A Review on Staged Design of Water Distribution Networks

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A REVIEW ON STAGED DESIGN OF WATER DISTRIBUTION NETWORKS

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Abstract

Water distribution networks (WDNs) evolve continuously over time. Changes in water demands and pipe deterioration require construction upgrades to be performed on the network during its entire lifecycle. However, strategically planning WDNs, especially for the long term, is a challenging task. This is because parameters that are essential for the description of WDNs in the future, such as climate, population and demand transitions, are characterized by deep uncertainty. To cope with future uncertainty, and avoid overdesign or costly unplanned and reactive interventions, research is moving away from the static design of WDNs. Dynamic design approaches, aim to make water networks adaptive to changing conditions over long planning horizons. A promising, dynamic design approach is the staged design of WDNs, in which the planning horizon is divided into construction phases. This approach allows short-term interventions to be made, while simultaneously considering the expected long-term network growth outcomes. The aim of this paper is to summarize the current state of the art in staged design of water distribution networks. To achieve that, we critically examined relevant publications and classified them according to their shared key characteristics, such as the nature of the design problem (new or existing network design, expansion, strengthening, and rehabilitation), problem formulation (objective functions, length of planning horizon), optimization method, and uncertainty considerations. In the process, we discuss the latest findings in the literature, highlight the major contributions of staged design on water distribution networks, and suggest future research directions.

Keywords
optimization, literature review, uncertainty, flexibility, robustness, design, long-term planning

1 INTRODUCTION

Water distribution networks (WDNs) are complex infrastructures that have been developed to supply areas with water for large planning horizons and without interruptions. At the same time, WDNs are also dynamic in nature. During their lifetime, networks age as their pipes gradually deteriorate, leakages increase and their components fail. Moreover, urban development and demographic variations make demands placed upon the network increase. Consequently, construction interventions during the lifecycle of the network are necessary in order to cope with these increasing pressures.

Due to the high capital outlay of WDN infrastructures, the construction upgrades required are made under a limited budget, which is also provided gradually during the lifecycle of the network. Furthermore, the interventions are irreversible, in the sense that once they are implemented, they cannot easily be reversed. These interventions are also interdependent because they influence each other's performance [1]. For these reasons, how interventions are prioritized is critical, because it can affect the performance of the whole network in the longer term.

In theory, if decision makers knew how the network's forces of change evolve through time, they would be able to plan strategically the required interventions in a cost-efficient way, without compromising the performance of the WDN. However, most (if not all) critical forces of change such as urban development, population variations and consumer behaviour are difficult to forecast. This is because these forces are influenced by factors such as climate, socio-economic conditions, and technology, which are characterised by the so-called 'deep uncertainty' [2].

Traditionally, decision makers cope with future uncertainty by designing networks that work for a 'best guess' of future demand. However, this approach often leads to either overdesigned or underdesigned infrastructures, which require costly reactive interventions to align with actual requirements in the future. For that reason, the research community recently started moving away from static designs of WDNs and towards more dynamic approaches. One such approach is staged design, in which the planning horizon is divided into multiple construction phases.

In this work, we review the literature on staged design and how this methodological approach can be modified from its deterministic formulation in ways that incorporate future uncertainties into the design process and allow the development of robust and flexible designs.

2 STAGED DESIGN

To more formally define staged design, we start with the definition of the static, single-objective optimization problem. An equivalent formulation also holds for the more general many-objective optimization problem [3]. A single-objective optimization problem for the optimal design of a water distribution network can be defined as:

$$minimize\ or\ maximize\ f(x), \tag{1}$$

subject to:

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

$$b_j\,(x) \geq\ 0, \qquad \mathrm{j} \in \mathrm{J} = \{1, \dots, \mathrm{n}\}, \qquad n \geq 0 \tag{3}$$

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

where f is the objective function (usually a cost function), equations (2)-(4) are different types of constraints and x refers to the decision variables.

Analogously, staged optimization is the problem of identifying a sequence of actions that need to be taken over a number of N_{st} consecutive stages during the planning horizon, to maximize or minimize an overall objective function, subject to specific constraints at each stage:

$$minimize\ or\ maximize\ F\big[f(x_1), \dots, f\big(x_{N_{st}}\big)\big] \tag{5}$$

subject to:

$$a_{i,s}\,(x_s) = 0, \qquad i \in I = \{1, \dots, m\}, \qquad m \geq 0, \qquad \forall\ s = [1, \dots, N_{st}] \tag{6}$$

$$b_{j,s}\,(x_s) \geq\ 0, \qquad \mathrm{j} \in \mathrm{J} = \{1, \dots, \mathrm{n}\}, \qquad n \geq 0, \qquad \forall\ s = [1, \dots, N_{st}] \tag{7}$$

$$c_{k,s}\,(x_s) \leq 0, \qquad k \in K = \{1, \dots, p\}, \qquad p \geq 0, \qquad \forall\ s = [1, \dots, N_{st}] \tag{8}$$

where f is an objective function calculated at each stage s of the planning horizon, F is some aggregation (sum, average etc.) function of the values of f calculated at each stage, and expresses the overall objective function to be optimized over the whole planning horizon. x_s are the decision variables at each stage s, and equations (6)-(8) are constraints at each stage of the optimization. The solution to the staged optimization problem can be expressed as $x = (x_1, \dots, x_S)$ i.e. a sequence of decisions at each stage of the planning horizon. The above definition can be extended to describe multi-objective staged optimization problems as well.

One observation that can be derived from this definition is that actions to be taken at each stage of the planning horizon cannot conflict with actions taken at previous stages. Therefore, staged optimization is not a series of individual optimization problems. It is a series of intercorrelated problems that aim at identifying an optimal sequence of solutions which are contiguous with one another. It should also be noted that a series of individual optimal solutions at each stage of the planning horizon does not guarantee that the overall solution is also optimal. On the contrary, sub-optimal solutions at certain stages might influence the choice of actions at later stages in such a way that, in the end, the overall sequence of decisions leads to the minimization/maximization of the overall objective function.

The main advantage of staged optimisation in the optimal design of WDNs is that it allows making decisions for the present, while simultaneously considering the expected long-term network growth outcomes. In the literature, staged optimisation has also been coupled with uncertainty considerations to develop either "robust" (under a range of scenarios) or flexible designs.

3 LITERATURE OVERVIEW

This literature overview is divided into three sections. In the first section, publications that solve classic staged optimization problems without consideration of uncertainty are presented. The second section is about methodologies that aim to develop robust staged designs, i.e. designs that work well under a range of scenarios. Finally, in the last section, we review publications that use staged optimization as a tool to develop flexible designs under uncertainty.

3.1 Deterministic staged optimization

Like static optimization approaches, staged optimization has also been used for the design and upgrade (strengthening, expansion, and rehabilitation) of WDNs. One of the first publications on staged optimization is Lekane et al. (1978) [4], where the long term design of a tree water network was approached as a multi-stage linear problem. In this publication, the authors assumed that the evolution of the consumption of the network was known for the whole planning horizon. Indeed, the assumption that the changes in the network that make construction interventions necessary are known (such as future demands and pipe deterioration), is a key characteristic of staged design problems (Figure 1). More specifically, in the literature, these changes can be either prespecified at each stage [5] or modelled to follow a specific function. For example, in [6] and [7] demands are assumed to grow linearly over time. Other "known" drivers of change include pipe break rates [8] and leakage [9], network expansion [6], energy cost [5], and how customer consumption changes in response to water tariff increases [10, 11].

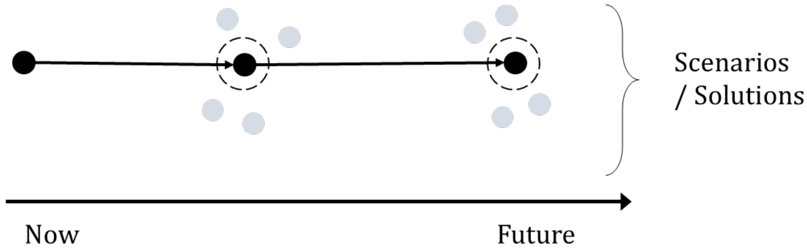

Figure 1: Deterministic staged design (adapted from Kang and Lansey [12]*). In deterministic staged optimization it is assumed that the drivers of changes such as future water demands and pipe deterioration are known.*

In staged design, the sequence of decisions that need to be made over the planning horizon is incorporated into the optimization process via the objective function. Single objective problems aim at the minimization of the accumulated cost at each stage of the planning horizon ([4, 5, 8, 10, 11, 13, 14]). For the optimization, the total cost is converted into total present cost, calculated using Present Value Analysis (PVA) concepts [15] and prespecified discount and interest rates. Multi-objective staged design problems account simultaneously for the total present cost and a second (conflicting) objective, which is also modified to account for the whole planning horizon, such as benefit [8], the volume of water lost [9], and reliability expressed as the minimum pressure surplus [6].

The optimization algorithms used in the literature to solve staged design problems include deterministic algorithms such as linear programming ([4, 10, 11, 14]), and generalized reduced gradient techniques [5]. Nature-inspired (heuristic) algorithms were also used, though mainly genetic algorithm variations ([6–9, 13]). However, given that a set of actions needs to be taken at each stage, the search space of the optimization algorithm increases exponentially, making the optimization process computationally expensive. With that in mind, Minaei et al. [7] proposed some modifications to improve computationally the algorithm proposed by Creaco et al. [6]. In their work, the modifications proposed included "efficient encoding of solutions based on practical considerations and engineering judgement, and engineering of populations". Tanyimboh and Kalungi also attempted to reduce the size of the optimization problem by using maximum entropy flows to generate optimal network designs [10, 11, 14].

The length of the planning horizon varies depending on the application area. Staged optimization problems that focus on rehabilitation ([5, 8–11, 13, 14]) considered shorter planning horizons (5-25 years). Design, expansion and strengthening problems considered longer planning horizons ranging from 20 to 100 years. Finally, the intervention time steps were usually prespecified without having necessarily equal lengths. Only Tanyimboh and Kalungi ([10, 11, 14]) explored various time step lengths using dynamic programming to further minimize the total cost.

Creaco et al. [6] and Lekane et al. [4] both compared static with staged designs and found that staged designs are more cost-effective in the long run. Creaco et al. showed that with staged design, the overdesign and underdesign of networks can be avoided, and noticed that to achieve long-term optimal solutions a higher initial investment is often required. Halhal et al. [8] demonstrated that the value of economic parameters such as inflation and interest rate influences whether higher investments will be allocated towards the beginning or end of the planning horizon. Finally, Minaei et al. [7] found that pipe roughness played an important role only in the optimization of lower-cost designs (smaller networks).

3.2 Taking account of uncertainty in staged optimization

Staged optimization aims to develop network design for the long term; hence some researchers recognize that the uncertainty that characterizes key input parameters cannot be ignored. As water consumption is a critical input parameter for the design of the network, several researchers choose to incorporate the uncertainty of water demand into the optimization process. One way to do that is to identify a set of plausible futures and attempt to deal with uncertainty by way of robustness, by finding a solution that satisfies all the generated scenarios (Figure 2).

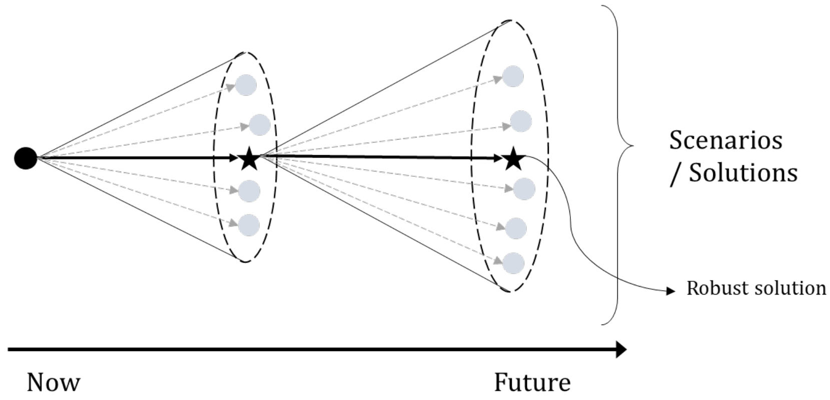

Figure 2: Robust staged optimization (adapted from Kang and Lansey [12]*). The goal of robust staged optimisation is to find a solution that works well enough for a range of scenarios.*

Just like static optimization is modified to accommodate solutions for staged design, staged design optimization is modified to account simultaneously for a set of plausible scenarios. For instance, Yi and Tiesong [16] considered that the demand follows a normal or uniform distribution with an increasing average and variance. Then 100 demand scenarios were generated, each one associated with a probability, and the goal was to minimize the expected total cost. Creaco et al. [17] modelled the growth rate of the demand as a discrete (low, medium and high growth rate) random variable with an assigned probability mass function. They solved a multi-objective problem that involved (i) the minimization of the present value cost of the solution implemented, and (ii) the minimization of the minimum pressure surplus observed over the lifecycle of the network and for each demand scenario. A similar route was followed by Dell'Aira et al. [18] who also considered the demand-growth rate as a discrete random variable, and generated multiple random scenarios to test the candidate solutions during the optimization. The solutions were evaluated by calculating the overall cost of the system and by averaging the resilience index over the whole planning horizon and over all the scenarios generated.

To avoid performing many simulations at each step of the optimization process, some researchers accounted for uncertainty after the optimization process was completed (or partially completed). Sirsant and Reddy [19] started by solving a deterministic optimization problem using life cycle costs as an objective function and a minimum value of resiliency as a constraint. Then they obtained the solution from the deterministic optimization, to run additional optimization iterations, but this time they replaced resiliency with reliability (which requires multiple simulations for its calculation). To calculate reliability, they generated scenarios by assuming that the demand is a random variable with mean the deterministic demand values at each stage and a coefficient of variation equal to 0.1. Sirsant and Reddy [20] also approached the same problem as a multi-objective problem where they minimized the cost, and maximized the resilience and then the reliability. After the optimization, the solutions of the Pareto front were ranked using an Analytical Hierarchy Process (AHA) using three criteria (i) costs, (ii) hydraulic and (iii) mechanical reliability. Marques and Cunha [21] and Cunha et al. [22, 23] also solved deterministic problems that were evaluated after the optimization under a range of scenarios. Marques and Cunha [21] generated a set of 200 equally probable scenarios, but only solved a deterministic design problem using the average demand scenario. Then they used multicriteria decision analysis to rank the performance of a number of generated alternative solutions under the 200 scenarios. Cunha et al. [22, 23] followed a similar approach by first identifying optimal solutions for a number of reference scenarios that covered a wide spectrum of possible conditions. Then they evaluated each solution under a range of scenarios using multicriteria decision analysis considering four criteria. The four criteria in [23] were cost, carbon emissions, resilience, and reliability, and the four criteria in [22] were cost, pressure deficits, velocity limits and supply deficits.

Most of the aforementioned methodologies concern the design, strengthening and expansion of the network, except for work in [18] and [21], which combined both the design and rehabilitation of the network. The optimization algorithms used include genetic algorithm variations [16–18], simulated annealing [21–23], and a hybrid differential evolution and dynamic programming [19, 20]. All networks used for the demonstration of the above methodologies have less than 30 nodes, except one real network with 914 nodes, which was used by Sirsant and Reddy [19]. Finally, the planning horizon ranges from 50 to 100 years. Only Yi and Tiesong [16] used a shorter 10-year planning horizon to demonstrate their methodology.

The literature gives useful insights regarding staged design under uncertainty. Creaco et al. [17] compared the design obtained from a staged deterministic approach with the design obtained from their methodology. They found that taking account of uncertainty in demand growth produces slightly oversized infrastructures (especially in the first phase of the construction) when future conditions are not known with certainty. Dell'Aira et al. [18] approached holistically the problem of design and rehabilitation and found that pipe ageing influences the optimal solution less than the growth of leakage. Sirsant and Reddy also arrived at a similar conclusion; they found that solutions that accounted for uncertain demands resulted in higher lifecycle costs [19] and that the break rate of pipes affected both the lifecycle costs as well as the estimated mechanical reliability of the network [20]. Finally, Cunha et al. [23] showed that the inclusion of carbon emissions as an optimal solution selection criterion favoured optimal designs that reinforced the network in the later phases of its planning horizon.

3.3 Staged optimization as a tool to obtain flexible designs

In the previous section, uncertainty is addressed by developing fixed staged solutions that perform well for as many scenarios as possible. In this section, we focus on work that attempted to provide flexible solutions allowing the water network development to become adaptive to several plausible future scenarios. To achieve that, both uncertainties and solutions are described by means of multi-stage scenario trees. Each branch in the scenario tree of uncertainties represents a plausible future that may or may not be connected to a probability of occurrence. Likewise, each branch in the solution tree represents a set of staged interventions to accommodate the corresponding (in the scenario tree) plausible future.

Assuming that all information about the network is known at the initial design stage, then the tree-like solution has a starting point, which is common for all future scenarios. The key in flexible design is to account simultaneously for 'all' different plausible futures and to identify a set of initial interventions that will allow the network to evolve to different future states in a way that requires few modifications for alternative future scenarios (Figure 3).

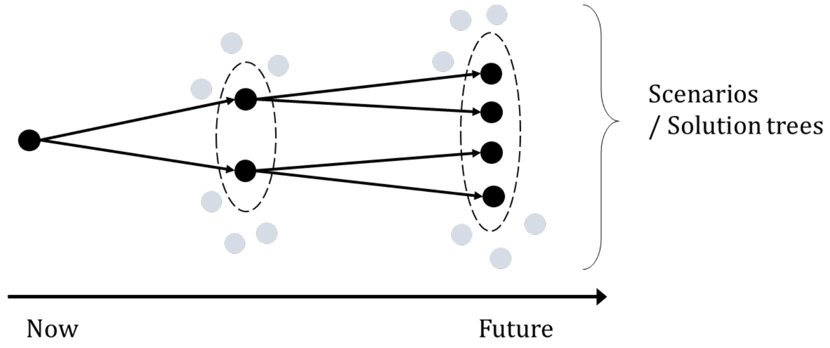

Figure 3: Flexible design optimization. The key in flexible design is to identify a set of initial interventions that will allow the network to evolve to different future states in a way that requires few modifications for alternative future scenarios.

In the literature, scenario trees are used to represent uncertainties in the demand [1, 24, 25] as well as in the spatial expansion of the network [26–29]. To account for uncertainty in the optimization process, Huang et al. [24] presented uncertainty as a scenario tree with 9 branches and optimized by minimizing the total present lifecycle cost over all the scenarios weighted by their probability of occurrence. Tsegaye et al. [26] incorporated uncertainties in a hypothetical network considering only increases in demands due to possible expansions of the network in new areas. They considered that all 4 scenarios were equally probable and optimized over their total cost.

Marques et al. published a series of papers where plausible scenarios were represented using Real Options [27–29]. In [27] the authors minimized the weighted (based on the probability of occurrence of each scenario) total lifecycle costs over all the scenarios and used in their objective a regret term to consider the differences between the cost of the flexible solution and the optimum cost for each scenario individually. Marques et al. [28] solved the problem by considering also carbon emissions in the objective function and in [29] they solve a many-objective optimization problem. The authors used four objectives that included (i) total pressure deficit (summed for each scenario, stage, and network node), (ii) total undelivered demand (summed for each scenario, time stage, and network node). (iii) total costs (iv) and total carbon emissions.

Basupi and Kapelan [1, 25] developed a decision tree solution, but instead of representing uncertainties in the demands in a tree-like form, they considered that demands follow a Gaussian probability density function with increasing mean and standard deviation over time. This means that branches in the solution tree do not represent implementations tailored to individual scenarios. Instead, a set of fine-tuned demand thresholds were used to trigger intervention decisions. Consequently, each solution pathway was robust for a range of scenarios. During optimization, a large number of samples were generated (each corresponding to one of the available intervention pathways) and the solution performance was calculated by averaging the lifecycle cost and the resilience index of the network across all samples.

To identify a flexible design that accommodates multiple scenarios, the optimisation algorithm has to consider an exponentially increased search space compared to the case of a fixed staged design problem. This is because different actions need to be taken not only at each stage of the planning horizon, but also under each individual scenario. In an attempt to tackle this problem, Kang and Lansey [12] found the optimal solution for each scenario individually and identified the common first-stage interventions across the solutions. Then, they assumed that these interventions will be implemented at the first stage of the planning horizon and excluded them from the set of decision variables to reduce the algorithm's search space.

The optimization algorithms used in almost all publications of this section were nature-inspired algorithms, such as genetic algorithm variations [12, 24–26] and simulated annealing [27–29].

Only Basupi and Kapelan in [1] generated flexible designs based on engineering judgement to demonstrate their methodology for evaluating flexibility in WDNs designs. All networks used to demonstrate methodological approaches in the reviewed literature had less than 20 nodes. The planning horizon varied between 10 and 100 years.

It was found that flexible designs have improved performance and that they are more cost-effective under uncertain conditions when compared with deterministic staged designs ([1, 12, 24–26]). Of course, for a perfectly known future, scenario-optimal solutions are less expensive than flexible ones [12, 25], but this extra cost "acts as an insurance policy" [25] when forecasts deviate significantly from reality. Marques et al. [27] found that flexible designs are more expensive in the initial phase than static designs created for the first construction period. However, when a larger horizon was considered, flexible designs cost less than solutions that ignored several future scenarios. In [28] the authors also found that the consideration of carbon emissions led to optimal designs with larger diameters. This is because larger diameters decreased the energy expenditure and therefore the cost of carbon emissions was reduced. Finally, Basupi and Kapelan [1, 25] found that their proposed flexible designs were more sensitive to the discount rate than demand uncertainty, hence they concluded that the discount rate is a parameter that needs to be carefully selected.

4 DISCUSSION

This literature overview showed that staged optimization of WDNs (in its broader sense) constitutes an improvement over traditional static approaches both in terms of lifecycle costs and overall network performance. This is because staged optimization allows to plan strategically the incremental development of WDN, therefore short-term interventions can be prioritized, without neglecting the expected long-term growth outcomes of the network. Research showed that staged designs that were slightly oversized in the beginning of the planning horizon were the ones that coped better with ("known") future changes. However, it is not possible to predict the future accurately, and as such, unexpected costs can still arise. Although additional costs at the beginning of the planning horizon are to be expected, staged design can be used as a tool to develop robust or flexible designs under uncertainty. These designs tend to be more expensive than the scenario-optimal solutions, but it has been argued that they are cost effective and perform better when a range of uncertainties is considered.

A major challenge in staged design is that the optimization process is computationally expensive. The reason is that a set of decisions needs to be identified for each stage of the planning horizon, and in the case of flexible designs, for each possible future scenario. In most publications, the proposed approaches were demonstrated using small network sizes, a limited number of intervention stages and plausible scenarios, while the decision variables focused primarily on pipe sizing alone. Although some methods to improve the computational efficiency of optimisation algorithms have shown promising results, there is still room for further research, for example in the direction of Surrogate Based Optimisation (SBO)[30].

Another challenge in staged optimization is that certain parameters require careful selection. For example, it was demonstrated that flexible design solutions were sensitive to the discount rate selection and that the discount rate also influenced how investments were allocated over the planning horizon. Moreover, it was shown that considerations of pipe roughness change were also important for small scale networks. Consequently, it is possible that the optimization process is influenced by other parameters as well, which have not been considered yet, such as water quality and short-term operations. So far, there is limited work on whether and to what extent different drivers of change influence the optimization process for the long term.

Most publications reviewed in the current work consider future uncertainties in demands and for network expansion. The different scenarios were generated stochastically, or were represented in a tree-like form, and in some cases, they were also connected to a probability of occurrence. However, demands, network expansions and intervention decisions are influenced by a range of highly uncertain parameters such as demographic changes, socioeconomic situation, technological developments, climate change, etc. This means that the robust and flexible approaches presented can still fail if reality differs from all hypothesized scenarios – as it often does. And even though robust and flexible approaches can, in principle, be revised at each phase of the planning horizon and include new information available at that phase, there is no work that provides a formal mechanism of how this can be achieved. The wider literature presents a range [31] of explicitly adaptive methods for decision making under deep uncertainty. Examples include dynamic adaptive planning [32] and dynamic adaptive policy pathways [33], and some of these methodologies have already been applied in the water sector. For instance, Beh et al. have successfully utilized a dynamic adaptive optimization approach to the problem of urban water supply augmentation [34]. With the appropriate modifications, these approaches or other similar ones might prove to be useful tools for the design of WDNs under deep uncertainty.

5 CONCLUSIONS

In this work, we have reviewed some of the most prominent publications on staged optimization of WDN. From deterministic staged designs to robust and flexible ones, this review focused on how the traditional static optimization approaches can be modified to incorporate sequential decision making and future uncertainty. We also discussed different optimization algorithms used in the literature, how different future scenarios were generated, the size of the networks used and the length of the planning horizon.

Our review demonstrates that staged optimization (in the broader sense) is a valuable tool for the generation of WDN designs that are better than traditional static designs both in terms of lifecycle costs and overall network performance under uncertainty. This is because staged optimization allows for the prioritization of short-term interventions without neglecting the expected long-term growth outcomes of the network. Further research is required to improve the computational efficiency of staged optimization algorithms, to investigate how different parameters (such as discount rate, water quality, and short-term operation) affect the long-term network performance, and to make the current flexible design methodologies more dynamic and adaptive to new emerging information.

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