget from the very beginning. The SMGA encodes only those decision variables which are active thereby reducing the search space. • Results: SMGA displays outstandingly superior performance over the standard GA for the real network. • Test networks: (1) Small looped network with 15 pipes (incl. 9 nodes), (2) real network with 167 pipes and 1 reservoir for a town of 50000 inhabitants in Morocco (incl. 115 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
12. Savic and Walters (1997) [42] SO Optimal WDS design and strengthening using GA.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Network solver based on the EPANET. Optimisation method: GANET [208] using GA.	• A program GANET for least-cost pipe network design is developed, implementing a modified GA. The modifications include, for example, the use of Gray codes instead of binary codes, allowing some infeasible solutions to join the population and help guide the search. • Discrete diameters solutions (obtained by GANET) are compared to split-pipes and continuous diameters solutions, previously published in the literature by [14,114,115,204]. • Results: GANET produced good designs without unnecessary restrictions imposed by split-pipe or linearising assumptions. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81].
13. Cunha and Sousa (1999) [102] SO Optimal WDS design using SA.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes, (2) min pipe diameter. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Newton method to solve hydraulic equations to obtain flows and heads. Optimisation method: SA.	• The optimisation problem is solved as follows: initial set of pipe diameters is selected, hydraulic equations are solved using a Newton method, constraints are checked, SA is performed and the process is repeated until the optimal solution is found. • Discrete diameters solutions (obtained by SA) are compared to split-pipes, continuous diameters, as well as discrete diameter solutions, previously published in the literature by [14,42,49,114,115,204,209–211]. • Results: SA can provide high quality solutions for network design problems. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49].
14. Gupta et al. (1999) [188] SO Optimal WDS strengthening and expansion using GA with search space reduction.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating minimum residual head. Constraints: (1) Min residual head, (2) min desirable velocity in a pipe. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: ANALIS [212]. Optimisation method: GA.	• In GA, the solution is represented by a chromosome to avoid the conversion of binary coding to discrete pipe sizes. • The test networks are stratified into upper, middle and lower diameter sets using engineering judgment, which helps reduce the search space and facilitate faster convergence to the optimum. • Results: GA provides a better solution in general while compared with the NLP technique. Additionally, the GA convergence considerably improved by providing initial information on network stratification. • Test networks: (1) Network with 38 pipes (incl. 23 nodes), (2) same as network (1) with a significantly different demand pattern, (3) network with 52 pipes (incl. 31 nodes), (4) same as network (3) with a different demand pattern, (5) network with 28 pipes (incl. 18 nodes), (6) network with 13 pipes (incl. 11 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
15. Halhal et al. (1999) [131] MO Optimal WDS rehabilitation and strengthening over a planning horizon (i.e., 10 years) using SMGA.	Objective (1): Maximise the present value of the benefit of the network rehabilitation over the planning period (incorporating the welfare index), using the following performance criteria: (a) carrying capacity, (b) physical integrity of the pipes, (c) system flexibility, (d) water quality. Objective (2): Minimise (a) the present value of the rehabilitation costs over the planning period. Constraints: (1) Rehabilitation costs less than or equal to the budget. Decision variables: String comprising 3 substrings (1) location substring: pipe numbers of pipes scheduled for rehabilitation (integer), (2) decision substring: rehabilitation option (integer), (3) timing substring: year of rehabilitation execution (integer). Note: One MO model including both objectives.	Water quality: A general water quality consideration. Network analysis: Unspecified solver (steady state). Optimisation method: SMGA.	• Carrying capacity is represented by the hydraulic performance, which is calculated as the sum of nodal pressure excesses and shortfalls weighted by the demand flows. Physical integrity is included as a function of the breakage repair costs, with new pipes considered break-free. System flexibility is determined as a function of the number of new parallel pipes. Water quality is included as a function of the length of renewed and/or lined old pipes having Hazen-Williams coefficient below a specified limit. Old corroded pipes are considered to cause the development of microorganism and discoloured water. • SMGA has flexible coding and variable string length. Its difference from a conventional GA is that it uses, besides common GA operators, a process of concatenation. Basically, it starts with a population of one-element strings corresponding to a single decision variable (e.g., rehabilitation option for one pipe only) and gradually increases the length of the strings as populations evolve. The advantage of the SMGA is in reducing the space searched, while considering only the pipes which need alteration as opposed to all pipes in a conventional GA. • Results: The impact of varying parameters (interest and inflation rates, welfare index, pipe roughness) on the optimal solutions is presented. For example, higher welfare index enables greater initial investment and benefit. • Test networks: (1) Simple system with 15 pipes and 1 reservoir (incl. 9 nodes).
16. Montesinos et al. (1999) [86] SO Optimal WDS strengthening using GA.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes, (2) max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Newton-Raphson method [10]. Optimisation method: GA.	• A modified GA with several changes to selection and mutation is introduced. "In each generation a constant number of solutions is eliminated, the selected ones are ranked for crossover and the new solutions are allowed to undergo at most one mutation". The GA convergence significantly increases as a result of these modifications. • A penalty factor is defined as a function of a number of constraint violations (not taking into account the degree of violation). • Results: The modified GA found the best-known solution for the test network in fewer evaluations than previous GA algorithms. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
17. Walters et al. (1999) [99] MO Optimal WDS strengthening, expansion, rehabilitation and operation with multiple loading conditions and two approaches to model tanks using SMGA. Note: Discussion: [213], Erratum to Discussion: [214]	Objective (1): Maximise the weighted sum of the benefits of the network rehabilitation, using the following performance criteria: (a) nodal pressure shortfall, (b) storage capacity difference, (c) tank operating level difference or tank flow difference. Objective (2): Minimise (a) the capital cost of the network including pipes, pumps, tanks, (b) present value of the energy consumed during a specified period. Constraints: (1) Pressure constraints for different loading patterns, (2) flow constraints into and out of the tanks. Decision variables: String comprising 2 substrings (1) location substring: pipes, pumps, tanks (integer of 1 or 2 digits), (2) decision substring (expansion/rehabilitation options): pipes, pumps, tanks (integer of 1, 2 or 5 digits). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Unspecified solver (steady state). Optimisation method: SMGA.	• Two approaches to model tanks are tested, which differ in a way they determine the operating levels for new tanks. The first approach computes tank levels analytically during the network analysis, the second approach includes tank levels as independent variables. For the test network, both approaches yielded similar results, with the first approach obtaining more robust solutions in slightly increased computational time. • The previously published SMGA [63,131] is expanded to include not only pipe rehabilitation, but also pump and tank installations as decision variables. Variable mutation rate as a function of the string length and the nature of the decision variable is used. For more information about SMGA, see [131]. • Results: Two solutions are presented, the cheapest feasible solution and the most operationally satisfactory solution (preferred by the authors). These solutions are 4–5% cheaper than any previously published solutions to the Anytown problem. • Test networks: (1) Anytown network (incl. 19 nodes) [84].
18. Costa et al. (2000) [60] SO Optimal WDS design and operation using SA.	Objective (1): Minimise the capital cost of the network including (a) pipes, (b) pumps, (c) present value of pump energy costs. Constraints: (1) Min head bound on demand nodes. Decision variables: (1) Pipe diameters (discrete), (2) pump sizes (discrete).	Water quality: N/A. Network analysis: Newton-Raphson method [10]. Optimisation method: SA.	• Operating costs of pumps are calculated in terms of operating hours per year. The network model presents a realistic representation of the pump behaviour, including the head characteristic curve. • Results: The algorithm reaches optimal solutions with the average number of 11817-13454 simulations for the test networks. • Test networks: (1) Gravity network with one reservoir (incl. 9 nodes), (2) network with one pump and one reservoir (incl. 10 nodes), (3) network with one pump and 2 reservoirs (incl. 11 nodes).
19. Dandy and Hewitson (2000) [120] SO Optimal WDS design, strengthening and operation including water quality considerations using GA with search space reduction.	Objective (1): Minimise (a) the capital cost of new pipes, pumps and tanks, present value of (b) pump energy costs, (c) likely cost to the community due to waterborne diseases, (d) likely community cost due to disinfection by-products, (e) community cost of chlorine levels that exceed acceptable limits, (f) cost of disinfection, (g) penalty cost for violating constraints. Constraints: (1) Min pressure at the demand nodes, (2) tanks must refill at the end of the cycle. Decision variables: (1) Sizes of new and duplicate pipes, (2) sizes of new pumps and tanks, (3) locations of new pumps and tanks, (4) decision rules for operating the system, (5) dosing rates of chloramine/chlorine at selected points.	Water quality: Chloramine, chlorine. Network analysis: EPANET (extended period simulation (EPS)). Optimisation method: GA.	• A total of 6 different demand patterns are used, ranging from peak instantaneous to 38 days of winter demand. • The periods of simulation for each season, which reflect the residence times for a season, were found to be necessary in order to reach a pseudo steady state for that season. • The problem is very complex (the GA string consists of 222 integer variables) with long run times. To reduce the size of the search space, a run with peak instantaneous demand was undertaken, then a run with peak daily demand. Out of 206 only 40 pipes that were duplicated in either of these runs were included as options in the total system analysis. It was found that better overall convergence occurred if the GA was run with hydraulic analysis only for several first generations, water quality analysis was subsequently added. • Results: The advantages of including design, operations and water quality in a single framework are demonstrated. In the design phase, allowance can be made for reducing residence times, thus improving water quality. • Test networks: (1) Yorke Peninsula, a rural area west of Adelaide, Australia.

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
20. Vairavamoorthy and Ali (2000) [43] SO Optimal WDS design and strengthening incorporating a linear transfer function (LTF) model to approximate network hydraulics using GA.	Objective (1): Minimise (a) the capital cost of the network (pipes), (b) penalty for violating the pressure constraints. Constraints: (1) Min/max pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Steady state hydraulic solver based on the gradient method [215]. Optimisation method: GA.	• Real coding is applied instead of binary coding (binary and Gray coding often generate redundant states which do not represent any of the design variables). • A variable penalty coefficient is introduced that depends on the degree of constraint violation. • LTF model is proposed which approximates the hydraulic behaviour of the system, so there is no need for each population member to be evaluated by a hydraulic solver. Instead, the LTF is used to estimate pressures for each string generated by the GA. • Results: Obtained solutions are favourable while compared to the results of previous studies [42,85,216]. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) New York City tunnels (incl. 20 nodes) [81].
21. Dandy and Engelhardt (2001) [130] SO Optimal WDS rehabilitation (considering only pipe replacement) over a planning horizon (i.e., 20 years) using GA.	Objective (1): Minimise (a) the system cost of the rehabilitated network (pipes)—present values of pipe failure costs (i.e., repair costs of existing and new pipes) and pipe replacement costs are considered. Constraints (case 1): N/A. Constraints (case 2): (1) Allowable budget for each time step (i.e., 5-year block). Constraints (case 3): (1) As above in the case 2, (2) min pressure at the nodes, (3) max velocity in the pipes. Decision variables (case 1): (1) Replacement decision (0 = no replacement, 1 = replace). Decision variables (case 2): (1) Timing of the replacement (integer) ("all pipe representation"); or (1) pipe to be replaced (integer), (2) timing of the replacement (integer) ("limited pipe representation"). Decision variables (case 3): (1)–(2) as above in the case 2, (3) diameter of the new pipe (integer).	Water quality: N/A. Network analysis: EPANET (Case 3 only). Optimisation method: GA.	• The economic analysis of the system is undertaken in three stages as follows. • Case 1 "single time-step case" is to decide if the pipes need immediate replacement or should be left in operation. • Case 2 "multiple time-step case" is to schedule pipe replacements for the next 20 years, in 5-year steps. • Case 3 "multiple time-step case with changing diameters" is to determine the diameter of the replaced pipes, which is included as a decision variable. • Failure prediction equations were developed for the test network based on recorded failure data. • Two ways to represent chromosomes in GA are considered. One is "all pipe representation", which includes the decision bit for all the pipes in the network; the other is "limited pipe representation", where an upper limit to the number of pipes to be replaced is considered. The size of the search space for the latter representation is smaller than the first one, therefore it is considered a more preferable representation. • Results: The GA demonstrated ability to schedule future works. • Test networks: (1) The EL103N pressure zone, Adelaide, Australia.

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
22. Wu and Simpson (2002) [88] SO Optimal WDS strengthening using fast messy GA (fmGA).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: fmGA.	• A self-adaptive boundary search strategy is proposed for selection of the penalty factor within the GA. It evolves and adapts the penalty factor, so the search is guided to the boundary of the feasible and infeasible spaces. The penalty factor is treated as another decision variable (part of the solution string). In addition, a heuristic rule is developed to adjust the lower and upper boundaries of the penalty factor. • Results: The proposed algorithm finds the least-cost solution in the case study more effectively than a GA without the boundary search strategy. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81].
23. Eusuff and Lansey (2003) [103] SO Optimal WDS design and strengthening using shuffled frog leaping algorithm (SFLA).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for pressure head violations. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: SFLA.	• SFLA is a hybrid between particle swarm optimisation (PSO) (which provides local search tool) and shuffled complex evolution (SCE) algorithm (which helps move towards global solution). • The difference between the SFLA and GA is that in the SFLA an improved idea can be passed between all individuals of the population versus parent-child only interaction in GA. • Results: When compared to GA and SA in regards to the efficacy, SFLA is more efficient as it found the best-known optimal solutions in fewer iterations. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81].
24. Maier et al. (2003) [104] SO Optimal WDS strengthening, expansion and rehabilitation using ant colony optimisation (ACO).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete), (2) pipe rehabilitation options (binary).	Water quality: N/A. Network analysis: WADISO [217], final solutions checked by EPANET. Optimisation method: ACO.	• The main difference between GA and ACO is in generating the trial solutions. In GAs, trial solutions are represented as strings of genetic material, new solutions are obtained by modifying previous solutions, so the system memory is embedded in the actual trial solutions. In ACO, the system memory is contained in the environment, rather than the trial solutions, hence ACO may be more advantageous in certain types of applications. • A modification is made to the way pheromone concentration is changed, which ensures that the method does not get trapped in a local optimum. • Results: The comparison of GA and ACO shows that ACO is a good alternative to GA, having found the same solution in a similar number of iterations for the 14-pipe network, and a better (lower cost) solution with a significantly higher computational efficiency for the New York City tunnels. • Test networks: (1) 14-pipe network with two supply sources (incl. 10 nodes) [20], (2) New York City tunnels (incl. 20 nodes) [81].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions $^{+}$, Constraints **, Decision Variables $^{++}$)	Water Quality Network Analysis Optimisation Method	Notes
25. Liong and Atiquzzaman (2004) [157] SO Optimal WDS design using SCE.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure head bound. Constraints: (1) Min nodal pressure head bound, (2) min/max bound on pipe sizes. Decision variables: (1) Pipe sizes (converted to commercially available diameters).	Water quality: N/A. Network analysis: EPANET. Optimisation method: SCE [218].	• SCE is an evolutionary algorithm (EA) combined with a simplex algorithm [219]. The original SCE algorithm is modified to accommodate high number of decision variables. • The SCE algorithm is compared to the GA, SA, GLOBE [220] and SFLA. • Results: For the two-loop network, SCE converged after a significantly lower number of function evaluations, and for both test networks, SCE found an optimal solution notably faster, than other optimisation techniques. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49].
26. Broad et al. (2005) [87] SO Optimal WDS strengthening including water quality considerations using offline artificial neural networks (ANNs) and GA.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating pressure head, (c) penalty cost for violating chlorine residual. Constraints: (1) Min/max pressure at the nodes, (2) min/max chlorine residual at the nodes. Decision variables: (1) Pipe diameters, (2) chlorine dosing rates.	Water quality: Chlorine. Network analysis: Offline ANN. Optimisation method: GA.	• The methodology uses ANN as a substitute for a simulation model in order to reduce the computational time. • Because it is unlikely that ANN is able to perfectly represent the simulation model, two techniques are used to combat ANN inaccuracies as follows. • The first technique is to ensure feasibility, so solutions found by the ANN-GA are evaluated by EPANET in 3 stages: (i) each new best solution found by the ANN-GA is evaluated by EPANET; (ii) several top solutions are evaluated by EPANET when GA converges; (iii) local search is conducted after GA convergence. • The second technique is to adjust the constraints to cater for ANN underestimating or overestimating pressure and chlorine residuals. • Results: While optimising with ANN, the most time is spent on training the ANN. If the training time is included, the overall time saving for ANN-GA is 21% compared to EPANET-GA. Otherwise, ignoring the training time, the ANN-GA is 700 faster than EPANET-GA. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81].
27. Farmani et al. (2005) [65] MO Optimal WDS design and strengthening using non-dominated sorting genetic algorithm II (NSGA-II) and strength Pareto evolutionary algorithm 2 (SPEA2).	Objective (1): Minimise (a) the design cost of the network (pipes). Objective (2): Minimise (a) the maximum individual head deficiency at the network nodes. Objective (3) (only for the EXNET test network): Minimise (a) the number of demand nodes with head deficiency. Constraints: N/A. Decision variables: (1) Pipe diameters (discrete). Note: Two MO models, the first including objectives (1) and (2) (applied to the New York City tunnels and Hanoi network); the second objectives (1), (2) and (3) (applied to the EXNET network).	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II and SPEA2 are compared.	• NSGA-II and SPEA2 are compared in terms of non-dominated fronts obtained by these algorithms, using (i) graphical presentation, (ii) binary ε-indicator, (iii) binary coverage indicator, (iv) (only for EXNET test network) volume-based indicator. • Results: NSGA-II and SPEA2 are comparable and have the potential to find Pareto optimal solutions for WDS design problems. The results further show that SPEA2 outperformed NSGA-II in both MO optimisation problems, which is illustrated by graphical presentation as well as all indicators. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49], (3) simplified EXNET water network (serves a population of approximately 400000) [82].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
28. Keedwell and Khu (2005) [44] SO Optimal WDS design using a combined cellular automaton for network design algorithm (CANDA) and GA (CANDA-GA) including an engineered initial population.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min/max pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: CANDA-GA.	• A heuristic-based cellular automaton (CA) [221] approach is introduced to provide a good initial population of solutions for GA runs. • A CA consists of an interconnected set of nodes that use a number of rules to update the state of every node according to the states of neighbouring nodes. The rules here are based on the intuitive knowledge of how the WDSs operate, so they are similar to engineering judgment. An important feature of the CA is that updates for every node are performed in parallel. CA does not produce the best solutions but it is capable of producing a good approximate solution in much less network simulations than GA. • Results: For the two-loop network, the results of GA and CANDA-GA are similar, with CANDA-GA producing a slightly better solution. For both real networks, CANDA-GA finds feasible solutions whereas GA fails to do so. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) network A: real network with a single reservoir and 632 pipes, UK (incl. 535 demand nodes) [222], (3) network B: real network with a single reservoir and 1277 pipes, UK (incl. 1106 nodes).
29. Ostfeld (2005) [53] SO Optimal design and operation of multiquality WDSs including multiple loading conditions and water quality considerations using GA.	Objective (1): Minimise (a-D ?) the construction costs of pipes, tanks, pump stations and treatment facilities, (b-OP ??) annual operation costs of pump stations and treatment facilities. Constraints: (1) Min/max heads at consumer nodes, (2) max permitted amounts of water withdrawals at sources, (3) tank volume deficit at the end of the simulation period, (4) min/max concentrations at consumer nodes, (5) removal ratio constraints. Decision variables: D: (1) Pipe diameters, (2) tank max storage, (3) max pumping unit power, (4) max removal ratios at treatment facilities, OP: (5) scheduling of pumping units, (6) treatment removal ratios.	Water quality: Unspecified conservative parameters. Network analysis: EPANET (EPS). Optimisation method: GA.	• Time horizon is 24 h, with a varied energy tariff and unsteady water flow conditions. Similar to [223], cyclic water quality behaviour is not accomplished, so the results depend on the initial settings of the concentrations at the nodes. • Multiple loading conditions (demands) are used. • Sensitivity analysis is performed with the following modifications to the data or constraints. The two-loop network: increased minimum pressure constraint at one consumer node, increased maximum concentration limit for all consumer nodes, increased operational unit treatment cost coefficient. The Anytown network: reduced unit power cost of pump construction and energy tariffs, altered pressure and concentration constraints at one consumer node, decreased elevation at one consumer node. • Results: The model explicitly addresses the conjunctive design and operation problem of quantity, pressure and quality simultaneously under unsteady hydraulics, but is expensive in terms of the computational resources. • Test networks: (1) Two-loop network with 3 sources (incl. 6 demand nodes) [223], (2) Anytown network [84] with modifications (incl. 16 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
30. Vairavamoorthy and Ali (2005) [189] SO Optimal WDS design using GA with a pipe index vector (PIV) and search space reduction in a three-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Explicit mathematical formulation (steady state for peak demands). Optimisation method: GA with PIV.	• PIV, a measure of the relative importance of pipes regarding their hydraulic performance in the network, is introduced. Using PIV, impractical and infeasible regions can be excluded from the search space, enabling quicker generation of feasible solutions resulting in substantial computational time savings. • The proposed method involves the following three steps: (i) establishing tighter bound constraints on all pipes using simple heuristics before the GA starts; (ii) calculating a pipe index, ranking the pipes and dividing them into groups (i.e., constructing PIV), and generating the initial population using PIV; (iii) reducing the search space during the GA itself. • It is found that calculating pipe indices is computationally expensive, therefore a surrogate measure is proposed to compute them. • Results: The proposed method outperforms the standard GA in both convergence and computational time. • Test networks: (1) Alandur network, Madras, India (incl. 82 nodes) [224], (2) Hanoi network (incl. 32 nodes) [49].
31. Vamvakeridou-Lyroudia et al. (2005) [93] MO Optimal WDS strengthening, expansion, rehabilitation and operation considering multiple loading conditions using GA with fuzzy reasoning.	Objective (1): Minimise (a) the design cost of the network including pipes, pumps and tanks. Objective (2): Maximise the benefit/quality of the solution, using the following system performance criteria (constraints): (a) min pressure at the nodes, (b) max velocity in the pipes, (c) safety volume capacity for tanks, (d) safety volume capacity for the network as a whole, (e) pump operational capacity, (f) operational volume capacity for tanks, (g) filling capacity for tanks, (h) operational volume capacity for the network as a whole, (i) filling capacity for the network as a whole. Constraints: N/A. Decision variables: (1) Commercially available pipe diameters (integer), (2) cleaning/lining of existing pipes (binary: 0 = no action, 1 = cleaning/lining), (3) the number of new pumps (integer) with pre-defined operation curve, (4) volume of a new tank (integer, 0 = no tank), (5) min operational level of this tank (integer). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: GA combined with fuzzy reasoning.	• Fuzzy reasoning is introduced. System performance criteria are individually assessed by fuzzy membership functions and combined using fuzzy aggregation operators. A fuzzy set and fuzzy membership functions are defined for each performance criterion/each loading/each network element, based on previous experience [225]. Membership functions are provided with linguistic tags (e.g., "tolerant", "strict", "very strict") to enable implementation of decision maker requirements for specific network elements. • Fuzzy aggregation operators used are weighted means and classic fuzzy intersection, which are ANDlike aggregators covering a wide range and varying in strength. The model is flexible: if a decision maker wishes to omit one or more criteria, the weight assigned to it can be set to zero. On the contrary, should more criteria be added (e.g., resilience), the modular approach allows for additions and modifications, without affecting the structure of the multiobjective model and algorithm. • A novel approach for the inclusion of tanks within the GA is proposed, taking into account the tank shape. • Results: A better solution in terms of cost is obtained than any other previously published, despite the multiple criteria applied for the extensive and stricter benefit function. • Test networks: (1) Anytown network (incl. 19 nodes) [84].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
32. Atiquzzaman et al. (2006) [64] MO Optimal WDS design using NSGA-II.	Objective (1): Minimise (a) the design cost of the network (pipes). Objective (2): Minimise (a) the total pressure deficit at the network nodes. Constraints: (1) Pipe diameters limited to commercially available sizes, (2) min pressure at the nodes, (3) lower and upper limit of total pressure deficit, (4) lower and upper limit of total network cost. Decision variables: (1) Commercially available pipe diameters (integer). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II.	• The aim is to yield "alternative" solutions, which are particularly useful when the associated network cost of the optimal solution is beyond the available budget. Hence, solutions provided are within the (i) available budget and (ii) tolerated total nodal pressure deficit. The total pressure deficit is accompanied with the list of nodes at which pressure deficit occurs and a value of their individual nodal pressure deficit. This information assists in deciding whether the magnitude of the pressure violation may be tolerated. • Results: There is more than one solution with the same network cost and yet different total pressure deficits. Additionally, there are several solutions with about the same total pressure deficit for the same network cost. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14].
33. Geem (2006) [105] SO Optimal WDS design and strengthening using harmony search (HS).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) the penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: HS.	• An improved HS algorithm, which adopts both memory consideration and pitch adjustment operations, is proposed. The algorithm is compared to the methods previously used in the literature, including LP, GA, SA and tabu search (TS). • Results: For all test networks, the HS obtained either the same or 0.28–10.26% cheaper solution than other algorithms. The HS also required fewer function evaluations than other meta-heuristic algorithms. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81], (4) GoYang network, South Korea (incl. 22 nodes) [226], (5) BakRyun network, South Korea (incl. 35 nodes) [227].
34. Keedwell and Khu (2006) [66] MO Optimal WDS design using cellular automaton and genetic approach to multi-objective optimisation (CAMOGA) and NSGA-II including an engineered initial population.	Objective (1): Minimise (a) the design cost of the network (pipes). Objective (2): Minimise (b) the total head deficit at the network nodes. Constraints: (1) Max total head deficit. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: CAMOGA and NSGA-II are compared.	• An extension of the paper by [44] including a novel hybrid CAMOGA. • CAMOGA consists of the following two phases: (i) CANDA [44] to generate good 'near' Pareto-optimal solutions with only a small number of iterations; (ii) NSGA-II to enhance and expand the solutions found in the previous step. • The paper also compares the performance of CAMOGA and NSGA-II using a visual comparison of obtained Pareto fronts and the S-metric [228]. • Results: CAMOGA can provide good solutions with very few network simulations, and that it outperforms NSGA-II in the efficiency of obtaining similar Pareto fronts. • Test networks: (1) Network A: real network with a single reservoir and 632 pipes, UK (incl. 535 demand nodes) [222], (2) network B: real network with a single reservoir and 1277 pipes, UK (incl. 1106 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
35. Reca and Martínez (2006) [50] SO Optimal WDS and irrigation network design using GA.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes, (2) min/max flow velocities. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: Genetic algorithm pipe network optimisation model (GENOME) using GA.	• GENOME is developed particularly for optimisation of looped irrigation networks. It is based on a GA with modifications and improvements to adapt for this specific problem. • An integer coding scheme is used to code the chromosomes. A stochastic sampling mechanism based on the "roulette wheel algorithm" is used for selection. Three crossover strategies are used: one-point, two-point and uniform. • Results: The results are compared to 20 previous studies (for two-loop network) and 17 previous studies (for Hanoi network) from the literature. They indicate that GENOME is able to obtain the best published results in a reasonable computational time. However, some adjustments would be required to improve its performance for complex networks. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes).
36. Samani and Mottaghi (2006) [51] SO Optimal WDS design, operation and maintenance using integer LP (ILP). Note: Discussion: [229]	Objective (1): Minimise (a) the capital cost of the network (pipes), (b) capital, operation and maintenance costs of pumps and reservoirs. Constraints: (1) Only one pipe diameter per network branch, (2) only one pump or reservoir per network location, (3) min/max pressure at the nodes, (4) min/max velocity in the pipes. Decision variables: (1) Integer variables related to pipe diameters and pumps/reservoirs.	Water quality: N/A. Network analysis: Unspecified hydraulic solver (a single loading condition). Optimisation method: Linear interactive discrete optimiser (LINDO) program using BB method.	• Nonlinear objective function and constraints are linearised. • A procedure that iterates between a hydraulic solver and ILP solver is employed. • The test network (1) is used to demonstrate the validity of the procedure as it can be solved by enumeration. • An issue related to poorly selected initial decision variables is reported, when no feasible solution could be found and the program will stop. This issue can be overcome by setting wider limits for the pressure and velocity constraints to provide a better initial guess of decision variables. • Results: The proposed method can find good solutions; for the two-loop network, the solution obtained is comparable to previously published results in the literature. The proposed method converges very quickly. • Test networks: (1) Simple network with 3 pipes and one reservoir in a looped system (incl. 3 nodes), (2) two-loop network supplied by gravity (incl. 7 nodes) [14], (3) network with 15 pipes, 2 reservoirs, a pump and a check valve (incl. 15 nodes).
37. Suribabu and Neelakantan (2006) [106] SO Optimal WDS design using PSO.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: PSONET program using PSO.	• PSONET program, which uses PSO algorithm, is developed and its performance compared to the previous studies from the literature having applied GA, SA, SFLA and shuffled complex algorithm (SCA). • Results: For both test networks, the PSO obtained competitive solutions, but in a lower number of function evaluations than GA, SA and SFLA. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
38. Babayan et al. (2007) [89] MO Optimal robust WDS strengthening considering uncertainties in future demands and pipe roughnesses using NSGA-II.	Objective (1): Minimise (a) the design cost of the network/rehabilitation. Objective (2): Maximise (a) the level of network robustness. Constraints: (1) Design/rehabilitation options are limited to the discrete set of available options. Decision variables: (1) Design/rehabilitation option index (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II.	• Network robustness is represented by the probability that the nodal pressure head is equal to or above the minimum requirement for that node, considering the uncertainties in (i) the future demands and (ii) pipe roughnesses. These uncertainties are assumed to be independent and random following some pre-specified probability density function. • To reduce computational complexity, the original stochastic formulation of robustness objective is replaced by the deterministic formulation. • The model is able to handle uncertainties in different types of parameters and with various probability distribution functions. • Results: When compared to deterministic solutions from the literature, the obtained results demonstrate that "neglecting uncertainty in the design process may lead to serious underdesign of water distribution networks". • Test networks: (1) New York City tunnels (incl. 20 nodes) [81].
39. Lin et al. (2007) [166] SO Optimal WDS design and strengthening using scatter search (SS).	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: SS.	• SS, a population-based evolutionary method, is introduced and compared to the algorithms previously used in the literature, including GA, SA, SFLA, ACO and TS. • Results: The SS is able to obtain solutions as good as or better than the other methods both in the quality of solution and efficiency. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81].
40. Perelman and Ostfeld (2007) [61] SO Optimal WDS design, operation and maintenance using cross entropy (CE).	Objective (1): Minimise (a) (all test networks) the design cost of the network (pipes), (b) (test network (3) only) construction costs of pumps and tanks, (c) (test network (3) only) operation and maintenance costs of pumps. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: CE for combinatorial optimisation [230].	• An adaptive stochastic algorithm, based on the CE for combinatorial optimisation, is proposed. In this method flows, heads and pipe diameters are solved simultaneously. • Results: The CE found the best-known solution for the two-loop network, and improved the best-known solutions for the test networks (2) and (3). For all test networks, the solutions were obtained with a considerably lower number of function evaluations than previously reported in the literature [42,231]. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) two-loop network with pumping and storage (incl. 7 nodes) [231].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
41. Tospornsampan et al. (2007) [112] SO Optimal WDS design and strengthening with split pipes using SA.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure at the nodes, (2) min/max diameter for the pipes, (3) min discharge for the pipes, (4) the total length of pipe segments equal to the length of the corresponding link, (5) nonnegativity for pipe segment lengths. Decision variables: (1) Two pipe diameters for each link (discrete), (2) pipe segment lengths (continuous) for the first diameter.	Water quality: N/A. Network analysis: Not specified. Optimisation method: SA.	• Split-pipe design of looped WDSs is proposed. • The number of decision variables for split-pipe design is triple to the number of links. For each link, two pipe diameters and the segment length for the pipe of the first diameter need to be calculated. • A constraint of the minimum pipe segment length, which must be equal or more than 5% of its link length, is imposed to the Hanoi network. • Results: The obtained solutions are compared to the solutions from the literature for both split-pipe and single pipe designs. The proposed methodology found the lowest cost solutions yet published to date for all tested networks. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81].
42. Zecchin et al. (2007) [156] SO Optimal WDS design and strengthening using ACO.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) the penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete). Note: Formulated in [201].	Water quality: N/A. Network analysis: EPANET. Optimisation method: ACO (5 algorithms).	• The paper compares 5 different formulations of ACO algorithms, namely the original one: ant system (AS) [232], and four variations: ant colony system (ACS) [233], elitist ant system (AS_{elite}) [232], elitist rank ant system (AS_{rank}) [234], max-min ant system (MMAS) [235]. • Results: "AS_{rank} and MMAS stand out from the other ACO algorithms in terms of their consistently good performances". They also outperformed all other algorithms previously applied to same test networks in the literature. • Test networks: (1) Two reservoir network (incl. 10 nodes) [20], (2) New York City tunnels (incl. 20 nodes) [81], (3) Hanoi network (incl. 32 nodes) [49], (4) double New York City tunnels (incl. 39 nodes) [201].
43. Chu et al. (2008) [167] SO Optimal WDS strengthening using immune algorithm (IA).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Not specified. Optimisation method: IA and modified IA (mIA) are compared.	• IA, a heuristic algorithm which imitates the immune system defending against the invaders in a biological body, is introduced. The objective function and constraints are represented by antigens, the string of decision variables is represented by antibodies. Crossover and mutation operators from GA are used in producing the new antibodies to avoid the local minima. • Additionally, mIA is developed. Within the mIA optimisation procedure, GA is used (due to its good global search capability) to screen the initial repertoire (initial strings) of the IA. • Results: Both the IA and mIA found solutions as good as those obtained by GA and fmGA in other studies, in significantly fewer evaluations. Moreover, mIA exhibits far superior computational efficiency than GA or IA individually. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
44. Jin et al. (2008) [95] MO Optimal WDS rehabilitation and operation using NSGA-II with artificial inducement mutation (AIM) to accelerate algorithm convergence.	Objective (1): Minimise (a) the rehabilitation cost of the network involving pipe replacement, (b) energy cost for pumping. Objective (2): Minimise (a) the sum of the velocity violations (shortfalls or excesses) weighted by the pipe flow. Objective (3): Minimise (a) the sum of pressure violations (excesses) weighted by the node demand. Constraints: (1) Pipe diameters limited to available standard diameter set. Decision variables: (1) Pipe diameters (real). Note: One MO model including all objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II with AIM.	• A new mutation method called AIM is introduced, which acceleratingly directs the population convergence to the feasible region, and then uses normal mutation (i.e., one point random mutation) searching for the best solution within the feasible region. • To evaluate algorithm performance, the optimisation problem is solved by NSGA-II with and without AIM. • The test network to be optimised is an existing network displaying too high pipe velocities and too low nodal pressures in some areas due to an increase in water consumption. The optimisation aims to rehabilitate the network by replacing existing pipes with larger diameter pipes (no cleaning or lining of pipes is considered). • Results: NSGA-II with AIM outperforms NSGA-II without AIM in terms of convergence speed as well as the quality of the solutions obtained. • Test networks: (1) Network resembling the EPANET Example 3 (incl. 92 nodes) network [236].
45. Kadu et al. (2008) [45] SO Optimal WDS design using GA with search space reduction.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: GRA-NET, a hydraulic solver based on gradient method [215]. Optimisation method: GA-WAT program using GA.	• GRA-NET and GA-WAT are developed. • A modified GA is used with the following operators: the tournament selection, the multiparent, universal parent and basic crossover, a nonuniform and neighbour mutation [237–239]. The operators are selected randomly. • Self-adapting penalty multiplier to handle the constraints and scaled fitness function are used. • Real-coding scheme, in which discrete diameters are directly used to form solution strings, is adopted. • The solution space is substantially reduced by applying the critical path method [191] as follows. A tree is identified that approximates the original looped network, the links are classified as primary and secondary. Primary links are the pipes forming the shortest paths from the source to each demand node. Hydraulic gradient levels are obtained at the intermediate demand nodes, then flows and diameters for the links are obtained. Candidate diameters are obtained for each link based on the previous information and these are used in generating the initial population of GA. • Results: The modified GA with search space reduction is more effective, especially for large networks. • Test networks: (1) Single source network with 7 links (incl. 5 demand nodes), (2) Hanoi network (incl. 32 nodes) [49], (3) two-reservoir network with 34 links (incl. 26 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
46. Ostfeld and Tubaltzev (2008) [54] SO Optimal WDS design and operation considering multiple loading conditions using ACO.	Objective (1): Minimise (a) the pipe construction costs, (b) annual pump operation costs, (c) pump construction costs, (d) tank construction costs, (e) penalty function for violating pressure at nodes. Constraints: (1) Min/max pressure at consumer nodes, (2) max water withdrawals from sources, (3) tank volume deficit at the end of the simulation period. Decision variables: (1) Pipe diameters, (2) pump power at each time interval.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: ACO, compared to the previous study also using ACO [104].	• Time horizon is 24 h, with a varied energy tariff. • Multiple loading conditions (demands) are used. • Sensitivity analysis is performed for algorithm parameters, such as the maximum number of iterations, the discretisation number, quadratic and triple penalty functions, the initial number of ants, the number of ants subsequent to initialisation, the number of best ants solutions for pheromone updating. • Results: The proposed ACO produced better results than the ACO of [104]. However, it is difficult to anticipate which method is better in general as the performance always depends on model calibration for a specific problem. • Test networks: (1) Two-loop network with 3 sources (incl. 6 demand nodes) [223], (2) Anytown network [84] with modifications (incl. 16 nodes).
47. Perelman et al. (2008) [62] MO Optimal WDS design, strengthening, operation and maintenance using CE.	Objective (1): Minimise (a) (both test networks) the design cost of the network (pipes), (b) (test network (2) only) construction costs of pumps and tanks, (c) (test network (2) only) operation and maintenance costs of pumps. Objective (2): Minimise (a) the maximum pressure deficit of the network demand nodes. Constraints: N/A. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: CE for combinatorial optimisation [230].	• An extension of the paper by [61] to a multi-objective optimisation approach, particularly by using the rank of the generated elite solutions to update the CE probabilities instead of using fitness function values. • CE is compared to NSGA-II using the following performance metrics: (i) generational distance [240]; (ii) distance measure [241] for assessing the proximity of individual solutions of a Pareto front to the best approximated Pareto front; (iii) distribution measure [241] for evaluating the diversity of the solutions along the Pareto frontier. • Results: The CE method demonstrates a high potential of receiving good solutions with a relatively low number of function evaluations. It is robust and reliable, and provides improved results when compared to the NSGA-II. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) two-loop network with pumping and storage (incl. 7 nodes) [231].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
48. Van Dijk et al. (2008) [152] SO Optimal WDS design and strengthening using GA with an improved convergence.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: Genetic algorithm network optimisation (GANEO) program using GA.	• GANEO program, based on GA, is developed. Modifications are made to crossover and mutation to improve GA convergence. • A new approach of determining penalty for not meeting the pressure requirements at the nodes depending on the degree of failure and importance of the pipe (higher or lower flow) is developed. • Results: GANEO produced comparable results, in a limited number of generations in relation to other GA-based methods used in the literature. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49], (3) two-loop network supplied by gravity (incl. 7 nodes) [14].
49. Wu et al. (2008) [71] MO, SO Optimal WDS design and operation including greenhouse gas (GHG) emissions using multi-objective GA (MOGA).	Objective (1): Minimise (a) the capital cost of the network including pipes and pumps, (b) present value of pump replacement costs, (c) present value of pump operating costs (due to electricity consumption). Objective (2): Minimise GHG emissions including (a) capital GHG emissions (due to manufacturing), (b) present value of operating GHG emissions (due to electricity consumption). Constraints: (1) Min flowrate in pipes. Decision variables: (1) Pipe sizes (discrete), (2) pump sizes (discrete), (3) tank locations (discrete). Note: One MO model including both objectives, one SO model including objective (1).	Water quality: N/A. Network analysis: EPANET. Optimisation method: MOGA (based on NSGA-II).	• Present value analysis (PVA) using Gamma discounting is applied to evaluate operating costs and pump replacement costs during the life of the system. • Evaluation of GHG emissions is undertaken using life cycle analysis (LCA), where only pipes are considered as they account for most of the material usage. Two sources of emissions are considered: emissions during manufacturing of pipes and during operation of the system. Embodied energy analysis (EEA) is performed to evaluate the former, whereas PVA to evaluate the latter. • A single average energy tariff is used. • The constraints are handled by constrained tournament selection method. • For both test networks, multi-objective and single-objective optimisation is performed. For the first network, a full enumeration of solutions is also carried out to show that the MOGA has found all Pareto optimal solutions. • Results: There is a significant tradeoff between economic and environmental objectives. Considerable reduction in GHG emissions can be achieved by a reasonable increase in the cost. The discount rate values have significant impacts on the PVA results. • Test networks: (1) One-pipe pumping system (incl. 1 node), (2) multi-pump system (incl. 4 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
50. Dandy et al. (2009) [127] SO Optimal expansion, strengthening and operation of wastewater, recycled and potable water systems for planning purposes using GA.	Objective (1): Minimise the total design cost of (a) wastewater, (b) recycled and potable networks. Constraints: Wastewater system: (1) Max surcharge in gravity sewers, (2) min/max velocity in rising mains, (3) treatment plant capacity. Potable/recycled systems: (4) Min pressure at the nodes. Decision variables: Wastewater system: Options for (1) trunk sewers upgrades, (2) new diversion sewers, (3) pump stations upgrades, (4) new pump stations, (5) new storage facilities, (6) new treatment plants. Potable/recycled systems: Options for (7) new/duplicate pipelines, (8) new/expanded pump stations, (9) new storages, (10) valve settings, (11) pump controls, (12) potable top-ups, (13) flowrates from sources.	Water quality: Not specified. Network analysis: Not specified. Optimisation method: GA.	• Optimisation of wastewater, recycled and potable water systems is performed simultaneously by linking together two optimisation models, one for wastewater and the other for recycled and potable water. The interface between those two models occurs at wastewater and recycled water treatment plants (WTPs). Three different combinations of locations of the plants are considered. Linking the wastewater solution with the potable/recycled water solutions involves pairing solutions from compatible source scenarios. • The optimisation of recycled/potable water systems is undertaken for a 24-h dry summer day demand for ultimate build out (year 2030) using 5-year increments. Possible future demands of a potential new development are considered. • Results: The feasibility of an integrated approach to the planning problem considered is demonstrated. This approach "is likely to make third pipe systems more attractive and to lead to significant savings in the use of limited water supplies". • Test networks: (1) Hume/Epping corridor, north Melbourne, Australia.
51. di Pierro et al. (2009) [67] MO Optimal WDS design using ParEGO and LEMMO with a limited number of function evaluations.	Objective (1): Minimise (a) the total cost of the network (pipes). Objective (2): Minimise (a) the head deficit. Constraints: (1) Min head at the nodes. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET (EPS for the test network (2)). Optimisation method: Hybrid algorithms ParEGO [192] and LEMMO [242].	• The paper aims to use algorithms capable of satisfactory performance with a limited number of function evaluations. • ParEGO is based on surrogate modelling "Kriging" to model the search landscape from solutions visited during the search [192]. LEMMO is based on the hybridisation of the evolutionary search with machine learning techniques. These algorithms are tested against Pareto envelope-based selection algorithm II (PESA-II) [243] which can address simultaneously proximity and diversity (two success measures) of an approximation of the Pareto front and performed well on difficult problems. The best solutions for the problems have been obtained by PESA-II. • Results: For the network (1), LEMMO can achieve results similar to PESA-II with a significant (90%) reduction in hydraulic simulations. For the network (2), it performed well in identifying solutions interesting from an engineering perspective (i.e., solutions with small pressure deficit). ParEGO performed worse than LEMMO, but it can still be successfully applied to reduce the number of function evaluations for small to medium-size problems. • Test networks: (1) Medium-size network with 34 pipes, Apulia, Southern Italy (incl. 24 nodes) [244], (2) network A: real network with a single reservoir and 632 pipes, UK (incl. 535 demand nodes) [222].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
52. Geem (2009) [160] SO Optimal WDS design and strengthening using particle swarm HS (PSHS).	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: PSHS.	• An application of a particle swarm concept to the original HS algorithm to enhance its performance is presented. • The memory consideration operation in HS is replaced by the particle swarm operation where the new harmony (new vector) is formed with a certain probability (called particle swarm rate) using the best-known solution vector. • PSHS is compared with several other methods, such as GA, SA, SFLA, ACO, CE, HS, SS, and mixed SA and TS (MSATS). • Results: The PSHS algorithm performed well, especially for small-scale and medium-scale networks, for which it found the best solution in a lower number of evaluations than other methods. For the large networks, it was inferior only to HS. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50], (4) New York City tunnels (incl. 20 nodes) [81].
53. Giustolisi et al. (2009) [141] SO, MO Optimal robust WDS design considering uncertainties in demands and pipe roughness using optimised multi-objective GA (OPTIMOGA) with a two-phase procedure.	Objective (1) (for a deterministic phase): Minimise (a) the design cost of the network (pipes), (b) pressure deficit at the critical node (i.e., the worst-performing node). Objective (2) (for a stochastic phase): Minimise (a) the design cost of the network (pipes). Objective (3) (for a stochastic phase): Maximise (a) the robustness of the network. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete) (for both deterministic and stochastic problems), (2) future nodal demands (for stochastic problem only), (3) future pipe roughnesses (for stochastic problem only). Note: One SO model (i.e., deterministic) including objective (1); one MO model (i.e., stochastic) including objectives (2) and (3).	Water quality: N/A. Network analysis: Demand-driven analysis [11]. Optimisation method: OPTIMOGA [245].	• The network robustness is defined based on the worst-performing node (that is a constraint should be fulfilled at the most critical node). • The optimisation consists of two phases as follows: (i) the optimal design is found deterministically (a single-objective problem); (ii) using the obtained solutions as initial population, the robust design is found multi-objectively (cost minimisation and robustness maximisation) and stochastically considering future nodal demands and pipe roughnesses uncertain variables. This two-phase procedure is to reduce the computational time required by the stochastic phase. • Several probability density functions (mainly beta functions) are introduced and tested to model uncertain variables in different ways. • Results: The proposed two-phase optimisation procedure results in noticeable computational savings. "The entire procedure permits the simultaneous realisation of two major objectives: overall network robustness can be improved and the most important mains in terms of network reliability may be identified from the difference in the deterministic and stochastic solutions. Results illustrate the procedure's effectiveness in yielding information of practical engineering value". • Test networks: (1) Apulian network, Southern Italy (incl. 23 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] **SO/MO *** **Brief Description**	**Optimisation Model (Objective Functions $^{+}$, Constraints **, Decision Variables $^{++}$)**	**Water Quality** **Network Analysis** **Optimisation Method**	**Notes**
54. Krapivka and Ostfeld (2009) [117] SO Optimal WDS design with split pipes using a combination of GA and LP (GA-LP) in a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes, (2) sum of pipe segment lengths must be equal to the link length, (3) nonnegativity of segment lengths. Decision variables: (1) Lengths of pipe segments of known diameters (so called split-pipe decision variables). Note: Formulated in [116].	Water quality: N/A. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Combined GA-LP.	• An extension of the paper by [116] with the following modifications: • To solve the outer problem, a GA is used instead of SA. • The solution is constrained to the lowest cost spanning tree layout with the spanning tree chords (the missing pipes) kept at the minimum permissible diameters. (This solution is further improved by the GA). • Results: The results obtained are similar to the results presented in [116]. The proposed methodology is superior to the standard GA (without the refinement of using a spanning tree with minimal chord diameters). • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14].
55. Mohan and Babu (2009) [168] SO Optimal WDS design using heuristic-based algorithm (HBA).	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min head at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: HBA.	• Heuristic optimisation method, which uses implicit information provided by the network, is proposed. Initially, all pipes are assigned the minimum available diameter size, then all diameters are increased until minimum head requirement at the nodes is met. Finally, certain diameters are decreased or increased based on the head loss information from the network. • HBA is compared to other heuristic optimisation methods (rule-based gradient approach, CANDA) as well as stochastic optimisation methods (GA, SA, SFLA). • Results: HBA finds a better solution than other heuristic methods. Compared to stochastic methods, the cost obtained by HBA is slightly higher, but the number of evaluations is significantly lower. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49].
56. Mora et al. (2009) [158] SO Optimal WDS design using HS with optimised algorithm parameters.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Not specified. Optimisation method: HS.	• The aim of the paper is to find the most suitable combination of HS parameters, which would ensure not only a better solution to be obtained, but also a lower number of iterations to reach such a solution. Parameters considered are harmony memory size (HMS), memory considering rate (HMCR) and pitch adjustment rate (PAR). • HS parameters are optimised using a statistical analysis of the HS performance, for which 54,000 simulations is performed with varying values of HS parameters. The optimal cost of 6081 thousands, the smallest value ever published for the Hanoi network in the literature, was only found 4 times out of 54,000. • The concept of "good solutions" is introduced. It is the capacity of an algorithm to obtain a set of solutions, which exceed the minimum cost by no more than 3%. • Results: HMS has a key influence on obtaining good solutions and also on the number of iterations, while PAR does not have a great impact on the results. • Test networks: (1) Hanoi network (incl. 32 nodes) [49].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
57. Rogers et al. (2009) [100] SO Optimal WDS expansion, operation and maintenance planning with reliability and water quality considerations over a planning horizon (i.e., 25 years) using GA.	Objective (1): Minimise the life cycle cost of the network including (a) capital costs, (b) energy costs, (c) operation costs, (d) maintenance costs, (e) penalty cost for violating constraints. Constraints: (1) Min pressure at the nodes, (2) min/max storage facility levels, (3) min/max watermain velocities. Decision variables: Options for (1) watermains (pipe sizing and routes), (2) new pump stations, (3) pump station expansions, (4) elevated storage facilities, (5) reservoir expansions, (6) control valves, (7) expansions at the two existing water purification plants (WPPs), (8) pressure zone configurations (pressure zone boundaries).	Water quality: Water age (as a surrogate measure for water quality). Network analysis: EPANET. Optimisation method: GANET using GA, and a heuristic solver for postprocessing.	• The following optimisation strategy is adopted: • Preliminary capacity-driven solutions are generated and evaluated by EPANET-GANET. Design criteria (e.g., the minimum sizing of specific infrastructure elements) are updated to ensure that the final solutions meet reliability and water quality requirements. This process is repeated to arrive at near optimal solutions. • The review of near optimal solutions led to a reduction in the number and variety of the decision variable options. For example, pressure zone configuration options were eliminated from the optimisation model and were run as separate optimisation problems. • The optimisation results are evaluated using H20Map Water, a GIS-enabled hydraulic simulation package. Operating scenarios involving critical infrastructure failures are developed and tested. • A heuristic solver is used to arrive at the final optimal solution from near optimal solutions generated by GA. • Results: The results assisted in formulating practical conclusions and recommendations for large and complex WDS optimisation problems. • Test networks: (1) City of Ottawa WDS, Canada.
58. Tolson et al. (2009) [180] SO Optimal WDS design and strengthening using hybrid discrete dynamically dimensioned search (HD-DDS).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameter option numbers (integer).	Water quality: N/A. Network analysis: EPANET. Optimisation method: HD-DDS.	• An adaptation of the paper by [246] for continuous optimisation to discrete optimisation with a new termination criterion. • HD-DDS, which is not a population-based algorithm, combines global and two local search techniques (i.e., hybrid approach). Local search heuristics used are "one-pipe change" and "two-pipe change", which cycle through all possible ways to change the solution by modifying the diameter of one or two pipes at a time, respectively. No parameter tuning is required as there is only one parameter with a fixed value. Constraints are handled equivalently to Deb's tournament selection in GAs [148]. • A hydraulic simulator is only required for a fraction of the solutions evaluated. • The results are compared to the results from the literature obtained by other heuristics including GA, CE, PSO, MSATS and MMAS (ACO). • Results: The ability of HD-DDS to find near global optimal solutions is the same or better than other heuristics while being more computationally efficient. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) double New York City tunnels (incl. 39 nodes) [201], (3) Hanoi network (incl. 32 nodes) [49], (4) GoYang network, South Korea (incl. 22 nodes) [226], (5) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
59. Banos et al. (2010) [107] SO Optimal WDS design using memetic algorithm (MA).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes, (2) min/max flow velocities. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: MA.	• MA, an extension of EAs which apply local search processes in the agents, is introduced. MA is compared to GA, SA, MSATS, SS using SA as a local searcher (SSSA) and binary linear integer programming (BLIP) method. • To compare the algorithms, the termination criterion used is the number of fitness function evaluations (except for BLIP that does not have a fitness function), which is a function of the number of links and possible pipe diameters. To avoid the randomness due to the use of different initial solutions, they are all obtained by taking the largest diameter pipes in the test networks. To achieve a good performance of each metaheuristic, a parametric analysis is performed. • The computer model called MENOME (metaheuristic pipe network optimisation model) [247] is used which integrates all algorithms, EPANET, a graphical user interface (GUI) and database management module. • Results: A dominance of MA over other algorithms is demonstrated, particularly for large-size problems. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].
60. Bolognesi et al. (2010) [169] SO Optimal WDS design and strengthening using genetic heritage evolution by stochastic transmission (GHEST).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the head constraint. Constraints: (1) Min head at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: GHEST.	• GHEST, a multi population evolutionary strategy method, is introduced. It uses two different complementary processes to search for the optimal solution. The first process synthesizes and transmits the genetic patrimony (heritage) of the parent solutions using their statistical indicators, while the second process called "shuffle" avoids local minima when the evolutionary potential of the population appears to be exhausted. • An extensive comparison of GHEST with previously used optimisation methods (such as ACO, GA, HS, LP, MSATS, PSHS, SA, SCE, SFLA) from the literature is presented. • Results: GHEST is able to find the same or better solution when compared to other algorithms. In particular, better results using a decreased number of evaluations are achieved for large-size problems. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81], (4) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
61. Cisty (2010) [113] SO Optimal WDS design with split pipes using a combined GA and LP method (GALP) in a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) The sum of the unknown lengths of the individual diameters in each section has to be equal to its total length, (2) total pressure losses in a hydraulic path between a pump/tank and every critical node should be equal to or less than the known value (based on the minimum pressure requirements), (3) the lengths are positive (and greater than a nominated minimum value). Decision variables: (1) Lengths of selected pipe diameters for each section.	Water quality: N/A. Network analysis: Explicit mathematical formulation, EPANET used only for the computation of friction headlosses. Optimisation method: GALP.	• A split-pipe design is used. Hence, search space is smaller comparing to optimising pipe diameters, because the chromosomes correspond to the number of loops in the network rather than the number of pipes. • LP is more reliable to find the global optimum than heuristic methods, but is only suitable for branched networks. Therefore, GA is used to decompose the looped network into a group of branched networks, then LP is applied to optimise those branched networks. So, GA is used as an outer algorithm, LP as an inner algorithm, embedded into a GA fitness function. • It is suggested to refine the methodology by introducing a preprocessing stage with half the genes in the chromosomes. This stage is dealt with a suitable GA method, then the solutions are passed onto the main stage with full chromosomes. A postprocessing stage can be included, which also refines the solutions, again using only half the genes in the chromosomes, but a different half than in the preprocessing stage. • Fine tuning GA parameters is not necessary, as the algorithms performs consistently with different parameter values. • The extensions of the Hanoi network are introduced in order to test the method on greater problems. Those extensions are built so that the optimal solution can be evaluated. It is thus possible to compare the results produced by GALP with the global solutions for the problems. • Results: GALP consistently finds better solutions than those presented in the literature. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) double Hanoi network (incl. 62 nodes), (3) triple Hanoi network (incl. 92 nodes).
62. Filion and Jung (2010) [142] SO Optimal WDS design including fire flow protection using PSO.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) cost of potential economic damages by the fire (expected conditional fire damages). Constraints: (1) Max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: PSO.	• Potential fire damages are incorporated directly into the objective function and are assigned a weight to reflect their importance relative to design costs. • New integration-based method to estimate the expected damages by the fire is developed. The uncertainty in needed fire flow (NFF) is included. Maximum day demands are considered to be known. • Minimum pressure constraint is excluded since corresponding violations are "accounted for in the damage component of objective function under the maximum day demand+fire condition". • Sensitivity analysis is performed to investigate the sensitivity of diameters, design costs, fire damages and total costs to changes in mean and standard deviation of fire flow. • Tradeoff curves for design costs and fire damage costs are generated. • Results: The uncertainty in fire flow has a little impact on pipe sizing and cost for the two-loop network. For the real-world network, 150 mm diameters provide adequate hydraulic capacity and make design costs and damages insensitive to fire damage weighting. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) real-world network (incl. 29 nodes) [248].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
63. Mohan and Babu (2010) [170] SO Optimal WDS design using honey bee mating optimisation (HBMO).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the head constraint. Constraints: (1) Min head at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: HBMO [249].	• HBMO is introduced, different values of parameters tested and the sensitivity analysis presented. • Performance of HBMO in terms of the obtained solution and number of evaluations is compared to the other algorithms (GA, SA, SFLA) from the literature. • Results: The multiple-queen colony is essential with the number of queen bees increasing with the increase in the number of pipes in the system. HBMO can obtain comparable results as other algorithms using a reduced number of evaluations. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49].
64. Prasad (2010) [98] SO Optimal WDS strengthening, expansion, rehabilitation and operation with a new approach for tank sizing considering multiple loading conditions using GA.	Objective (1): Minimise the capital cost of the network including (a) pipes, (b) pumps, (c) tanks, (d) present value of the energy cost. Constraints: (1) Min pressure at the nodes, (2) max velocity in the pipes, (3) volume of water pumped greater than or equal to the system daily demand, (4) tanks recover their levels by the end of the simulation period, (5) total tank inflows greater than or equal to total tank outflows, (6) bounds on decision variables. Decision variables: For pipes: (1) New/duplicate diameters (integer), (2) options for existing pipes (0 = no change, 1 = clean and line). For pumps: (3) the number of pumps (integer). For tanks: (4) Location (integer), (5) total volume (real), (6) min operational level (real), (7) ratio between diameter and height (real), (8) ratio between emergency volume and total volume (real).	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: GA.	• A new approach for tank sizing is proposed, which eliminates explicit consideration of some operational constraints. • EPS is conducted for each trial solution during the optimisation to enable accurate calculation of energy cost. • The pressure constraints are treated as hard constraints, so they are not to be violated. In contrast, all other constraints are treated as soft constraints, so the sum of normalized violation must be less than a specified value. Constraint handling is undertaken by ranking the solutions. • Two scenarios are analysed, the first considering all constraints except pressure constraints for normal day loading and the second considering all constraints. • Results: Designs obtained are cheaper comparing to designs proposed by other researchers under similar performance conditions, but with different tank sizing methods. The solution for the first scenario violates pressure constraints for normal day loading as expected. The solution for the second scenario is superior in terms of both the cost and hydraulic performance. • Test networks: (1) Anytown network (incl. 19 nodes) [84].
65. Suribabu (2010) [171] SO Optimal WDS design, strengthening, expansion and rehabilitation using differential evolution (DE).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete at the initialisation, converted to continuous in the DE process and back to discrete before the selection for the next generation), (2) pipe rehabilitation options.	Water quality: N/A. Network analysis: EPANET. Optimisation method: DE [250].	• DE resembles an EA and differs in an application of crossover and mutation. • The 14-pipe test network requires expansion and possibly rehabilitation (with pipes being cleaned, duplicated or left alone). • DE is compared to other optimisation methods (such as ACO, GA, HS, PSO, SA, SCE, SFLA) from the literature. • Results: DE proves to be very effective as it finds optimal or near optimal solutions with a lower number of functions evaluations. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81], (4) 14-pipe network with two supply sources (incl. 10 nodes) [20].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
66. Wu et al. (2010) [77] MO, SO Optimal WDS design and operation including GHG emissions over a planning horizon (i.e., 100 years) using water system multi-objective GA (WSMGA).	Objective (1): Minimise (a) the capital cost of the network including pipes and pumps (i.e., purchase and installation of pipes and pumps, and construction of pump stations), (b) present value of pump replacement/refurbishment costs, (c) present value of pump operating costs (i.e., electricity consumption). Objective (2): Minimise GHG emission cost including (a) capital GHG emissions (i.e., manufacturing and installation of pipes), (b) present value of operating GHG emissions (i.e., electricity consumption). Constraints: (1) System must be able to deliver at least the average flow(s) on the peak day to the tank(s). Decision variables: (1) Pipe sizes (discrete), (2) pump sizes (discrete). Note: One MO model including both objectives; one SO model summing up objectives (1) and (2).	Water quality: N/A. Network analysis: Not specified. Optimisation method: WSMGA (used for both single-objective and multi-objective problems, based on NSGA-II).	• An extension of the paper by [72] including carbon pricing while accounting for GHG emissions priced at a certain level (i.e., monetary value). • The question is raised "whether the introduction of carbon pricing under an emission trading scheme will make the use of a multi-objective optimisation approach obsolete or whether such an approach can provide additional insights that are useful in a decision-making context". A comparison between using single-objective and multi-objective approaches is presented. • A pipe network service life of 100 years and a pump service life of 20 years are assumed. • Because the test network (1) is very small with only 442 solutions, full enumeration and non-dominated sorting was used to optimise the system instead of GA. • Results: A multi-objective approach requires more computational effort and domain knowledge than a single-objective approach, but provides decision makers with more detailed information by showing the tradeoffs between the conflicting objectives. The authors note that the price of carbon has no effect on the tradeoff, hence it is recommended not to be used for the WDS optimisation of accounting for GHG emissions, resulting in the tradeoff between system costs in dollars and GHG emissions in tons. • Test networks: (1) Simple network with 1 tank and 1 pump station with 10 fixed speed pumps (FSPs) (incl. 1 node), (2) network with 1 pump, 8 pipes and 3 tanks (incl. 5 nodes).
67. Wu et al. (2010) [72] MO Optimal WDS design and operation including GHG emissions over a planning horizon (i.e., 100 years) using WSMGA.	Objective (1): Minimise (a) the capital cost of the network including pipes and pumps (i.e., purchase and installation of pipes and pumps, and construction of pump stations), (b) present value of pump replacement/refurbishment costs, (c) present value of pump operating costs (i.e., electricity consumption). Objective (2): Minimise GHG emissions including (a) capital GHG emissions (i.e., manufacturing and installation of pipes), (b) present value of operating GHG emissions (i.e., electricity consumption). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe sizes (discrete), (2) pump selection (discrete), (3) tank location selection (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: WSMGA (based on NSGA-II with several modifications).	• PVA is used to account for future costs and emissions. A number of different discount rates is used in PVA for the evaluation of objective functions. • Two discount rate scenarios are used. In the first scenario, costs are discounted at different rates and GHG emissions are not discounted at all. In the second scenario, costs and GHG emissions are all discounted at the same rate. • A system design life of 100 years and a pump service life of 20 years are assumed. • Results: There is a significant tradeoff between the two objectives for both discount rate scenarios. This tradeoff notably improves the decision maker's understanding of the search space and shows which design is the most economical in reducing GHG emissions. It is found that the Pareto front is very sensitive to the discount rates, thus the selection of discount rates has a considerable impact on final decision making. • Test networks: (1) Simple network with one source, 9 pipes and one tank location (selected from two possible locations) (incl. 4 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
68. Geem and Cho (2011) [161] SO Optimal WDS design using parameter setting free HS (PSF HS).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: PSF HS.	• The paper develops a new method for dynamic updating of the two major parameters in HS, HMCR and PAR, without resorting to trial and error approach to set their values. The authors argue that even though metaheuristic algorithms have their advantages over the traditional algorithms, their disadvantage is a tedious and time consuming setting of parameters. • Basically, the parameters HMCR and PAR are set up automatically, but two other parameters are needed to do so: number of iterations with central parameter values and amount of noise effect. Proper values for these two amounts need to be investigated in the future. • Results: PSF HS found the global solution 10 times out of 20 runs for the two-loop network, as opposed to the standard HS finding it only twice. This favourable result is believed to be due to automatic parameter settings in the iterations. Good results are obtained for the Hanoi network as well, reaching the global solution in fewer iterations than other algorithms (ACO, CE, GA, HS, SS). • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49].
69. Geem et al. (2011) [159] SO Optimal WDS design using HS.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure at the nodes, (2) min/max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: HS.	• The velocity constraint is included to eliminate water hammer and sedimentation in pipes. • The methodology was intended to apply to three test networks, but only one test network is presented. Other test networks considered were the two-loop network [14] and the Hanoi network [49]. However, the methodology was not suitable for those test networks due to the velocity constraint for pipes. • A comparison of HS with LP, which was originally used to design the test network by [251], is presented. • Results: HS obtains about 20% cheaper solution than LP. • Test networks: (1) Yeosu network, South Korea (incl. 19 nodes) [251].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
70. Goncalves et al. (2011) [52] SO Optimal WDS design and operation using a decomposition-based heuristic with a three-phase procedure.	Objective (1): Minimise (a) the investment cost of pipes, (b) investment cost of pumps and the power cost, (c) energy cost of the system. Constraints: (1) Each hydrant visited by exactly one path, (2) each junction/withdrawal visited at the most by one path, (3) a single diameter selected for an arc, (4) one pressure class selected for an arc, (5) min/max velocity in arcs, (6) max pressure in arcs, (7) min pressure at the hydrants, (8) min/max height for a pump at the nodes, (9) min/max land area to irrigate downstream the arcs, (10) binary and nonnegativity constraints. Decision variables: (1) Arc included into the route (0 = no, 1 = yes), (2) diameter assigned to the arc (0 = no, 1 = yes), (3) pressure class assigned to the arc (0 = no, 1 = yes), (4) pump installed at the node (0 = no, 1 = yes), (5) pumping height of installed pumps, (6) water flow in arcs, (7) land area to irrigate downstream the arcs.	Water quality: N/A. Network analysis: Explicit mathematical formulation. Optimisation method: Steiner tree constructive-based heuristic followed by improved local search heuristic (first subproblem), simple calculation of flows and irrigated areas (second subproblem), CPLEX [207] (third subproblem).	• The paper solves optimal design of a non-looped irrigation system. The problem considered is to find the routes from sources to consumer nodes, water flows in pipes and irrigated areas downstream of pipes, and diameters and thicknesses of pipes, and locations and powers of pumps. • Two new mixed binary nonlinear formulations of the problem are proposed: an initial model and a reformulated model to reduce nonlinearities of the initial model. • To solve the problem, it is sequentially decomposed into the following three subproblems: (i) building the network layout; (ii) computing the water flows and irrigated areas (a system of linear equations); (iii) dimensioning the network pipes and pumps, and locating the pumps (a mixed binary linear problem (MBLP)), defined for the network tree, flows and irrigated areas resulting from the previous two subproblems. • The computational experiments are undertaken using 12 randomly generated networks built from a real network in Portugal [252] to simulate different real case situations. This real network consists of three different zones and contains one source, 39 hydrants, 13 junctions and 279 pipes. • Results: The proposed methodology is suitable for the problem at hand, with the average relative optimality gap calculated for all cases with known optimum 2.30%. • Test networks: (1)–(12) Small test networks consisting of five different types (depending on the dimension of the network irrigated area), each possessing 10 nodes and a number of arcs (ranging between 20 and 40).
71. Haghighi et al. (2011) [178] SO Optimal WDS design using a combined GA and ILP method (GA-ILP) in a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure limits, (2) min/max velocity in the pipes, (3) only one diameter for each pipe can be assigned. Decision variables: (1) Zero-unity variables related to the pipe diameters.	Water quality: N/A. Network analysis: EPANET. Optimisation method: GA-ILP.	• Using ILP, the search space thus the number of evaluations is considerably reduced. • For ILP purposes, the looped network is transformed into a quasi-branched network by ignoring one pipe in each loop. These ignored pipes are not optimised in the ILP, but are assigned a fixed diameter for the objective function calculation. The quasi-branched network is optimised using a BB method. This process creates an inner loop. GA creates an outer loop, where the pipes which were ignored are optimised. The method iterates between ILP and GA. • Results: The GA-ILP method finds the optimal solution in a very fast and efficient manner, which is due to ILP preventing blind and time consuming searches in the GA and promoting each chromosome to a near optimal design. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) two-reservoir network with 34 links (incl. 26 nodes) [45].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
72. Qiao et al. (2011) [163] SO Optimal WDS design using improved PSO (IPSO).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraints. Constraints: (1) Min/(max) pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Not specified. Optimisation method: IPSO.	• The optimisation method combines PSO with disturbance (in order to escape local minima) with DE (in order to keep the population diversity). • IPSO performance is compared with several other methods such as HBMO, Lagrange's method (LM), PSO, random search technique (RST), SFLA and SS. • Results: IPSO performs well and reduces the possibility of trapping into a local optimum. • Test networks: (1) Serial network with 3 pipes (incl. 3 nodes) [253], (2) branched network with 3 pipes (incl. 3 nodes) [253], (3) two-loop network supplied by gravity (incl. 7 nodes) [14].
73. Wu et al. (2011) [73] MO Optimal WDS design and operation including GHG emissions over a planning horizon (i.e., 100 years), analysing sensitivity of tradeoffs between economic costs and GHG emissions, using WSMGA.	Objective (1): Minimise (a) the capital cost of the network including pipes and pumps (i.e., purchase and installation of pipes and pumps, and construction of pump stations), (b) present value of pump replacement/refurbishment costs, (c) present value of pump operating costs (i.e., electricity consumption). Objective (2): Minimise GHG emissions including (a) capital GHG emissions (i.e., manufacturing and installation of pipes), (b) present value of operating GHG emissions (i.e., electricity consumption). Constraints: (1) Min pressure at the nodes, (2) min flowrates within the system. Decision variables: (1) Pipe sizes (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: WSMGA (based on NSGA-II with several modifications).	• An extension of the papers by [72,77] including sensitivity of tradeoffs between total economic costs and GHG emissions to electricity tariff and generation (i.e., emission factors). Three electricity tariff options and three emission factor options both over a time horizon of 100 years are considered. • The pump power estimation method [74] is used to estimate the maximum pump capacity and the annual electricity consumption for calculation of pump operating costs and operating GHG emissions. • To test the sensitivity of the optimisation results to the electricity tariff and emission factors, two optimisation scenarios (each for one factor) are considered. In each scenario, one factor is varied and the remaining factor is set at the moderate value of the three options considered, giving a total of 5 combinations of the two factors. • Results: Electricity tariffs impact significantly on the cost of the network, but little on GHG emissions. High electricity tariffs in the future can remove some networks from the Pareto front, indicating further possible reduction of GHG emissions by managing the water and energy industries jointly. In contrast, emission factors have no effect on the cost of the network. • Test networks: (1) Network with 1 pump, 8 pipes and 3 tanks (incl. 5 nodes) (adapted from [77]).

Table A1. *Cont.*

ID. Authors (Year) [Ref] **SO/MO *** **Brief Description**	**Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)**	**Water Quality** **Network Analysis** **Optimisation Method**	**Notes**
74. Zheng et al. (2011) [111] SO Optimal WDS design and strengthening using a combined NLP and DE method (NLP-DE) in a three-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes, (2) min/max diameter of pipes. Decision variables: (1) Pipe diameters (continuous for NLP, discrete for DE where continuous diameters are rounded to the nearest commercial pipe sizes after the mutation process).	Water quality: N/A. Network analysis: Explicit mathematical formulation for NLP, EPANET for DE. Optimisation method: NLP-DE.	• The methodology consists of three distinct steps as follows. • The shortest distance tree is determined for a looped network. This tree is part of the network graph, which contains only shortest paths from the sources to all demand nodes. It is assumed that the effective way to deliver demands is along the shortest path. The shortest distance tree is identified using a Dijkstra algorithm, which is modified in this paper to cover multisource WDSs. • A NLP solver is applied to the obtained shortest distance tree to optimise pipe diameters. The energy conservation constraint is not considered for NLP, because the shortest distance tree has no loops. The NLP solution with continuous diameters is an approximate solution to the original WDS. Missing pipes from the shortest distance tree are assigned the minimum allowable diameters. • A DE algorithm is applied to optimise the original looped network. The initial population for DE is seeded with diameters in the proximity of the continuous pipe sizes obtained by a NLP solver and with the minimum allowable diameters assigned to the missing pipes in the previous step. • Results: NLP-DE found optimal solutions with an extremely fast convergence speed. In addition, it found the new lowest cost solutions for the test networks (3) and (4). • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49], (3) Zhi Jiang network, China (incl. 113 demand nodes), (4) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].
75. Artina et al. (2012) [70] MO Optimal WDS design using parallel NSGA-II.	Objective (1): Minimise (a) the design cost of the network (pipes). Objective (2): Minimise (a) the penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: Parallel NSGA-II.	• Parallelisation of NSGA-II is implemented in order to reduce the computational time and improve the quality of solutions obtained. • Two parallel models, global and island, are used. In the global model, the selection and mating is performed globally, but "at each generation the fitness evaluation of solutions is distributed in a balanced way". In the island model, the population is divided into several subpopulations (i.e., islands), which evolve independently, but occasionally a migration between islands occurs. Additional parameters are necessary in the island model, being frequency and number of migrating solutions and the criterion for selecting the migrants. • Results: The global model reduces the computational time. On the other hand, the island model improves the quality of solutions due to an introduction of fundamental changes in the algorithm exploration method. Some parameter configurations (i.e., criteria for selecting the migrants) in the island model can find better solutions compared with the serial version of the algorithm. More observations are made in relation to the configuration of island model. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) Modena network, Italy (incl. 272 nodes) [254].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
76. Bragalli et al. (2012) [147] SO Optimal WDS design and strengthening using MINLP.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pipe diameters/pipe cross sectional areas, (2) min/max hydraulic heads, (3) flow bounds. Decision variables: (1) Pipe flows, (2) pipe diameters/pipe cross sectional areas, (3) hydraulic heads at junctions.	Water quality: N/A. Network analysis: Explicit mathematical formulation. Optimisation method: BONMIN (an open source MINLP code) [255] using BB method.	• The methodology starts with preliminary smooth continuous NLP relaxation which accurately models the problem. In the model, the discrete objective function (due to discretised cost data) is transformed into a continuous polynomial, and headloss in pipes (Hazen-Williams) has a smooth relaxation. Subsequently, the diameters are discretised by introducing additional binary variables indicating when a specific diameter is selected for a pipe. They are further replaced by a cross sectional area (in the constraints), which removes the nonlinearities and nonconvexity from flow bound constraints. Finally, a MINLP solver can be applied. The MINLP code has been adapted to better suit the model formulation. • The quality of the solutions obtained is checked by (i) comparing with the lower bounds on the solutions obtained using the global optimisation software Baron [256]; (ii) comparing with other results from the literature obtained mainly by metaheuristics; (iii) implementing and comparing with mixed-integer LP (MILP) technique. • Results: Effective solutions are presented, both in terms of quality and accuracy, which are immediately usable in practice as diameters decrease from the sources towards the points further away from the sources (which is not the case for majority of the methods presented in the literature). • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) Blacksburg network (incl. 31 nodes) [257], (4) New York City tunnels (incl. 20 nodes) [81], (5) Foss_poly_0 network, Italy (incl. 37 nodes) [254], (6) Foss_iron network, Italy (incl. 37 nodes) [254], (7) Foss_poly_1, Italy (incl. 37 nodes) [254], (8) Pescara network, Italy (incl. 71 nodes) [254], (9) Modena network, Italy (incl. 272 nodes) [254]. • Note: Test networks (5)–(9) are available from www.or.deis.unibo.it/research_pages/ORinstances/ORinstances.htm (accessed on 10 September 2017).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
77. Kang and Lansey (2012) [26] SO Optimal WDS design and operation including the integrated transmission-distribution network considering multiple loading conditions using GA with an engineered initial population.	Objective (1): Minimise (a) the pipe construction (the sum of the base installation cost, trenching and excavation, embedment, backfill and compaction costs, and valve, fitting, and hydrant cost), (b) pump construction cost, (c) pump operation cost (energy consumed by pumps), (d) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes for three demand loading conditions (average, instantaneous peak and fire flows). Decision variables: (1) Pipe sizes, pump station capacity including (2) pump sizes and (3) the number of pumps.	Water quality: N/A. Network analysis: EPANET. Optimisation method: GA (for optimisation), a new heuristic (for generating an engineered initial population to improve the GA convergence).	• The optimisation of integrated transmission-distribution network is presented. The distribution network (a part of the system which delivers water to individual households) is usually not considered in the WDS design optimisation because of the large number of variables. • A new heuristic is proposed to generate initial population considering hydraulic behaviour of the system, so the velocities in the selected pipe sizes fall below the pre-defined flow velocity threshold. To maintain the diversity in the optimisation process, half of the initial population is generated by the new heuristic and the other half randomly. • The following main assumptions are made: no uncertainty in demand, one constant efficiency parameter to represent pumps, constant energy tariff, and one fire flow demand pattern. • There are 4 design scenarios considered: (i) the distribution network is excluded from the model; (ii) the distribution network is included in the model, but its pipe sizes are fixed at minimum values (i.e., are not optimised); (iii) and (iv) both transmission and distribution networks are included in the model, the initial population is generated by the proposed heuristic and randomly, respectively. • Results: The comparison of scenarios (i) and (ii) shows that the pipes in the transmission network tend to be oversized if the distribution network is excluded from the model. The comparison of scenarios (iii) and (iv) shows that the new heuristic considerably improves the convergence of the GA in terms of speed as well as the quality of the solution. • Test networks: (1) Real system with one source, one pump station and 1274 pipes (incl. 936 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions $^{+}$, Constraints **, Decision Variables $^{++}$)	Water Quality Network Analysis Optimisation Method	Notes
78. Kanta et al. (2012) [92] MO Optimal WDS redesign/rehabilitation (pipe replacement) including fire damage and water quality objectives using non-dominated sorting evolution strategy (NSES).	Objective (1): Minimise (a) the potential fire damage, calculated as lack of available fire flows at selected hydrant nodes taking into account the importance of a hydrant location. Objective (2): Minimise (a) the water quality deficiencies, represented by a performance function on chlorine residual at selected monitoring nodes reflecting governmental regulations for drinking water quality. Objective (3): Minimise (a) the system redesign cost, expressed as a ratio of actual redesign cost over maximum expected redesign cost. Constraints: (1) Min pressure at the hydrant nodes, (2) pipe diameters limited to commercially available sizes, (3) max number of pipe decision variables (i.e., pipes to be replaced). Decision variables: (1) Pipes selected for replacement (integer), (2) diameters of replaced pipes (integer). Note: One MO model including all objectives.	Water quality: Disinfectant (i.e., chlorine). Network analysis: EPANET (demand-driven analysis to calculate the fire flows, using a hydrant lifting technique to satisfy the pressure constraint). Optimisation method: NSES.	• The method provides the flexibility to select a mitigation plan for urban fire events best suited for decision makers' needs. • NSES, a modification of NSGA-II for an evolution strategy (ES)-based implementation to address difficulties for heuristics posed by WDS optimisation problems, is proposed. It differs from the standard NSGA-II in the application of specialised operators, such as representation, mutation and selection. • NSES is tested on three test problems of varying degrees of difficulty and compared to NSGA-II and PAES using a deviation metric [258]. Subsequently, it is applied to a WDS optimisation problem using two scenarios, fire flow at three and six hydrants, respectively. • EPANET simulations are executed as follows. Fire flow analysis is performed separately for each hydrant. Water quality analysis (incl. hydraulics) is simulated without a fire flow demand over 168 hours to reach dynamic equilibrium for chlorine residuals. • Results: NSES outperforms (for three test problems used) both NSGA-II and PAES in spreading solutions across the Pareto front and in maintaining solution diversity. NSES also demonstrated the capability to produce Pareto optimal solutions across several objectives. However, almost no solutions were found in the 'high fire flow—low water quality—high cost' region of the objective domain, which is influenced by the disinfectant decay parameters and the characteristics of the particular WDS. • Test networks: (1) Virtual city of Micropolis (incl. 1262 nodes) [259,260].
79. McClymont et al. (2012) [194] SO Optimal WDS rehabilitation (pipe resizing) using ES with evolved mutation heuristics.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure at the nodes, (2) max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Not specified. Optimisation method: ES.	• A decision tree generative hyper-heuristic approach is presented which uses genetic programming (GP) to evolve novel mutation heuristics for the WDS design optimisation. The decision tree is based on domain knowledge in the form of node head conditions to inform the mutation to upstream pipes. For example, the upstream pipes may be too large or too small if a node has excessive head or head deficit, respectively. • Mutation heuristics evolve using NSGA-II and are evaluated on their ability to search for good solutions to the Hanoi test problem. The best 5 mutation heuristics are compared against a tuned Gaussian mutation using the Anytown network and three real networks. • Results: The importance of testing evolved heuristics for over-fitting is highlighted. Mutation heuristics display an improvement in performance over traditional heuristics such as Gaussian mutation. • Test networks: (1) Anytown network (incl. 19 nodes) [84], (2) real network with 7 pipes, (3) real network with 29 pipes, (4) real network with 81 pipes.

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
80. Sedki and Ouazar (2012) [172] SO Optimal WDS design and strengthening using a combined PSO and DE method (PSO-DE).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: PSO-DE.	• A hybrid PSO-DE method is developed to overcome the problem of premature convergence in PSO. In this method, PSO finds the region of optimal solution, then combined PSO and DE find the optimal point. • PSO-DE is compared to the standard PSO as well as other methods from the literature (ACO, CE, GA, HS, SA, SFLA, SS). • Results: For the two-loop and Hanoi networks, PSO-DE found the best-known solution in fewer iterations than other algorithms. For the New York City tunnels, PSO-DE found a slightly better feasible solution in a lower number of evaluations than the solution reported in the literature to date. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81].
81. Wu et al. (2012) [74] MO Optimal WDS design, operation and maintenance including GHG emissions, incorporating variable speed pumps (VSPs) using MOGA.	Objective (1): Minimise the total economic cost of the system including (a) capital cost (i.e., purchase, installation and construction of network components), (b) present value of operating costs (i.e., electricity consumption due to pumping), (c) present value of maintenance and end-of-life costs. Objective (2): Minimise the total GHG emissions of the system including (a) capital GHG emissions (i.e., manufacturing and installation of network components), (b) present value of operating GHG emissions (i.e., electricity consumption due to pumping), (c) present value of maintenance and end-of-life emissions. Constraints: (1) Min flowrates within the system. Decision variables: (1) Pipe sizes (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: MOGA.	• The aim is to incorporate VSPs into an optimal design of WDSs. • A pump power estimation method is developed to incorporate VSPs. This method uses a flow control valve (FCV) combined with an upstream reservoir to represent a pump in the system, so that the flows (via FCV) into the downstream tanks are maintained as close as possible to the required flows. Therefore, the task of determining the most appropriate FCV setting for calculating pump power is formulated as a single-objective minimisation problem subject to multiple flow constraints. To solve this problem, the false position method [261] in conjunction with EPANET is used. • VSPs are compared to FSPs within the defined multi-objective optimisation problem. • In the case study, only capital and operating costs and emissions are considered (maintenance and end-of-life costs and emissions are omitted). • Results: The use of VSPs leads to significant savings in total cost as well as GHG emissions. "The effectiveness of replacing FSPs with VSPs in reducing operating costs and emissions is more significant for a smaller pipe diameter system with higher dynamic heads (friction losses) relative to static heads". • Test networks: Network with 1 pump, 8 pipes and 3 tanks (incl. 5 nodes) [77].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
82. Fu et al. (2013) [97] MO Optimal WDS strengthening, expansion, rehabilitation and operation including multiple loading conditions and water quality objective applying many-objective visual analytics using ε-NSGA-II.	Objective (1): Minimise the capital cost for network expansion/rehabilitation including (a) pipes, (b) storage tanks, (c) pumps. Objective (2): Minimise (a) the operating cost of the system (i.e., energy cost for pump operation) during a design period. Objective (3): Minimise hydraulic failure of the system, expressed by the total system failure index (SFI) combining (a) nodal failure index and (b) tank failure index. Objective (4): Minimise (a) the fire flow deficit, representing the potential fire damage. Objective (5): Minimise (a) the total leakage of the system, considering background leakage from pipes only (calculated based on the pipe pressure). Objective (6): Minimise (a) the water age. Constraints: N/A. Decision variables: (1) Pipe diameters for new pipes (integer), (2) options for existing pipes including cleaning and lining or duplicating with a parallel pipe (integer), (3) tank locations (integer), (4) the number of pumps in operation during 24 hours (integer). Note: One MO model including all objectives.	Water quality: Water age (as a surrogate measure for water quality). Network analysis: Pressure-driven demand extension of EPANET (EPANETpdd) (EPS). Optimisation method: ε-NSGA-II.	• The optimisation model is formulated with no constraints, because the objective functions used meet all the criteria. • Nodal hydraulic failure is quantified as a fraction of time during which pressure at the node drops below the required pressure, the consequence of which is defined as water shortage at this node relative to the total demand of the entire WDS at that time. • Tank hydraulic failure is identified by the water level at the end of EPS being lower than at the beginning of simulation, which can cause potential problems for the following time period. • Five loading conditions are considered: average day flow, instantaneous flow, and three fire flow conditions. • The fire flow deficit objective is considered as the average deficit across the three fire flow conditions. • The leakage and water age are calculated for the average day flow condition. • ε-NSGAII is chosen over NSGA-II as it has a better computational efficiency, which is important for many-objective optimisation due to a high computational burden. • Visual analytics are used to explore the tradeoffs between 6 objectives. The visualisation of the 6 objectives is achieved by placing three objectives (capital costs, system failure and leakage) on axes in a 3D chart, and representing the other 3 objectives through the colour, orientation and size of the cones which indicate the solutions. Also, lower-dimensional subproblem tradeoffs can be observed using convention Pareto fronts in 2D and 3D. • Results: The results indicate relationships between individual objectives. For example, the capital and operating costs have a very different relationship with water age and leakage, which would not be revealed if the costs were aggregated into one objective. This paper highlights benefits therefore of many-objective optimisation approach in supporting more informed, transparent decision-making in the WDS design process. • Test networks: (1) Anytown network (incl. 19 nodes) [84].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
83. Kang and Lansey (2013) [121] MO Scenario-based robust optimal planning of an integrated water and wastewater system considering demand uncertainties using NSGA-II.	Objective (1): Minimise (a) the systems initial construction cost (pipes, pumps, tanks, wastewater plants), (b) expected operation and maintenance costs, (c) adaptive construction cost to expand the system if needed, (d) penalty cost for violating constraints. Objective (2): Minimise (a) the variability of actual costs across scenarios for the design solution, calculated as the standard deviation. Constraints: (1) Min pressure at the nodes, (2) min velocity in the sewer pipes, (3) max pump station capacities, (4) max storage tank sizes. Decision variables: (1) Pipe sizes (discrete), (2) pump station capacities (discrete), (3) wastewater treatment plant capacities (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Not specified. Optimisation method: NSGA-II.	• Scenario-based multi-objective robust optimisation (SMORO) model for planning and designing a regional scale integrated water and wastewater system is proposed. SMORO solves deterministic problems in a scenario-based structure to effectively implement the stochastic factors inherent in the problem. • Uncertain parameters in the model are potable and reclaimed water demands, which are implemented through scenarios. A set of 5 scenarios (base condition, low growth, high growth, low reclamation, high reclamation) is developed, with the same probability assigned to each scenario. • Initially, the problem is solved individually for every scenario as regular single-objective optimisation problems. Subsequently, postoptimisation regret computation is performed. The regret cost is an overpayment or a supplementary cost due to overdesign or underdesign, respectively, owing to the implemented decision being made with imperfect information about the future. “In other words, the regret cost represents the risk that the implemented decision will be more costly than a decision made”. Finally, the multi-objective problem with two objectives (costs and variability) is solved simultaneously for all scenarios. • Results: A single-objective solution is cost effective only for the design scenario; but in all other cases is inferior with possibly substantial regret cost. In contrast, SMORO provides a robust and flexible system design via a balanced solution in terms of initial investment and future risk. It is demonstrated that system demand is the most critical uncertainty in system design. • Test networks: (1) Water system planning (water supply and reuse water networks) in southeast Tucson, Arizona.

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
84. McClymont et al. (2013) [144] MO Optimal WDS design and rehabilitation including the water discolouration risk using NSGA-II and SPEA2 integrated with a new heuristic Markov-chain hyper-heuristic (MCHH).	Objective (1): Minimise (a) the cost of network infrastructure (pipes), (b) penalty for violating the pressure constraint, (c) penalty for violating the velocity constraint. Objective (2): Minimise (a) the water discolouration risk expressed as the sum of cumulative potential material after daily conditioning shear stress for all pipes in the network, (b) penalty for violating the pressure constraint, (c) penalty for violating the velocity constraint. Objective (3): Minimise (a) the sum of the cumulative head excess, (b) penalty for violating the pressure constraint, (c) penalty for violating the velocity constraint. Constraints: (1) Min head at the nodes, (2) max velocity in the pipes. Decision variables: (1) Pipe diameters. Note: One MO model including all objectives.	Water quality: Water discolouration. Network analysis: EPANET, discoloration propensity model (DPM). Optimisation method: NSGA-II and SPEA2 integrated with MCHH.	• This paper presents least-cost design of WDSs with a reduced risk of water discolouration (i.e., self-cleaning networks), thus reduced long-term maintenance and operational burdens of the system. • A new heuristic MCHH is proposed. It is applied after each generation of solutions having been attained and evaluated. Essentially, MCHH learns which simple heuristic within the algorithm (e.g., crossover, mutation) performs most effectively and adjusts the likelihood of their selection accordingly. • For the optimisation, NSGA-II and SPEA2 are integrated with MCHH. Four extra heuristics in addition to crossover and mutation are supplied to the algorithms with MCHH. Both the original algorithms NSGA-II and SPEA2 and the MCHH variants are run on the problem. • For comparison, NSGA-II and SPEA2 are also integrated with two other hyper-heuristics (Simple Random and TSRoulWheel). • To calculate the discoloration risk, DPM software which implements a cohesive transport model (CTM) [262,263] is used. So, the algorithms are linked with both EPANET and DPM. • Results: An improvement in performance obtained by MCHH variants over the original algorithms is demonstrated. When compared with Simple Random and TSRoulWheel, it is shown that MCHH is able to find a wider range of solutions across the networks. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Anytown network (incl. 19 nodes) [84], (3) Hanoi network (incl. 32 nodes) [49], (4) small network with 68 pipes, South West of England (incl. 52 nodes), (5) medium-size network with 107 pipes, South West of England, (incl. 81 nodes), (6) large network with 213 pipes, South West of England (incl. 160 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] **SO/MO *** **Brief Description**	**Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)**	**Water Quality** **Network Analysis** **Optimisation Method**	**Notes**
85. Zhang et al. (2013) [134] SO Optimal design, strengthening, expansion and operation of a reclaimed WDS considering demand uncertainty with the time-staged construction over a planning horizon (i.e., 20 years) using ILP.	Objective (1): Minimise (a) the cost of installing pipes, (b) cost of constructing pump stations, (c) pump energy cost of operating the system, at the stage one (time horizon 0–10 years), (d) expected cost of installing additional pipes, pumps and operating the system, at the stage two (time horizon 10–20 years). Constraints: (1) Min pressure at the nodes for peak demands, (2) min pressure at the nodes for average demands, (3) only one pipe size selected for each link, (4) only one pump size selected for average demands, (5) only one pump size selected for peak demands, (6) ensuring that the existing pump station is either expanded or a new one constructed at the stage two, (7) binary constraints. Decision variables (stage 1): (1) Pipe of size *j* installed in link *i*, (2) pump size *p* installed at station *s* for peak demands, (3) same as (2) for average demands. Decision variables (stage 2): (4) Additional pipe of size *k* installed for link *i*, (5) if no pump installed at stage 1, pump size *p* installed at station *s* for peak demands, (6) if pump installed at stage 1, additional pump of size *p* installed at station *s* for peak demands, (7) pump size *p* installed at station *s* for average demands. Note: All decision variables are binary (0 = no, 1 = yes).	Water quality: N/A. Network analysis: Explicit mathematical formulation. Optimisation method: GAMS CPLEX solver [207] using branch and cut method.	• The paper presents a two-stage stochastic integer problem for a planning horizon of 20 years, so there are 2 stages of construction decisions: current decisions (for time horizon 0–10 years) and expansion decisions in 10 years' time (for time horizon 10–20 years). • The network structure is branched (due to reliability not being as important in a reclaimed water network), nonlinear hydraulic equations are linearised. • Preprocessing methods are developed to reduce the dimensionality of the problem (i.e., reducing the number of pipe and pump decisions). The network is separated into subnetworks, and pipe and pump size reduction is performed for each subnetwork. The set of permissible pipe diameters is reduced using velocity constraints. Each subnetwork is solved separately. • Uncertain future demands in expansion prospects (stage 2) of the system are considered. The uncertainties are handled by a discrete set of scenarios, with 81 scenarios used in the test problem. • Sensitivity analysis is performed to test changes in total cost, and pipe and pump decisions under varying demands, energy costs, annual discount rates and pipe material prices. • Results: Preprocessing considerably reduces problem dimension, improves solution quality, and enables to solve large problems. In regards to sensitivity analysis, mean demands are the most significant driving factor with respect to total costs. • Test networks: (1) Network with one source (wastewater treatment plant), 4 pump stations and 56 pipes (incl. 56 demand nodes).
86. Zheng et al. (2013) [46] SO Optimal design of a multisource WDS using network decomposition and DE in a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: DE (the modification based on the approach of [171] to manage a discrete problem).	• The proposed method consists of the following two steps. • Network decomposition: A graph decomposition method is developed to divide the original network into subnetworks, so that the only one unique source supplies each subnetwork. • Multistage optimisation: Each subnetwork is optimised (i.e., first-stage optimisation) using DE. The combined optimal solutions for the subnetworks produce an approximate solution for the total network. However, this approximate optimal solution needs to be further improved because some of the pipes were not included in the optimisation due to network partitioning. Therefore, the entire original network is optimised (i.e., second-stage optimisation) using the initial population seeded from the optimal solutions of the subnetworks obtained from the first-stage optimisation. • Results: The final solution from the second-stage optimisation is close to the approximate solution found in the first-stage optimisation. Comparison with the standard DE (a whole of network optimisation) and other methods from the literature demonstrate that the proposed method exhibits better performance in terms of solution quality and convergence speed. • Test networks: (1) Two-reservoir network (incl. 4 nodes), (2) two-reservoir network with 34 links (incl. 26 nodes) [45], (3) real three-reservoir network, China (incl. 199 demand nodes), (4) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
87. Zheng et al. (2013) [173] SO Optimal WDS design and strengthening using a self-adaptive DE method (SADE).	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min head at the nodes. Decision variables: (1) Pipe diameters (integer, with continuous values created during the mutation process which are then truncated to the nearest integer size).	Water quality: N/A. Network analysis: EPANET. Optimisation method: SADE.	• The paper introduces three new contributions as follows. • Mutation weighting factor (F) and crossover probability (CR) parameters of the SADE are encoded into a solution string and hence are adapted through evolution (i.e., are not pre-specified). • F and CR parameters are applied at the individual level rather than generational level like in the standard DE, so different parameters can be used for different individuals. • A new termination criterion for the SADE is proposed. The algorithm is terminated when all the individuals in the population have similar objective function values, which is checked using the coefficient of variation. • Constraint tournament selection [148] is used to handle constraints. • A sensitivity analysis is performed for different population sizes. • Results: The SADE displays good performance for both the solution quality and efficiency, with a reduced need to fine-tune algorithm parameter values. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49], (2) double New York City tunnels (incl. 39 nodes) [201], (4) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].
88. Zheng et al. (2013) [149] SO Optimal WDS design and strengthening using non-crossover dither creeping mutation-based GA (CMBGA).	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: CMBGA.	• Unlike the standard GA, the proposed CMBGA does not use crossover. It only uses selection and newly proposed dither creeping mutation replacing generally used bitwise mutation. The new parameter is randomly generated throughout the algorithm run rather than being preselected. It is also varies for each individual of the population. • To handle constraints, constraint tournament selection [148] is used. • CMBGA is compared with 4 other GA variants, including a crossover-based GA with bitwise mutation (SGA), a crossover-based GA with creeping mutation (CGA), a non-crossover GA with traditional bitwise mutation (NBGA), and a crossover dither creeping mutation GA (CDGA). • Results: CMBGA exhibits improvements in finding optimal solutions compared with the other GA variants and displays a comparable performance to the other EAs (MMAS and HD-DDS). • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49].

Table A1. *Cont.*

ID. Authors (Year) [Ref] **SO/MO *** **Brief Description**	**Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)**	**Water Quality** **Network Analysis** **Optimisation Method**	**Notes**
89. Aghdam et al. (2014) [164] SO Optimal WDS design and strengthening using accelerated momentum PSO (AMPSO).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: AMPSO.	• A new version of PSO called AMPSO is proposed in order to increase the convergence rate of the algorithm and avoid getting trapped in local optima. • The increased convergence rate is achieved by introducing new adaptive terms into the velocity update equation of the algorithm. These terms decrease or increase the movement step size relative to being close or far from the global optimum, respectively. The convergence rate can be thus enhanced by large or short steps proportional to the value of the cost function. • To avoid getting trapped in local minima, so-called momentum terms are introduced into the position updating formula of the algorithm. These momentum terms "determine the influence of the past position changes on the current direction of movement in the search space". • AMPSO is compared with three other heuristic methods from the literature (GA, ACO and PSO-DE). • Results: AMPSO exhibits the efficiency when compared with other heuristics. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) New York City tunnels (incl. 20 nodes) [81].
90. Bi and Dandy (2014) [27] SO Optimal WDS design and strengthening including water quality considerations using online ANN and DE.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) the net present value of chlorine cost over a planning horizon. Constraints: (1) Min head at the nodes, (2) min chlorine concentration at the nodes. Decision variables: (1) Pipe diameters (discrete), (2) chlorine dosage rates at the WTPs.	Water quality: Chlorine. Network analysis: Online ANN. Optimisation method: DE.	• ANN is proposed to replace a hydraulic and water quality simulator in order to reduce the computational effort of those simulations. Online DE-ANN method is designed, where ANN is retrained throughout the optimisation process (so called online ANN) to improve approximation of the portion of search space under consideration and DE performs the optimisation. A local search strategy is used to improve the final solution obtained by DE-ANN. • To reduce the run time, the ANN training is performed only for the selected critical nodes, which are determined before the optimisation using data from EPANET. There are 3 parameters used for training: the size of the training data, the number of generations between retrainings, and the number of retrainings. • To ensure the feasibility of generated solutions at each generation, the best solution is compared to the previous generations' best solution. If different, it is checked by EPANET for feasibility, if cheaper, it is noted as the current best solution. • The demands for the test network (1) are constant, whereas for the test networks (2) and (3) they vary within the 24 h cycle. • The performance of the proposed online DE-ANN method is compared with the DE-EPANET method and offline DE-ANN method where the ANN model is trained only at the beginning of the optimisation (see, for example, [87,264]. • Results: The online DE-ANN outperforms the offline DE-ANN in terms of efficiency and solution quality. In comparison to DE-EPANET, the online DE-ANN displays a substantial improvement in computational efficiency, while still producing good quality solutions. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) modified New York City tunnels (incl. 20 nodes), (3) hypothetical Jilin network (incl. 28 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
91. Creaco et al. (2014) [118] MO Optimal WDS design, strengthening and expansion accounting for construction phasing in prefixed time intervals (i.e., 25 years) over a planning horizon (i.e., 100 years) using NSGA-II.	Objective (1): Minimise (a) the total present worth construction cost of the network (pipes), calculated as the sum of the present worth costs of the n upgrades, (b) penalty for violating the pressure surplus constraint. Objective (2): Maximise (a) the network reliability, calculated as the minimum pressure surplus over the whole construction time. Constraints: (1) Pressure surplus bigger or equal to zero. Decision variables: (1) Pipe diameters (coded as integer numbers), with the genes consistently ordered (within each individual) according to the construction phases. Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Demand-driven analysis [11]. Optimisation method: Modified NSGA-II.	• The aim is to optimise a phased WDS construction in prefixed time intervals over an expected life cycle, where nodal demands increase in time without uncertainty. • Modified NSGA-II used encodes genes with integer numbers instead of real numbers. • The solutions provide the pipe diameters which have to be laid in the various sites (inclusive of pipes laid in parallel to existing pipes) at the various time intervals. • The following two scenarios are considered for network growth: (i) the network topology is constant in time, so no network expansion occurs over the planning horizon; (ii) the network topology changes in time, so network expansion occurs over the planning horizon. • Three different types of optimisation are performed for each network scenario as follows: (i) four construction phases with 25-year intervals over 100-year planning horizon; (ii) one construction phase over 25-year planning horizon; (iii) one construction phase over 100-year planning horizon. The objective is to assess how construction phasing affects network design. • Results: Optimisation of WDS design with construction phasing leads to better results than the traditional single construction phase approach. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14].
92. Ezzeldin et al. (2014) [165] SO Optimal WDS design using integer discrete PSO (IDPSO).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes, (2) min/max pipe diameters. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Newton-Raphson method [10]. Optimisation method: IDPSONET program using IDPSO.	• A new boundary condition and a new initialisation method are proposed for PSO. • The boundary condition is called billiard boundary condition. When a particle reaches the boundary, it is reflected back to the search space with its velocity remaining the same (only the sign changes). This technique gives the particle a bigger chance to find its global solution. Usually, a velocity clamping technique is used in PSO. The new boundary condition is tested against 5 other boundary conditions for the two-loop network. • In a new initialisation method, the initial position of the solution vector is set to one side of the boundary with the maximum available diameters. • Results: IDPSO reached the known optimal solution in a reduced number of evaluations for the two-loop network, and it improved the solutions previously found in the literature for the two-reservoir network. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) two-reservoir network with 34 links (incl. 26 nodes) [45].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
93. Johns et al. (2014) [155] SO Optimal WDS design, strengthening and operation using adaptive locally constrained GA (ALCO-GA).	Objective (1): Minimise (a) (all test networks) the design cost of the network (pipes), (b) (test network (4) only) cost of tanks, (c) (test network (4) only) pump energy cost. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete), (2) (test network (4) only) tank locations (binary), (3) (test network (4) only) the number of pumps in operation during 24 h at every 1-h time step (binary).	Water quality: N/A. Network analysis: Not specified. Optimisation method: ALCO-GA.	• Heuristic-based mutation operator which utilises hydraulic head information and an elementary heuristic to allow earlier location of feasible solutions in the optimisation process are proposed. • Constraint handling is performed through the use of the modified mutation operator. • If only the heuristic-based mutation operator is applied (i.e., without random bitwise mutation) throughout the whole optimisation process, it causes premature convergence on a suboptimal solution. Therefore, the fitness gradient monitor is employed, which controls the probability that the heuristic-based mutation operator is used based on the rate of convergence of the best solution in the population. • Results: ALCO-GA displays faster convergence than the standard GA and often obtains better solutions than solutions from the literature obtained by the standard GA. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) New York City tunnels (incl. 20 nodes) [81], (3) network B: real network with a single reservoir and 1277 pipes, UK (incl. 1106 nodes), (4) modified Anytown network (incl. 19 nodes) [84] (the options to duplicate/clean/line existing pipes are removed).
94. McClymont et al. (2014) [68] MO Optimal WDS rehabilitation (pipe resizing) using ES with evolved mutation operators in a three-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes). Objective (2): Minimise (a) the total head deficit at the nodes. Constraints: N/A. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Not specified. Optimisation method: ES.	• An extension of the paper by [194] developing a hyper-heuristic approach by using GP to evolve (optimise) mutation operators for the bi-objective WDS design optimisation. • A generative hyper-heuristic framework consists of the following three phases. • Initialisation phase, which generates random population of mutation operators and sample network designs (using the Hanoi training network) which are fixed. • Generation phase, which creates an optimisation loop, where the mutation operators are varied and evaluated using sample network designs. The best mutation operators are then selected to propagate into the next generation and the process repeats until a termination criterion is met. SPEA2 is used to optimise mutation operators. • Evaluation phase, which evaluates the best evolved mutation operators and applies them to a set of three test networks (the Anytown network and two real networks). • A comparison of the best 10 varied evolved mutation operators with each other and also with the standard Gaussian mutation operator is performed using the hypervolume indicator [265]. • Results: The method enables to classify the evolved mutation operators in terms of their robustness and impact on convergence characteristics. • Test networks: (1) Anytown network (incl. 19 nodes) [84], (2) real network with one source, (3) real network with two sources.

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
95. Roshani and Filion (2014) [124] MO Optimal WDS rehabilitation, strengthening, expansion and operation with asset management strategies over a planning horizon (i.e., 20 years) using NSGA-II with event-based coding.	Objective (1): Minimise the present value of the capital costs of the network including (a) pipe replacement, (b) pipe duplication, (c) pipe lining, (d) installation of new pipes. Objective (2): Minimise the present value of the operating costs including (a) lost water to leakage, (b) break repair, (c) electricity to pump water. Constraints: (1) Max yearly annual budget for the total of all costs (excluding leakage), (2) min pressure at the nodes, (3) max velocity in the pipes. Decision variables: (1) Time of rehabilitation, (2) place of rehabilitation, type of rehabilitation including (3) the diameter of a pipe being replaced/duplicated and (4) the diameter of a new pipe in an area slated for future growth, (5) the type of lining technology used. Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II.	• An event-based algorithm for optimal timing of water main rehabilitation is introduced. A new gene coding scheme, which reduces the chromosome length, thus saves computer memory and increases speed of convergence, is developed. The chromosome length is reduced by only coding the rehabilitation events, rather than coding all years of the planning horizon (20 years) with mostly zero entries where no rehabilitation occurs. • Savings achieved using asset management strategies by synchronising road reconstruction works with water main replacement/rehabilitation (called infrastructure adjacency discount) and obtaining discounts for purchasing large numbers of water main pipes (called quantity discount) are accounted for. • Four scenarios are used to investigate the impact of different asset management strategies on the optimisation process, where different variations of infrastructure adjacency discounts, quantity discounts and annual budget constraints are applied. • Pipe leakage, pipe break and pipe roughness forecasting models are used. Sensitivity analysis is performed to examine the sensitivity of the capital and operation costs to uncertainties in water demands, initial break rate, break growth rate, initial leak rate, leak growth rate, and pipe roughness. • Results: A budget constraint prohibits from investing early and heavily in pipe rehabilitation. This pipe rehabilitation postponement leads to an increase in operation costs linked to leakage, breaks and energy use in unimproved pipes. The capital and operation costs decrease when applying discounts, with pipe lining being favoured over pipe replacement and duplication. • Test networks: (1) Fairfield network in Amherstview and Odessa, Ontario, Canada.
96. Zheng et al. (2014) [179] SO Optimal WDS design and strengthening using a combined binary LP and DE method (BLP-DE) in a three-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the nodal head requirement. Constraints: (1) Total head loss used by the pipes (from the source to a node) should be less than the value of the head at the source minus the head requirement at a node, (2) only one pipe diameter selected for each link. Decision variables: (1) Pipe diameters (binary for BLP, continuous for DE rounded to the nearest commercially available discrete diameters after the mutation process).	Water quality: N/A. Network analysis: EPANET Optimisation method: BLP-DE.	• The proposed BLP-DE method takes advantages of both BLP (being able to efficiently provide a global optimum for a tree network) and DE (being able to generate good quality solutions for a loop network with a reduced search space). However, this method is not appropriate for least-cost design of networks, which have only loops or only trees. • The proposed BLP-DE method involves the following three stages: (i) network decomposition into trees and the core using a graph algorithm; (ii) optimisation of the trees using BLP; (iii) optimisation of the core using DE while incorporating the optimal solutions for the trees. • Results: For the New York City tunnels and Hanoi networks, BLP-DE found the best-known solutions with a significantly improved efficiency compared to numerous other algorithms from the literature. For the real network, BLP-DE found better quality solutions than standard DE (SDE) also with an improved efficiency. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49], (3) real network with one source and 96 pipes, China (incl. 85 demand nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
97. Basupi and Kapelan (2015) [135] MO Optimal flexible WDS strengthening, expansion, rehabilitation and operation considering demand uncertainty and optional intervention paths in prefixed time intervals (i.e., 25 years) over a planning horizon (i.e., 50 years) using NSGA-II.	Objective (1): Minimise the total intervention cost including (a) capital cost of rehabilitation intervention, (b) pump energy consumption cost. Objective (2): Maximise (a) the end-of-planning horizon system resilience, using a resilience index [266]. Constraints: (1) Min head requirement at the nodes. Decision variables: Intervention options (discrete) including (1) addition of new pipes, (2) duplication/cleaning/lining of existing pipes, (3) addition and (4) sizing of new tanks, (5) pump schedules, (6) threshold demands (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II.	• Future demand uncertainty, following a probability density function, is considered. Simulations (Monte Carlo or Latin Hypercube) around the traditionally projected water demand are employed to reflect the possible scenarios of future demand realisation at certain decision points. • Decision trees are used to represent the uncertain demands and the respective flexible design intervention plans. The decision tree has optional intervention paths consisting of a set of intervention measures. There is path-dependence, which means that the extent of future design interventions depends on the previous intervention path undertaken. • Planning horizon of 50 years, divided into two design stages of 25 years, is used. • The proposed flexible design with optional intervention paths into the future is compared with the deterministic design with a single set of interventions for each design stage's future demand in the analysed planning horizon. • The sensitivity analyses of both the cost discount rate and the standard deviation scenarios across the planning horizon are investigated. • Results: The optimal flexible design under future demand uncertainty outperforms the corresponding optimal deterministic design in terms of the cost and resilience objectives, because it enables the system to adapt in addition to simply postpone interventions. The flexible design methodology is more sensitive to the cost discount rate than the level of demand uncertainty. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Anytown network (incl. 19 nodes) [84].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
98. Bi et al. (2015) [108] SO Optimal WDS design using GA with an engineered initial population.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraints. Constraints: (1) Min/(max) pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: GA (for optimisation), a new heuristic called prescreened heuristic sampling method (PHSM) (for generating an engineered initial population to improve the GA convergence).	• A new PHSM is proposed to determine the initial population of the EAs using engineering experience and domain knowledge to improve convergence of the algorithms. • The PHSM procedure is designed as follows: (i) assigning pipe sizes based on the knowledge that pipe diameters decrease with a greater distance from sources; (ii) adjusting pipe sizes based on the velocity threshold; (iii) ensuring diversity in the initial population by generating it from a distribution, so pipe diameters from step (ii) have the highest probability of being selected. • PHSM is compared to Kang and Lansey's sampling method (KLSM) [26] and two other sampling methods which do not use domain knowledge, such as random sampling (RS) and Latin hypercube sampling (LHS). • The number of decision variables of 7 test networks used varies from 34 to 1274. • Results: PHSM outperforms other sampling methods in terms of computational efficiency as well as the solution quality, and its advantage increases with network size. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) extended Hanoi network (incl. 32 nodes) (a number of diameter options is increased), (3) Zhi Jiang (ZJ) network, China (incl. 113 demand nodes) [111], (4) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50], (5) rural network (incl. 379 nodes) [154], (6) Foss_poly_1, Italy (incl. 37 nodes) [147], (7) modified Kang and Lansey's network (KLmod) (incl. 936 nodes) [26].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
99. Creaco et al. (2015) [136] MO Optimal WDS design, strengthening and expansion accounting for demand uncertainty and construction phasing in prefixed time intervals (i.e., 25 years) over a planning horizon (i.e., 100 years) using NSGA-II.	Objective (1): Minimise (a) the total present worth construction cost of the network including (a) the cost of installing pipes at new sites, (b) cost of installing pipes in parallel to existing pipes. Objective (2): Maximise (a) the network reliability, calculated as the minimum pressure surplus over the whole construction time. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (coded as integer numbers). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Demand-driven analysis [11]. Optimisation method: Modified NSGA-II.	• An extension of the paper by [118] taking into account uncertainty in demand growth. "The uncertainty in the water demand is obtained by expressing the parameters of the demand-growth model by means of a (discrete) random variable of given probability mass function". • A set of 81 demand-growth scenarios is developed, the first three of which have a constant demand-growth rate, whereas the others have a randomly variable demand-growth rate over the planning horizon. The reliability which is maximised in the second objective is in fact a discrete random variable, reflecting different demand-growth scenarios. • Four construction phases with 25-year intervals over 100-year planning horizon are considered. The number of pipes to be inserted at each phase is assumed to be known. • Different types of optimisation are performed: (i) probabilistic second objective optimisation using the entire set of 81 demand-growth scenarios; (ii) deterministic second objective optimisations, applying a constant demand-growth rate (i.e., the first three demand-growth scenarios), where the second objective function is the crisp minimum temporal surplus (instead of the discrete random variable) over the planning horizon. • Results: Optimisation of construction phasing, accounting for demand growth uncertainty, leads to the network being sized more conservatively (larger pipe diameters are evident mainly in the first construction phases), which makes the network more flexible to adapt itself to various conditions of demand growth over time. • Test networks: (1) Network of a town in northern Italy (incl. 26 nodes) [267], skeletonised from the original network [268].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
100. Dziedzic and Karney (2015) [119] SO Optimal WDS design, strengthening and operation considering multiple loading conditions over a planning horizon (i.e., 20 years) using cost gradient-based heuristic method with computational time savings.	Objective (1): Minimise (a) the pump energy cost, (b) damage cost, (c) capital cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: Cost gradient-based heuristic method.	• The aim is to reduce the computational time of the optimisation process of a WDS with multiple loading conditions. • A gradient search is applied and the objective function is approximated by shortening the extended period analysis. So, a shorter time period is used to estimate the hydraulic variations of the system and the costs for the full planning horizon. The demands within the shorter time cycle (TC) should match the demand probabilities in the full analysis period and their variation. • The ratio between the gradients of energy dissipation cost, damage cost and pipe cost is calculated at each iteration (i.e., one TC). The pipes with the minimum and maximum cost gradient ratios are identified, the pipe with a minimum (below 1) and maximum (above 1) cost ratio is downsized and upsized, respectively. • Hourly iterations were used initially to generate a rough solution, which was then optimised with the 100-day TC to represent demand variations. Significantly, these short TC results, when extrapolated, accurately depict the costs of the full 20-year planning horizon. The optimisation process took approximately 1 h. • The damage cost is computed according to the pressures (the probabilities are given) from EPANET. Three types of damage are considered: (i) the pressure falls below 14 m and fire erupts simultaneously; (ii) the pressure is between 14 and 26 m causing for example backup pumps to fail; (iii) the pressure is above 88 m potentially leading to a pipe burst. • Four additional scenarios were optimised: reduced demand, increased damage cost, increased energy cost, and varying roughness. • Results: Shorter TCs can be used to approximate full time horizon costs. The method is useful in cases where more computationally intensive methods are infeasible. • Test networks: (1) Anytown network (incl. 19 nodes) [84].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
101. Marques et al. (2015) [122] SO Optimal WDS design, strengthening, expansion and operation with a real options (ROs) concept and demand uncertainty, accounting for construction phasing in prefixed time intervals (10–20 years) over a planning horizon (60 years) using SA.	Objective (1): Minimise (a) the cost of the initial solution to be implemented in year zero (for interval 0–20 years) incl. pipes, pumps and pump energy costs, (b) cost of the future conditions incl. pipes, pumps and pump energy costs (cost of all scenarios weighted by the corresponding probability of each scenario), (c) regret term incl. pipes, pumps and pump energy costs (squared differences between the cost of the solution to implement and the optimal cost for each scenario). Constraints: (1) Min/max pressure at the nodes, (2) min pipe diameter, (3) only one commercial diameter assigned to a pipe. Decision variables: (1) Pipe diameters (discrete), (2) pump heads.	Water quality: N/A. Network analysis: EPANET. Optimisation method: SA.	• The ROs concept is proposed, which allows flexibility to be included in the decision making process. The regret term introduced in the objective function captures a situation of making decisions without perfect information (i.e., an implemented solution can be suboptimal and the regret term represents the risk of such a decision). • Uncertainties in future demands are implemented. Three demand conditions are used, one of them considers instantaneous peak discharge and fire flow at one node. • Various network expansion options are considered to predict alternative future developments. • Combining all the different conditions and expansion options, a total of 8 scenarios are derived, which form a decision tree. • Planning horizon of 60 years divided into 4 intervals is used. It is assumed that interval 1 (T = 1, 20 years) requires no modifications and conditions will not change. T = 2 and T = 3 are 10-year intervals with potential network expansion. Pumps should be replaced in T = 2 and T = 4. Also in T = 4, the demand should be predicted, two scenarios here are demand increasing by 20% and demand remaining constant. For the first 40 years, the demand would increase at a constant rate of 10% per decade. • In order to understand the difference of using ROs in the flexible design of WDSs, the ROs concept and a traditional design are compared. • Results: Compared to a traditional design, the ROs solution enables saving resources if an extended and uncertain planning horizon is considered. Accordingly, the ROs solution has a higher initial cost (the first 20 years), yet the total cost over 60 years is lower. • Test networks: (1) Simple network supplied from a single reservoir (incl. 10 nodes), inspired by [269].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
102. Marques et al. (2015) [137] MO Optimal WDS design, expansion and operation with a ROs concept and network expansion uncertainty, accounting for construction phasing in prefixed time intervals (20 years) over a planning horizon (60 years) using multi-objective SA.	Objective (1): Minimise (a) the cost of the initial solution to be implemented in year zero (for interval 0–20 years) incl. pipes, pumps, pump energy costs, carbon emissions cost for pipes and energy (b) cost of the future conditions incl. pipes, pumps, pump energy costs, carbon emissions cost for pipes and energy (cost of all scenarios weighted by the corresponding probability of each scenario). Objective (2): Minimise (a) total pressure violations for future scenarios (the sum of pressure violations for each scenario, each interval (starting from T = 2), each demand condition and each network node). Constraints: (1) Min pressure at the nodes, (2) min pipe diameter, (3) only one commercial diameter assigned to a pipe. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: Multi-objective SA.	• An extension of the papers by [122,270] considering a multi-objective approach with carbon emissions and uncertainties related to the future expansion scenarios of the network. • Similar to [122,270], ROs concept is applied, which uses a decision tree to reflect different scenarios (there is a total of 8 scenarios). • Planning horizon of 60 years divided into 3 intervals is used. Two kinds of minimum pressures are considered: desirable and admissible. In the first interval (T = 1, 20 years), the pressure cannot fall below the desirable minimum pressure. • The constraint of minimum pressure at the nodes aims to obtain higher values, thus fewer pressure violations, for scenarios with high occurrence probabilities. • The test network used can be expanded into four different areas, and also one area can be depopulated. • Results: The carbon emission costs have an insignificant influence on the objective function value. Energy and pipe costs are conflicting objectives. • Test networks: (1) Network supplied by three reservoirs (incl. 14 nodes) inspired by the study of [271].
103. McClymont et al. (2015) [29] SO Optimal WDS design and operation, investigating linkages between algorithm search operators and the WDS design problem features, using elitist EA.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) the energy cost of running pumps. Constraints: (1) Min/max pressure at the nodes, (2) max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete), (2) pump statuses (binary).	Water quality: N/A. Network analysis: EPANET. Optimisation method: Elitist EA.	• The aim is to bring insight into the interaction between an algorithm search operator and the WDS design problem. For that purpose, 60 artificial test networks are designed specifically, so they isolate individual features. These networks are then used to evaluate the impact of network features on operator performance. • "The method is as follows: (1) select operators, (2) select problems, (3) identify problem features, (4) synthesize artificial problems, (5) test on artificial problems, (6) analyse results and determine linkages, (7) select the most appropriate operators for selected problems, (8) test on actual problems, (9) analyse results". Such a systematic and quantitative approach provides detailed information (e.g., what linkages, if any, exist between the performance of an operator and certain WDS features) about an algorithm's suitability to optimise certain types of problem. • The following 6 operators are tested: mutation (random and 1 step size variation), crossover (uniform and n-point), and pipe smoothing and pipe expander (designed specifically for WDS problems). • Two types of experiments were conducted, one to test the effects of operators individually, the other to test the effect of the pairs of operators. • Results: Operator performance and problem search spaces are linked, which is verified using three well known benchmark problems. • Test networks: (1)–(60) Artificial networks based on 3 simple systems (looped, branched and hybrid), (61) two-loop network supplied by gravity (incl. 7 nodes) [14], (62) Hanoi network (incl. 32 nodes) [49], (63) Anytown network (incl. 19 nodes) [84].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
104. Roshani and Filion (2015) [132] MO Optimal WDS rehabilitation, strengthening, expansion and operation with GHG emissions over a planning horizon (i.e., 20 years) using NSGA-II with event-based coding.	Objective (1): Minimise the present value of the capital costs of the network including (a) pipe replacement, (b) pipe duplication, (c) pipe lining, (d) installation of new pipes. Objective (2): Minimise the present value of the operating costs including (a) lost water to leakage, (b) break repair, (c) electricity to pump water, (d) carbon cost associated with electricity use. Constraints: (1) Min pressure at the nodes, (2) max velocity in the pipes. Decision variables: (1) Time of rehabilitation, (2) place of rehabilitation, type of rehabilitation including (3) the diameter of a pipe being replaced/duplicated and (4) the diameter of a new pipe in an area slated for future growth, (5) the type of lining technology used. Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II.	• An extension of the paper by [124] including energy use and GHG emissions linked to electricity consumption due to pumping, leakage, and increases in pipe wall roughness due to pipe aging. The paper also analysis impact of two carbon reduction strategies (carbon tax and discount rates) on WDS rehabilitation. • Event-based rehabilitation timing approach of [124] is used. • Six carbon-abatement scenarios are examined, involving different combinations of carbon tax and discount rates, for two different GHG emissions intensity factors (low and high yearly emissions). • Results: Adopting a low discount rate and levying a carbon tax has a small impact on energy use and GHG emissions reduction. A low discount rate and the application of a carbon tax has a modest impact on leakage and pipe breaks reduction, and encourages an early rehabilitation investment to reduce the ongoing costs of leakage, pipe repair, energy, and GHG emissions. • Test networks: (1) Fairfield network in Amherstview and Odessa, Ontario, Canada.
105. Sadollah et al. (2015) [174] SO Optimal WDS design and strengthening using improved mine blast algorithm (IMBA).	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: IMBA.	• An improved algorithm based on a mine blast algorithm (MBA) is developed for least-cost design of WDSs. MBA is inspired by the process of mine explosions. Similar to other metaheuristics, it starts with an initial population (the number of shrapnel pieces), further followed by exploration and exploitation phases. • The modifications in the IMBA concern the exploitation phase and distance reduction of each shrapnel piece. In particular, the exploitation equations are modified to avoid problems with the dimension of the search space, where the perception of direction is replaced by moving to the best solutions. • IMBA is compared to a large number of other algorithms (14 to 17 for each test network) in terms of the solution quality and computational effort. • Results: IMBA reached a cheaper design than other algorithms for at least one test network. For the other two test networks, IMBA found the best-known design in fewer function evaluations. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) New York City tunnels (incl. 20 nodes) [81], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
106. Saldarriaga et al. (2015) [47] SO Optimal WDS design using optimal power use surface (OPUS) method paired with metaheuristic algorithms.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Not specified. Optimisation method: OPUS combined with: GA in REDES, GA in GANETXL, GA in MATLAB, HS in REDES, SA in MATLAB, greedy algorithm in REDES.	• The OPUS algorithm is paired with metaheuristic methods whereby the solutions obtained through OPUS are used as hot start (i.e., initial population) for the metaheuristics applied subsequently. • The OPUS method uses deterministic hydraulic principles drawn from analysing energy use and flow distribution in the network. • Results: The proposed optimisation method consistently marginally reduces the costs obtained through the OPUS algorithm (up to 1%) and substantially increases the number of iterations in every case (around 3 orders of magnitude). Authors argue, therefore, that it is not worth "to refine a solution that is already very close to the optimum and required minimum computational and human effort to be reached" (through the OPUS algorithm). • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50], (3) Taichung network, Taiwan (incl. 20 nodes) [272], (4) hypothetical network R28 (incl. 39 nodes) created at the Water Distribution and Sewer Systems Research Centre (CIACUA) of the University of Los Andes in Bogota, Colombia.
107. Stokes et al. (2015) [76] MO Optimal WDS design and operation including GHG emissions over a planning horizon (i.e., 100 years), investigating the effect of changing tank reserve size (TRS), using Borg multi-objective EA (MOEA).	Objective (1): Minimise (a) the construction costs of the network (pipes, pumps, tanks), (b) operating costs (electricity consumed by pumps). Objective (2): Minimise GHG emissions associated with the system (a) construction, (b) operation (electricity consumed by pumps). Constraints: (1) Min pressure at the nodes, (2) the total volume pumped equal to or greater than the total demand during the EPS. Decision variables: (1) Pipe diameters (discrete), (2) pump types (discrete), (3) pump scheduling decision variable (continuous). Note: One MO model including both objectives. For the test network (1), both design and operation components are included; for the test network (2) (D-town), only operation components are included.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Borg MOEA [273].	• The effect of changing (i) the storage tank balancing volume or TRS and (ii) time-varying emissions factors (EFs) on the minimisation of costs and GHG emissions in WDSs is investigated. • Four different TRS scenarios (for 3, 6, 12 and 24-h supply under average-day demand) and two different EF cases (an estimated 24-h time-varying EF (EEF) curve and an average EF (AEF)) are used. The TRS volumes are altered by changing the tank diameter, rather than lower and upper water levels which would impact on the system hydraulic. • Planning horizon of 100 years is considered and is used for calculating electricity costs, GHG emissions and pump replacement costs. • Peak and off-peak electricity tariffs are used. • Results: A larger TRS can help to reduce GHG emissions when the emissions intensity of electricity fluctuates during each day. This reduction in GHG emissions represents only 2–4% for a new WDS, but occurs with no additional cost as it allows pumping to be moved to the off-peak tariff period. However, when these fluctuations do not occur or are not considered when evaluating pumping operational GHG emissions (i.e., AEF is used), increasing the TRS results in no reduction of the cost or GHG emissions. • Test networks: (1) Two-pump network with 23 pipes (incl. 15 nodes), (2) modified D-town network (incl. 348 non-zero demand nodes) from the battle of the water networks II (BWN-II) [58,274].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
108. Stokes et al. (2015) [75] MO Optimal WDS design and operation including GHG emissions considering varying emission factors, electricity tariffs and water demands using NSGA-II.	Objective (1): Minimise (a) the design costs of the network (pipes and pumps), (b) operating costs (electricity consumed by pumps). Objective (2): Minimise GHG emissions associated with the system (a) design (pipes), (b) operation (electricity consumed by pumps). Constraints: (1) Min pressure at the nodes, (2) the sum of the instantaneous pump supply equal to or greater than the sum of the instantaneous water demands. Decision variables: (1) Pipe diameters (discrete), (2) pump types (discrete), (3) pump schedules (discrete options representing the time at which a pump is turned on/off, using a time step of 30 minutes). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: NSGA-II.	• Water distribution cost-emission nexus (WCEN) computational freeware framework is introduced for consolidating computational tools to solve WDS optimisation problems. A range of time-dependent operational conditions (e.g., EFs, electricity tariffs, water demands, pumping operational management options) can be considered. • For this study, hydraulic and pumping operational simulation, cost and GHG emissions calculation and MO heuristic optimisation are integrated. • Four operational scenarios are used: the first scenario reflects "standard" practices (i.e., steady state simulation with an average emission factor, electricity tariff and water demand), the other 3 scenarios use additional simulation complexity and flexibility (i.e., unsteady state simulation with varying emission factors, electricity tariffs and water demands). • Results: Compared to standard simulation practices, considering both short-term (e.g., daily) and long-term (e.g., monthly and annual) variations can significantly affect the design, pumping operational management options as well as their costs and GHG emissions. • Test networks: (1) Simple network with 23 pipes (incl. 15 nodes) [76].
109. Wang et al. (2015) [195] MO Optimal WDS design, strengthening and rehabilitation of well-known benchmark problems with the aim to obtain the best-known approximation of the true Pareto front using various MOEAs.	Objective (1): Minimise (a) the design costs of the network (pipes). Objective (2): Maximise (a) the network resilience [275]. Constraints: (1) Min/max pressure at the nodes (max pressure only for some test networks), (2) max velocity in the pipes (only for some test networks). Decision variables: (1) Diameters of new or duplicate pipes (integer) (duplicate pipes only for some test networks), (2) cleaning of existing pipes or do-nothing option (integer) (only for some test networks). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: Five state-of-the-art MOEAs are used including AMALGAM [276], Borg [273], NSGA-II [258], ε-MOEA [277], ε-NSGA-II [278].	• The aim is to obtain the best-known approximation of the true Pareto front (PF) for a set of benchmark problems, in order to create a single point of reference. • MOEAs parameters are not fine-tuned, instead the recommended settings are used. • An innovative projection plot is applied to facilitate the MOEAs comparison in terms of convergence and diversity. • Results: The true PFs for small problems and the best-known PFs for the other problems are obtained. No algorithm is completely superior to the others. Nevertheless, NSGA-II shows generally the best achievements across all the benchmark problems. • Test networks: (1) Two-reservoir network [83], (2) two-loop network supplied by gravity (incl. 7 nodes) [14], (3) BakRyan network, South Korea (incl. 35 nodes) [227], (4) New York City tunnels (incl. 20 nodes) [81], (5) Blacksburg network (incl. 31 nodes) [257], (6) Hanoi network (incl. 32 nodes) [49], (7) GoYang network, South Korea (incl. 22 nodes) [226], (8) Fossolo network, Italy (incl. 37 nodes) [254], (9) Pescara network, Italy (incl. 71 nodes) [254], (10) Modena network, Italy (incl. 272 nodes) [254], (11) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50], (12) Exeter network (serves a population of approximately 400,000) [82].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
110. Zheng (2015) [196] SO Optimal WDS design and strengthening using four DE variants with a comparison of their searching behaviour.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete, with continuous values adjusted to the closest discrete sizes according to [111]).	Water quality: N/A. Network analysis: EPANET. Optimisation method: DE (4 variants).	• The aim is to investigate the impact of different parameterisation strategies on the DE's searching performance (exploration and exploitation) through the real-time behaviour analysis using a series of proposed metrics. • The following four variants of DE algorithm are used: (i) the SDE algorithm with fixed mutation (F) and crossover (CR) parameter values; (ii) the dither DE (dDE) variant [279] with the randomised F; (iii) the modified dDE (MdDE) variant with the randomised F and CR; (iv) the SADE variant [173] with the self-adapted F and CR along the searching progress. The modified DE is proposed specifically for this study. • Six performance metrics, which measure search quality, search progress and convergence, are used to compare DE algorithms. • Results: The dDE, MdDE and SADE outperformed the SDE algorithm only in the middle to later searching periods. The SADE offered a larger number of improved solutions than the other DE variants in the exploitative periods. The MdDE has a greater exploratory ability than the SADE in the later searching period, hence found better solutions when a very large computational budget was available for the complex test network (3). • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50], (3) large network with five reservoirs and 1278 pipes (incl. 936 nodes), originally introduced by [26], modified by [280].
111. Zheng et al. (2015) [69] MO Optimal WDS design considering multiple loading conditions using multi-objective DE algorithm (MODE) with a graph decomposition technique.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure head constraint. Objective (2): Maximise (a) the minimum head excess across the network of multiple demand loading cases, (b) penalty for violating the pressure head constraint. Constraints: (1) Min/max allowable pipe diameters. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET (EPS for the second objective). Optimisation method: MODE.	• The graph decomposition technique is proposed to improve the efficiency of MOEAs for WDS design optimisations. It allows to decompose the original network into a series of more manageable subnetworks (subproblems), which are optimised individually with significantly higher efficiency than the original network. Subsequently, the propagation method is used to evolve Pareto fronts of the subnetworks towards the Pareto front of the original full network without the need to run the hydraulic simulation of the full network. • MODE, based on a single-objective DE algorithm [111], is developed. For comparison purposes, MODE is applied in conjunction with as well as without the graph decomposition technique when the whole network is optimised directly (referred to as SMODE). MODE is also compared with NSGA-II applied to the whole network optimisation. • Results: MODE exhibits significantly better performance than both conventional full-search methods SMODE and NSGA-II and its efficiency is more notable for larger networks. • Test networks: (1) Real-world network with 112 pipes and 24 demand loading cases, China (incl. 99 demand nodes), (2) BWN network with 433 pipes and 24 demand loading cases (incl. 387 demand nodes) [281].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
112. Zheng et al. (2015) [48] SO Optimal WDS design using DE, analysing impact of algorithm parameters on its search behaviour.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete, with continuous values produced in the initialisation and mutation processes of DE converted to the nearest discrete pipe diameters).	Water quality: N/A. Network analysis: EPANET. Optimisation method: DE.	• The aim is to investigate search behaviour (exploration and exploitation) of DE as a function of the two control parameters: mutation weighting factor (F) and crossover probability (CR). The six metrics are developed to measure the population variance, search quality, convergence properties, the percentage of the time spent in feasible and infeasible regions, and the percentage of improved solutions within each generation. • The results are compared with prior theoretical results using WDS design problems. Test problems used (Hanoi, ZJ and Balerma networks) have different sizes and complexity (34, 164 and 454 decision variables, respectively). • Results: An improved knowledge on search behaviour of DE via parameters F and CR is obtained. It was found that (i) there is excellent agreement between predicted and observed population variance as well as the lower bound of parameter F; (ii) DE performance is more dominated by parameter F; (iii) high CR value (CR > 0.8) often reduces DE's diversity with a rapid speed likely resulting in premature convergence. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) Zhi Jiang (ZJ) network, China (incl. 113 demand nodes) [111], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].
113. Zhou et al. (2015) [175] SO Optimal WDS design and strengthening using discrete state transition algorithm (STA).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: Newton-Raphson method [10]. Optimisation method: Discrete STA [282]. Note: Continuous STA [283].	• A reduction in the computational complexity of solving network continuity equations (linear equations) and energy equations (nonlinear equations) simultaneously is presented. Basically, some pipe flows are initially fixed as known to solve the linear equations and then substituted into the nonlinear equations. Consequently, the number of network linear and nonlinear equations is reduced to the number of closed simple loops. • For the two-loop network, the influence of penalty coefficient and one of the STA parameters called the search enforcement (SE) on the algorithm performance is studied. The knowledge gained is used in the optimisation of other test networks. • Results: The penalty coefficient has a significant impact on the search ability and solution feasibility, whereas SE does not affect the STA performance explicitly. Discrete STA is able to find the best-known solutions with fewer function evaluations. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) New York City tunnels (incl. 20 nodes) [81], (4) triple Hanoi network (incl. 92 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
114. Andrade et al. (2016) [143] SO Optimal WDS design with improved offline ANNs to replace water quality simulations and the probabilistic approach to generate training data sets, using GA.	Objective (1): Minimise (a) the system cost of the network (the pipe and installation costs). Constraints: (1) Min pressure at the nodes, (2) min chlorine concentration at the nodes. Decision variables: (1) Pipe diameters (discrete), (2) chlorine dosages at the water source (discrete).	Water quality: Chlorine. Network analysis: EPANET, offline ANN (for water quality analyses). Optimisation method: GA.	• The aim is to improve the performance of an offline ANN applied to the WDS design problems in terms of their architecture and training data, which affect their speed and accuracy. • The probabilistic approach is introduced to generate a large set of networks (training data sets) resembling those analysed by an optimisation method after its initial iterations. ANNs trained with these networks are compared against ANNs trained with conventional random networks. • The conventional multi-ANN architecture versus two single ANN architectures are also compared. Regarding the multi-ANN architecture, there are multiple ANNs each individually forecasting concentration at a single node. Concerning the first single ANN architecture, concentrations at all network nodes are forecast. The second single ANN architecture has only one output neuron (for one node) to estimate the minimum concentration in a WDS regardless of its location. • Therefore, six types of ANNs, resulting from the combinations of the two training data sets (the new introduced one and conventional random) and the three ANN architectures are analysed with respect to speed and accuracy. • Results: For a small WDS, there is no advantage in using multi-ANN architecture with a single output neuron over single ANN architectures; a probabilistic data set has no advantage over a conventional random data set. For a large WDS, multi-ANN architecture with a single output neuron outperforms the two other architectures analysed; a probabilistic data set is significantly superior to a conventional random data set. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) modified Kang and Lansey's network (incl. 517 demand nodes) [26].
115. Jabbary et al. (2016) [181] SO Optimal WDS design using a modified central force optimisation algorithm (CFOnet).	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty cost of violating the pressure constraint, (c) penalty cost of violating the velocity constraint. Constraints: (1) Min/max commercial pipe diameters, (2) min/max velocity in the pipes, (3) min/max pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: CFOnet.	• CFOnet, a deterministic metaheuristic method based on the rules of gravity, is applied to the WDS design optimisation. CFO uses a set of probes flying through space. The probes move under the influence of an accelerated force created by the gravitational attraction of masses in decision space. Due to the large computed acceleration values in the WDS problem, a normalisation operator is introduced to decelerate the probes so they remain inside of the decision space. Among the modifications, a new deterministic mutation operator is proposed, which prevents the algorithm to be locally trapped. • The method is compared with the original CFO method and other methods (GA, GA-ILP, PSO, LP) previously applied to the two test networks considered. • Results: CFOnet shows significantly better results over CFO, 55% and 94% improvement for the Kadu and Khorramshahr networks, respectively. When compared to other methods (GA, GA-ILP and PSO) for the Kadu network and LP for Khorramshahr network, the improvement is 3–4%. • Test networks: (1) Kadu network (incl. 26 nodes) [45], (2) Khorramshahr network (incl. 39 nodes) [284].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
116. Schwartz et al. (2016) [123] SO Optimal robust WDS design and operation considering multiple loading conditions and demand uncertainty using the robust counterpart (RC) approach and CE.	Objective (1): Minimise the construction and operation costs of the network including (a) pipe capital costs, (b) tank capital costs, (c) pump station capital cost, (d) energy costs related to the operation of the system during a TC of operation. Constraints: (1) Min/max tank water volumes at the last time period of the cycle, (2) min desired nodal heads, (3) tank closure constraints defined by the difference between the tank water level at the start and end of the TC. Decision variables: (1) Pipe diameters (discrete), (2) pump station heads at all time periods reflecting the pump curve needed for the system.	Water quality: N/A. Network analysis: Explicit mathematical formulation (nonlinear equations are linearised). Optimisation method: CE for combinatorial optimisation [230,285].	• The RC approach, which incorporates the uncertainty without the need for full stochastic information, is used. • The approach utilises characteristics of data distribution as opposed to assuming the entire probability density function. It uses simple statistical measures such as mean and covariance matrix to replace the original stochastic model with the deterministic model. Ellipsoidal uncertainty set, required by RC, is constructed using the mean value and the covariance matrix, according to the user-defined protection level. An obtained solution is robust and optimal to all possible scenarios in the uncertainty set. • Multiple time periods and multiload consumption patterns taking into account the temporal and spatial correlations simultaneously are used. • The system is tested under two different probability distributions, normal and uniform, on two test networks. • Results: The proposed method is robust under both normal and uniform distributions. Some of the tank volume obtained for a high protection level will not be utilised in reality and will perform as a safety factor withstanding the unexpected consumption unlike the deterministic solution. • Test networks: (1) Simple network (incl. 3 demand nodes) adopted from [286], (2) network with 2 sources and 65 pipes (incl. 48 demand nodes) adopted from [14].
117. Sheikholeslami and Talatahari (2016) [150] SO Optimal WDS design using a newly developed swarm-based optimisation(DSO) algorithm.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: DSO algorithm.	• A new DSO algorithm, which integrates accelerated PSO with big bang-big crunch (BB-BC) algorithm, is proposed for optimal design of WDSs. • To preserve the diversity of the swarm and avoid premature convergence to local optima, BB-BC concepts are introduced into the global and local search steps of accelerated PSO. In addition, a harmony memory concept from the HS algorithm is adopted to ensure that the particles do not leave the search space. • A modified constraint tournament selection is used for handling the constraints. Another rule is added stating that infeasible solutions with slight violations are considered as feasible, which is to maintain the diversity of the population. • Results: While comparing with other methods from the literature, DSO found the best-known solutions in a lower number of evaluations for the GoYang and Hanoi networks, and exhibited comparable performance for the Balerma network. • Test networks: (1) GoYang network, South Korea (incl. 22 nodes) [226], (2) Hanoi network (incl. 32 nodes) [49], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
118. Sheikholeslami et al. (2016) [162] SO Optimal WDS design using a combined cuckoo-HS algorithm (CSHS) in a two-phase procedure.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: CSHS algorithm.	• The proposed CSHS algorithm is a two-phase algorithm. It employs the cuckoo search (CS) algorithm in the first stage, and the HS algorithm in the second stage. • To overcome the weaknesses of CS (i.e., slow convergence rate and no information exchange between the individuals of the population), some HS components are integrated with CS. HMCR enables CS to use a memory containing the search history, which assists in generating new solutions; PAR from HS serves as a mutation operator and speeds up the convergence. • A self-adaptive technique is used to adjust HMCR and PAR during the optimisation process to alter the performance of the algorithm. • Dynamic penalty factor which increases towards the end of the optimisation process is used. • Sensitivity analysis is performed for the main parameters of the algorithm (scaling factor, discovering probability of alien eggs/solutions) using the Hanoi network. • Results: CSHS outperformed the standard CS and the majority of other meta-heuristics previously applied to the test networks in terms of efficiency. • Test networks: (1) Hanoi network (incl. 32 nodes) [49], (2) double Hanoi network (incl. 62 nodes), (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50], (4) network of a town in southeast China (incl. 192 demand nodes) [281].
119. Zheng et al. (2016) [28] MO Optimal WDS design and strengthening, analysis and comparison of the searching behaviour of NSGA-II, self-adaptive multi-objective DE (SAMODE) and Borg.	Objective (1): Minimise (a) the total network cost, including pipe material and construction costs. Objective (2): Maximise (a) the network resilience. Constraints: (1) Min/max pressure at the nodes, (2) min/max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: NSGA-II, SAMODE, and Borg are compared.	• An extension of the paper by [195] analysing the run-time searching behaviour of MOEAs to understand how they arrive at their final performance. Six performance metrics, categorised as solution quality, spacing and convergence metrics, are used to measure algorithm's search effectiveness and convergence properties in both the objective and decision spaces. • The relationship between algorithm operators and behavioural properties is analysed. • Results: A fundamental understanding of the working mechanisms of MOEAs is developed. Guidance on the selection of appropriate algorithms (operators) for particular optimisation problems is provided. NSGA-II is good at obtaining solutions covering a large extent of the Pareto front, and Borg is a good choice when computational resources are limited. • Test networks: (1) New York City tunnels (incl. 20 nodes) [81], (2) Hanoi network (incl. 32 nodes) [49], (3) Fossolo network, Italy (incl. 37 nodes) [254], (4) Pescara network, Italy (incl. 71 nodes) [254], (5) Modena network, Italy (incl. 272 nodes) [254], (6) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
120. Avila-Melgar et al. (2017) [109] SO Optimal WDS design using EA in a grid computing environment.	Objective (1): Minimise (a) the design cost of the network (pipes). Constraints: (1) Min/max pressure at the nodes, (2) min/max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: EA.	• An evolutionary method is coupled with EPANET to create an EA for solving water distribution network design (EA-WDND) problems. • The method is implemented in a grid environment and uses parallel computing techniques. • Results: EA-WDND obtains the best-known solution for the two-loop network. The best solution found for the Balerma network is an improvement of 12.5% over the current best-known solution. • Test networks: (1) Two-loop network supplied by gravity (incl. 7 nodes) [14], (2) Hanoi network (incl. 32 nodes) [49], (3) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].
121. Cisty et al. (2017) [30] MO Optimal WDS design using NSGA-II with a two-phase procedure and search space reduction.	Objective (1): Minimise (a) the design cost of the network (pipes). Objective (2): Minimise (a) the total head deficit in the network. Constraints: N/A. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A Network analysis: Not specified. Optimisation method: NSGA-II (for both phases of the optimisation procedure).	• A two-phase optimisation procedure is proposed as follows: in the first phase, suboptimal solutions are searched for; in the second phase, the optimisation problem is solved with a reduced search space based on these solutions. • The first phase consists of running NSGA-II several times with varying parameters (population size, number of generations, crossover and mutation). The aim is to obtain different suboptimal solutions. • The second phase has the following two alternatives: (i) diameters from the first phase's suboptimal solutions are used; (ii) flows in the pipes from suboptimal solutions are used. In both cases, the search space is reduced by introducing upper and lower bounds of diameters for all the pipes based on the diameters and flows obtained in the first phase. • The recommendations regarding the use of the proposed methodology are as follows. If a solution with the lowest cost possible is sought after, perform approximately 10 optimisation runs in the first phase and subsequently use the first alternative (with diameters) of the second phase. If a solution with the shortest computational time is required, perform only one optimisation run in the first phase and subsequently use the second alternative (based on the flows) of the second phase. • Results: Compared with previous results from the literature, the proposed methodology displays a slightly better performance in terms of the cost as well as the computational effort. The key finding from the computational experiments is that it is possible to obtain competitive results with simple, existing optimisation methods provided their adequate and methodological utilisation. • Test networks: (1) Balerma irrigation network, Almeria, Spain (incl. 447 nodes) [50].

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
122. Muhammed et al. (2017) [90] MO Optimal WDS strengthening using a cluster-based technique and NSGA-II in a two-phase procedure.	Objective (1): Minimise (a) the total capital cost of duplicated pipes. Objective (2): Minimise (a) the total number of demand nodes with pressure below the minimum pressure requirement. Constraints: (1) The sum of the pressure deficiencies in all the nodes with negative pressure. Decision variables: (1) Pipe diameters (discrete). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET. Optimisation method: GANETXL [208] using NSGA-II.	• The optimisation procedure consists of the following two phases: (i) the network is partitioned into a number of clusters (subsystems); (ii) the pipes which can have a direct impact on system performance are identified and considered as design variables in the optimisation. • The network is mapped into an undirected graph. For network clustering, the modularity-based method is applied to divide the graph into clusters with stronger internal than external connections. • The clustering method is implemented using an open source program Gephi [287], widely used for graph network visualisation. • The only rehabilitation option considered is pipe duplication. Candidate pipes for rehabilitation are selected based on three strategies: (i) rehabilitation of intercluster water transmission pipes with pressure deficiencies; (ii) rehabilitation of feed pipelines between the clusters with pressure deficiencies, or pipes in the path between sources and clusters; (iii) the combination of the previous two strategies. • Results: Strategy (iii) generated a Pareto front which dominates the Pareto fronts obtained by the other two strategies. It also shows a better performance when compared with the whole search space (all pipes used as design variables) and engineering judgement-based optimisation strategies. • Test networks: (1) EXNET water network (incl. 1891 nodes) [82].
123. Shokoohi et al. (2017) [78] MO Optimal WDS design including water quality objective using ACO.	Objective (1): Minimise (a) the construction cost of the network (pipe cost, excavation, demolition etc.), (b) chlorine cost calculated as one-year chlorine usage (applied in the tanks). Objective (2A): Maximise (a) water quality reliability based on chlorine residual [145]. Objective (2B): Maximise (a) water quality reliability based on water age. Objective (2C): Maximise (a) combined water quality reliability based on both chlorine residual and water age. Constraints: (1) Min/max pressure at the nodes, (2) max velocity in the pipes. Decision variables: (1) Pipe diameters (discrete), (2) tank heads (discrete), (3) chlorine injection dosages in the tanks (discrete). Note: Three two-objective optimisation models, where the objective (1) is combined with either objective (2A), (2B) or (2C).	Water quality: Chlorine, water age. Network analysis: EPANET (EPS). Optimisation method: ACO.	• The aim is to investigate the effect of water quality on WDS design. • A new water age penalty curve is developed. The existing chlorine residual penalty curve [288] is used. • Project lifetime considered is 22 years. • The following four scenarios are analysed, all of them using EPS: • (i) Hydraulic analysis is based on demand-driven simulation method (DDSM), objectives (1) and (2A) are used. • (ii) Hydraulic analysis is based on head-driven simulation method (HDSM), min pressure constraint is not considered, another constraint to secure at least 95% supply of water demand is applied, objectives (1) and (2A) are used. • (iii) DDSM method is used, objectives (1) and (2B) are considered. • (iv) DDSM method is used, objectives (1) and (2C) are considered, hence both chlorine residual and water age are used as the water quality parameters. • Results: Scenario (i) offers cheaper solutions than the original design (i.e., already constructed in Jahrom). Scenario (ii) has cheaper solutions than scenario (i), but there is a risk of pressure deficit at some nodes. Scenario (iii) offers only marginal improvement in the reliability objective with a relatively significant increase in the construction costs. In scenario (iv), all the differences between solutions are in chlorine reliability, so water age reliability does not have any significant impact on solutions. • Test networks: (1) Jahrom WDS, zone 3, South of Iran (incl. 44 nodes).

Table A1. *Cont.*

ID. Authors (Year) [Ref] SO/MO * Brief Description	Optimisation Model (Objective Functions +, Constraints **, Decision Variables ++)	Water Quality Network Analysis Optimisation Method	Notes
124. Zheng et al. (2017) [176] SO Optimal WDS design and strengthening using convergence-trajectory controlled ACO (ACO_{CTC}) algorithm with parameter-adaptive strategy.	Objective (1): Minimise (a) the design cost of the network (pipes), (b) penalty for violating the pressure constraint. Constraints: (1) Min pressure at the nodes. Decision variables: (1) Pipe diameters (discrete).	Water quality: N/A. Network analysis: EPANET. Optimisation method: ACO_{CTC}.	• Parameter-adaptive strategy for ACO algorithms is developed, which enables pre-specified parameter trajectories to be followed and ensures the convergence to increasingly higher fitness subregions in decision space for a given computational budget. The algorithm parameters are automatically adjusted to balance search diversification and intensification (exploration and exploitation). • ACO_{CTC} is based on AS_{rank} [234]. • A total of eight different convergence trajectories (ranging from emphasis on high diversification to high intensification) and three computational budgets (low, moderate and high) are applied to six test networks. • Results: There is a strong relationship between the convergence trajectory in decision space and the searching quality in objective space. The convergence trajectories can significantly impact on the solution quality. The trajectory with a slight emphasis on intensification performed best overall, irrespective of the computational budget. New best-known solutions were found for the Pescara, and Kang and Lansey's test networks. • Test networks: (1) New York City tunnels (NYTP) (incl. 20 nodes) [81], (2) Hanoi network (HP) (incl. 32 nodes) [49], (3) Fossolo network (FOS) , Italy (incl. 37 nodes) [254], (4) Pescara network (PES), Italy (incl. 71 nodes) [254], (5) Balerma irrigation network (BN), Almeria, Spain (incl. 447 nodes) [50], (6) Kang and Lansey's network (KL) (incl. 936 nodes) [26].

Notes: * SO = Single-objective (approach/model), MO = Multi-objective (approach/model). + Objective function is referred to as 'objective' in the column below due to space savings. ** Conservation of mass of flow, conservation of energy, and conservation of mass of constituent (for water quality network analysis) are not listed. ++ Control variables are listed, state variables resulting from network hydraulics are not necessarily listed. ? D = Design. ?? OP = Operation.

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