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Review

A Review of Sources of Uncertainty in Optimization Objectives of Water Distribution Systems

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Abstract: Many studies have applied optimization to the planning, design, rehabilitation or operation of water distribution systems. Recent reviews of the research literature in this area have identified hundreds of papers that address these topics. The objectives considered include variables measuring direct impact of the system such as cost, energy, greenhouse gas emissions, as well as performance variables such as pressure deficit and system reliability. Very few of these studies have considered the effects of the various sources of uncertainty on the objectives considered. The sources of uncertainty include model related uncertainty such as uncertainty in model structure and parameters (e.g., pipe roughness and chemical reaction rates for water quality studies), data related uncertainty such as uncertainty in water demand due to natural variability in the short-term or population growth and/or climate change in the long-term, and human related uncertainty such as lack of knowledge about the physical network as well as modelling errors. This paper is aimed at reviewing the relative importance of these various sources of uncertainty on the key optimization objectives. It also summarizes the key literature in this area and identifies areas where there have been few publications.

Keywords: uncertainty; optimization; objectives; water distribution system

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1. Introduction

Methods for the optimization of water distribution systems (WDS) have been presented in the research literature for decades. Optimization can be applied to the planning, design, rehabilitation or operations of WDS. A number of review papers on the optimization of water distributions systems have been published in recent years, including a review of 107 papers on the subject of optimization of WDS operations [1], a review of 124 papers on the subject of WDS design [2], a review of the various optimization techniques that have been applied to WDS [3], an overview of multiobjective optimization methods applied to WDS [4] and a review of methods for real-time control of WDS [5].

This review considers the effects of uncertainty within WDS planning, design, rehabilitation and operations. Uncertainty is an important but less prominent theme in a number of optimization studies being either single or multi-objective. Whether applied to the domains of planning, design, rehabilitation or operations, uncertainty and optimization studies often share common overall themes.

The three main sources of uncertainty are model/algorithm uncertainty, data/input uncertainty and human related uncertainty. These are explained in more detail in Section 2.

This paper is aimed at reviewing the major sources of uncertainty in the optimization of WDS and their impact on the various objectives considered. The review will be in two parts. Firstly, the relative importance of each source of uncertainty on the various objectives is reviewed. Secondly, the extent to which the impact of each source of uncertainty on each objective has been addressed in previous literature is analysed. From this, future research needs are identified.

The papers selected in this review have been identified from the review papers listed above. These have been supplemented by a comprehensive search using the Web of Science and keywords that combine "optimization", "uncertainty" and "water distribution systems" or "water distribution networks". The scope of the assessment was restricted to studies that incorporate optimization of a distribution system or network, therefore excluding many uncertainty studies relating to water resources options that do not consider water networks. Numerous studies on optimization alternatives implicitly acknowledge uncertainty, but the preference here has been to review explicit representation of uncertainty.

2. Sources of Uncertainty and Their Relative Importance in Relation to Optimization Objectives

In this section, an assessment is made of the relative importance of various sources of uncertainty on the objectives considered in the optimization of WDS. Figure 1 shows the steps involved in the application of optimization to WDS planning, design or rehabilitation and illustrates the three main sources of uncertainty, namely:

1. Model/algorithm uncertainty (e.g., pipe roughness values or chemical reaction rates);
2. Data/input related uncertainty (e.g., uncertainty in water demands due to natural variability, population growth and/or climate change); and
3. Human related uncertainty (e.g., lack of knowledge about the network or ambiguity in the framing or decision making process).

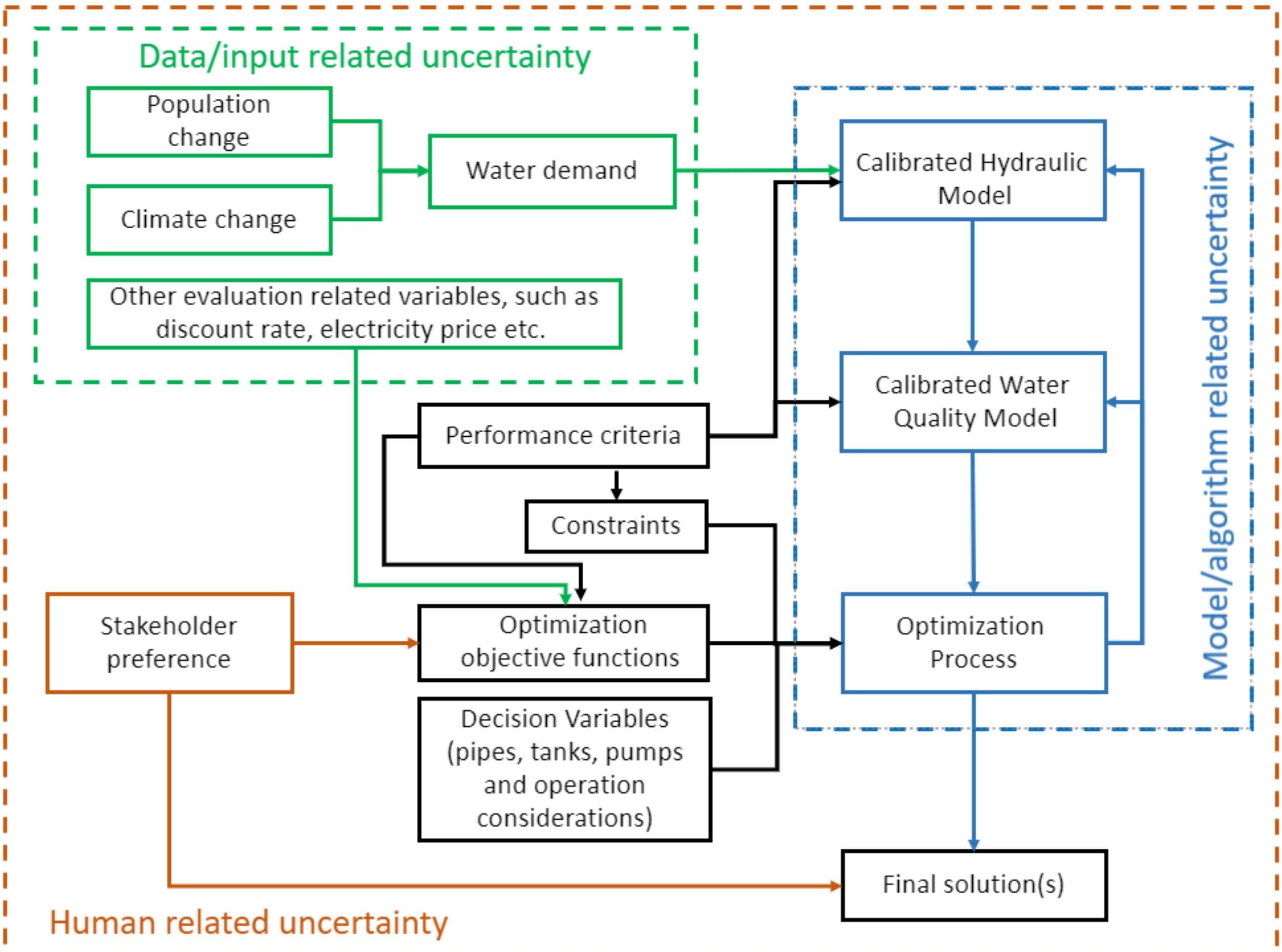

Figure 1. Steps involved in optimizing the planning, design or rehabilitation of WDS and the various sources of uncertainty.

Figure 2 shows the steps involved in system operations and the three main sources of uncertainty. This differs from system planning, design or rehabilitation in that the time horizons are often much shorter and the optimization can be updated frequently based on observations of the current or forecast states of the system. However, optimization of operations has similar sources of uncertainty as the optimization of planning, design and rehabilitation. The relative importance of these sources for operations can differ from the other cases due to the shorter time horizon and the opportunity to collect real time data from the system.

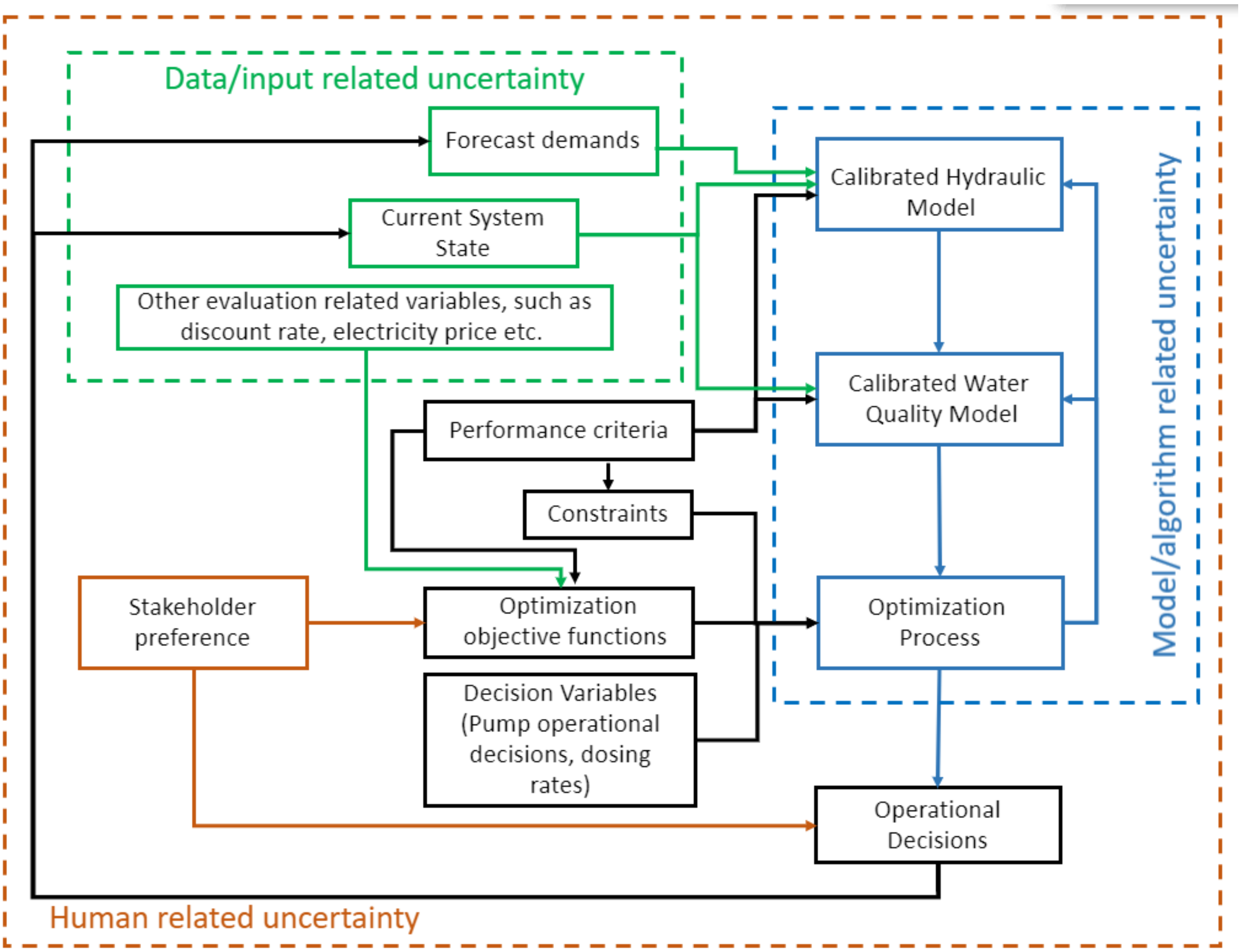

Figure 2. Steps involved in Optimizing the Operations of WDS and the Various Sources of Uncertainty.

The various sources of uncertainty are discussed in more detail below.

Model/algorithm uncertainty is related to either model structure or model parameters. It should be noted that application of optimization to the planning, design, rehabilitation or operations of WDS requires a calibrated hydraulic model and a calibrated water quality model (if water quality is being considered), as shown in Figures 1 and 2. Model structure uncertainty refers to the discrepancy between the mathematical representation of reality and the reality itself [6]. Model parameter uncertainty is the uncertainty in model parameter values, for example, pipe roughness factors, which cannot be directly measured and therefore need to be determined in a model calibration process [6,7]. Model parameters for WDS optimization can also include other variables when additional models are used for specific purposes. For example, chemical reaction rates are also model parameters that need to be calibrated when a water quality model is used [8]. Similar uncertainty exists due to the selection of an optimization algorithm and the algorithm parameter values used in the optimization process [9,10].

As shown in Figures 1 and 2, input/data uncertainty refers to uncertainty in measurement data, for example, data used for model development or input data used for system simulation [11]. Typical data used in WDS simulation and optimization includes water demands at nodes for both the short- and long-term, costs and energy of both network components and operations, the discount rate used for life-cycle cost calculations, and other variables related to the evaluation of specific objective functions and constraints, such as carbon cost or water quality variables.

Human-related uncertainty includes the modellers' incomplete knowledge of the system [6] or differing preferences of stakeholders that may affect the entire solution process from problem formulation and optimization to final decision analysis [11]. Similarly, there are broader aspects of the decision framework relating to planning or design, such as the level of risk aversion or weighting of objectives, that involve less-tangible human related sources of uncertainty. Hence, human-related uncertainty is shown in Figures 1 and 2 as potentially affecting all parts of the process.

These three sources of uncertainty can be correlated. Model structure uncertainty is often due to the simplification of a complex system, e.g., by aggregating demand at junction nodes or lumping storage in each demand zone [6]. However, it can also be a result of imperfect representation of the real-world system using a mathematical model based on imperfect understanding of the system [12]. Model parameter uncertainty can be a result of input/data uncertainty or errors introduced in the model calibration process [13]. It can also be caused by human-related uncertainty.

The impacts of these sources of uncertainty on the various objectives used in the optimization of WDS as discussed in this paper is subjective and is based on a comprehensive review of the research literature. The objectives considered include cost, energy, greenhouse gas emissions, water quality, hydraulic performance and other system specific objectives. The relative impacts are summarised in Table 1 and are described in more detail below for the various types of optimization studies.

Note that, in this paper, the term reliability refers to the probability that the system will satisfy its performance criteria over a specified time period in terms of meeting demands, satisfying minimum pressures and supplying water of suitable quality. Low levels of reliability can be caused by poor system design or operation or unexpected events such as high demands, pipe breaks, pump breakdowns or water quality intrusions.

2.1. Water Distribution System Planning and Design

The optimal planning and design of water distribution systems (WDS) involves choosing the system components such as: pipe diameters (and sometimes locations), tank sizes and locations, pump sizes and locations, valve locations and settings and operational decisions, where the latter are typically approximated or simplified. While the planning of WDS often involves staging the expansion of these systems over a long period of time, (typically over a 25 to 100 year horizon); system design refers to the selection of specific network components for construction and/or installation in the near future. In this study, system upgrades or modifications within an existing network are considered separately as rehabilitation.

The aim of WDS planning and design is to achieve desired performance levels by satisfying constraints including nodal water demands (potentially for multiple future demand projection scenarios), adequate service level pressure heads at consumer nodes and the maintenance of hydraulic laws via mass balance and energy conservation [14–16]. While a primary objective is to determine optimal hydraulic performance, the problem may be augmented to consider related aspects such as the optimal staging of the construction of the network elements [16–18] or the availability of funds to complete the initial construction of the system [19].

Table 1. Relative importance of the various sources of uncertainty on each objective (three ticks indicates a high level of importance, two ticks a medium level and one tick a low level of importance; n/a means not applicable).

		Sources of Uncertainty							
Optimization Category	**Optimization Objectives**	**Model**	**Optimization Method**	**Data—Randomness in Demand**	**Data—Randomness in Other Variables (e.g., Mechanical, Water Quality, . . .)**	**Data—Long-term Changes in Demand**	**Data—Long-term Changes in Other Variables**	**Human—Lack of Knowledge**	**Human—Stakeholders Preferences**
WDS planning/design	Min capital cost	✓	✓	✓✓	✓	✓✓	✓✓	✓✓✓	✓
	Min life-cycle cost	✓✓	✓	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓
	Min life-cycle energy/emissions	✓✓	✓	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓
	Max flexibility	✓✓✓	✓	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓✓✓
	Max hydraulic performance (e.g., hydraulic capacity, system reliability)	✓	✓	✓✓✓	✓✓	✓✓✓	✓✓	✓✓✓	✓✓
	Max water quality performance	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓✓	✓✓✓	✓
WDS rehabilitation	Min capital cost	✓	✓	✓	✓✓	✓✓	✓✓	✓✓✓	✓
	Min operation cost	✓	✓	✓✓	✓✓	✓✓✓	✓	✓✓✓	✓
	Min life-cycle cost	✓	✓	✓✓	✓✓	✓✓✓	✓✓	✓✓✓	✓
	Min life-cycle energy/emissions	✓	✓	✓✓	✓✓	✓✓✓	✓✓	✓✓✓	✓
	Min water loss	✓	✓	✓	✓	✓✓	✓	✓✓✓	✓
	Max hydraulic performance (e.g., hydraulic capacity, supply reliability)	✓	✓	✓✓✓	✓✓	✓✓✓	✓✓	✓✓✓	✓
WDS operation	Min life cycle cost	✓	✓	✓✓	✓✓	n/a	n/a	✓✓✓	✓
	Min operating cost	✓	✓	✓✓	✓✓	n/a	n/a	✓✓✓	✓
	Max hydraulic efficiency (e.g., pump power, pump switches)	✓	✓	✓✓	✓✓	n/a	n/a	✓✓✓	✓
	Min energy consumption/GHG emissions	✓✓	✓	✓✓✓	✓✓	n/a	n/a	✓✓✓	✓
	Max water quality	✓✓✓	✓	✓✓✓	✓✓	n/a	n/a	✓✓✓	✓
	Min average/maximum water age	✓	✓	✓✓✓	✓✓	n/a	n/a	✓✓✓	✓

There are a wide variety of optimization planning and design problems including metropolitan supply networks, irrigation networks, pumping head works and transmission pipelines. Each of these cases can have a variety of objectives (as listed in Table 1) including: satisfying typical hydraulic performance objectives, minimization of total life cycle cost (initial system installation, operations, pipe breakage repair and replacement and/or refurbishment costs) [19], total life cycle energy or greenhouse gas emissions [20], satisfying an optimum level of reliability (in various forms), maintaining a minimum level of chlorine residual concentration and ensuring a maximum level of disinfection by-products is not exceeded to ensure adequate water quality [21].

Table 1 summarises the relative importance of the various sources of uncertainty on these objectives.

Whether uncertainty is represented in the formulation of a model or optimization problem is strongly linked to the aims of a study. Often there is significant variability in the objectives due to uncertainty in one or more of the inputs to the model. For example, the following model inputs may be uncertain: nodal pressure heads, pipe diameters, network topology, pump and efficiency curves, electricity supply mix of fossil fired sources/renewables and tank water surface levels [22]. Typically, uncertainty in one or more of these inputs is represented using a continuous probability distribution about a representative mean value, and characterised by a measure of variability such as the standard deviation, often taken as 10% of the mean [15,22,23]. Given the spatial nature of WDS, the probability distribution may be multivariate to include a spatial correlation structure, but this specification can be complicated such that many studies will apply a univariate distribution of probability independently at multiple sites. Some variables in the model may be represented using probabilities of discrete events, such as with the incidence of pipe bursts. In most instances, the inputs carry the specification of the system uncertainty, and there is not a separate model term for 'model errors' as is common in other areas, such as hydrology [24].

For the design of new systems the following inputs should be much more certain: pipe diameters, network topology and pump efficiency curves as these are values selected by the designer. On the other hand, model parameters such as pipe roughness values are uncertain and can be estimated based on pipe material and diameter and should allow for some level of deterioration over the life of the system.

Analysis techniques for planning and design of WDS include single objective optimization, multi-objective optimization, scenario analysis, Monte Carlo simulation and multi-criteria decision-making. WDS expansion problems have previously been framed mostly as single-objective optimization problems considering cost minimization subject to system reliability, minimum pressure levels and maximum velocities as constraints [19]. Multi-objective optimization provides greater opportunity to consider uncertainty in the system and the impact it has on performance metrics of that system.

Short term events affecting system reliability (see columns for Data randomness in Table 1) include: insufficient water pressure head [14], expected operational pipe breakage accidents [14] such as leakages and bursts, pump and equipment failure, power outages [22], an increase in daily extreme temperatures and water quality events [21] and a water supply deficit due to insufficient storage capacity [22]. Impacts of these short-term events include: water loss, potentially huge repair costs, traffic congestion and even loss of life [14,21]. In addition, motors and electronics within pumping units may fail due to increased extreme daily temperatures. Power systems are integral to water systems being connected through pumps, valves and SCADA. Thus, vulnerabilities may result due to interdependency of the water system with other infrastructure systems. Causes of short term events include human error in operations and third-party damage of network (see last two columns of Table 1 for human factors). Necessary actions include shutting valves to isolate parts of the network for repair [14]. Important information in assessment of reliability include water distribution system parameters, maintenance records and pipe repair and replacement records [14].

Longer term sources of uncertainty (see Table 1) include changes in nodal water demand (population growth, per capita water consumption, climate and seasonal change such as increase in average temperature), deterioration of pipes including changes in pipe roughness with time resulting in reduction of carrying capacity [19,22], changes in greenhouse gas emission factors (dependent on the degree of renewable electricity generation versus fossil fuel generation) and changes in temperature (mean values and extremes). For example, electricity generation and agricultural industries in particular may need increasing amounts of water in a hotter future [21]. Future uncertainties need to be considered in the design of WDS [19]. Water demand is one of the most crucial input variables [19]. In the past, historical weather conditions have often been used for planning and design, thereby assuming stationarity of variability of water demand conditions [21]. Engineers must adapt infrastructure systems to ensure reliability into the future.

2.2. Water Distribution System Rehabilitation

Water distribution system rehabilitation refers to the refurbishment or replacement of critical WDS components, usually pipes or pumps, to ensure system performance is maintained. A number of objectives have previously been considered for WDS rehabilitation. These are listed in Table 1. They include capital cost [25–30], operations cost [27–30], annual average cost [31], life-cycle cost [32–38], and life-cycle energy consumption [39] or emissions [30]. Many studies also have included hydraulic performance measures as an objective, such as the minimization of the pressure head deficit [26] or water loss [34], and maximization of network capacity, e.g., in the form of the resilience index [37]. In addition, a commonly considered optimization objective for WDS rehabilitation optimization studies, especially those considering uncertainty, include the measure of the overall system hydraulic performance in terms of the probability of meeting the required demands or pressures. These types of optimization objectives are typically referred to as reliability objectives [25,33,35,40]. Finally, in a few studies, case study specific optimization objectives are used, such as mechanical reliability that is defined as one minus the probability of network breakdowns over a specified period [41] or serviceability after natural hazards such as earthquakes [40,42].

In a similar way to WDS planning and design, uncertainty from a number of sources may affect the effectiveness of WDS rehabilitation strategies in achieving expected objectives. Firstly, as all engineering analysis relies on models, uncertainty associated with model structure and parameters can have an impact over the actual performance of optimized rehabilitation strategies. For WDS rehabilitation specifically, apart from a hydraulic model representing the WDS, leak or break forecasting models and pipe roughness growth models may also be used [30]. As models are the representation of the real-world system in the optimization process, they have an impact on all of the optimization objectives considered. Secondly, data/input uncertainty may only have impact on the objective functions that are calculated based on the corresponding data/input. For example, the cost of network components may only affect the capital cost of network rehabilitation, and the energy cost will only affect the operation cost or life-cycle cost which includes operations cost. However, uncertainty in water demands will affect all objective functions considered as the main function of WDS is to deliver water of adequate quantity, quality and pressure to the users. Finally, human-related uncertainty will also contribute to most if not all objectives considered. The lack of knowledge will affect the development of a simulation-optimization model, upon which the evaluation of all objective functions relies upon. Stakeholders' preferences will affect the formulation of the fundamental optimization problem, thus all objective functions considered.

Although there is some research on the uncertainty in WDS models [43,44] and its impact on real-time operation of WDS [6], there is very limited research comparing the impact of different sources of uncertainty on WDS rehabilitation optimization. Based on research for other water systems, model related uncertainty in general has less impact compared to input/data related uncertainty [45], while human related uncertainty may lead to different problem formulations that result in very different optimization result. This conclusion is partially validated by a study by Wang et al. [46], where the authors investigated the impact of problem formulation (including the definition of objective functions and decision variables) and the selection of optimization algorithms on WDS rehabilitation optimization. The authors found that the definition of objective functions have the most significant impact on the optimized rehabilitation strategies, with different objective functions leading to completely different potential solutions and optimal Pareto fronts. This is followed by the definition of decision variables represented using two different pipe categorization methods, which mainly affected the shapes of the resulting Pareto fronts, whereas different optimization algorithms lead to very similar optimal fronts, with a more effective algorithm leading to solutions with slightly improved objective function values.

2.3. Water Distribution System Operations

The operation of WDS involves the use of pumps and/or valves to transfer water within the network to meet demands and to ensure that tank water levels as well as pressures and velocities within the pipe network are within acceptable limits. It can also include the dosing and/or boosting of disinfectant to meet water quality criteria or objectives in the network.

There are several approaches to optimizing the operation of pumps and valves within a water distribution system [1]. These include: (a) explicit operational optimization; (b) implicit operational optimization; and (c) real time control.

In explicit operational optimization, pumps and/or valves are operated at certain times of the day over a fixed time horizon [47] or for a selected duration [48] to optimize a set of objectives for forecast or assumed nodal demands. In this type of optimization, there is no feedback from the actual demands to modify the operating decisions. If the actual demands differ significantly from the assumed values, the operating decisions will no longer be optimal.

In implicit operational optimization, decisions such as switching a pump on or off or opening or closing a valve are based on certain hydraulic criteria (called "trigger levels") in the network. These criteria might typically be the water level in one or more tanks [49] or the flow through a pump [50]. The trigger levels are determined using optimization for one or several sets of projected demands. If the actual demands differ from the assumed values, the operations (pump and valve operations) will occur at different times than those obtained in the optimization and the system will operate in a sub-optimal way.

Real time control [5,51,52] involves optimizing operations over a planning horizon (usually a few hours up to a few days) using forecast demands. These decisions are then implemented for the first time step and a further optimization is carried out at the end of the time step for the next planning horizon based on updated data obtained from the system. Evolutionary algorithms and economic model predictive control have been applied to real time control. In some cases, the optimization uses an ensemble of forecast demands in order to take into account uncertainty in the forecasts. Real time control produces the best outcomes in terms of optimizing the objectives, but it requires detailed SCADA data and more sophisticated algorithms for its implementation compared with other two methods.

Optimal operation can also include water quality considerations. This can be achieved by adding water quality constraints to the pump and valve scheduling problem [53], by minimizing the cost or mass of disinfectant as an explicit objective [54] or by minimizing the deviations of disinfectant concentrations from desired levels at critical nodes in the network [55].

Optimization of system operation usually includes a single objective (for example, cost or energy), although some studies have used multiple objectives. The objectives considered in the literature for optimizing operations are given in Table 1.

An accurate and calibrated hydraulic model of the system is an essential prerequisite in order to optimize operations within a WDS. It is assumed that uncertainties due to a lack of knowledge of the network are at minimum, as these should be identified in the calibration and testing of the model before the optimization of system operations is carried out. Pipe roughness values can be estimated based on documented information of these factors based on the age, material and diameter of the respective pipes. A calibration exercise is then usually carried out using measured tank levels, pressures and flows in the network during one or more extended period simulations. However, there are usually not enough measurements to estimate the pipe roughness factor for every pipe in the system, so it is a common practice to group pipes of the same age, material and diameter and assume that they have the same roughness factor. This introduces some uncertainty into the optimization.

As shown in Table 1, the main sources of uncertainty for water distribution system operations are the short-term demands at nodes [56–58] and the chemical decay coefficients, including wall decay [59,60]. In a simple transfer system such as pumping water from one tank to another or a small number of tanks, the demands can be measured in real time. Forecasting future demands using time series models or artificial neural networks is relatively straightforward in this case. However, in more complicated networks it is not feasible to measure the demands at all nodes in real time. In this case, it is usual to make use of an assumed pattern of load factors for each group of nodes that have similar land use and/or socio-economic characteristics. The base demand at each node can be determined from the numbers and types of consumers receiving supply from the node and/or billing information. This latter information is often only collected monthly or quarterly and so may be a poor source of information for forecasting short-term demands.

Chemical decay coefficients for disinfectants can be measured in the laboratory, but will vary with the quality of the source water (particularly with the concentration of various organic substances). Furthermore, there is uncertainty about the best equation to use for chemical decay as various studies suggest that first order, second order or parallel order decay equations provide the best fit to the measured data [59,61]. This is reflected by the high level of model uncertainty on the water quality objective in Table 1. An additional source of uncertainty in water quality modelling is due to mixing in tanks. Various simplified models exist including completely mixed, first in first out (FIFO) and last in first out (LIFO) as well as multi-compartment models [62]. The appropriate model to use depends on the inlet and outlet structures of the tank as well as its shape. Careful calibration is required to obtain the best model for each tank.

The greatest uncertainty in terms of chemical reactions is caused by the so called “wall decay” [60]. This is the reaction of the disinfectant with biofilms on the pipe wall as well as the pipe material itself. Every pipe in a WDS has its own wall reaction coefficient. It is generally assumed that pipes of the same age, material and diameter have the same wall reaction coefficient. This is not necessarily true as the build-up of biofilms throughout the system depends on factors such as the previous history of disinfectant levels in the pipe and possible scouring of biofilms due to high velocities. Despite the availability of real-time monitoring equipment for measuring disinfectant levels, it is not feasible to collect sufficient water quality data in a WDS system to enable calibration of the wall decay coefficients for all pipes in the system. This introduces considerable uncertainty into forecasts of water quality throughout the system, which will impact the optimization outcomes of system operations.

The uncertainty for many of the above factors is associated with lack of knowledge. Ultimately, this is the largest source of uncertainty for system operations as shown in Table 1.

3. Review of Literature on Sources of Uncertainty on Optimization Objectives

3.1. Water Distribution System Planning and Design

There is a wide range of WDS planning problems that are the subject of optimization under uncertainty, including staging of network expansions and pipe duplication [63], life-cycle and energy costing [20], sensor placement [64], optimal mix of water sources [65] and hydropower cost analysis [66]. Table 2 shows the extent to which the various sources of uncertainty on optimization objectives have been investigated in the literature. Table 2 shows that the majority of papers reflect uncertainty in hydraulic parameters, present-day water demands and long-term uncertainties associated with a changing climate (demands, energy). Many studies are focussed on cost minimization, hydraulic performance (including reliability), but there is a growing prevalence of studies emphasizing design flexibility and life-cycle analysis (see Table 2).

WDS typically have a long design life, which can be extended considerably once the infrastructure is built. Because of the long time periods involved, planning studies have many associated uncertainties [67]. Demand uncertainty is the most prevalent form of uncertainty considered over long time horizons [56,68,69] since it is plausible for the requirements of a network to change significantly over time. However, Table 2 shows that there are not a lot of papers relating to "Data-long term changes in demand". Given the long design life, a prominent theme is the need for designs to prioritise flexibility and adaptability rather than fixed staging interventions [63]. When optimization takes into account the need for flexibility, it leads to different types of solutions [70]. Flexibility is incorporated in most studies via multiple planning scenarios, such as demand scenarios [67]. Adaptive design implies that planning optimization is not a once-off activity but is periodic and progressive over the life of the infrastructure.

A significant additional factor associated with long time horizons is the anticipation of climate change that affects water demand above and beyond the ordinary level of uncertainty in future demand planning [63,71]. This type of uncertainty is termed 'deep uncertainty' [72] since it is more fundamental than unknowns in model structure or parameters (such as pipe roughness values) but represents uncertainty in the problem framing, for example, the selection of representative concentration pathways in climate models. This type of uncertainty is accommodated within planning via the use of scenarios that indicate the range of possible outcomes of interest, such that designs should be robust across multiple scenarios [63,71]. Care is needed in the selection of scenarios and how they are combined to form a preferred design since there are human factors involved in deciding on the preferred requirements (i.e., a contributing factor of deep uncertainty), for example, the degree of risk aversion [73].

Another significant source of uncertainty over extended time periods is the discount rate for estimating net present costs [20,74,75]. Table 2 shows that there are few papers relating to "Data-long term changes in other variables." Due to a recent emphasis on climate change, an increasing number of papers address the need for carbon abatement through objectives that explicitly represent emissions [70] or implicitly via the minimization of energy requirements [20,56].

The ability to perform multi-objective optimization has permitted additional planning objectives beyond cost and hydraulic performance that are typically related to objectives with significant uncertainty, such as water quality or reliability objectives. There is therefore uncertainty that comes with deciding on the objectives and, once a Pareto-front is derived, how to utilise that information for planning purposes [70]. This is an example of human factors associated with optimization that involve uncertainty. There are few research papers that couple the specific WDS optimization problem with the broader context and uncertainties of human decision-making (Table 2).

Table 2. Summary of the Extent to which each Source of Uncertainty in Relation to each Objective is Investigated in Previous Literature (three ticks indicates significant coverage, two ticks a moderate level of coverage and one tick little or no coverage; n/a means not applicable).

		Sources of Uncertainty							
Optimization Category	**Optimization Objectives**	**Model (e.g., Model Structure and Parameter, e.g., Pipe Roughness or Chemical Reaction Rates for Water Quality Considerations)**	**Optimization Algorithm (e.g., Algorithm and Algorithm Parameters)**	**Data—Randomness (Natural Variability) in Demand**	**Data—Randomness (Natural Variability) in Other Variables (Mechanical, Water Quality, . . .)**	**Data—Long-term Changes in Demand (Due to Population Growth, Climate Change)**	**Data - Long-term Changes in Other Variables, e.g., Carbon Tax, Hazards**	**Human—Lack of Knowledge**	**Human—Stakeholders Preferences**
WDS planning/design	Min capital cost	✓✓✓	✓✓✓	✓✓✓	✓✓	✓✓✓	✓	✓	✓
	Min life-cycle cost	✓✓	✓	✓	✓	✓	✓	✓	✓
	Min life-cycle energy/emissions	✓	✓	✓✓✓	✓	✓	✓	✓	✓
	Max flexibility	✓	✓✓✓	✓✓✓	✓	✓✓	✓	✓	✓
	Max hydraulic performance (e.g., hydraulic capacity, system reliability)	✓✓✓	✓✓✓	✓✓✓	✓✓	✓✓	✓✓	✓	✓
	Max water quality performance	✓✓✓	✓✓✓	✓✓✓	✓✓	✓✓✓	✓	✓✓	✓
WDS rehabilitation	Min capital cost	✓	✓✓	✓	✓	✓✓	✓✓	✓✓	✓✓
	Min operation cost	✓	✓	✓	✓	✓✓	✓✓	✓✓	✓
	Min life-cycle cost	✓	✓	✓✓✓	✓	✓	✓	✓	✓
	Min life-cycle energy/emissions	✓	✓	✓	✓	✓	✓	✓	✓
	Min water loss	✓	✓	✓	✓	✓	✓	✓	✓
	Max hydraulic performance (e.g., hydraulic capacity, system reliability)	✓	✓✓✓	✓✓✓	✓✓✓	✓	✓✓	✓	✓✓✓
WDS operation	Min life cycle cost	✓	✓✓✓	✓	✓✓	n/a	n/a	✓	✓
	Min operating cost	✓	✓✓✓	✓✓✓	✓✓	n/a	n/a	✓	✓
	Max hydraulic efficiency (e.g., pump power, pump switches)	✓	✓✓	✓✓	✓✓	n/a	n/a	✓	✓
	Min energy consumption/GHG emissions	✓	✓	✓	✓	n/a	n/a	✓	✓
	Max water quality	✓✓	✓	✓✓	✓	n/a	n/a	✓	✓
	Min average/maximum water age	✓	✓	✓	✓	n/a	n/a	✓	✓

3.2. Water Distribution System Rehabilitation

Data uncertainty due to the random nature of the variables (e.g., natural variability) is the most commonly considered source of uncertainty in WDS rehabilitation studies and has been considered in almost half of the papers reviewed on system rehabilitation (Table 2). The randomness in water demand due to natural variability in particular is often considered (e.g., [26]). In most of these studies, this uncertainty contributes to the probability of the network meeting hydraulic performance requirements (e.g., required pressure or water demands). Among these studies, the minimization of life-cycle cost is often an additional objective that is included in the optimization.

Data uncertainty due to long term changes such as climate change and population growth is another common source of data uncertainty that is considered in WDS rehabilitation (see Table 2). This long-term uncertainty which will typically affect water demand, which has been considered in half of the studies considering long-term data uncertainty (e.g., [28]. Long-term water demand uncertainty affects both capital and operational cost as well as energy consumption and associated emissions. However, most WDS rehabilitation studies have focused on its impact on cost, while its impact on other optimization objectives such as energy/GHG emissions or hydraulic performance have often not been considered. In addition, the impact of long-term changes in other variables, such as carbon tax and hazards have also been considered (e.g., [30]), with studies mainly focusing on their impact on the cost and hydraulic performance related objective functions.

Human-related uncertainty is also a common source of uncertainty considered in WDS rehabilitation [11]. Although the lack of knowledge has only been considered in one study where the minimization of capital and operation costs are considered as objectives, the impact of stakeholders' preference between the various objective functions have been investigated in several studies. Stakeholder's preference can affect all of the objective functions considered, depending on the stakeholder groups included [76]. In the studies reviewed, the objectives considered include cost and hydraulic performance related functions.

Finally, model related uncertainty (either related to model structure or model parameters), although being a source of uncertainty in many WDS design [6], has not been investigated in any of the studies reviewed on WDS rehabilitation. However, in a number of studies, the performance of a number of different optimization algorithms have been compared (e.g., [26,40,77,78]). In these studies, the objectives investigated include both capital cost and hydraulic performance related functions.

3.3. Water Distribution System Operations

Table 2 shows the extent to which the impact of uncertainty on the various objectives in system operation has been considered in the literature.

The most common form of uncertainty considered in the WDS operations literature is data uncertainty arising from natural randomness and unpredictability of nodal water demands. A number of papers consider the impact of this source of uncertainty on operating costs [56–58,79], water quality [80] and hydraulic performance and safety storage cost [79]. Data uncertainty from other variables and their impact on various objectives include uncertainty in the natural recharge of aquifers and its impact on total life cycle costs [81], uncertainty in energy prices and its impact on operating cost, hydraulic performance and safety storage cost [79].

The effect of model uncertainty, in particular simplifications of the water distribution network model on water quality, is considered by Nono and Basupi [80]. There are many papers that focus on comparing the performance of various optimization algorithms in terms of a number of objectives including operating cost [49,82–88], hydraulic performance [83,89,90] and water quality [91]. These papers enable the uncertainty associated with the choice of algorithm to be evaluated.

Uncertainty due to long term changes in demand or other variables are not relevant to the optimization of system operation.

Finally, despite human error being the most important source of uncertainty in system operations (as outlined in Section 2.3), no studies could be found that evaluated the effects of this source of uncertainty on the objectives of system operations.

4. Conclusions

Many studies have been carried out involving the optimization of the planning, design, rehabilitation or operation of WDS. These have been summarised in a number of review papers. While many of these studies are single objective, there is a growing literature of studies that address multiple objectives. Typical objectives include minimizing capital or life cycle cost, minimizing energy consumption or greenhouse gas emissions, maximizing flexibility and maximizing water quality.

Accounting for uncertainty is a fundamental issue of importance to the long-term planning, design, rehabilitation and operation of WDS. There are many sources of uncertainty within these decision processes, and they have been categorized in this paper as model/algorithm uncertainty, data/input uncertainty and human related uncertainty. This paper summarises the various sources of uncertainty, their importance relative to the optimization objectives considered and the extent to which the impact of these sources of uncertainty on the system objectives have been considered in the literature.

Not surprisingly, the different sources of uncertainty can have varying impacts on the various objectives considered in the optimization of WDS.

Firstly, in relation to model/algorithm uncertainty, a major source of model uncertainty for water quality objectives is due to a basic lack of understanding of the chemical processes including reactions of the disinfectant with organics in the water supply and with biofilms on pipe walls. This receives a moderate coverage in the literature.

An assessment of algorithm uncertainty can be made through the considerable number of studies in the literature that compare the performance of various optimization algorithms. However, this is not considered to be a major source of uncertainty.

In relation to data /input uncertainty, a major source of uncertainty is randomness in nodal demands. This has received reasonable coverage in the research literature. Long-term changes in nodal demands due to population growth or climate change can also be a major source of uncertainty for planning, design and rehabilitation studies. This has received sparse coverage in the research literature.

Uncertainty due to natural variability of variables other than demand is of medium importance and there are a few studies that address its impact.

Finally, human related uncertainty through lack of knowledge or understanding is considered to be the largest source of uncertainty. Despite this, here is little or no literature that explicitly evaluates this uncertainty on the system objectives.

5. Recommendations for Further Work

Based on an assessment of the relative importance of the various sources of uncertainty and how well they have been analysed in the literature, the following recommendations for further work arise from this study:

More research is needed into the behaviour of disinfectants in WDS and their reaction with organics in the water column and with biofilm on pipe walls. This is needed for studies where water quality is an important consideration.

Better methods to forecast nodal demands in the short and long term are also needed as this is a major source of uncertainty in all areas related to the optimization of WDS.

Finally, much more research is needed into human related sources of uncertainty and their impacts on all of the objectives identified in this study.

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