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

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Abstract

Optimisation of the operation of water distribution systems has been an active research field for almost half a century. It has focused mainly on optimal pump operation to minimise pumping costs and optimal water quality management to ensure that standards at customer nodes are met. This paper provides a systematic review by bringing together over two hundred publications from the past three decades, which are relevant to operational optimisation of water distribution systems, particularly optimal pump operation, valve control and system operation for water quality purposes of both urban drinking and regional multiquality water distribution systems. Uniquely, it also contains substantial and thorough information for over one hundred publications in a tabular form, which lists optimisation models inclusive of objectives, constraints, decision variables, solution methodologies used and other details. Research challenges in terms of simulation models, optimisation model formulation, selection of optimisation method and postprocessing needs have also been identified.

Keywords: Water distribution systems; optimisation; literature review; pump operation; water quality; valve control

1 Introduction

Water distribution systems (WDSs) represent a vast infrastructure worldwide, which is critical for contemporary human existence from all social, industrial and environmental aspects. As a consequence, there is pressure on water organisations to provide customers with a continual water supply of the required quantity and quality, at a required time, subject to a number of delivery requirements and operational constraints. A level of flexibility exists in the WDSs, which enables the supply of required water under different operational schedules, more or less economically. This flexibility gives opportunity for optimisation of WDS operation.

Since the 1970s, substantial research has addressed the optimisation of operation of WDSs (Ormsbee and Lansey 1994) with two main areas of focus. The first area includes pump operation, as pump operating costs constitute the largest expenditure for water organisations worldwide (Van Zyl et al. 2004). Optimal operation of pumps is often formulated as a cost optimisation problem (Savic et al. 1997). The second area includes optimisation of water quality across the water distribution network. This research area emerged in the 1990s following the U.S. Environmental Protection Agency (EPA) promulgating "rules requiring that water quality standards must be satisfied at consumer taps rather than at treatment plants" (Ostfeld 2005).

Development in the use of various methods to optimise operation of WDSs is not only an interesting subject for research, but also very complex. Initially, these techniques included deterministic methods, such as dynamic programming (DP) (Dreizin 1970; Sterling and Coulbeck 1975a; Zessler and Shamir 1989), hierarchical control methods (Coulbeck et al. 1988a; Coulbeck et al. 1988b; Fallside and Perry 1975; Sterling and Coulbeck 1975b), linear programming (LP) (Alperovits and Shamir 1977; Schwarz et al. 1985) and nonlinear programming (NLP) (Chase and Ormsbee 1989). Since the 1990s, metaheuristic algorithms, such as genetic algorithms, simulated annealing, to name a few, have been applied to the optimal operation of WDSs with increased popularity. Their attractiveness for this type of optimisation is due to their potential to solve nonlinear, nonconvex, discrete problems for which deterministic methods incur difficulty (Maier et al. 2014; Nicklow et al. 2010). In recent years however, deterministic methods have started to reappear, because they are more computationally efficient, thus more suitable for real-time control, as well as other applications (Creaco and Pezzinga 2015). An example of the former is Derceto Aquadapt, a commercial software used for real-time optimisation of valve and pump schedules (Derceto 2016), which uses LP as the base algorithm.

2 Aim, scope and structure of the paper

The aim of this paper is to provide a comprehensive and systematic review of publications for operational optimisation of WDSs since the end of the 1980s to nowadays to contribute to the existing review literature (Lansey 2006; Ormsbee and Lansey 1994; Walski 1985). Publications included in this review address optimal pump operation, valve control and optimal system operation for water quality purposes of both urban drinking and regional multiquality WDSs.

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 different structure and purpose. The main text is structured according to publications' application areas (pump, water quality and valve control) and general classification. This classification is used because it captures all the main aspects of an operational 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 this part of the paper is to provide current status, analysis and synthesis of the current literature, and suggest future research directions.

The table forms a significant part of the paper referring to over a hundred publications and is structured chronologically. It contains detailed classification of each paper, including optimisation models (i.e., objective functions, constraints, decision variables), water quality parameters, network analyses and optimisation methods used, as well as other relevant information. The purpose of the table is to provide an exhaustive list of publications on the topic (as much as feasible) detailing comprehensive and thorough information, so it could be used as a single reference point to identify one's papers of interest in a timely manner. Therefore, it represents a unique and important contribution of this paper.

The structure of the paper is as follows:

- The main review: (3) Application areas, (4) General classification of reviewed publications, (5) Future research, (6) Summary and conclusion, (7) List of terms, (8) List of abbreviations.
- The table: (9) Appendix.

3 Application areas

3.1 Pump operation

Typically, electricity consumption is one of the largest marginal costs for water utilities. The price of electricity has been rising globally, making it a dominant cost in operating WDSs. Pump operation is optimised in order to achieve a minimal amount of energy consumed by pumps. Pumps are controlled either explicitly by times when pumps operate (so called pump scheduling), or implicitly by pump flows (Bene et al. 2013; Nitivattananon et al. 1996; Pasha and Lansey 2009; Zessler and Shamir 1989), pump pressures, tank water trigger levels (Broad et al. 2010; Van Zyl et al. 2004) or pump speeds for variable speed pumps (for example Hashemi et al. (2014), Ulanicki and Kennedy (1994), Wegley et al. (2000)). These controls are specified as decision variables and their formulations are reviewed in Ormsbee et al. (2009). The most frequently used is *explicit pump scheduling*, which can be specified by (i) on/off pump statuses during predefined equal time intervals (for example Baran et al. (2005), Ibarra and Arnal (2014), Mackle et al. (1995), Salomons et al. (2007)), (ii) length of the time (in hours) of pump operation (Brion and Mays 1991; Lopez-Ibanez et al. 2008), (iii) start/end run times of the pumps (Bagirov et al. 2013). The former, although the most frequently used, requires a large number of decision variables for (real-world) WDSs with numerous pump stations, which increases the size of the search space. The latter two methods reduce the number of variables hence decrease the size of the search space. This reduced search space helps the optimisation algorithm to quickly achieve a satisfactory pump schedule. Concerning the methods for search space reduction, an open question is how to perform it without compromising the fidelity of the optimisation model and undue simplification of the real system.

Pump operating costs comprise of costs for energy consumption due to pump operation and costs due to the maintenance of pumps. Energy consumption normally incurs energy consumption charge and demand charge. The former is based on the kilowatt-hours of electric energy consumed by pumps during the billing period (Ormsbee et al. 2009) and is often the only component of operating costs used in the pump optimisation problem (for example Jamieson et al. (2007), Kim et al. (2007), Ulanicki et al. (1993)). Demand charge is usually based on the peak energy consumption during a specific time period (Ormsbee et al. 2009), and often determined over a time scale much longer (weeks-months) than the time period considered for optimisation (hours-days). As it is not easily incorporated in the optimisation model (McCormick and Powell 2003), it has been included as a constraint (Gibbs et al. 2010a; Selek et al. 2012) or as an additional objective besides pump operating costs (Baran et al. 2005; Kougias and Theodossiou 2013; Sotelo and Baran 2001). Whether demand charges are included as a constraint or an objective depends largely on the optimisation technique selected for solving the pump operation problem. The shape of the resulting solution space (i.e., the solution neighbourhood structure) or the ease with which an additional constraint is incorporated determines the best optimisation method to use. The approach for including maximum demand charges into overall costs, which takes into account the uncertainty in the future water demand, makes an already difficult problem of pump operation planning an even greater challenge.

Similar to demand charges, pump maintenance costs are also difficult to quantify. They are usually included using a surrogate measure such as the number of pump switches (Lopez-Ibanez 2008). It is assumed that a reduction in the number of pump switches results in the reduction of the pump maintenance costs (Lansey and Awumah 1994). The number of pump switches has been considered as a constraint (Boulos et al. 2001; Lansey and Awumah 1994; Lopez-Ibanez et al. 2008; Selek et al. 2012; Van Zyl et al. 2004), alternatively, pump energy costs and pump maintenance costs have been considered as a two-objective optimisation problem (Bene et al. 2013; Kelner and Leonard 2003; Lopez-Ibanez et al. 2005; Savic et al. 1997). The advantage of considering pump switches as an objective over incorporating them as a constraint is in the ability to investigate a complete trade-off between maintenance and other costs when the former is selected. However, an open research question with regard to pipe maintenance costs within an operational optimisation problem relates to whether there are more appropriate expressions for characterising this type of wear and tear costs.

A multi-objective approach has been increasingly applied (Figure 1) to pump optimisation problems to include considerations other than costs. Other objectives considered, apart from demand charge and pump maintenance costs mentioned above, were the difference between initial and final water levels in storage tanks (Baran et al. 2005; Sotelo and Baran 2001), the quantity of pumped water (Kougias and Theodossiou 2013), greenhouse gas (GHG) emissions associated with pump operations (Stokes et al. 2015a,b) and operational reliability (Odan et al. 2015). Most recently, water quality has been traded off against pump operating costs (Arai et al. 2013; Kurek and Ostfeld 2013; Kurek and Ostfeld 2014; Mala-Jetmarova et al. 2014) with the finding that those objectives are conflicting. Similarly, water losses due to leakage and pump operating costs were identified as conflicting objectives (Giustolisi et al. 2012). Minimisation of just pumping costs moves the pumping to the night time when the pressures in the system are higher, producing increased leakage. When water losses are introduced as an objective, more pumping occurs during the day time and leakage reduces (Giustolisi et al. 2012).

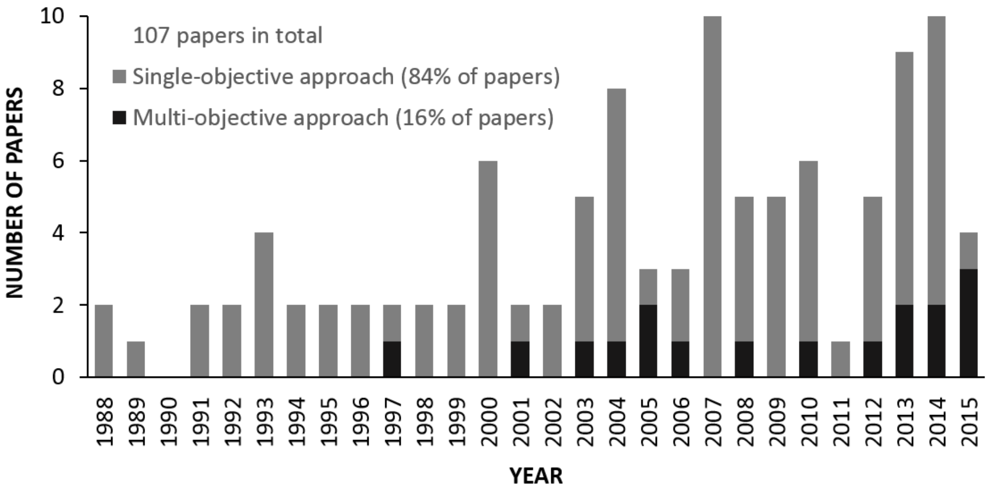


Figure 1: Papers (from the appendix table) by year and optimisation approach

While the single-objective approach benefits from being able to identify one best solution, which is then implemented, multi-objective methods normally produce a set of trade-off (Pareto) solutions, which requires an additional step to select only one of the solutions. Selecting a single solution from a potentially large non-dominated set is likely to be difficult for any decision maker. This subsequent selection process makes the multi-objective approach less desirable by the operators who often require a clear decision to implement. This mismatch leads to the research question of the most promising way for selecting the best solution from the Pareto set, which may involve providing the decision makers with a globally representative subset of the non-dominated set that is sufficiently small to be tractable.

3.1.1 Real-time control

Time is an important factor for industrial applications. In real-time planning and control of WDSs, there is need for optimal schedules to be found in a timely manner based on demand forecasts and be implemented via the SCADA (Supervisory Control and Data Acquisition) system. Evidence from the literature suggests that computational efficiency of metaheuristic algorithms in conjunction with the network simulator, such as EPANET, for large WDSs is not sufficient, however.

Several authors have investigated how to decrease computational effort of the network simulator and/or an optimisation algorithm to provide an optimal solution in real-time. Time consuming extended period simulations (EPS) could be replaced with surrogate models such as artificial neural networks (ANN) (Broad et al. 2010), interpretive structural modelling (ISM) (Arai et al. 2013) or reduced (i.e., skeletonised) models (RM) (Shamir and Salomons 2008). ANNs, which are applied most frequently, were used to determine real-time, near optimal control of WDSs by integrating with GA incorporating demand forecasting (based on seasonal, weekly and daily periodic components) and operating continually based on SCADA data and demand forecast updates (Martinez et al. 2007; Rao and Alvarruiz 2007; Rao and Salomons 2007; Rao et al. 2007; Salomons et al. 2007; Shamir et al. 2004). Surrogate models can be developed prior to the optimisation run, in which case optimisation is not gated by the time consuming network simulator, or they can be validated within the optimisation loop where the network simulator is employed sparingly. An open question is how to control the error of the surrogate model to ensure that the solution found is still optimal when the full network simulator is employed to validate it.

Optimisation methods used for real-time control include LP (Jowitt and Germanopoulos 1992; Pasha and Lansey 2009), NLP (Cembrano et al. 2000), progressive optimality algorithm combined with heuristics (Nitivattananon et al. 1996), adaptive search algorithm (ASA) (Pezeshk and Helweg 1996), GA integrated with ANN (Shamir et al. 2004), and LP combined with a greedy algorithm (LPG) (Giacomello et al. 2013).

Real-time control depends crucially not only on the ability of the optimisation algorithm to find a good solution in near real-time, but also on the effectiveness of the model used to forecast future state of the system for an operational decision window. These aspects make real-time pump control much more difficult problem to solve as opposed to when optimisation is used for planning purposes.

3.2 Water quality

3.2.1 Urban drinking water distribution systems

There does not seem to be a unique optimisation model for the operation of drinking WDSs. The following three basic single-objective models exist in the literature. The first optimisation model minimises pump operating time/costs (Dandy and Gibbs 2003; Goldman and Mays 1999; Sakarya and Mays 1999; Sakarya and Mays 2000; Sakarya and Mays 2003) with addition of water treatment costs (Ulanicki and Orr 1991), costs of water at sources (Brdys et al. 1995) and utility turnout costs (Murphy et al. 2007) subject to water quality and other constraints. The second optimisation model minimises the (costs of) total disinfectant mass dose (Boccelli et al. 1998; Fanlin et al. 2013; Prasad et al. 2004; Rico-Ramirez et al. 2007; Tryby et al. 2002), which may consider the number and locations of booster disinfection stations. The third optimisation model minimises disinfectant concentration deviations at customer demand nodes from desired values (Goldman et al. 2004; Kang and Lansey 2009; Munavalli and Kumar 2003; Propato and Uber 2004a; Propato and Uber 2004b; Sakarya and Mays 1999; Sakarya and Mays 2000; Sakarya and Mays 2003). These models are sometimes combined in various ways (Biscos et al. 2003; Biscos et al. 2002; Gibbs et al. 2010a; Ostfeld and Salomons 2006).

What is the difference in the solution obtained when applying those models? Sakarya and Mays (2000) considered the first and third optimisation model with the following outcomes. Different pump schedules were found using these models. Optimal solutions for the first model considering either pump operating time or pump operating costs were very similar. For the third model considering concentration deviations, nonetheless, the optimal solution had higher value of pump operating time/costs than for the first model. The explanation provided was that the objective function implemented in the third model (i.e. concentration deviations) does not force the algorithm to reduce pump operating time/costs further after all of the constraints are satisfied. Ostfeld and Salomons (2006) discovered that pumping costs are significantly reduced if water quality is absent from the optimisation model and conversely, that the best water quality outcome corresponds to the highest pump operating costs. This competing nature of tradeoff between water quality and operating costs was confirmed by Arai et al. (2013), and Kurek and Ostfeld (2014).

Those models were improved by the incorporation of control valves to direct disinfectant laden-water where required (Kang and Lansey 2009; Kang and Lansey 2010) and by inclusion of uncertainties on demands, pipe roughness and chemical reactions of the disinfectant (Rico-Ramirez et al. 2007). Furthermore, a multi-objective approach was applied with additional objectives being the number of instances of not meeting quality requirements (Ewald et al. 2008; Kurek and Brdys 2006), the costs of tanks (Kurek and Ostfeld 2013), and the number of polluted nodes and operational interventions (OIs) as responses to WDS contamination (Alfonso et al. 2010).

Water quality parameters (such as chlorine) were typically modelled as non-conservative using first order decay kinetics, except for Murphy et al. (2007) and Prasad and Walters (2006), who used water age as a substitute for water quality. Optimisation methods used were mainly LP and mixed integer nonlinear programming (MINLP) (for example Arai et al. (2013), Biscos et al. (2003), Boccelli et al. (1998)) and metaheuristic algorithms (GA, NSGA-II, SPEA2) linked with a network simulator EPANET (for example Alfonso et al. (2010), Dandy and Gibbs (2003)). Most recently in order to reduce computational effort, EPANET was replaced by the ISM (Arai et al. 2013) and ANN (Wu et al. 2014b).

Introduction of water quality considerations increases the complexity of the optimisation 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. Furthermore, the ability to model multiple constituents throughout the water distribution system via the EPANET Multi-Species Extension, EPANET-MSX (Shang et al. 2016), also comes with a further loss in computational efficiency. However, these complex simulations are sometimes necessary as network operational conditions often impact on various water quality constituents, e.g., discolouration that occurs due to erosion of particulate material layers. Consequently, there is a need to develop even more computationally efficient optimisation methods that can be run in real-time, which take complex water quality behaviour into account.

3.2.2 Regional multiquality water distribution systems

Multiquality WDSs are “systems in which waters of different qualities are taken from sources, possibly treated, conveyed and supplied to the consumers” (Ostfeld and Salomons 2004). They deliver water to more than one customer group, who have different water quality requirements. The first optimisation models for multiquality WDSs considered pump operating costs only (Mehrez et al. 1992; Percia et al. 1997).The system operating costs were later extended to also include costs of water at sources (Cohen et al. 2000b), water treatment costs (Ostfeld and Shamir 1993a; Ostfeld and Shamir 1993b), water conveyance costs (Cohen et al. 2000a) and yield reduction costs due to watering crops with low quality water (Cohen et al. 2000a; Cohen et al. 2000c). These costs were combined into one objective, with water quality requirements at customer demand nodes included as constraints.

Subsequent studies performed analyses to explore sensitivity of the solution to modifications of model data and constraints (Cohen et al. 2004; Cohen et al. 2009; Ostfeld 2005; Ostfeld and Salomons 2004) and to compare performance of different optimisation methods (Cohen et al. 2003). The emphasis of these analyses was to investigate the impact of individual operating costs on total system costs and the relationship between different customer groups, such as drinking and irrigation.

Water quality parameters (such as salinity, magnesium, sulphur) were typically modelled as conservative, except for Ostfeld and Shamir (1993b), who modelled non-conservative parameters in reservoirs using first order decay. Additionally, Ostfeld et al. (2011) included chemical water instability, which can result from mixing desalinated water with surface or groundwater, using calcium carbonate precipitation potential (CCPP). Optimisation problems in the above papers were solved as single-objective. Most recently, Mala-Jetmarova et al. (2014) included water quality as an additional objective into an optimisation model and explored tradeoffs between water quality and pumping costs, confirming results of Arai et al. (2013), and Kurek and Ostfeld (2014) indicating conflicting relationship between water quality and pumping cost objectives. Interestingly, when two water quality objectives (each representing a separate water quality parameter) are incorporated together with a pumping cost optimisation into a model, the relationship between water quality and pumping costs is not necessarily conflicting (Mala-Jetmarova et al. 2015). This hypothesis represents a further research challenge to be tested on a different set of realistic case studies of various configurations to ascertain whether the objectives are conflicting or they can be somehow integrated, leading to reduced optimisation problem complexity.

3.3 Valve control

Valve controls were used in conjunction with both optimal pump operation and optimal system operation for water quality purposes. These valve controls were implemented in optimisation models as decision variables. In regards to minimisation of pump operating costs, those decision variables were represented by continuous valve statuses (Biscos et al. 2002; Biscos et al. 2003; Ulanicki and Orr 1991; Ulanicki et al. 2007), binary valve statuses (Biscos et al. 2002; Biscos et al. 2003; Giustolisi et al. 2012; Jamieson et al. 2007), valve positions (Ulanicki and Kennedy 1994; Wu et al. 2014a) or valve openings/opening ratios (Cembrano et al. 2000; Cohen et al. 2000c; Martinez et al. 2007; Ostfeld and Salomons 2004; Rao et al. 2007; Rao and Salomons 2007), flows through valves (Carpentier and Cohen 1993; Jowitt and Germanopoulos 1992), valve headlosses or headloss coefficients (Cohen et al. 2000b; Cohen et al. 2009; Kelner and Leonard 2003), and pressure reducing valve (PRV) settings (Murphy et al. 2007; Salomons et al. 2007; Shamir and Salomons 2008).

In water quality optimisation models, valves were used, via their binary statuses (open or closed), to improve water quality at customer nodes by rerouting flows (Prasad and Walters 2006) and to minimise pollutant contamination across a network (Alfonso et al. 2010). Additionally, percentages/degrees of valve closures (Kang and Lansey 2009; Kang and Lansey 2010) or openings (Ostfeld and Salomons 2006) were used to optimise chlorine levels across a network.

In general, the pumping flow is often the main decision variable used in operational optimisation of WDSs. Valves often play an indirect role in meeting the constraints, such as balancing of levels in interconnected reservoirs (e.g., Ulanicki et al. 2007) and/or pressure regulation (e.g., to control leakage, Giustolisi et al. 2015). However, in water quality optimisation, they may also be one of the main decision variables.

4 General classification of reviewed publications

Based on the selected literature analysis, the following are the four main criteria for the classification of operational optimisation for WDSs: (i) application area, (ii) optimisation model, (iii) solution methodology and (iv) test network.

4.1 Application area

As described in Section 3, there are three application areas: pump operation (Section 3.1), water quality management (Section 3.2) and valve control (Section 3.3). Figure 2 displays distribution of those application areas across the papers analysed (and listed in the appendix table) as follows:

- The largest portion of papers (41%) is concerned with optimisation of pump operation only.
- Optimisation of pump operation combined with valve control, water quality, or both valve control and water quality are represented quite evenly by 15%, 15% and 11% of papers, respectively.
- Optimisation of water quality exclusive of any other operational controls (i.e. pumps and/or valves) is addressed in 15% of papers.
- The smallest portion of papers (3%) is concerned with optimisation for water quality purposes combined with valve control.

The above apparent prevalence of purely pump operation focused papers is not surprising and occurs mostly due to historical reasons. Namely, following the first studies focusing on WDS design optimisation, the idea of using optimisation in operational studies (i.e., for cost reduction by manipulating pump flows over time) was the next one to be addressed by the research community. The introduction of water quality criteria, with or without valve control for pressure management (e.g., for leakage control) or water quality manipulation, appeared much later in the literature. Lately, more emphasis was put on holistic assessment of WDS operation, and thanks to more sophisticated simulation and optimisation methods having been introduced.

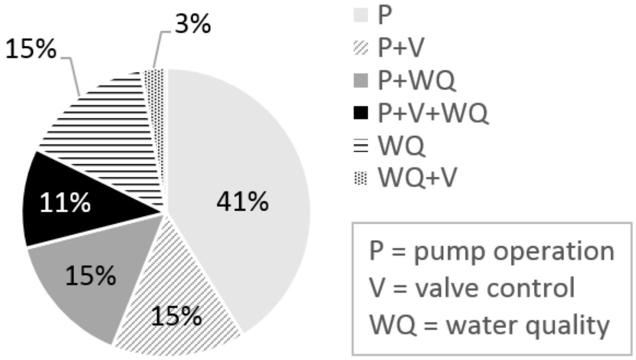


Figure 2: Papers (from the appendix table) by application areas

4.2 Optimisation model

Regarding optimisation models, each is mathematically defined by three types of components: objectives, constraints and decision variables. Figure 3 indicates how many of these components are included in the optimisation models (of papers analysed in the appendix table), which indicates the degree of complexity of the formulation. Note that not all 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 four, with a vast majority of models (84%) being single-objective. The proportion of multi-objective optimisation models, including 2, 3 or 4 objectives is only 8%, 6% and 2%, respectively.
- The number of constraints incorporated in optimisation models ranges from one to nine. The largest proportion of optimisation models uses 3 or 4 constraints, or 29% and 22%, respectively. The proportion of optimisation models using 1-2 and 5-9 constraints totals to 49% (see Figure 3(b) for more details). Please note that hydraulic constraints (such as conservation of mass of flow, conservation of energy, and conservation of mass of constituent) were not included in these statistics as they are normally included as implicit constraints and forced to be satisfied by WDS modelling tool, such as EPANET.
- The number of types of a decision (i.e. control) variable included in optimisation models ranges from one to seven. A majority of optimisation models, 41% and 33%, uses one or two types of a decision variable, respectively. Use of more than two types of a decision variable is less frequent and the number of such models tends to decrease with the increasing number of decision variables used.

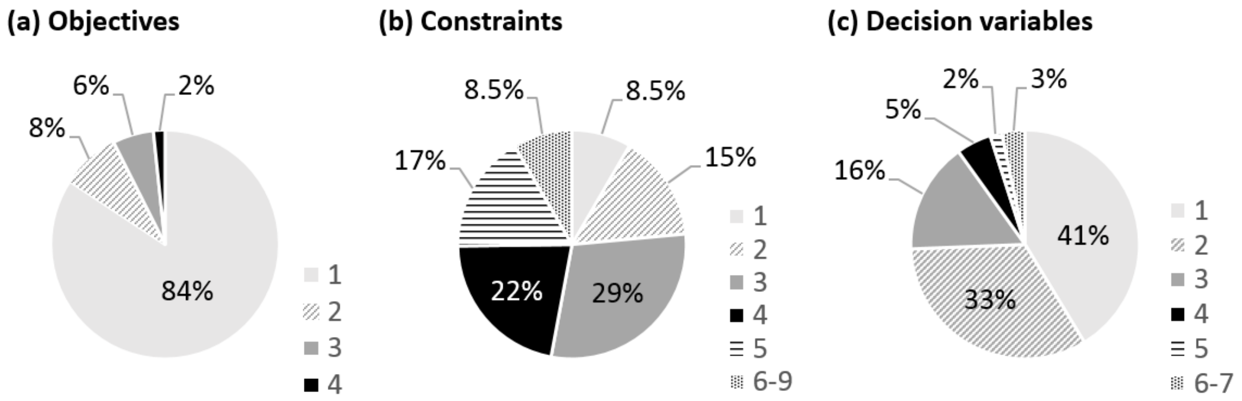


Figure 3: Optimisation models (of papers from the appendix table) by: (a) number of objectives, (b) number of constraints, (c) number of types of a decision variable, in an optimisation model

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 WDS operators. On the other hand, the number of constraints used in the formulation of the problem depends on the complexity of the system and the number of operational criteria expressed as constraints rather than objectives. Finally, the number and types of decision variables depend on what is controllable (what can be changed) in WDS under consideration. Two related unresolved research questions are: (i) how to select the best formulation for the problem at hand; and (ii) how sensitive the ultimate selection of solution(s) is to the problem formulation selected (Maier et al., 2014).

4.2.1 General optimisation model

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

$$Minimise\left(f_1(x), f_2(x), \ldots, f_n(x)\right) \quad (1)$$

subject to:

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

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

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

where Equation (1) represents objective functions to be minimised, Equations (2)-(4) three types of a constraint, while x represents decision variables (for details, see Table 1).

Table 1: Components of a general optimisation model

Optimisation model component	**Description**	**Reference (an example)**
Objective functions $f_1(x)$, $f_2(x)$, …, $f_n(x)$	*Pump operating costs*, consisting of energy consumption charge and demand charge	Kougias and Theodossiou (2013)
	Pump maintenance costs, represented, for example, by the number of pump switches	Lopez-Ibanez et al. (2005)
	GHG emissions associated with pump operation	Stokes et al. (2015a)
	Water treatment costs	Cohen et al. (2009), Ostfeld et al. (2011)
	Disinfectant dosage mass or costs	Rico-Ramirez et al. (2007)
	Water quality deviations at customer demand nodes	Propato and Uber (2004a,b)
	Pressure deficit at customer demand nodes	Min/max pressure at nodes only as a constraint, Ostfeld and Tubaltzev (2008)
	Other operational objectives, for example, cost of water	Ostfeld and Salomons (2004)
Constraints $a_i(x) = 0$, $b_i(x) \leq 0$, $c_i(x) \leq 0$, respectively	*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	Rossman (2000)
	System constraints given by limitations and operational requirements of a WDS, for example, minimum and maximum water levels at storage tanks, water deficit/surplus at storage tanks at the end of the simulation period	Lopez-Ibanez et al. (2005)
	Constraints on decision variables x, for example, limits on pump schedules/speeds, the number of pump switches or disinfectant doses	Ghaddar et al. (2014) (limits on pumps), Propato and Uber (2004a,b) (limits on disinfectant doses)
Decision variables x to control	*Pumps*: either pump schedules, pump start/end run times, pump flows, pump heads/pressures, pump speeds or storage tank water trigger levels	Lopez-Ibanez et al. (2005) (schedules), Bagirov et al. (2013) (times), Bene et al. (2013) (flows), Price and Ostfeld (2014) (heads), Kurek and Ostfeld (2014) (speeds), Broad et al. (2010) (trigger levels)
	Valves: either valve flows, headlosses or opening ratios	Carpentier and Cohen (1993) (flows), Cohen et al. (2009) (headlosses and ratios)
	Water quality: either explicitly by disinfectant dosage rates (urban drinking WDSs) or implicitly by pumps drawing water from different water sources (urban drinking and regional multiquality WDSs)	Propato and Uber (2004a,b) (explicitly by disinfectant doses), Ostfeld et al. (2011) (implicitly by pumps)

Table 1 provides a generic set of components used for formulating an optimisation problem involving 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

Optimisation methods have developed significantly since the 1970s. Deterministic methods used initially (Brion and Mays 1991; Carpentier and Cohen 1993; Coulbeck et al. 1988a; Coulbeck et al. 1988b; Lansey and Awumah 1994; Ulanicki and Kennedy 1994; Ulanicki et al. 1993; Zessler and Shamir 1989) started being supplemented by metaheuristics during the mid 1990s (Figure 4). The first of these methods introduced was a genetic algorithm (GA) (Boulos et al. 2001; Lingireddy and Wood 1998; Mackle et al. 1995; Moradi-Jalal et al. 2004; Wu et al. 2014a), which was also used with modifications (Bene et al. 2010;

Selek et al. 2012; Wu 2007) or in combination with local search methods (i.e. hybrid methods, Figure 4) (Savic et al. 1997; Van Zyl et al. 2004) to increase its efficiency. Other metaheuristic algorithms included particle swarm optimisation (PSO) (Wegley et al. 2000), ant colony optimisation (ACO) (Hashemi et al. 2014; Lopez-Ibanez et al. 2008; Ostfeld and Tubaltzev 2008), nondominated sorting genetic algorithm II (NSGA-II) (Prasad et al. 2004), strength Pareto evolutionary algorithm 2 (SPEA2) (Kurek and Ostfeld 2013), harmony search algorithm (HSA) (Kougias and Theodossiou 2013), limited discrepancy search (LDS) (Ghaddar et al. 2014) and other multi-objective algorithms (Baran et al. 2005).

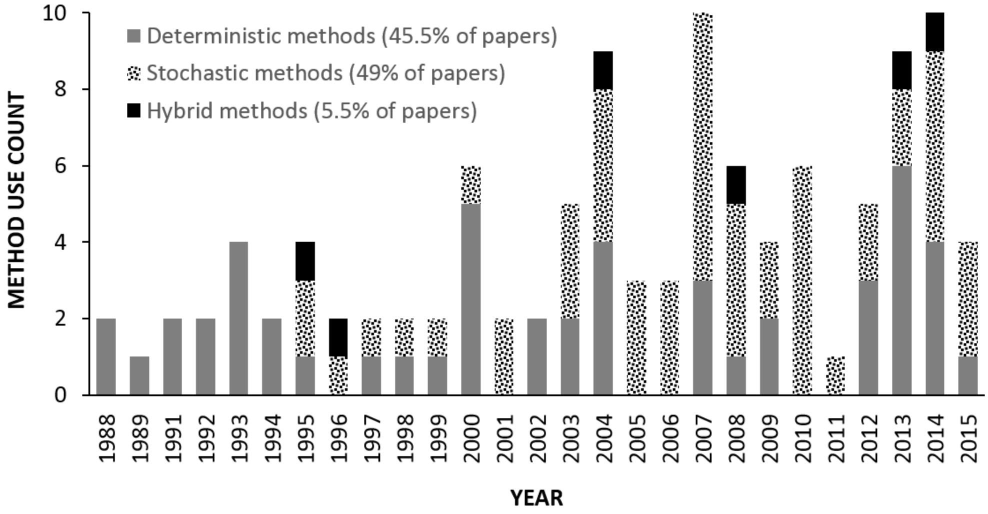


Figure 4: Optimisation methods (of papers from the appendix table) by year

Recent advancements show, nevertheless, that these metaheuristics linked with a network simulator (i.e. EPANET) may prevent implementation for large WDSs in real-time, due to considerable computational effort required (Giacomello et al. 2013). For this reason, more efficient deterministic methods have been increasingly applied (Arai et al. 2013; Bagirov et al. 2008; Bagirov et al. 2013; Bagirov et al. 2012; Bene et al. 2013; Gleixner et al. 2012; Goryashko and Nemirovski 2014; Kim et al. 2015; Kim et al. 2007; Price and Ostfeld 2013a; Price and Ostfeld 2013b; Price and Ostfeld 2014; Reca et al. 2014; Ulanicki et al. 2007). Parallel programming techniques (Ibarra and Arnal 2014; Wu and Zhu 2009) are also used to reduce computation time. However, even with parallel programming techniques and more efficient deterministic optimisation methods, WDS simulations may still be computationally prohibitive especially as the fidelity of the model and the number of decision variables increase.

Further efforts to improve computational efficiency of various optimisers led to the development and integration of surrogate models (metamodels) within optimisation algorithms. Surrogate models are efficient tools used to replace and approximate network simulations which can be very computationally expensive and/or may become an obstacle in real-time implementations. To date, two types of a surrogate model were applied to optimisation of WDS operation being artificial neural networks (ANN) (Broad et al. 2005; Broad et al. 2010; Martinez et al. 2007; Rao and Alvarruiz 2007; Rao and Salomons 2007; Rao et al. 2007;

Salomons et al. 2007; Shamir et al. 2004) and interpretive structural modelling (ISM) (Arai et al. 2013).

ANNs, which are by far the most commonly used surrogate models, are based upon real neurological structures and can be represented as directed graphs. They consist of nodes interconnected by links and are commonly arranged into an input layer (representing model inputs), multiple intermediate layers and an output layer (representing model outputs). They do not approximate all simulation mechanisms of a network model, but only model inputs such as decision (control) variables and model outputs such as state variables (Broad et al. 2010). In contrast, ISM captures an underlying hierarchical structure of the system and identifies relationships (direct or indirect) between its facilities. As such, it enables understanding of fundamental principles of complex systems such as WDSs. ISM is defined mathematically by a matrix and similarly to ANN they can be represented as a directed graph.

The choice of the solution methodology, and whether it incorporates the equations representing the behaviour of the real system directly in the formulation of the problem, or it uses a network simulator (with or without the use of a surrogate model to reduce the calls to the simulator), depends on the type of problem being considered, the level of expertise of the analyst and the familiarity with the particular method/tool. However, there is no clear justification provided in many of the papers as to why a particular methodology has been selected and/or why another methodology has not been tested. Quite often, this choice is based on the literature survey done by the authors of the paper, rather than on an objective comparison of the tests performed using implementations of two or more solution methodologies. Maier et al. (2015) stress that these aspects make it difficult to progress towards the development of meaningful guidelines for the application of different optimisation methods. Hence, an interesting research question for further studies would be how to select the best optimisation method for a particular WDS operational problem. This process would require a thorough comparison of a number of solution methodologies on a representative selection of problems as, for example, it has been done for multi-objective WDS design (Wang et al. 2015).

4.4 Test network

Large variety of test networks has been used in operational optimisation of WDSs. These networks vary in size and complexity, from small systems with one source, one pump and a few nodes (see for example, Bene and Hos (2012), Price and Ostfeld (2014)) to large real-world WDSs with multiple reservoirs, hundreds of pumps and thousands of nodes (see for example, Murphy et al. (2007)). Figure 5 categorises test networks used (in the papers listed in the appendix table) by network size, expressed in terms of the number of nodes within a network. Networks, for which the number of nodes can be identified from the paper or references provided, are included only. Figure 5 reveals that a majority of the networks used (80%) are limited in size to 100 nodes, from which about one half of the networks (36%) includes only up to 20 nodes.

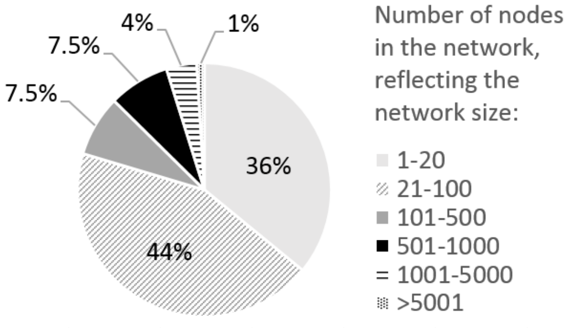


Figure 5: Test networks (of papers from the appendix table) by network size

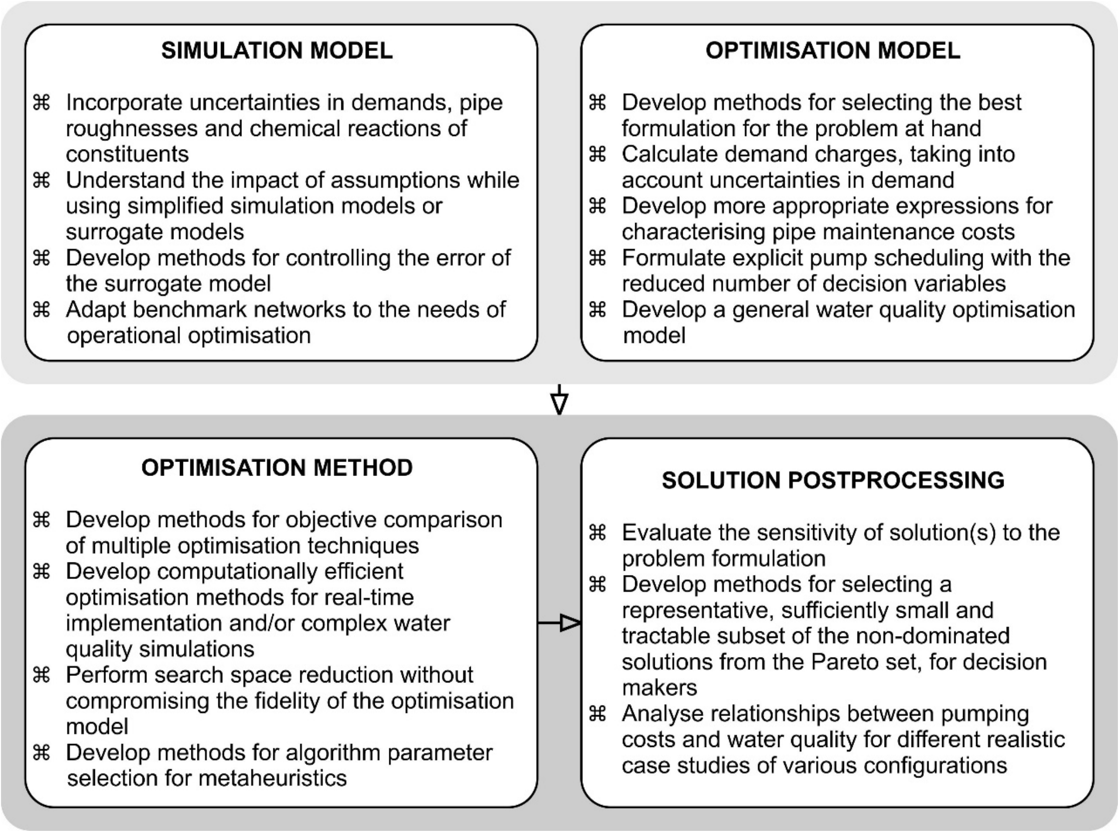
Figure 5 illustrates that similar to other problems in operations research literature, various WDS operational formulations and optimisation methods used have usually been assessed using computationally cheap, small networks to facilitate initial algorithm development and implementation. As real-world networks contain hundreds of thousand elements (including pumping stations, reservoirs and valves), a single EPS simulation can take minutes or even hours to execute even on powerful desktop computers. This extended time can become especially obstructive when real-time control is considered. Consequently, large networks are being simplified for the purpose of optimisation (Cembrano et al. 2000; Jowitt and Germanopoulos 1992; Ulanicki et al. 1993), or reduced (so called reduced models (RM)) (Shamir and Salomons 2008) by applying mathematical manipulation, such as the methodology proposed in Ulanicki et al. (1996).

Similar to network size, frequency of use of test networks varies considerably, as some networks have been used only once, while others quite frequently and by numerous authors. For example, there are two test networks, which have been used (in the papers listed in the appendix table) 10 or more times. The first is Anytown network (Walski et al. 1987) with 19 nodes (and 1 source, 1 pump station, 2 tanks), which was applied 10 times, and the second is EPANET Example 3 (USEPA 2013) with 92 nodes (and 2 sources, 2 pump stations, 3 tanks), which was applied 14 times. Anytown is a hypothetical WDS, whereas EPANET Example 3 is based on a real WDS of Navato, California. The possible reasons for those networks being more popular than others is their data availability and their flexibility to be modified to suit a range of optimisation models inclusive of water quality considerations.

The similar situation with the lack of large and complex networks has been experienced by researchers working in the WDS design field, where there used to be a limited availability of realistically large benchmark problems for testing of optimisation algorithms. For that reason, a number of research groups have been working on development of either water distribution test networks (Jolly et al. 2014) or tools for automatic generation of such networks of varying size and levels of complexity (De Corte and Sörensen 2014). An open question still remains, how these tools or benchmark networks can be adapted to the needs of operational optimisation of WDS as most of the systems do not include all the elements required for such optimisation (e.g., pump stations/pumps, valves and reservoirs).

5 Future research

Future research challenges for operational optimisation of WDSs are listed in Figure 6 and grouped according to steps involved in optimisation: (i) simulation model, (ii) optimisation model, (iii) optimisation method, and (iv) solution postprocessing. In regards to simulation models, methodologies need to be developed to account for uncertainties in demands, pipe roughnesses and chemical reactions of constituents as incorporation of those uncertainties into optimisation models is very rare (Goryashko and Nemirovski 2014; Rico-Ramirez et al. 2007). In contrast, it is important to develop understanding of the impact of assumptions while using simplified simulation models or surrogate models (for example in real-time control) and to control the error of the surrogate model to ensure that the solution found is still optimal. Benchmark test networks developed for WDS design (De Corte and Sörensen 2014) need to be adapted for operational optimisation of WDS as most of the systems do not include all the elements required for such optimisation (e.g., pump stations/pumps, valves and reservoirs).



SIMULATION MODEL

- Incorporate uncertainties in demands, pipe roughnesses and chemical reactions of constituents
- Understand the impact of assumptions while using simplified simulation models or surrogate models
- Develop methods for controlling the error of the surrogate model
- Adapt benchmark networks to the needs of operational optimisation

OPTIMISATION MODEL

- Develop methods for selecting the best formulation for the problem at hand
- Calculate demand charges, taking into account uncertainties in demand
- Develop more appropriate expressions for characterising pipe maintenance costs
- Formulate explicit pump scheduling with the reduced number of decision variables
- Develop a general water quality optimisation model

OPTIMISATION METHOD

- Develop methods for objective comparison of multiple optimisation techniques
- Develop computationally efficient optimisation methods for real-time implementation and/or complex water quality simulations
- Perform search space reduction without compromising the fidelity of the optimisation model
- Develop methods for algorithm parameter selection for metaheuristics

SOLUTION POSTPROCESSING

- Evaluate the sensitivity of solution(s) to the problem formulation
- Develop methods for selecting a representative, sufficiently small and tractable subset of the non-dominated solutions from the Pareto set, for decision makers
- Analyse relationships between pumping costs and water quality for different realistic case studies of various configurations

Figure 6: Future research challenges

Concerning optimisation models, an open question is how to select the best formulation for the problem at hand (Maier et al. 2014). This formulation also involves development of the approach for including maximum demand charges into overall operating costs, which would take into account the uncertainty in the future water demand. Development of more appropriate expressions for characterising pipe maintenance costs is also required to include this type of wear and tear costs into an operational optimisation problem. Explicit pump scheduling would benefit from an improved optimisation model, which would decrease the number of decision variables, thus reduce the size of the search space and enable application to more complex and extensive real-world problems. Regarding optimisation problems with water quality aspects, future research may consider the development of an optimisation model with an inbuilt flexibility for a general WDS, which could be customised for a specific WDS.

A methodology for an objective comparison of optimisation methods should be developed, so the best optimisation method for a particular case can be selected. Further, there is a need to develop computationally efficient optimisation methods which can be run in real-time, as well as take complex water quality behaviour into account. Concerning the methods for search space reduction, an open question is how to perform it without compromising the fidelity of the optimisation problem and undue simplification of the real system. While using metaheuristic algorithms, methodologies for algorithm parameter selection such as in Gibbs et al. (2010b) and Zheng et al. (2015) need to be developed.

In regards to solution postprocessing, the question remains how sensitive the ultimate selection of solution(s) is to the problem formulation selected (Maier et al. 2014). In multi-objective optimisation approach, methods need to be developed for selecting the best solution(s) from the Pareto set, which is representative and sufficiently small to be tractable. A further research challenge is to analyse relationships between pumping costs and water quality using a set of realistic case studies to ascertain whether they are conflicting objectives or they can be somehow integrated, leading to reduced optimisation problem complexity.

6 Summary and conclusion

This paper presented a literature review of optimisation of operation of WDSs since the end of 1980s to nowadays. The papers reviewed are concerned with optimal pump operation inclusive of real-time control, valve control and optimisation for water quality purposes for urban drinking as well as regional multiquality WDSs. The value of the paper is that it brings together the majority of journal publications for operational optimisation of WDS, two hundred in total, which have been published over the past three decades. It describes the current status, provides synthesis and suggests future research directions. Uniquely, it also contains extensive information for over one hundred publications in a tabular form, listing optimisation models inclusive of objectives, constraints, decision variables, solution methodologies used and other details.

The main future research challenges are identified as follows. The basic requirement for optimal operations is an accurate and reliable simulation model. However, the lack of understanding and accepted means for incorporating uncertainties in demand forecasting and network behaviour prediction models (both quantity and quality) are, among others, the factors limiting wider implementation of those models. Furthermore, there is no universal agreement among researchers and practitioners on how to formulate an operational optimisation problem and include all relevant objectives and constraints, while still allowing an efficient search for the best solution to implement. Although optimisation methods are well researched, there is no agreement on what optimisation method is best for a particular WDS operation problem, which requires a concerted effort by the research community to develop methods for objective comparison and validation. Finally, postprocessing of results, and multi-objective (Pareto) solutions in particular, poses another research challenge as there is no universally accepted method for selecting only one solution, which can be implemented in a real system. Therefore, water distribution operational optimisation problems are far from being solved, despite the large body of literature on this subject published over the last 20-30 years.

7 List of terms

- 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.
- Simulation model = Mathematical model or software used to solve hydraulics and water quality network equations.
- 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.
- 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.

8 List of abbreviations

ACO = ant colony optimisation
ADP = approximate dynamic programming
AMALGAM = a multialgorithm genetically adaptive method
ANN = artificial neural network
ARIMA = autoregressive integrated moving average
ASA = adaptive search algorithm
CCPP = calcium carbonate precipitation potential
CNSGA = controlled elitist nondominated sorting genetic algorithm
CWQ = consistent water quality (sources)
D = design
DAN2-H = hybrid dynamic neural network
DBP = disinfection by-products
DCA = direct calculation algorithm
DP = dynamic programming
DPG = decomposed projected gradient

DRAGA = dynamic real-time adaptive genetic algorithm

EA = evolutionary algorithm

EF = emission factor

ENCOMS = energy cost minimisation system

EPS = extended period simulation

fmGA = fast messy genetic algorithm

FMS = full mixing step

FP = full parameterisation (approach)

GA = genetic algorithm

GAPS = genetic algorithm for pump scheduling

GHG = greenhouse gas (emissions)

H-W = Hazen-Williams (head-loss equation)

HSA = harmony search algorithm

ILDS = improved limited discrepancy search

IP = integer programming

ISM = interpretive structural modelling

ISS = in-station scheduling

IWQ = inconsistent water quality (sources)

LDS = limited discrepancy search

LLS = linear least square

LP = linear programming

LPG = linear programming combined with a greedy algorithm

LRO = linear robust optimal (policy)

MILP = mixed integer linear programming

MINLP = mixed integer nonlinear programming

MIP = mixed integer programming

MIQP = mixed integer quadratic programming

MO = multi-objective

MOGA = multiple objective genetic algorithm

NLP = nonlinear programming

NPGA = niched Pareto genetic algorithm

NPV = net present value

NSGA = nondominated sorting genetic algorithm

NSGA-II = nondominated sorting genetic algorithm II

OI = operational intervention

OP = operation

OPTIMOGA = optimised multi-objective genetic algorithm

PBA = particle backtracking algorithm

PMS = partial mixing step

POWADIMA = potable water distribution management (a research project)

PP = partial parameterisation (approach)

PRV = pressure reducing valve

PSO = particle swarm optimisation

Q-C = flow-quality (model)

Q-H = flow-head (model)

Q-C-H = flow-quality-head (model)

QP = quadratic programming

RM = reduced model (i.e. skeletonised model of a WDS)

RR = replacing reservoir

SA = simulated annealing

SARIMA = seasonal autoregressive integrated moving average

SCADA = supervisory control and data acquisition

SDW = safe drinking water

SLO = series of the local optima

SO = single-objective

SPEA = strength Pareto evolutionary algorithm

SPEA2 = strength Pareto evolutionary algorithm 2

SQP = sequential quadratic programming

TDS = total dissolved solids

TOC = total organic carbon

WDS = water distribution system

WTP = water treatment plant

9 Appendix

ID. Authors (Year) **SO/MO*** **Brief description**	**Optimisation model (objective functions^{+}, constraints**, decision variables^{++})**	**Water quality** **Network analysis** **Optimisation method**	**Notes**
1. Coulbeck et al. (1988a) SO Optimal pump operation considering fixed speed, variable speed and variable throttle pumps using hierarchical approach.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max reservoir water levels, (2) min/max flows through pump stations, (3) min/max speed for variable speed pumps, (4) min/max throttle valve factor for throttle pumps. Decision variables: (1) The number of pumps which are switched on (discrete), (2) pump speeds (continuous), (3) throttle valve factors (continuous).	Water quality: N/A. Network analysis: Explicit mathematical formulation (unsteady state). Optimisation method: N/A.	• Hierarchical decomposition framework of pump scheduling problem into three levels is proposed as follows. (i) Upper level, which includes dynamic optimisation of reservoirs in order to find the optimal reservoir trajectories. (ii) Intermediate level, which included static optimisation of pump groups. (iii) Lower level, which includes static optimization of individual pump stations. • Proposed time horizon is 24 hours divided into 24 hourly time stages. • It is assumed that a demand prediction is available. • The upper level problem can be solved using DP or subgradient NLP techniques. • Test networks: N/A.
2. Coulbeck et al. (1988b) SO Optimal pump operation considering variable speed and variable throttle pumps using hierarchical approach.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max reservoir water levels, (2) min/max flows through pump stations, (3) min/max speed for variable speed pumps, (4) min/max throttle valve factor for throttle pumps. Decision variables: (1) The number of pumps which are switched on (discrete), (2) pump speeds (continuous), (3) throttle valve factors (continuous).	Water quality: N/A. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: A proposed algorithm.	• Extension of the paper by Coulbeck et al. (1988a) including new algorithms for lower level problem to optimise operation of individual pump stations. • The proposed algorithms are based on a decomposition approach. Optimality and convergence analysis is presented. • At this stage of the optimization procedure the reservoir levels, pump station flows and the number of pumps which are switched on are obtained from the upper and intermediate levels. As the intermediate level problem was implemented, feasible pump station heads and flows had to be chosen, which means that the solutions obtained for the lower level are not the optimal solutions for the overall problem. • Algorithm is tested using 3 different pump station configurations consisting of variable speed pump groups, variable throttle pump groups and a mixture of variable speed and variable throttle pump groups. • Test networks: (1) A combination of pump stations.
3. Zessler and Shamir (1989) SO Optimal pump operation of regional WDSs using DP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Pump station discharge limits, (2) reservoir volume lower/upper limits (can be different for each time interval), (3) initial and final reservoir volumes. Decision variables: (1) Pump station discharges.	Water quality: N/A. Network analysis: A non specified network simulator (EPS). Optimisation method: Progressive optimality method (iterative DP).	• Network is divided into subsystems, each consisting of a pump and upstream and downstream reservoir. • Simulator is used to generate the energy-cost-versus-discharge function for each pump station. • Time horizon is 24 hours divided into 1-hour intervals. Iterative optimisation algorithm progresses over time horizon, dealing with two adjacent time steps sequentially over all subsystems, one at a time. When dealing with one subsystem, the only parameters which vary are

			the reservoir volumes. Optimisation stops when reservoir volumes do not change between iterations by more than a specified tolerance. • <u>Test networks:</u> (1) Real-world regional water supply system Ein Ziv, Israel.
4. Brion and Mays (1991) SO Optimal pump operation using NLP.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge), (b) penalty term for the head bounds, (c) penalty term for the tank volume deficit. <u>Constraints:</u> (1) Lower/upper bounds on the duration the pump operates within each time interval, (2) lower/upper pressure head bounds, (3) lower/upper tank water level bounds, (4) volume deficit in tanks at the end of the scheduling period. <u>Decision variables:</u> (1) Duration of the pump operation time during time period (continuous).	<u>Water quality:</u> N/A. <u>Network analysis:</u> KYPIPE (Wood 1980) (EPS). <u>Optimisation method:</u> NLP solver GRG2 (Lasdon and Waren 1984).	• KYPIPE handles hydraulic constraints and lower/upper bounds on tank water level. Bounds on the pressure head and tank volume deficit are converted into penalty terms using an augmented Lagrangian method and added to the objective function. • Time horizon is 24 hours divided into 2-hour intervals. • The following assumptions are considered. First, the decision to turn on the pump can be made only at the beginning of each time interval. Second, the duration of the pump operation time is a continuous variable, and can take a minimum value of zero and a maximum value equal to the length of the time interval (i.e. 2 hours). These limitations can be offset by the use of shorter time intervals, but at the expense of longer computation times. • Global optimum cannot be guaranteed. • <u>Test networks:</u> (1) WDS for city of Austin Northwest B pressure zone (incl. 98 nodes), Texas.
5. Ulanicki and Orr (1991) SO Optimal pump operation suitable for large-scale drinking WDSs using LP.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge), (b) water treatment costs. <u>Constraints:</u> (1) Lower/upper limits of reservoir operating ranges, (2) treatment work set-point limits, (3) treatment work efficiency, (4) reservoir flow limits, (5) system flow limits, (6) min pressure in the system. <u>Decision variables:</u> (1) Pump control vector (continuous for variable speed pumps and control valves, and discrete for the actual number of pumps in use), (2) treatment works set points vector (continuous).	<u>Water quality:</u> Not specified. <u>Network analysis:</u> A system simulator (EPS). <u>Optimisation method:</u> Simplex method for lower level problem, a non specified method for upper level problem.	• Time distribution function is introduced. The optimisation problem is defined in terms of this time distribution function instead of original control variables. Time horizon is 24 hours. • Two level optimisation structure, lower/upper level, is used. Lower level problem is a LP problem, whereas upper level problem is a continuous NLP problem with linear constraints. • <u>Test networks:</u> (1) System with two treatment works, four pump stations, two contact tanks and two reservoirs.
6. Jowitt and Germanopoulos (1992) SO Optimal pump operation in real-time considering both energy and demand charges using LP.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge and demand charge). <u>Constraints:</u> (1) Constraints on the hours of pumping, (2) min/max volume at storages, (3) initial and final volume at storages, (4) min/max flow rate through valve connecting storages, (5) max licensed abstraction of water	<u>Water quality:</u> N/A. <u>Network analysis:</u> Extended period network simulation model (Germanopoulos 1988). <u>Optimisation method:</u> Revised simplex method.	• Original problem is simplified into a LP problem. Time horizon is 24 hours, which is divided into control intervals. • Both unit and max demand electricity charges are considered. Max electricity charges are taken into account through an iterative procedure of a LP problem for varying restrictions on pump usage, until the best solution is obtained. • The methodology is robust with low computation time, hence it is suitable for real-time optimisation.

	at a source pump station over the optimisation period. Decision variables: (1) Length of time for which pump station operates, (2) flow rate through valves, (3) storage volumes at end of time intervals (i.e. control intervals).		• Test networks: (1) High Wycombe area network (incl. 87 nodes, but simplified network is used in the optimisation), UK.
7. Mehrez et al. (1992) SO Optimal pump operation of regional multisource multiquality WDSs in real-time using NLP.	Objective (1): Minimise (a) the pump operating costs (fixed energy charge and varying expenses). Constraints: (1) Max flow in pipes, (2) min/max reservoir volumes, (3) water quality upper limits at customer demand nodes, (4) pump operational conditions, (5) valve operational conditions. Decision variables: (1) Pump discharges, (2) solute concentration.	Water quality: Chloride, magnesium, sulphate, salinity considered as conservative. Network analysis: Explicit mathematical formulation (quasi state). Optimisation method: GAMS/MINOS using projected Lagrangian algorithm (Murtagh and Saunders 1982).	• Model is a short term for a planning horizon of 2 hours considering energy peak and off-peak times. Planning horizon is divided into two 1-hour intervals, assuming steady state conditions within each time interval. • In order to increase computational efficiency, solution methodology is divided into 3 phases. First two phases are used to validate an initial solution, the last phase is the actual optimisation. • Model is applied to a regional WDS system, which mixes water from aquifers and a desalination plant, and delivers it to irrigation and domestic customers. • Test networks: (1) Arava Rift Valley, Israel.
8. Carpentier and Cohen (1993) SO Optimal pump operation using DP.	Objective (1): Minimise (a) the pump operating costs (electric consumption charge), (b) water treatment costs. Constraints: (1) Min/max reservoir water levels. Decision variables: (1) On-off pump statuses (discrete), (2) flows through the valves (continuous).	Water quality: N/A. Network analysis: Explicit mathematical formulation. Optimisation method: Discrete dynamic programming.	• Decomposition and coordination techniques are used. The network is decomposed into a central control and peripheral subnetworks. Dual decomposition scheme is used to set up optimisation problems for all subnetworks, which are solved sequentially. • The flows in the interconnection valves between the central and peripheral networks are mostly coordinated by the central network. However, some subnetworks are also given a parallel control of the flow in the valve. As a result, two values are produced by the two optimization subproblems and the dual price variables are updated to equalise these values. This coordination process provides near optimal solutions, which may not be feasible. To obtain feasible solutions, the interconnection valve flows are fixed for each subnetwork at their computed values, and optimisation problems solved again using detailed model. • Time horizon is 24 hours divided into 1-hour intervals. • The paper also analyses leak detection, which is not included here as this topic is outside of scope of this review paper. • Test networks: (1) The network called RPO, west of Paris.
9. Ostfeld and Shamir (1993a) SO Optimal operation of multiquality WDSs for steady state conditions	Objective (1): Minimise (a) the costs of water at sources, (b) water treatment costs, (c) pump operating costs (energy consumption charge), (d) penalty costs for violation of pressure	Water quality: Not specified conservative parameters. Network analysis: Explicit	• Model is a short term for a planning horizon of 2 hours considering a constant energy tariff. • Concentration equations allow the algorithm to reverse flow directions during the algorithm iterations.

including the costs of water at sources, water treatment costs and pump energy costs using NLP.	head. <u>Constraints:</u> (1) Min/max pressure heads at selected internal (usually customer) nodes, (2) min/max discharges in arcs, (3) min/max concentrations at internal nodes, (4) max removal ratios of quality parameters at treatment plants. <u>Decision variables:</u> (1) Discharges in arcs (pipes and pumps), (2) treatment costs of quality parameter per unit volume of treated water.	mathematical formulation (steady state). <u>Optimisation method:</u> GAMS/MINOS using projected augmented Lagrangian algorithm (Murtagh and Saunders 1982).	• Artificial variables are introduced to enable to obtain mathematical solution even when the system cannot meet all the head constraints. A penalty parameter on these variables is added in the objective function. • Sensitivity analysis is performed to examine the sensitivity of results to changes in (1) the prices of water, (2) prices of treatment, (3) prices of energy, (4) head constraint at an internal node. • <u>Test networks:</u> (1) Two-loop network with 3 sources (incl. 6 demand nodes).
10. Ostfeld and Shamir (1993b) SO Optimal operation of multiquality WDSs for unsteady state conditions including the costs of water at sources, water treatment costs and pump energy costs using NLP.	<u>Objective (1):</u> Minimise (a) the costs of water at sources, (b) water treatment costs, (c) pump operating costs (energy consumption charge), (d) penalty costs for violation of pressure head. <u>Constraints:</u> (1) Min/max pressure heads at selected internal (usually customer) nodes, (2) min/max discharges in arcs, (3) min/max concentrations at internal nodes, (4) max removal ratios of quality parameters at treatment plants, (5) min/max reservoir levels. <u>Decision variables:</u> (1) Discharges in arcs (pipes and pumps), (2) treatment costs of quality parameter per unit volume of treated water.	<u>Water quality:</u> Not specified parameters, conservative in pipes, non-conservative in reservoirs (first order decay). <u>Network analysis:</u> Explicit mathematical formulation (unsteady state). <u>Optimisation method:</u> GAMS/MINOS using projected augmented Lagrangian algorithm (Murtagh and Saunders 1982).	• Extension of the paper by Ostfeld and Shamir (1993a) with the major differences listed as follows. • Model is an unsteady state with a planning horizon of 24 hours divided into time intervals of one to few hours, and a varied energy tariff. • Water quality parameters decay in reservoirs (but are conservative in pipes). • Sensitivity analysis is performed to test the sensitivity of results to changes in (1) the prices of water, (2) pump efficiency and (3) quality constraint at an internal node. • <u>Test networks:</u> (1) Two-loop network with 3 sources (incl. 6 demand nodes).
11. Ulanicki et al. (1993) SO Optimal selection of new pumps within given locations for an urban WDS as part of major redevelopment using LP.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge). <u>Constraints:</u> (1) Min/max pressure limits at network nodes, (2) initial and final water levels in reservoirs over 24-hour period are equal, (3) average reservoir flows over a time interval belong to the respective domain. <u>Decision variables:</u> (1) Control configurations (discrete).	<u>Water quality:</u> N/A. <u>Network analysis:</u> A network simulator (EPS). To establish boundary conditions of the test network within the larger system, GINAS5 (Coulbeck and Orr 1988) is used. <u>Optimisation method:</u> Numerical algorithms (Matheiss and Rubin 1980).	• The optimisation problem is formulated as a LP problem for a time horizon of 24 hours. Both fixed and variable speed pumps are considered. • The solution methodology constitutes a sequence of steps. All practical control configurations are created, simulation is run to obtain sets of results, a least-cost surface is constructed. The union of feasible and optimal control configurations is created, which represents the final results. Balances are checked, if they comply, the best configuration is selected, otherwise relevant steps are repeated. • Methodology is limited to up to 1,000 control configurations for a particular time instant. For the test network, the number of control configurations is reduced by engineering judgement and simulation experiments. • <u>Test networks:</u> (1) Part of London's WDS (incl. 433 nodes, but

			simplified network is used in the optimisation), UK.
12. Lansey and Awumah (1994) SO Optimal pump operation suitable for small to midsized WDSs for both real-time and longer planning horizons using DP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge) while limiting the number of pump switches. Constraints: (1) Min/max pressure heads in nodes, (2) min/max water levels in tanks, (3) initial and final water level in tanks are equal, (4) max number of pump switches for each time interval, (5) max number of pump switches for the planning horizon. Decision variables: (1) Pump combinations (binary, 0 = pump off, 1 = pump on).	Water quality: N/A. Network analysis: KYPIPE (Wood 1980) (EPS). Optimisation method: DP.	• Pump operation in real-time is solved, accounting for variations in water demands and energy costs. Time horizon is 24 hours divided into 2-hour intervals. • Pump switching is introduced to reduce the maintenance costs. • A two level approach is used to solve the problem: (1) off-line ‘preoptimisation’ to generate simplified hydraulics and energy consumption by simple nonlinear functions using polynomial least-square method. (2) On-line DP optimisation. • Sensitivity analysis is performed considering some operational decisions and other parameters which influence the accuracy and computational effort. • The model is applicable to small to midsized systems, with up to about 8 pumps and 1 tank. • Test networks: (1) WDS for city of Austin Northwest B pressure zone (incl. 98 nodes), Texas.
13. Ulanicki and Kennedy (1994) SO Optimal operation of WDSs including pump energy costs and water treatment costs using MINLP.	Objective (1): Minimise (a) the water treatment costs (based on volume of treated water), (b) pump operating costs (energy consumption charge). Constraints: (1) Customer demands, (2) operational conditions such as lower/upper water levels in tanks. Decision variables: (1) Pipe flows, (2) nodal heads, (3) water production (continuous), (4) valve positions (continuous), (5) pump speed (continuous), (6) the number of pumps switched on (discrete).	Water quality: N/A. Network analysis: Explicit mathematical formulation (unsteady state). Optimisation method: Lancelot package (Conn et al. 1992) using the augmented Lagrangian method, branch and bound algorithm.	• The optimisation problem is formulated as a MINLP problem. • Time horizon is 24 hours with 4 time steps. • Analogy with electrical networks is used to formulate a mathematical model of water flow in pipe network, such that pipe = nonlinear resistor, tank = capacitor, pump = source of energy, demand = load. Ohm’s law is applied to describe characteristics of individual elements. • A special model structure (sparsity) is used, which expresses how many pipes are connected to a node in contrast to the total number of pipes. • The scale of the optimisation problem is reduced by replacing pipes by equivalent nonlinear resistance, using a technique of (Zehnpfund and Ulanicki 1993). • Test networks: (1) Yorkshire Grid system with 2 sources (WTPs), 4 tanks, 5 pump stations and 10 pipes.
14. Brdys et al. (1995) SO Optimal operation of drinking WDSs integrating water quality and quantity using mixed integer linear programming (MILP) and GA.	Objective (1): Minimise the costs of (a) untreated water from the sources, (b) water treatment, (c) the quality control by injection at the junction nodes, (d) electricity due to pumping. Constraints: (1) Bounds on reservoir levels, (2) bounds on flows, (3) bounds on heads at chosen nodes, (4) bounds on constituent concentrations at demand nodes and selected	Water quality: Non-conservative parameters (first order kinetics). Network analysis: (i) Explicit mathematical formulation (unsteady state), (ii) EPANET. Optimisation method: (i) Implicit solver MOMIP	• A detailed mathematical formulation of the nonlinear non-convex mixed integer optimization problem is presented in Brdys and Chen (1995). • Three approaches are used to solve the problem in time horizon of 24 hours. • Implicit approach: The problem is transformed into an approximating MILP problem, for which efficient numerical solvers exist. The disadvantage is that for a very accurate approximation, the dimensionality of the problem increases significantly. The advantage is

	junction nodes. Decision variables: (1) Pump and valve controls, (2) integer variables controlling pump station operation structure (normal or bypass), (3) controlled flows, (4) treatment flows, (5) constituent concentrations.	(Ogryczak and Zorychta 1993), (ii) explicit solver GAUCSD (Schraudolph and Grefenstette 1992) using GA.	that an arbitrarily accurate approximation of the global min is obtained regardless of the starting point. • Explicit approach: The problem is solved using the hydraulic simulator combined with GA. Although the problem dimension is much smaller compared to the implicit approach, the total computational effort may be greater. Local optima can be caught easily and more effort is required to obtain the global solution. • Combined approach: The implicit method based on a rough approximation of the model provides starting points, subsequently the explicit method finds the global optimum. • Test networks: (1) Neuhaus water supply system, Germany (Schneider et al. 1993).
15. Mackle et al. (1995) SO Optimal pump operation using GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for violating constraints. Constraints: (1) Consumer demands, (2) min/max water levels in reservoirs, (3) volume deficit in reservoirs at the end of the scheduling period. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on, during a time interval).	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: GA.	• Model considers fixed speed pumps only. Time horizon is 24 hours divided into 1-hour intervals, with two electricity tariffs used. • Standard GA is modified by introducing ranking procedure, where population members are ranked based on their costs, each receives fitness equal to the order number within the ranked list, i.e. the most expensive solution obtains 1, the next 2, etc. • Paper predicts increased implementation of on-line (real-time) control in order to adjust planned pump schedules to compensate for differences between predicted and actual demands. • Test networks: (1) Simple system with 4 pumps and 1 reservoir.
16. Nitivattananon et al. (1996) SO Optimal pump operation in real-time considering both energy and demand charges using progressive optimality combined with heuristics.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge and demand charge). Constraints: (1) Min/max pump discharges, (2) min/max reservoir volumes, (3) initial and final reservoir volumes. Decision variables: (1) Pump discharges (continuous and discrete).	Water quality: N/A. Network analysis: Simplified system hydraulics (unsteady state). Optimisation method: Progressive optimality algorithm for multi-state DP problem, heuristics for discretising pump discharges and refining pump schedules, OPWAD (OPWAD 1994).	• Optimisation model is decomposed spatially into subsystems and time wise into long-term and short-term model. Long term model (i.e. 1 month, continuous pump discharges) estimates the demand charge and determines monthly pump operation. Subsequently, short-term model (i.e. 1 day, discrete pump discharges) refines pump discharges and pump combinations, which are finally rearranged by heuristics. This procedure is carried out for each subsystem. • Development of preoptimisation data is required. • Test networks: (1) Pittsburgh water supply system, Pennsylvania.
17. Pezeshk and Helweg (1996) SO Optimal pump operation considering both fixed and variable speed pumps in real-time suitable for large and complex	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max pressure at selected nodes (checkpoints). Decision variables: (1) Pump statuses (0 = pump off, 1 = pump on), (2) speed settings for	Water quality: N/A. Network analysis: KYPIPE (Wood 1980) (EPS). Optimisation method: ASA.	• Checkpoints (nodes) are strategically selected so that if the pressure at each checkpoint is within the min and max allowable limits, pressures at all nodes are also within allowable limits. • Pump stations are assigned an influence coefficient(s) which indicate their impact on the pressure at the checkpoints. Basically, pumps with the highest influence coefficients are turned on to correct the

networks using ASA.	variable speed pumps (0 = pump off, 1 = pump on at the highest speed, 2 = pump on at the second highest speed).		problematic pressure zones. • Pump curves are generated from field pump tests. • It is recommended that the ASA program be installed directly onto the SCADA system. • Test networks: (1) WDS of Memphis Light, Gas and Water, the water utility for Memphis (incl. 1127 nodes), Tennessee and surrounding Shelby County.
18. Percia et al. (1997) SO Optimal pump operation of regional multisource multiquality WDSs in real-time using NLP.	Objective (1): Minimise (a) the pump operating costs (fixed energy charge and varying expenses), (b) penalty costs for deviation from zero equality constraints for pumps and valves. Constraints: (1) Allowed head losses at links terminating at consumption sites, (2) min/max reservoir volumes, (3) mean required quality at the consumption sites, (4) pump operational conditions, (5) valve operational conditions. Decision variables: (1) Pump discharges, (2) artificial variables (for zero equality constraints).	Water quality: Conservative: chloride, magnesium, sulphate (only chloride used in implementation). Network analysis: Explicit mathematical formulation (quasi state). Optimisation method: GAMS/MINOS using projected Lagrangian algorithm (Murtagh and Saunders 1982).	• Extension of the paper by Mehrez et al. (1992). • Model is a short term quasi state for a planning horizon of 2 hours using energy peak and off-peak times both daily and seasonal. It identifies hourly pump schedules and water release policy from the reservoirs. • Similar to Mehrez et al. (1992), solution methodology is divided into 3 phases to increase computational efficiency. • The paper focuses on the structure of the model and the implementation procedure, rather than finding global optimum. The use of continuous functions for describing the on/off status of pumps and control valves enables a significant reduction in the degree of difficulty of the problem. • Model is applied to a regional WDS system, which mixes water from aquifers and a desalination plant, and delivers it to various customer groups. • Test networks: (1) Southern Arava Regional Water Distribution Network (incl. 29 nodes), Israel.
19. Savic et al. (1997) SO, MO Optimal pump operation applying both single-objective and multi-objective approach using hybrid GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for violating constraints. Objective (2): Minimise the number of pump switches. Constraints: (1) Min and max reservoir water levels, (2) recovery of the initial reservoir water level at the end of simulation. Decision variables: (1) Pump statuses (binary). Note: One SO model including objective (1), one MO model including both objectives.	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: Hybrid GA, where GA is combined with 2 local (neighbourhood) search techniques.	• Extension of the paper by Mackle et al. (1995) implementing (i) a hybridisation of GA and (ii) multi-objective approach. The improvement of GA includes progressive assignment of penalties for constraint violations, and introduction of feasibility of solutions as an additional objective to ensure that there are no infeasible solutions in final population. • The number of pump switches is used as a surrogate measure for pump maintenance costs. • Time horizon is 24 hours divided into 1-hour intervals. • Robustness of GA is tested using alterations of demands and initial reservoir water levels. • Test networks: (1) Simple system with 4 pumps and 1 reservoir.
20. Lingireddy and Wood (1998) SO Three examples demonstrating economic and hydraulic benefits	Objective (1): Minimize (a) the pump operating costs (energy consumption charge) while using variable speed pumps. Constraints: (1) Min piezometric surface over	Water quality: N/A. Network analysis: Head-flow-efficiency-speed curves for variable speed	• Three examples of benefits of using variable speed pumps are presented as follows. • Replacement of fixed speed pumps by variable speed pumps to maintain min pressure requirements while reducing the pumping costs

of using variable speed pumps to improve the operation of WDSs using GA.	the network. Decision variables: (1) Pump speeds.	pumps used; the direct calculation algorithm (DCA) to calculate the pump speeds (Wood et al. 1992); EPS. Optimisation method: GA in conjunction with DCA.	and lowering the leakage due to lower operating pressures. • Optimisation of pump operation using variable speed pumps (model described in the columns on the left). Time horizon is 24 hours with a varied energy tariff. It is noted that the "average amount of overhead storage available is considerably reduced using the variable speed pumps". • Potential use of variable speed pumps in controlling hydraulic transients. • Test networks: (1) Skeletonised medium sized WDS (incl. 16 nodes), (2) network based on an existing WDS (incl. 39 nodes), (3) simple pump-fed WDS (incl. 9 nodes).
21. Boccelli et al. (1998) SO Optimal scheduling of booster chlorination stations in drinking WDSs using LP.	Objective (1): Minimize (a) the total disinfectant mass dose, injected per scheduling cycle. Constraints: (1) Min/max disinfectant concentrations at monitoring locations. Decision variables: (1) Disinfectant doses.	Water quality: Chlorine (first order kinetics for chlorine decay). Network analysis: EPANET (EPS). Optimisation method: MINOS (Murtagh and Saunders 1987) using the simplex algorithm.	• The optimisation problem is formulated as a LP problem. A principle of linear superposition is used, which implies that disinfectant concentration at a monitoring location is the sum of all individual disinfectant injection influences. • Hydraulic dynamics and concentrations are assumed to be periodic, as well as disinfectant mass injection rates. This allows reducing infinite-time problem into finite-time problem. Time horizon is 24 hours. • "Among the five cases investigated, the best schedule was found when a booster station was located at a storage reservoir, eliminating the need to maintain significant residual in the large volume of tank water, for distribution during high demand periods". • Test networks: (1) Cherry Hill-Brushy Plains portion of the South Central Connecticut Regional Water Authority network (incl. 34 nodes), U.S.
22. Goldman and Mays (1999) SO Optimal pump operation with water quality constraints in drinking WDSs using simulated annealing (SA).	Objective (1): Minimize (a) the pump operating costs (energy consumption charge), (b) penalty function for violating constraints. Constraints: (1) Min/max nodal pressure heads, (2) min/max tank water levels, (3) min tank water level to provide emergency fire flow storage, (4) tank water level to recover at the end of simulation, (5) min/max chlorine concentrations. Decision variables: (1) Length of the pump operation time during time period (discrete).	Water quality: Chlorine. Network analysis: EPANET (EPS). Optimisation method: SA.	• Pump schedule repeats every 24 hours. Time horizon is 12 days divided into 1-hour intervals. This extended period is to wash out initial water quality conditions from the system and to reach steady state behaviour. • It is suggested that the SA program be adapted to the SCADA system due to the following benefits: real-time optimisation of pump operation for fire events or locally increased demands (flushing the system), unexpected chlorine level deficiencies. • Test networks: (1) North Marin Water District - Navato, California (incl. 102 nodes) (EPANET Example 3 (USEPA 2013)).
23. Sakarya and Mays (1999) SO Optimal pump operation for drinking WDSs considering water	Objective (1): Minimize (a) the deviations of the actual constituent concentrations from the desired values, (b) penalty function for violating bound constraints.	Water quality: Non-conservative parameter. Network analysis: EPANET (EPS).	• The optimisation problem is formulated as a NLP problem. • Two different penalty function methods are used for handling constraints, the augmented Lagrangian method and the bracket penalty method. These methods delivered similar results.

quality either as a constraint or an objective function using NLP.	Objective (2): Minimize (a) the total pump operation time, (b) as above. Objective (3): Minimize (a) the pump operating costs (energy consumption charge), (b) as above. Constraints (objective (1)): Lower/upper bounds on (1) pump operation time, (2) nodal pressure head, (3) storage water levels. Constraints (objectives (2-3)): (1)-(3) as above, (4) lower/upper bounds on nodal constituent concentrations. Decision variables: (1) Length of the pump operation time during time period (discrete), (2) penalty function parameters. Note: Three SO models, each including one objective.	Optimisation method: NLP solver GRG2 (Lasdon and Waren 1984).	• Time horizon is 12 days divided into 2-hour intervals with a constant energy tariff. Pump schedule repeats every 24 hours. • It was found out that if pump operation schedules are cyclic for a certain period, the system reaches steady state with the initial and final tank water levels being equal. Therefore, there is no need to use a constraint which forces tank water level to recover at the end of the simulation period. • The results demonstrate that using concentration violations as constraints gives better results than using the minimisation of the constituent concentration from the desired values as the objective function. • Test networks: (1) North Marin Water District Zone 1 (incl. 91 nodes) (EPANET Example 3 (USEPA 2013)).
24. Cembrano et al. (2000) SO Optimal operation of WDSs in real-time linked to the SCADA system using NLP.	Objective (1): Minimise the performance index including (a) the cost of water acquisition, (b) pump operating costs (energy consumption charge). Constraints: (1) Operational limits on reservoir volumes, (2) pressure limit at one junction node, (3) initial and final volumes in reservoirs are equal. Decision variables: (1) Pump set points (treated as continuous, converted into discrete), (2) valve ratios.	Water quality: N/A. Network analysis: WATERNET (Greco 1997) simulation module. Optimisation method: WATERNET optimal control module using generalised reduced gradient method (Abadie and Carpentier 1969).	• Optimal control strategies ahead of time are generated. The optimisation process consists of (i) obtaining current network status from the SCADA, (ii) predicting future demands using fuzzy inductive reasoning (Lopez et al. 1996), (iii) running optimisation. This process is executed and updated at regular intervals. • The original network model is simplified in order to reduce time of hydraulic simulation within the optimisation procedure. Optimisation results obtained are validated using the original (detailed) network model. • Time horizon is 24 hours (ahead of time) divided into 1-hour intervals. • Results demonstrate cost savings of 18%. • Test networks: (1) Sintra network (incl. 204 nodes, but simplified network is used in the optimisation), Portugal.
25. Cohen et al. (2000a) SO Optimal operation of multiquality WDSs considering water treatment plants (WTPs) and water quality requirements using NLP.	Objective (1): Minimise the cost of operation including (a) the water supply costs from sources, (b) water treatment costs, (c) transportation costs (related to hydraulic properties of a pipe), (d) yield reduction costs, (e) penalty costs for violating water quality constraints. Constraints: (1) Quality parameter function (interdependency of quality parameters), (2) pipe discharge limits, (3) supply discharge limits, (4) water quality limits for customers	Water quality: Salinity, magnesium, sulphur considered as conservative. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Modified projected gradient method.	• A flow-quality (Q-C) model is formulated. • The model equations are defined to allow the flow to reverse during the optimization procedure. The transportation cost function and dilution equations are smoothed using exponential smoothing procedure. The problem is reduced to a NLP problem with linear constraints. It is solved by decomposing the problem into inner-outer problems, which enables incorporation of a large number of water quality parameters. • Customers are categorised into three groups: (i) agricultural, (ii) domestic and industrial, (iii) customers with concentrations limits. Their requirements are implemented differently into the model, such as

	(iii), (5) treatment limits on removal ratios. Decision variables: (1) Water flow, (2) water quality distribution, (3) removal ratios in the treatment plants.		a relative yield function, the water treatment cost at customer connection points, and water quality constraints, respectively. • Test networks: (1) Water supply system in the Arava Valley (incl. 9 nodes), Southern Israel, (2) WDS of the Central Arava region (incl. 38 nodes), Southern Israel.
26. Cohen et al. (2000b) SO Optimal operation of multiquality WDSs considering pumps and valves using NLP.	Objective (1): Minimise the cost of operation including (a) the water supply costs from sources, (b) pump energy costs at boosters, (c) pump energy costs at pump stations. Constraints: Limits on discharges for (1) boosters, (2) valves, (3) pump stations, (4) sources, (5) limits on pressure heads at customer nodes, (6) limits on opening ratio of valves, (7) given discrete configurations of pump stations. Decision variables: Q_0-H problem: (1) pumping heads at pump stations, (2) headlosses in control valves, (3) artificial variables to assure a mathematical solution. Q-H problem: (4) circular flows.	Water quality: N/A. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Q_0-H (inner) problem solved using sequential LP. Q-H (outer) problem solved using projected gradient method coupled with the complex method.	• A flow-head (Q-H) model is formulated. • The original discrete optimisation problem is transformed into a continuous and smooth model. The head-flow performance curves for pumps are represented by smoothed two dimensional functions. The final problem is a NLP problem with linear constraints, which is decomposed into inner-outer problems. For a given initial flow distribution in the network Q_0, the Q_0-H problem (i.e. inner problem) is solved. The flow distribution is then modified by changing the circular flows (i.e. outer problem), such that the locally optimal solution at the next point has a better value of the objective function. This process is repeated until the termination criteria are satisfied. • Test networks: (1) Water supply system in the Arava Valley (incl. 9 nodes), Southern Israel, (2) WDS of the Central Arava region (incl. 38 nodes), Southern Israel.
27. Cohen et al. (2000c) SO Optimal operation of multiquality WDSs considering pumps, valves, WTPs and water quality requirements using NLP.	Objective (1): Minimise the total cost of operation including (a) the water supply costs from sources, (b) pump energy costs at boosters, (c) pump energy costs at pump stations, (d) water treatment costs, (e) yield reduction costs, (f) penalty costs for violating water quality constraints. Constraints: Limits on discharges for (1) boosters, (2) valves, (3) pump stations, (4) sources, (5) limits on pressure heads at customer nodes, (6) limits on pumping heads, (7) limits on opening ratio of valves, (8) quality parameter function (interdependency of quality parameters), (9) treatment limits on removal ratios. Decision variables: Q-C-H problem: (1) circular flows, (2) removal ratios in treatment plants, (3) water quality distribution. Q_0-H problem: (4) opening ratios of valves, (5) configurations of pump stations, (6) headlosses in control valves, (7) bypass flows.	Water quality: Salinity, magnesium, sulphur all considered as conservative. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Q_0-H (inner) problem solved using sequential LP. Q-C-H (outer) problem solved using projected gradient method coupled with the complex method.	• A comprehensive flow-quality-head (Q-C-H) model is formulated, which combines two previous Q-C and Q-H models (Cohen et al. 2000a,b). • The paper uses the solution methods developed earlier in Cohen et al. (2000a,b) for Q-C and Q-H subproblems as building blogs. Accordingly, the original integer NLP problem is transformed into a NLP problem with linear constraints. The problem is solved by decomposing the problem into inner-outer structures. • There are three customer groups with different water quality requirements: (i) agricultural, (ii) domestic and industrial, (iii) customers with concentrations limits. • Test networks: (1) Water supply system in the Arava Valley (incl. 9 nodes), Southern Israel, (2) WDS of the Central Arava region (incl. 38 nodes), Southern Israel.

28. Sakarya and Mays (2000), Sakarya and Mays (2003) SO Optimal pump operation for drinking WDSs considering water quality either as a constraint or an objective function using NLP.	Objective (1): Minimize (a) the deviations of the actual constituent concentrations from the desired values, (b) penalty function for violating bound constraints. Objective (2): Minimize (a) the total pump operation time, (b) as above. Objective (3): Minimize (a) the pump operating costs (energy consumption charge), (b) as above. Constraints (objective (1)): Lower/upper bounds on (1) pump operation time, (2) nodal pressure head, (3) storage water levels. Constraints (objectives (2-3)): (1)-(3) as above, (4) lower/upper bounds on nodal constituent concentrations. Decision variables: (1) Length of the pump operation time during time period (discrete), (2) penalty function parameters. Note: Three SO models, each including one objective.	Water quality: Non-conservative parameter. Network analysis: EPANET (EPS). Optimisation method: NLP solver GRG2 (Lasdon and Waren 1984).	• The optimisation problem is formulated as a NLP problem. Constraints are incorporated as penalty functions using augmented Lagrangian method. • Solution methodology is a two-step loop procedure, with the Lagrangian parameters update in the outer loop and GRG2-EPANET combination in the inner loop. • Time horizon is 12 to 50 days divided into 1-hour intervals, where 24-hour pump schedule is repeated over the time horizon. The length of the time horizon is to assure that steady state for both hydraulic and water quality analysis is reached, as well as periodic behaviour of water levels at storage tanks. • To reduce the number of EPANET calls, a simplified method is used as follows. When the change in control variables between consecutive iterations is small, the change in the state variables is assumed to be also small, therefore EPANET is not called and GRG2 continues to use the previous state variables. • Test networks: (1) Hypothetical WDS with 1 reservoir, 1 pump and 1 storage tank (incl. 17 nodes).
29. Wegley et al. (2000) SO Optimal pump operation considering variable speed pumps using PSO.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max nodal pressures, (2) min/max tank water levels, (3) min/max pump speeds. Decision variables: (1) Pump speeds (continuous).	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: PSO (Eberhart and Kennedy 1995).	• Variable speed pumps are considered. • PSO derives solutions from both local and global searches by using a value of the inertial weight. The search process for new solutions includes previously found best solutions. • Unlike GA, PSO uses continuous decision variables. Since PSO considers unconstrained problems, a penalty function is used to handle constraints. • Test networks: Not specified.
30. Boulos et al. (2001) SO Optimal pump operation using GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge and demand charge). Constraints: (1) Min/max pressure at nodes, (2) max flow velocity in pipes, (3) min/max water level in tanks, (4) volume deficit in tanks at the end of the scheduling period, (5) max number of pump switches. Decision variables: (1) Pump control settings (binary, 0 = pump off, 1 = pump on).	Water quality: N/A. Network analysis: H2ONet (EPS). Optimisation method: H2ONet scheduler using GA.	• The paper focuses on the development of an optimisation tool within H2ONet analyzer, which utilizes GA to generate the optimal pump schedules for groups of pumps in WDS over a time horizon of usually 24 hours. • The optimisation model uses the number of pump switches as a surrogate measure for pump maintenance costs. • The optimisation tool was tested and verified on a number of actual large scale WDSs. • Test networks: (1) Small network with 52 pipes, 1 treatment plant, 3 pumps located at treatment plant, 1 variable storage tank, 1 pressure reducing valve (PRV) (incl. 45 nodes).
31. Sotelo and Baran (2001)	Objective (1): Minimise (a) the pump	Water quality: N/A.	• The number of pump switches is used as a surrogate measure for pump

MO Optimal pump operation considering both energy and demand charges using SPEA.	operating costs (energy consumption charge). Objective (2): Minimise (a) the number of pump switches. Objective (3): Minimise (a) the difference between initial and final water levels in tanks. Objective (4): Minimise (a) max (daily) power peak (demand charge). Constraints: (1) Min/max reservoir water levels, (2) min/max pipeline pressure constraints. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on, for each hour of the day). Note: One MO model including all objectives.	Network analysis: Simplified hydraulic model, mass balance mathematical model (Ormsbee and Lansey 1994), EPS. Optimisation method: SPEA.	maintenance costs. • Max daily peak power is minimised, because it may be penalized by some electricity companies if it exceeds a contracted value. • Time horizon is 24 hours divided into 1-hour intervals, considering two energy tariffs and three demand loads (low, medium and high). • Constraints are handled by a heuristic algorithm. • Test networks: (1) Simplified system with 1 source, 5 pumps and 1 elevated reservoir (based on the main pump station in Asuncion, Paraguay).
32. Biscos et al. (2002) SO Optimal operation of drinking WDSs using MINLP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) weighted sum of squared deviations of storage volumes, (c) weighted sum of squared deviations of chlorine concentrations from set points. Constraints: (1) Valve openings between 0 and 1, (2) min/max flows in pipes, (3) min/max storage volumes, (4) min/max chlorine concentrations. Decision variables: (1) Continuous valve statuses (0 to 1), (2) binary valve statuses (0 or 1), (3) binary pump switching.	Water quality: Chlorine (first order decay). Network analysis: Explicit mathematical formulation (unsteady state). Optimisation method: Unspecified MINLP solver.	• The optimisation problem is formulated as a MINLP problem. • The model of the water distribution network is based on the use of a standard element. The standard element consists of a vessel with one input leg and two output legs. The vessel is assigned a liquid volume and chlorine concentration, whereas legs are associated with pressure available at their ends, valve statuses and pipe flows. The standard elements are linked together to define the entire system. • Time horizon is 48 hours. The optimisation is formulated as a predictive control problem with a moving period of 12 hours ahead of the present time. • Test networks: (1) A portion of the Durban WDS with 1 reservoir, 2 pumps and 4 storages, South Africa.
33. Tryby et al. (2002) SO Optimal location and injection doses of booster disinfectant stations for drinking WDSs using MILP.	Objective (1): Minimise (a) the total disinfectant mass applied. Constraints: (1) Min/max disinfectant concentrations at monitoring nodes, (2) zero disinfectant mass if a booster station is not present, (3) max number of booster disinfectant stations, (4) nonnegative dosage multipliers. Decision variables: (1) Presence of a booster disinfectant station at network location (binary, 0 = no, 1 = yes), (2) dosage multiplier (continuous).	Water quality: Chlorine (first order kinetics for chlorine decay). Network analysis: EPANET (EPS). Optimisation method: CPLEX (ILOG 2001) using the simplex algorithm.	• According to Boccelli et al. (1998), a principle of linear superposition is used for disinfectant dosage responses. • System hydraulic dynamics, and therefore the system demands which drive them, are periodic over a 24-hour cycle. Disinfectant dosage rate and disinfection concentration dynamics are assumed to be also periodic. • The tradeoff between the average disinfectant mass dosage rate and the number of disinfectant booster stations is examined. It was found out that the total average mass dosage rate depends not only on the number of sources, but also on how those sources are operated. "The total dosage rate decreases significantly as the first few booster stations are added-after which the marginal improvement in the total dosage rate per booster station diminishes".

			• It is concluded that booster disinfection has the potential to reduce aggregate exposure of the population to chlorine, while simultaneously improving disinfectant residual in the network periphery. • Test networks: (1) WDS with 1034 links (incl. 829 nodes) in eastern U.S.
34. Biscos et al. (2003) SO Optimal operation of drinking WDSs in real-time considering pumps, valves and water quality requirements using MINLP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) weighted sum of squared deviations of storage volumes, (c) weighted sum of squared deviations of chlorine concentrations from set points. Constraints: (1) Min/max storage volumes, (2) min/max chlorine concentrations, (3) valve openings between 0 and 1. Decision variables: (1) Continuous valve statuses (0 to 1), (2) binary valve statuses (0 or 1), (3) discrete pump statuses.	Water quality: Chlorine (first order decay). Network analysis: Explicit mathematical formulation (unsteady state). The hydraulic equations are simplified to be linear. Optimisation method: GAMS using MINLP solvers (Brooke et al. 1998).	• Extension of the paper by Biscos et al. (2002). • The optimization is realised in real-time, with a predictive control mechanism of 8 hours ahead of present time. The model requires the anticipation of a consumer demand profile, which is obtained from historical data stored by the SCADA system. The actual optimised volumes in storages and concentrations are used in the calculations at the next time step. With the time horizon of 24 hours, 32 hours of data should be fed into the model. • The optimisation procedure is based on a network model with a basic element, which consists of one input and two outputs, linked through a vessel of variable volume. Different components of the network such as pipes, storages, valves and pumps are all defined using the same basic element. The overall network is defined by linking those basic elements. • Test networks: (1) Network with 1 source, 4 storages, 1 pump station, 4 binary valves.
35. Cohen et al. (2003) SO Comparison of optimisation methods for solving optimal operation of multiquality WDSs.	Objective (1): Minimise the cost of operation including (a) the water supply costs from sources, (b) water treatment costs, (c) transportation costs (related to hydraulic properties of a pipe), (d) yield reduction costs, (e) penalty costs for violating water quality constraints. Constraints: (1) Quality parameter function (interdependency of quality parameters), (2) pipe discharge limits, (3) supply discharge limits, (4) water quality limits, (5) treatment limits on removal ratios. Decision variables: (1) Water flow, (2) water quality distribution, (3) removal ratios in the treatment plants.	Water quality: Salinity, magnesium, sulphur all considered as conservative. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Decomposed projected gradient (DPG) method and sequential quadratic programming (SQP) method are compared.	• Extension of the papers by Cohen et al. (2000a,c) using two DPG approaches, full mixing step (FMS) and partial mixing step (PMS), being tested against SQP. • Several scenarios (referred to as ‘cases’) are tested. These scenarios include modifications of the network (i.e. absence or presence of WTPs), the number of water quality parameters, constraints, cost of water at sources, penalty gain factor values, starting points (i.e. initial solutions), scaling (i.e. decision variables and/or their coefficients are on different scales). Scaling issues arise when treatment plants are introduced. • It was found that SQP obtains slightly better solutions for small networks, but is sensitive to the penalty gain factor, the choice of starting points and scaling. For bigger networks (20-50 pipes and nodes), SQP did not reach a feasible optimal solution. • Test networks: (1) Water supply system in the Arava Valley (incl. 9 nodes), Southern Israel (Cohen et al. 2000c), (2) WDS of the Central Arava region (incl. 38 nodes), Southern Israel (Cohen 1991).
36. Dandy and Gibbs (2003) SO	Objective (1): Minimize (a) the pump operating costs (energy consumption charge).	Water quality: Chlorine. Network analysis:	• Time horizon is 48 hours, but only last 24 hours are considered to remove effects of initial conditions. Two energy tariffs are used, peak

Optimal operation of drinking WDSs considering pumps and water quality requirements using GA.	Constraints: (1) Min/max chlorine concentrations. Decision variables: (1) Tank trigger levels for energy peak and off-peak periods to control pumps (different trigger levels may be set for peak and off-peak periods), (2) concentration of chlorine downstream of the pump.	EPANET (EPS). Optimisation method: GA.	and off-peak. • The system was first optimised without considering water quality. The GA results were then verified by complete enumeration and suitable GA parameters (i.e. population size) selected. • When taking into account water quality, the tank trigger levels are different than those when considering pumping costs only. The upper trigger level for the water quality case is lower during the peak period so as to reduce the detention time and loss of chlorine in the tank. • The tank trigger levels do not appear too sensitive to variations in demands neither are they too sensitive to the min required chorine concentration in the network. • Test networks: (1) Hypothetical network (incl. 15 nodes) with 1 reservoir from which water is pumped into a high level tank, which gravity feeds distribution system of 19 pipes and 6 loops.
37. Kelner and Leonard (2003) MO Optimal pump operation considering both fixed and variable speed pumps using GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the number of pump switches. Constraints: (1) Recovery of the initial reservoir water level at the end of simulation, (2) customer demands satisfied at any time, (3) min/max reservoir water levels. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on) for each hour of the day, (2) rotating speed of the pump (real), (3) pressure loss coefficient for the control valve (real). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: Genetic algorithm for pump scheduling (GAPS).	• The number of pump switches is used as a surrogate measure for pump maintenance costs. Both fixed and variable speed pumps are used. • Time horizon is 24 hours divided into 1-hour intervals. • GAPS combines ranking by multiple objective genetic algorithm (MOGA) (Fonseca and Fleming 1993) and penalised tournament selection scheme. • Gaps is written in C++ and was applied to several test cases by Poloni and Pediroda (2000); Van Veldhuizen and Lamont (1998); Zitzler et al. (2000) involving both continuous and discrete variables. • Test networks: (1) Real system with 3 reservoirs, 1 pump station with 3 pumps and 3 customers, located in Liege, Belgium.
38. Munavalli and Kumar (2003) SO Optimal scheduling of booster chlorine stations for drinking WDSs using GA.	Objective (1): Minimise (a) the squared deviation of the chlorine concentrations from a min required value at monitoring nodes, (b) penalty costs for violating min/max chlorine concentrations at monitoring nodes. Constraints: (1) Min/max chlorine concentrations at monitoring nodes. Decision variables: (1) Chlorine dosages applied at water quality sources over discrete time intervals (binary).	Water quality: Chlorine. Network analysis: Network hydraulics (EPS) solved by Tewarson-Chen adaptation of the Newton-Raphson iterative technique, water quality by Lagrangian time-driven method (Liou and Kroon 1987). Optimisation method: GA.	• The optimisation problem is formulated as a NLP problem. • It is assumed that chlorine dosage at water quality sources and network dynamics are cyclic over a simulation period. Time horizon is 24-672 hours depending on network size. • The location of water quality sources is determined through trial simulations. Water quality sources, at which chlorine dosages are estimated, include concentration, flow-paced (booster), set point or mass rate types. • Improved GA is used which includes niche operator and creep mutation. Water quality analysis is run for each iteration, which represents a considerable computational expense.

			• Both linear and nonlinear chlorine reaction kinetics are used. A principle of linear superposition is utilised for linear kinetics. It helps to compute chlorine concentrations without running water quality simulation model. • Test networks: (1) WDS of Brushy plains zone of the South Central Connecticut Regional Water Authority (incl. 34 nodes), U.S. (Clark et al. 1993; Boccelli et al. 1998), (2) North Marin Water District (incl. 91 nodes) (EPANET Example 3 (USEPA 2013)), (3) a portion of Bangalore city WDS (Kalasipalyam network) (incl. 23 nodes).
39. Cohen et al. (2004) SO Sensitivity of total operating costs of a multiquality WDS to various parameters of the problem using NLP.	Objective (1): Minimise the cost of operation including (a) the water supply costs from sources, (b) water treatment costs, (c) transportation costs (related to hydraulic properties of a pipe), (d) yield reduction costs, (e) penalty costs for violating water quality constraints. Constraints: (1) Quality parameter function (interdependency of quality parameters), (2) pipe discharge limits, (3) supply discharge limits, (4) water quality limits, (5) treatment limits on removal ratios. Decision variables: (1) Water flow, (2) water quality distribution, (3) removal ratios in the treatment plants.	Water quality: Salinity. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Projected gradient method.	• Extension of the paper by Cohen et al. (2000a) testing sensitivity of the solution to income from unit crop yield, water quality limits, conveyance costs, network topology and supply capacity of the source with the following outcomes. • Increase in the unit income from crop yield causes an increase in the total costs because more fresh water is used to increase the income from agriculture. • The total costs decrease with the increase in salinity limits, however the cost change is not significant due to low percentage of water used for drinking purposes. • The effect of conveyance cost as well as the supply capacity of the sources on the total costs is relatively small. • Overall, the highest sensitivity displays the income from unit crop yield. • Test networks: (1) WDS of the Central Arava region (without WTPs) (incl. 37 nodes), Southern Israel (Cohen 1991).
40. Goldman et al. (2004) SO Optimal operation of drinking WDSs including pumps and chlorine booster stations using NLP and SA.	Objective (1): Minimize (a) the deviations of the actual constituent concentrations from the desired values, (b) penalty function for violating bound constraints. Objective (2): Minimize (a) the total pump operation time, (b) as above. Objective (3): Minimize (a) the pump operating costs (energy consumption charge), (b) as above. Objective (4): Minimise (a) the amount of chlorine used by chlorine booster stations, (b) as above. Constraints (objective (1)): Lower/upper bounds on (1) pump operation time, (2) nodal pressure head, (3) storage water levels.	Water quality: 1) Non-conservative parameter, chlorine. Network analysis: EPANET (EPS). Optimisation method: NLP solver GRG2 (Lasdon and Waren 1984), SA.	• Mathematical programming is used to solve optimisation problems with objectives (1)-(3) (see also Sakarya and Mays (1999)), SA to solve optimisation problems with objectives (3)-(4). • Time horizon is: 12 days with 2-hour intervals for mathematical programming approach, 1 day with 1-hour intervals for SA (pump energy optimisation, objective (3)), and 7 days with 6-hour intervals (chlorine booster optimisation, objective (4)). • For pump energy optimisation (objective (3)), mathematical programming and SA are compared. NLP required about one third of the iterations than SA. However, SA was shown to be more flexible and adaptable than NLP. It is also noted that many unbalanced unfeasible solutions existed in the vicinity of the optimum solution of SA in contrast to NLP. • For chlorine booster optimisation (objective (4)), the hydraulic conditions of the system are constant, with demands and flow rates

	Constraints (objectives (2-3)): (1)-(3) as above, (4) lower/upper bounds on nodal constituent concentrations, (5) tank volume deficit at the end of simulation (only for SA approach). Constraints (objective (4)): (1) Lower/upper bounds on nodal constituent concentrations. Decision variables (objectives (1-3)): (1) Pump controls. Decision variables (objective (4)): (1) Flow rate at the chlorine booster stations. Note: Four SO models, each including one objective.		repeated every 24 hours. Chlorine booster pumps are treated as sources with fixed concentration. Two cases are analysed, the first with only 1 chlorine booster station, the second with 6 chlorine booster stations. The chlorine usage of the former case is considerably higher than the chlorine usage of the later case. • Challenges noted: No model incorporates design, operation and reliability of WDS together, no universally accepted definition of reliability, etc. • Test networks: (1) North Marin Water District Zone 1 (incl. 91 nodes) (EPANET Example 3 (USEPA 2013)), (2) WDS for city of Austin Northwest B pressure zone (incl. 98 nodes), Texas (Brion and Mays 1991), (3) Cherry Hill-Brushy Plains (incl. 34 nodes), South Central Connecticut Regional Water Authority (data same as in Boccelli et al. (1998)).
41. Moradi-Jalal et al. (2004) SO Optimal design and operation of irrigation networks using GA.	Objective (1): Minimise the total annual costs including (a) the pump operating costs (energy consumption charge) and maintenance costs, (b) depreciation cost of the initial investment. Constraints: (1) Max pump discharge, (2) total pump discharge equals to total demand for each time interval, (3) min/max pumping heads. Decision variables: (1) Pump system design including the type and the number of pumps, (2) pump system operation.	Water quality: N/A. Network analysis: Simplified hydraulic simulation within WAPIRA program (unsteady state). Optimisation method: WAPIRRA program using GA.	• WAPIRRA software is developed to be used by operators. It is spreadsheet based and uses Microsoft Excel for input data and output results. The software can work with any number of pumps, pump types, time steps, and different unit energy costs on every time step, but the maximum number of pumps used in a station is limited. • Time horizon is 1 year divided into monthly intervals. • Results for the optimum pump set are compared with 3 pre-sets of practical design. It is found out that savings in annual depreciation cost between the optimum set and pre-sets are not significant. The main savings, nearly 33%, occurred in the annual pump operating cost due to energy consumption. • Test networks: (1) The main pumping station of the Farabi Agricultural and Industrial Project, Iran.
42. Ostfeld and Salomons (2004) SO Optimal operation of multiquality WDSs including pump energy costs, water treatment costs and purchasing water costs using GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) water treatment costs, (c) purchasing water costs. Constraints: (1) Min/max pressure heads at the consumer nodes, (2) min/max concentrations at the consumer nodes, (3) max removal ratios at the treatment facilities, (4) max permitted amounts of water withdrawals at the sources, (5) tank volume deficit at the end of simulation. Decision variables: (1) Scheduling of the pumping units (binary), (2) control valve	Water quality: Salinity. Network analysis: EPANET (EPS). Optimisation method: OptiGA (Salomons 2001).	• Time horizon is 24 hours, with a varied energy tariff and unsteady water flow conditions. It is noted that cyclic water quality behaviour is not accomplished, so the results depend, to some extent, on the initial settings of the concentrations at the nodes. • Seven sensitivity analyses are undertaken, which explore the impact of data and constraints modifications on optimal solution. Sensitivity analyses include increasing unit water treatment cost at a WTP, increasing demand at a node, excluding a control valve, increasing unit water purchase cost at a source, increasing threshold concentration constraint at several nodes, switching a node from being a consumer node to being a source node, converting a tank into 3 equal floating tanks, reducing the elevation of the highest consumer node. • Test networks: (1) Two-loop network with 3 sources (incl. 6 demand

	settings (i.e. valve openings) (real), (3) treatment removal ratios at the treatment facilities (real).		nodes), (2) EPANET Example 3 (incl. 94 nodes) (USEPA 2013).
43. Prasad et al. (2004) MO Optimal location and injection rates of booster disinfectant stations for drinking WDSs using NSGA-II.	Objective (1): Minimise (a) the total disinfectant dose. Objective (2): Maximise (a) the volumetric percentage of water supplied with disinfectant residuals within specified limits, titled 'safe drinking water' (SDW). Constraints: (1) Nonnegative disinfectant doses, (2) lower bound on the value of the objective (2), (3) upper bound on disinfectant concentrations at monitoring nodes. Decision variables: (1) Locations of booster disinfection stations (integer), (2) disinfection injections schedules (real). Note: One MO model including both objectives.	Water quality: Disinfectant (first order kinetics for disinfectant decay). Network analysis: EPANET (EPS). Optimisation method: NSGA-II.	• The theory of linear superposition is used for water quality modelling to calculate concentrations at network nodes. All demand nodes are considered as monitoring nodes. • Hydraulics and booster injections are assumed to be cyclic, with a period of 24 hours. Time horizon is 1,008 hours. • Both constant mass and flow proportional type boosters are considered. • Tradeoffs between (i) disinfectant dose and the number of booster stations, and (ii) disinfectant dose and percentage of SDW (level of constraint satisfaction) are presented. It is concluded that "the addition of the first few booster stations reduces the total disinfectant dose significantly, after which the rate of reduction is insignificant". Additionally, "there is a critical point in the level of constraint satisfaction (about 99% SDW), after which the disinfectant dosage rate increases significantly in order to satisfy the remaining constraints". • Test networks: (1) Real network supplied by gravity (incl. 829 nodes), eastern U.S. (Tryby et al. 2002).
44. Propato and Uber (2004a) SO Optimal location and injection rates of booster disinfectant stations for drinking WDSs using mixed integer quadratic programming (MIQP).	Objective (1): Minimise (a) the squared deviation of the disinfectant (i.e. chlorine) concentration from desired values. Constraints: (1) Zero disinfectant doses if a booster station is not present, (2) max feasible value of disinfectant doses, (3) max number of booster disinfectant stations, (4) nonnegative disinfectant doses. Decision variables: (1) Disinfectant doses (i.e. injections) (continuous), (2) presence of a booster disinfectant station at network location (binary, 0 = no, 1 = yes).	Water quality: Chlorine. Network analysis: EPANET (EPS). Optimisation method: MATLAB (Moler 1980) using branch-and-bound algorithm (Bemporad and Mignone 2001).	• Extension of the paper by Propato and Uber (2004b) including locations of booster disinfectant stations as decision variables. • The optimisation problem is formulated as a MIQP problem with linear constraints. The size of problem is dependent only on the number of booster stations and injection rates and is independent on the number of consumer nodes or the size of the network. • Tradeoff between the number of booster disinfectant stations and water quality across the network is investigated. Conclusions are drawn for particular locations and dosages of chlorine booster stations and their impact on water quality across the network. • Test networks: (1) WDS with 1 source, 1 pump station, 1 tank (incl. 34 nodes) (Clark et al. 1993; Boccelli et al. 1998).
45. Propato and Uber (2004b) SO Optimal injection rates of booster disinfectant stations for drinking WDSs using quadratic programming (QP).	Objective (1): Minimise (a) the squared deviation of the disinfectant (i.e. chlorine) concentration from desired values. Constraints: (1) Nonnegative disinfectant doses. Decision variables: (1) Disinfectant doses (i.e. injections).	Water quality: Chlorine. Network analysis: EPANET (EPS). Optimisation method: MATLAB (Moler 1980) using linear least square (LLS) solver.	• The locations of booster stations are assumed to be known. • Disinfectant doses are periodic over 24-hour cycle. Time horizon is several days to reach stationary conditions. • Two chlorine source models are used: mass booster and flow-paced booster, because the input-output dynamics is linear. • The optimisation problem is formulated as a LLS problem. Objective function includes arbitrary weights on the contribution of disinfectant residual at each customer node. The paper includes comparison of LLS

			approach with LP approach of Boccelli et al. (1998). • "Booster disinfection can be effective in reducing network-wide variation in disinfectant residual, while reducing the total mass of disinfectant used". • Test networks: (1) WDS with 1 source, 1 pump station, 1 tank (incl. 34 nodes) (Clark et al. 1993; Boccelli et al. 1998).
46. Van Zyl et al. (2004) SO Optimal pump operation using hybrid GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for volume deficit in tanks at the end of the simulation period, (c) penalty costs for violating the limit on the number of pump switches. Constraints: (1) Min/max water levels in tanks, (2) no volume deficit in tanks at the end of the simulation period, (3) limit on the number of pump switches. Decision variables: (1) Tank trigger levels for energy peak and off-peak periods to control pumps (different trigger levels may be set for peak and off-peak periods).	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Hybrid GA, where GA is combined with 2 hillclimber (local) search methods, namely Hooke and Jeeves method, and Fibonacci method.	• Time horizon is 24 hours divided into 1-hour intervals. • GA identifies the region of an optimal solution and subsequently a hillclimber method finds a local optimum. The process is repeated until the termination criteria are met. • Due to the nature of the problem, hillclimber search methods are limited to methods, which use objective function values, not gradients. Hook and Jeeves method gives better results than Fibonacci method. • The efficiency of the hybrid GA is compared to pure GA and pure Hook and Jeeves method. The hybrid GA gives better solution and converges with the significantly lower number of function evaluations compared to pure GA. Pure Hooke and Jeeves method gives inferior solutions compared to both the hybrid GA and pure GA. • Test networks: (1) Small water distribution network with 1 source, 1 main pump station, 2 tanks at different elevations and 1 booster pump station (incl. 13 nodes), (2) Richmond WDS (incl. 836 nodes), UK.
47. Baran et al. (2005) MO Optimal pump operation considering both energy and demand charges using multiple evolutionary algorithms (EAs) being compared.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the number of pump switches. Objective (3): Minimise (a) the difference between initial and final water levels in tanks. Objective (4): Minimise (a) max (daily) power peak (demand charge). Constraints: (1) Min/max reservoir water levels, (2) min/max pipeline pressure constraints. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on, for each hour of the day). Note: One MO model including all objectives.	Water quality: N/A. Network analysis: Simplified hydraulic model, mass balance mathematical model (Ormsbee and Lansey 1994), EPS. Optimisation method: SPEA, NSGA, NSGA-II, CNSGA (controlled elitist nondominated sorting genetic algorithm), NPGA (niched Pareto genetic algorithm), MOGA are compared.	• Extension of the paper by Sotelo and Baran (2001) applying multiple EAs. • Optimisation problem is solved by six EAs (listed on the left). Unlike other EAs, SPEA works with two populations, where the second (archive) population stores the best solutions found during algorithm iterations. • Results from six EAs are compared using a set of six metrics proposed in Van Veldhuizen (1999). Average metric's values from 10 typical runs of each EA are used for comparison. SPEA gives the best overall results, followed by NSGA-II. • It is noted that to conduct a fair comparison of EAs is difficult due to various algorithm parameters, which affect the quality of the results and the efficiency of the algorithm. • Test networks: (1) Simplified system with 1 source, 5 pumps and 1 elevated reservoir (based on the main pump station in Asuncion, Paraguay).
48. Lopez-Ibanez et al. (2005) MO Optimal pump operation using	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the number of	Water quality: N/A. Network analysis: EPANET (EPS).	• The number of pump switches is used as a surrogate measure for pump maintenance costs. • Time horizon is 24 hours divided into 1-hour intervals, with two

SPEA2.	pump switches. Constraints: (1) Pressures at demand nodes, (2) min/max tank water levels, (3) tank volume deficit at the end of simulation. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on, for each hour of the day). Note: One MO model including both objectives.	Optimisation method: SPEA2.	electricity tariffs used. Fixed speed pumps are considered only. • Constraints are incorporated using a methodology based on the dominance relation (Deb and Jain 2003) rather than penalty function. • The results are assessed by means of empirical attainment surfaces (da Fonseca et al. 2001). The number of functions evaluations is 6,000 with 30 repetitions of each configuration. • Test networks: (1) Small water distribution network (incl. 13 nodes) (Van Zyl et al. 2004).
49. Ostfeld (2005) SO Optimal design and operation of multiquality WDSs including total construction costs and annual operation costs 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 simulation, (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: Not specified conservative parameters. Network analysis: EPANET (EPS). Optimisation method: GA.	• Time horizon is 24 hours, with a varied energy tariff and unsteady water flow conditions. Similar to Ostfeld and Salomons (2004), 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 data or constraints. Test network (1): increased min pressure constraint at one consumer node, increased max concentration limit for all consumer nodes, increased operational unit treatment cost coefficient. Test network (2): 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. • Test networks: (1) Two-loop network with 3 sources (incl. 6 demand nodes) (Ostfeld and Salomons 2004), (2) Anytown network (Walski et al. 1987) with modifications (incl. 16 nodes).
50. Kurek and Brdys (2006) MO Optimal location of booster chlorine stations for drinking WDSs using NSGA-II.	Objective (1): Minimise (a) the number of booster chlorine stations. Objective (2): Minimise (a) the mean value of chlorine concentrations. Objective (3): Minimise (a) the mean value of instances of not meeting quality requirements. Constraints: (1) Min/max number of booster stations, (2) min/max chlorine concentrations, (3) min chlorine concentration at treatment plants. Decision variables: (1) Presence of a booster station at network node (binary, 0 = no, 1 = yes), (2) chlorine concentrations at booster stations and treatment plants (real). Note: One MO model including all objectives.	Water quality: Chlorine Network analysis: EPANET (EPS). Optimisation method: MATLAB using modified NSGA-II.	• Multiple demand scenarios are considered. • 24-hour chlorination patterns are used for booster stations as well as water treatments plants. • Objective (2) allows defining min preferred chlorine concentration in the network by a user. • It was identified that chlorine concentrations in the network decrease with the increased number of chlorine booster stations. “However at some point adding another booster stations yields smaller improvements”. • It was also identified that different demand scenarios require different number of chlorine booster stations to ensure safe drinking water. • Test networks: (1) EPANET Example 3 (incl. 92 nodes) (USEPA 2013).
51. Ostfeld and Salomons (2006)	Objective (1) ‘Min Cost’: Minimise (a) the	Water quality: Chlorine	• Pump schedules are optimised in conjunctions with booster

SO Optimal operation of drinking WDSs including scheduling of pumps, scheduling of booster chlorination stations and their locations using GA.	pump operating costs (energy consumption charge), (b) booster chlorination operational injection costs, (c) booster chlorination design costs. Objective (2) 'Max Protection': Minimise (a) the difference between actual and max desired chlorine concentrations at consumer nodes. Constraints: (1) Min/max pressure at the consumer nodes, (2) min/max chlorine concentrations at the consumer nodes, (3) tank volume deficit at the end of simulation. Decision variables: (1) Locations of booster chlorination stations (integer), (2) pump schedules (binary), (3) control valve settings (i.e. valve openings) (real), (4) booster chlorination injection rates. Note: Two SO models, each including one objective.	(first order decay). Network analysis: EPANET (EPS). Optimisation method: OptiGA (Salomons 2001).	chlorination injection rates, because resulting disinfectant concentrations depend on the flow regime in the network, thus pump schedules. • Objective (2) 'Max Protection' maximises the system protection by maintaining chlorine residual as close as possible to upper bound level. • Time horizon is 24 hours, with a varied energy tariff. • Five sensitivity analyses are undertaken, which include an addition of an extra booster chlorination station, operation of booster chlorination stations for Max Protection, change of a booster chlorination cost coefficient, change of a lower chlorine concentration bound, exclusion of components (b) and (c) from the objective (1) 'Min Cost'. • It is identified that "the two problems of minimising energy cost and minimising the total CL [chlorine] dose injected are mutually connected-calling upon a multi-objective optimisation approach to further explore the tradeoff between these two goals". • Test networks: (1) EPANET Example 3 (incl. 94 nodes) (USEPA 2013).
52. Prasad and Walters (2006) SO Minimising water age by rerouting flows in the network to improve water quality using GA.	Objective (1): Minimise (a) the water age at network nodes (max, weighted average and average water age are considered), (b) penalty costs for violating pressure head. Constraints: (1) Min pressure at the nodes, (2) upper limit on the flow velocity in the pipes. Decision variables: (1) Settings of isolation valves (open/closed) represented by open/closed pipes.	Water quality: Water age (as a surrogate measure for water quality). Network analysis: EPANET (steady state, but results are tested by conducting an EPS). Optimisation method: GA.	• It is noted that various strategies can be used to minimize water age in the network, but this paper considers pipe closures only. • The type of GA used generates a connected tree network. This tree network is to ensure connectivity throughout the whole network, which standard GA algorithms fail to produce. The decision variables are represented by two sets of pipes. The first set represents pipes which are open and form a tree. The second set contains pipes which are open and addition of which to the tree layout form loops. • Test networks: (1) Network with 1 source and 47 pipes (incl. 34 nodes), (2) real network in UK with 632 pipes (incl. 535 nodes).
53. Jamieson et al. (2007) SO Optimal operation of WDSs in real-time using ANN and GA, the first paper of POWADIMA series.	Objective (1): Minimise (a) the pump operating costs. Constraints: Not specified. Decision variables: (1) Pump controls (binary), (2) valve controls (binary).	Water quality: N/A. Network analysis: ANN (process-driven, EPS) as a substitute for a hydraulic simulation model. Optimisation method: GA.	• The paper presents an introduction to the POWADIMA research project. It describes the concept of a design of a real-time control system for WDSs. In this concept, ANN is proposed to replace a hydraulic simulator to increase the computational efficiency. • The POWADIMA project is divided into 7 work packages, split between several universities. Subsequent papers (Alvisi et al. 2007; Martinez et al. 2007; Rao and Alvarruiz 2007; Rao and Salomons 2007; Salomons et al. 2007) describe various parts of the project. • SCADA and demand forecast are used. • ANN model is to be tested on Anytown network and applied to two real networks. • Test networks: (1) Anytown network (Walski et al. 1987) with

			modifications (incl. 19 nodes), (2) portion of Haifa WDS (incl. 112 nodes), Israel, (3) Valencia WDS (incl. 725 nodes), Spain.
54. Kim et al. (2007) SO Optimal pump operation using integer programming (IP).	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Reservoir lower limitation (determined by a statistical analysis based on correction of the demand forecasting model), (2) pump limitation. Decision variables: (1) The number of pumps required.	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: LINGO (LINDO 2014) using IP.	• Three methods were tested and compared for a 3 month period: (i) time index, (ii) multiple regression + time index, and (iii) Fourier series + transfer autoregressive integrated moving average (ARIMA). Time index and multiple regression methods were selected to forecast the hourly water demands for 2 week period. • Energy tariff varies monthly and hourly. • Test networks: (1) Supply system in southern part of Seoul, Korea.
55. Martinez et al. (2007) SO Optimal operation of WDSs in real-time using ANN and GA, the sixth paper of POWADIMA series.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) water production costs. Constraints: (1) Min/max pressure at demand nodes, (2) Min flow rate at pipes, (3) min/max tank water levels, (4) tank water level equal or above a prescribed level at a specified time each morning, (5) installed power capacity at pump stations. Decision variables: (1) Pump settings (on/off) for fixed speed pumps, (2) valve settings representing valve openings (binary coded).	Water quality: N/A. Network analysis: ANN (process-driven, EPS) as a substitute for a hydraulic simulation model (Rao and Alvarruiz 2007). Optimisation method: GA.	• Optimisation package DRAGA-ANN is used (Rao and Salomons 2007), which is linked with SCADA. • Test network is supplied from two WTPs, each equipped with a pump station and a tank. There are no booster pumps and tanks in the network itself, so the system is dependent largely upon gravity and several operating valves. Fixed speed pumps are considered. • Electricity tariffs vary hourly and monthly. • Time horizon is 24 hours divided into 1-hour intervals. Demand forecast, based on seasonal, weekly and daily periodic components, is discussed in the fourth paper of POWADIMA series (Alvisi et al. 2007). • Performance of the optimisation package was evaluated by running optimisation for the entire year of 2001 and comparing results with EPANET. • For the Valencia network, ANN is about 94 times faster than EPANET, while for the Haifa-A network (Salomons et al. 2007) it is about 25 times faster. • Test networks: (1) Valencia WDS (incl. 725 nodes), Spain.
56. Murphy et al. (2007) SO Optimal operation of a large drinking WDS considering water age using GA.	Objective (1): Minimise (a) the pumping power costs, (b) utility turnout costs, penalty costs for (c) violating the turnout flow constraints, (d) violating reservoir water level constraints, (e) average water age greater than 5 days. Constraints: (1) Constraints on flows via the utility turnouts, (2) min/max reservoir levels, (3) min/max reservoir return levels, (4) min reservoir turnover. Decision variables: (1) Pump on/off times, (2) flows and hours of operation for the utility	Water quality: Water age. Network analysis: EPANET (EPS). Optimisation method: GA.	• The redevelopment of the current system of the water utility in Las Vegas, Energy and Water Quality Management System, is presented to better address water quality issues. This system is used for daily operational planning since 2005. • Water age is used as a surrogate for disinfection by-products (DBP). • 3-day and 7-day operating cycles for a winter operation condition are used for the EPS of 27 and 28 days to allow water age to reach steady state. • Large number of decision variables (for a single GA run for a 3-day operating cycle, there is 13,968 hourly on/off pumping decisions) was significantly reduced by selecting feasible pump combinations rather than hourly on/off decisions for each pump, and other simplifications

	turnouts where water is purchased from another utility, (3) PRV settings, (4) flow control valves settings, (5) open/close pipe decisions.		of the pump schedules. • Optimization run times are estimated to be 139 days on a single computer, which is unacceptable for operational needs. Therefore, parallel computing is used to provide more realistic times. • Optimisation results represent 12.8% reduction in the average water age in reservoirs. • Test networks: (1) Large WDS in Las Vegas valley, U.S., containing approximately 8,000 pipe sections, 194 pumps and 28 reservoirs (incl. over 6000 nodes).
57. Rao et al. (2007) SO Optimal operation of WDSs in real-time linked to the SCADA system including pumps and valves using ANN and GA.	Objective (1): Minimize (a) system operating costs (energy and production). Constraints: (1) System operational constraints, (2) lower/upper limits on control variables (pump and valve settings), (3) lower/upper limits on state variables (tank water levels, pressures, flows). Decision variables: (1) Pump settings, (2) valve settings (open/closed).	Water quality: N/A. Network analysis: ANN (process-driven, EPS) as a substitute for a hydraulic simulation model. Optimisation method: ENCOMS incorporating GA and ANN.	• The paper presents an extension of the POWADIMA project, where GA and ANN are combined in a software ENCOMS. The system is generic and can be applied to any WDS due to customizability; ANN is first run off-line for a large number of simulations, then trained and tested. • Real-time control operates continually and is updated at short intervals by data transmitted from the SCADA and the updated demand forecasts. Time horizon is next 24 hours of system operation using 1-hour time step. • The repetitive nature of real-time control enables reduction in the number of generations used for the next update of the operating strategy. This is due to the existing operating strategy not being very different from the next operating strategy. The initialization process can be non-random, where a large portion of the current population is used as an initial population for the next step after the updates. • Test networks: (1) Valencia WDS (incl. 725 nodes), Spain.
58. Rao and Salomons (2007) SO Optimal operation of WDSs in real-time using ANN and GA, the third paper of POWADIMA series.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) cost of water at sources. Constraints: (1) Min/max pressure at junction nodes, (2) min/max velocities at pipes, (3) min/max tank water levels, (4) installed power capacity at pump stations. Decision variables: (1) Pump settings (on/off) for fixed speed pumps, (2) pump settings for variable speed pumps, (3) valve settings representing valve openings (binary coded).	Water quality: N/A. Network analysis: ANN (process-driven, EPS) as a substitute for a hydraulic simulation model (Rao and Alvarruiz 2007). Optimisation method: GA.	• ANN development is described in the second paper of POWADIMA series (Rao and Alvarruiz 2007). • As a constraint handling procedure, the multiplicative penalty method is used, in which the objective function is multiplied by a penalty factor proportional to the extent of the constraint violation. • Time horizon is 24 hours divided into 1-hour intervals. Demand forecast, based on seasonal, weekly and daily periodic components, is discussed in the fourth paper of POWADIMA series (Alvisi et al. 2007). • A dynamic version of the method, DRAGA-ANN, is developed, where the updated information (such as forecasted demands for the next 24 hours, current control settings and water levels from SCADA) is fed into the GA-ANN optimiser every hour in order to produce more up to date schedule. Only 1-hour schedules are implemented via the SCADA, whilst the remaining schedules are retained for re-initialising

			the control variables at the next time interval using the updated SCADA data. This approach can reduce the number of generations. • Test networks: (1) Anytown network (Walski et al. 1987) with modifications (incl. 19 nodes) (Rao and Alvarruiz 2007).
59. Rico-Ramirez et al. (2007) SO Optimal location and injection rates of booster disinfectant stations for drinking WDSs including uncertainties using stochastic decomposition algorithm.	Objective (1): Minimize (a) the cost of booster stations installation (first stage), (b) the cost of the disinfectant mass required to maintain concentration residuals within the network (second stage). Constraints: (1) The total max number of booster stations, (2) lower/upper bounds of disinfectant residual concentrations, (3) max disinfectant dosage multiplier, (4) nonnegative dosage multipliers. Decision variables: (1) Presence of a booster station at network node (binary, 0 = not, 1 = yes) (first stage), (2) disinfectant dosage (second stage).	Water quality: Disinfectant (first order decay). Network analysis: EPANET (EPS). Optimisation method: Stochastic decomposition algorithm.	• Extension of the paper by Tryby et al. (2002) incorporating uncertainties. • The optimisation problem is formulated as a two stage stochastic problem, the first stage is a MILP problem, the second stage is a LP problem. It indirectly incorporates uncertainties on demands, pipe roughness and chemical reactions of the disinfectant via linear coefficients of the proposed model, which are computed through EPANET. • A comparison with deterministic results is performed. The results indicate that the number of booster stations is larger and the total costs lower in the stochastic solution than in the deterministic solution. An explanation could be that increased flexibility and better disinfectant distribution exist due to the extra number of stations. However, the CPU time obtained in order of weeks could be prohibitive in some applications. • Test networks: (1) EPANET Example 2 (incl. 34 nodes) (USEPA 2013).
60. Salomons et al. (2007) SO Optimal operation of WDSs in real-time using ANN and GA, the fifth paper of POWADIMA series.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge. Constraints: (1) Min pressure at demand nodes, (2) min/max tank water levels, (3) tank water level equal or above a prescribed level at a specified time each morning, (4) installed power capacity at pump stations. Decision variables: (1) Pump settings (on/off) for fixed speed pumps, (2) valve settings (PRV).	Water quality: N/A. Network analysis: ANN (process-driven, EPS) as a substitute for a hydraulic simulation model (Rao and Alvarruiz 2007). Optimisation method: GA.	• Optimisation package DRAGA-ANN is used (Rao and Salomons 2007). Optimisation runs continuously in 1-hour intervals, implementing a new schedule via SCADA for the current time interval, then waiting for the next update of the SCADA data, which is to be used for the subsequent optimisation run together with updated demands and electricity tariffs. • Test network has hilly topography with 6 separate pressure zones, each supplied by a dedicated set of pumps and each containing one or more tanks. Network includes one PRV. Fixed speed pumps are considered. • Electricity tariffs vary three times a day, also with seasons, weekends and holidays. • Time horizon is 24 hours divided into 1-hour intervals. Demand forecast, based on seasonal, weekly and daily periodic components, is discussed in the fourth paper of POWADIMA series (Alvisi et al. 2007). • Performance of the optimisation package was evaluated by running optimisation for the entire year of 2000 and comparing results with EPANET. • Test networks: (1) Haifa-A WDS (incl. 112 nodes), Israel.

61. Ulanicki et al. (2007) SO Optimal operation of WDSs using SQP.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge, (b) water price at sources, (c) penalty cost associated with the final state of reservoir water levels. <u>Constraints:</u> (1) Min/max reservoir water levels, (2) min/max flows through pump stations, (3) the number of pumps in a pump station, (4) min/max pump speeds, (5) min/max valve openings, (6) min/max source flows. <u>Decision variables:</u> (1) Pump controls (integer), (2) pump speeds (continuous), (3) valve controls (continuous), (4) source flows (continuous).	<u>Water quality:</u> N/A. <u>Network analysis:</u> Explicit mathematical formulation (unsteady state). <u>Optimisation method:</u> SNOPT, SQP algorithm (Gill et al. 2002).	• Both fixed and variable speed pumps are considered. • Two stage suboptimal algorithm is used: (i) a relaxed continuous problem is solved to produce optimal reservoir trajectories, (ii) then a mixed integer solution is found using branch and bound and time decomposition. This paper deals with the first stage. The relaxed continuous problem is obtained by assuming that the integer variable of pump controls is continuous. • Reduced gradients of the objective and constraint functions are calculated. • Time horizon is 24 hours divided into 1-hour intervals. • Full parameterisation (FP) approach and partial parameterisation (PP) approach are compared. In the FP approach, all variables (control, state and algebraic) are treated as decision variables while in the PP approach, only control variables are treated as decision variables. Results show that results obtained by both approaches are very similar. However, PP approach requires fewer iterations with fewer variables, and can be integrated with an existing network models, which makes it attractive for industry applications. • <u>Test networks:</u> (1) Raw water and irrigation network (incl. 48 demand nodes), South of France.
62. Wu (2007) SO Optimal pump operation considering both fixed and variable speed pumps using fast messy GA (fmGA).	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge). <u>Constraints:</u> (1) Min/max pressure at nodes, (2) max allowable flow velocity, (3) min tank water level, (4) min/max disinfectant concentrations. <u>Decision variables:</u> (1) Pump statuses for fixed speed pumps (binary, 0 = pump off, 1 = pump on), (2) pump speeds for variable speed pumps (continuous).	<u>Water quality:</u> Disinfectant. <u>Network analysis:</u> Not specified solver (EPS). <u>Optimisation method:</u> fmGA (Wu and Simpson 2001).	• Constant and variable speed pumps are considered. • Time horizon is 24 hours divided into 1-hour intervals. • Solution for fixed speed pumps is compared with the solution for variable speed pumps, showing that the cost of pumping is smaller for variable speed pumps even though they operate continuously over a 24-hour period. • Results are compared with the results of the previous study (Mays 2000), which used mathematical programming (NLP) approach and SA (SA). It is illustrated that fmGA is more effective in searching for the optimal pump schedule. • <u>Test networks:</u> (1) EPANET Example 3 (incl. 91 nodes) (USEPA 2013), adapted from (Mays 2000).
63. Bagirov et al. (2008) SO Optimal pump operation using discrete gradient method.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for violating constraints. <u>Constraints:</u> (1) Min/max pressure at nodes, (2) min/max tank water levels. <u>Decision variables:</u> (1) On/off switches for the pumps (continuous), (2) pressure at each pump for each time interval (continuous).	<u>Water quality:</u> N/A. <u>Network analysis:</u> Not specified (EPS). <u>Optimisation method:</u> Discrete gradient method (Bagirov 2002).	• The optimisation problem is formulated as a nonsmooth optimisation problem. • Time horizon is 24 hours divided into 1-hour intervals, with peak and off-peak energy tariffs used. • The number of pump switches is included in the optimisation model as decision variables, not as constraints. The formulation allows for the pump switches to occur at any time, not at given discrete time intervals.

			• The results are compared with the real usage in December 2006 indicating energy cost savings. • Test networks: (1) Simplified model of Ouyen subsystem of the Northern Mallee Pipeline, Victoria, Australia.
64. Ewald et al. (2008) MO Optimal location of booster chlorine stations for drinking WDSs using a distributed multi-objective GA.	Objective (1): Minimise (a) the number of booster chlorine stations. Objective (2): Minimise (a) the mean value of chlorine concentrations. Objective (3): Minimise (a) the mean value of instances of not meeting quality requirements. Constraints: (1) Min/max number of booster stations, (2) min/max chlorine concentrations at booster stations and treatment plants. Decision variables: (1) Presence of a booster station at network node (binary, 0 = no, 1 = yes), (2) chlorine concentrations at booster stations and treatment plants (real). Note: One MO model including all objectives.	Water quality: Chlorine. Network analysis: EPANET (EPS). Optimisation method: Distributed multi-objective GA (based on the island GA) implemented using grid computing).	• Objective (2) evaluates disinfectant distribution throughout the network. • Objective (3) evaluates feasibility of the booster allocation and the corresponding control schedules. • Several demand scenarios are considered simultaneously. These scenarios are defined so that meeting the constraints for each of them entails meeting the constraints for all practical scenarios. • Grid implementation of a distributed multi-objective GA is based on a modified island GA, which uses independent subpopulations and subgenerations are computed using the modified NSGA-II. • The performance of the grid implementation is compared with a classic algorithm. It was found out that the algorithm with grid implementations reduced overall computation time and reached better solutions (over the same running time) than the classic algorithm. • Test networks: (1) Chojnice drinking WDS (incl. 188 nodes), Poland.
65. Lopez-Ibanez et al. (2008) SO Optimal pump operation using ACO compared to hybrid GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max tank water levels, (2) min pressure at demand nodes, (3) tank volume deficit at the end of simulation, (4) max number of pump switches. Decision variables: (1) On/off duration periods (in hours) for each pump (integer).	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: ACO, compared to hybrid GA (Van Zyl et al. 2004) and simple GA.	• Time horizon is 24 hours. • The solution space is reduced by introducing a constraint on the number of pump switches, and having a decision variable representing on/off durations for each pump as opposed to a binary representation of on/off statuses for every hour of the day. • Rather than using penalty function for constraint violations, the constraint violations are ordered by the importance and solutions are ranked. The ranking makes feasible solutions always preferable over infeasible solutions. • Test networks: (1) Small water distribution network (incl. 13 nodes) (Van Zyl et al. 2004), (2) Richmond WDS (incl. 836 nodes), UK.
66. Ostfeld and Tubaltzev (2008) SO Optimal design and operation of WDSs including construction costs and annual operation costs 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 simulation. Decision variables: (1) Pipe diameters, (2)	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: ACO, compared to the previous study also using ACO (Maier et al. 2003).	• Time horizon is 24 hours, 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, a 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. • The proposed ACO produced better results than ACO of Maier et al. (2003). However, it is difficult to anticipate which method is better in general as the performance always depends on model calibration for a

	pump power at each time interval.		specific problem. • Test networks: (1) Two-loop network with 3 sources (incl. 6 demand nodes) (Ostfeld and Salomons 2004), (2) Anytown network (incl. 16 nodes) (Walski et al. 1987) with modifications.
67. Shamir and Salomons (2008) SO Optimal operation of WDSs in real-time using a reduced model (RM) and GA.	Objective (1): Minimise (a) the pump energy costs. Constraints: (1) Constraints on tank water levels, (2) constraints on demand junction pressures. Decision variables: (1) Pump statuses for fixed speed pumps, (2) valve statuses (pressure reducing and pressure regulating valves).	Water quality: N/A. Network analysis: Not specified solver (EPS), RM is used. Optimisation method: GA.	• The paper is based on the POWADIMA work. ANN is not used, instead a reduced (skeletonised) model of the network is developed to reduce the simulation time. The RM is created by an algorithm developed by Ulanicki et al. (1996). • Time horizon is 24 hours, but only schedules for 1 hour ahead of the current time are implemented via SCADA. After 1 hour, the SCADA data is updated from field data, which is used for the subsequent optimisation run to obtain new schedules and so on. • Unlike in the POWADIMA project, a simple demand forecast is used. Recorded daily quantities by pump stations in 2004 are used to produce demands, which are divided equally among the nodes according to an hourly pattern based on a similar WDS. • The skeletonised network reduces simulation time about 15 times. • The developed RM-GA methodology is tested for 2 months in 2004, January (low demands) and July (high demands). Compared to operation by the system operators, cost savings are in order of 10%. • Test networks: (1) Haifa-B WDS (incl. 867 nodes, a reduced model 77 nodes), Israel.
68. Cohen et al. (2009) SO Optimal operation of regional multiquality WDSs considering the total operation costs, inclusive of water supply, pump energy and water treatment costs using projected gradient method.	Objective (1): Minimise the total cost of operation including (a) the water supply costs from sources, (b) pump energy costs at boosters (c) pump energy costs at pump stations, (d) water treatment costs, (e) yield reduction costs, (f) penalty costs for violating water quality constraints. Constraints: Limits on discharges for (1) boosters, (2) valves, (3) pump stations, (4) sources, (5) limits on pressure heads at customer nodes, (6) limits on pumping heads, (7) limits on opening ratio of valves, (8) quality parameter function (interdependency of quality parameters), (9) treatment limits on removal ratios. Decision variables: Q-C-H problem: (1) circular flows, (2) removal ratios in treatment plants, (3) water quality distribution. Q_0-H	Water quality: Salinity, magnesium, sulphur all considered as conservative. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: Projected gradient method.	• Extension of the paper by Cohen et al. (2000c) using the same optimisation model and applied to the three following case studies: (A) Network without treatment plants and salinity as the only water quality parameter, (B) network with treatment plants and salinity as the only water quality parameter, (C) network with treatment plants and three conservative water quality parameters. • The paper emphasises the relation between irrigation and drinking water supply through the same system, where there are agricultural irrigation customers on one hand and on the other hand village drinking water customers within one WDS. • Most of the paper is devoted to describing a real regional multiquality network in semi-arid climate in Israel with a complete hydraulic and water quality solution for optimal operation. • The results are as follows. In the case study (A), yield loss is the highest part of the total operation costs. In the case study (B), addition of treatment plants results in savings (more than one third) in the total operation costs, the majority of these savings are due to yield loss reduction. In the case study (C), there are higher total operation costs

	problem: (4) opening ratios of valves, (5) configurations of pump stations, (6) headlosses in control valves, (7) bypass flows.		than in (B) but lower than in (A). • Test networks: (1) WDS of the Central Arava Valley (incl. 38 nodes), Southern Israel.
69. Kang and Lansey (2009) SO Optimal operation of drinking WDSs in real-time combining optimal settings of valves and chlorine booster injection doses to improve water quality using GA.	Objective (1): Minimise (a) the difference between the actual and specified min chlorine concentration at nodes. Constraints: (1) Min/max chlorine concentrations at nodes, (2) min/max pressure head at nodes, (3) volume deficit at tanks at the end of the decision period posed as limit on tank water level. Decision variables: (1) Source chlorine injection rates, (2) booster chlorine injection rates, (3) control valve settings (% of valve closure).	Water quality: Chlorine. Network analysis: EPANET (EPS, and steady state to predict system pressure). Optimisation method: GA.	• Real-time optimisation model is presented. Control valves are used to alter flow distribution and direct chlorine laden-water where required. • Demand forecasting is synthetically generated for each node during the simulation period by adding random deviations to base demand patterns. Demand forecasting is conducted every 6 hours. • To predict pressure at nodes, steady state simulation is undertaken by EPANET to avoid overestimating the system pressure while demands are declining using an EPS. • Decision time step is 1 hour for both demand forecasts and decision variables. • For each run, only the first 6-hour solutions are implemented since a new set of decisions will be determined with improved demand forecasts after 6 hours. • Test networks: Not specified.
70. Ormsbee et al. (2009) SO A review of optimisation formulations, both explicit and implicit, used for a pump scheduling problem.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min pressure at nodes, (2) pump starting time to be less than pump stopping time (for unrestricted explicit formulation). Decision variables: (1) Pump controls.	Water quality: N/A. Network analysis: N/A. Optimisation method: N/A.	• The paper reviews approaches to formulate a pump scheduling problem in terms of decision variables. • Implicit formulation: decision variables are represented by either pump flows, pump pressures or tank trigger levels. • Restricted explicit formulation: decision variables are represented by duration (in hours) of pump operation. • Unrestricted explicit formulation: decision variables are represented by start/end times for pump operations. • Composite explicit formulation: a single decision variable is introduced for each pump station and each time interval. It consists of an integer identifying pump combination which operates and time interval percentage during which this pump combination operates. This formulation significantly reduces the total number of decision variables. • Test networks: N/A.
71. Pasha and Lansey (2009) SO Optimal pump operation in real-time using LP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max tank water levels, (2) bounds on pump station flows. Decision variables: (1) Pump station discharges.	Water quality: N/A. Network analysis: A simplified linear model (EPS). Optimisation method: LP.	• Time horizon is 24 hours divided into 1-hour intervals. • The optimisation problem is formulated as a LP problem, which is solved in real-time. Model is limited to a single tank system. • First, the WDS physical data is collected. Second, a simplified linear WDS model is developed based on offline extensive simulation using linear regression. Third, forecast demands are derived. Four, LP model is formed using these demands and LP WDS model in order to determine the optimal pump stations discharges. Last, those discharges

			are converted into actual pump operations. • The global solution may not be ensured due to linearisation inaccuracies, but a comparable solution is obtained in real-time. • Test networks: (1) Anytown network (incl. 19 nodes) (Walski et al. 1987).
72. Wu and Zhu (2009) SO Optimal pump operation considering both fixed and variable speed pumps using parallel computing and GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Limits on pressure at nodes, (2) limits on pipe flow velocity, (3) limits on storage tanks. Decision variables: (1) Pump schedules.	Water quality: N/A. Network analysis: Not specified solver (EPS). Optimisation method: fmGA.	• Time horizon is 24 hours. • The paper compares different paradigms for parallel computing on a single multi core PC and a cluster of PCs; task parallelism, data parallelism and hybrid parallelism. • Scalable and portable parallel optimisation framework is applied to a pump scheduling problem. The parallel computing model found the same solutions in less than 50% of execution time compared to the sequential model. It is concluded that N+1 processes seem to gain maximum speedup on an N-core CPU. • Test networks: (1) EPANET Example 3 (incl. 91 nodes) (USEPA 2013), adapted from (Mays 2000).
73. Alfonso et al. (2010) MO, SO Optimisation of operational responses by manipulating valves, hydrants and pumps to contamination of WDSs using NSGA-II and GA.	Objective (1): Minimise (a) the number of polluted nodes (NPN), polluted at least one time step during the simulation period. Objective (2): Minimise (a) the number of the operational interventions (OIs) needed. Constraints: (1) Positive nodal pressures, (2) topological checking to ensure network connectivity, (3) technical operational capacity to implement interventions. Decision variables: (1) OIs for valves, hydrants and pumps (binary, 0 = closed/switched off, 1 = open/switched on). Note: One MO model including both objectives, one SO model combining objectives (1) and (2) into one objective function.	Water quality: Conservative contaminant. Network analysis: EPANET (EPS). Optimisation method: MO: NSGAX software (Barreto et al. 2006) using NSGA-II; SO: GLOBE software (Solomatine 1999) using GA.	• Objective (1) represents the damage to public health associated with the contamination of the network. A ‘polluted node’ is a node with pollution concentration above a specified threshold. • Objective (2) represents the operational effort required to set the network to a desirable condition (e.g. closing certain valves and/or opening hydrants for flushing the contaminant). In real life applications, however, the actual costs associated with the OI should be used. • COPA module developed in Borland Delphi is used to link GLOBE/NSGAX with EPANET. • Due to the very large search space requiring an enormous computational effort, two-phase procedure is adopted to eliminate some of the decision variables during the optimisation process thus reduce the computation time. • For both test networks, three scenarios (SC1 to SC3) of injecting contaminant into the network are analysed. • Three basic factors exist in all solutions found, such as (i) isolating the contaminant, (ii) flushing it out and/or (iii) diluting it. • Test networks: (1) Simple hypothetical network with 41 pipes and 1 source (incl. 25 nodes), (2) real WDS in Villavicencio, Sector 11 (incl. 247 nodes), Colombia.
74. Bene et al. (2010) SO Optimal pump operation using	Objective (1): Minimise (a) the pump operating costs (energy consumption charge; demand charge included by constraint (3)).	Water quality: N/A. Network analysis: Explicit mathematical formulation	• Time horizon is 24 hours divided into 1-hour intervals, with peak and off-peak energy tariffs used. • The principle of neutrality is used and implemented to balance the

neutral search technique with micro GA.	<u>Constraints:</u> (1) Min/max reservoir capacity, (2) volume deficit in reservoirs at the end of the scheduling period, (3) upper limit on the total power consumed by a pump station (i.e. the limit on the number of pumps allowed to run simultaneously). <u>Decision variables:</u> (1) On/off pump statuses.	(friction losses considered negligible compared to the geodetic height differences, unsteady state). <u>Optimisation method:</u> Neutral search technique with micro GA (Coello and Pulido 2001).	evolutionary search through grouping. Based on objective function, similar individuals are grouped. Fitness functions are assigned to these groups, thus the individuals within a group have equal fitness. The aim is to decrease the selection pressure on the highly fit individuals introducing higher diversity. • The constraints are merged with the objective function as such that the superiority of feasible solutions over infeasible ones is strictly ensured. • Neutral search with micro GA is compared to two conventional GA approaches with constraints handled by penalty method and the method of Powell and Skolnick (1993). Neutral search shows good performance without the need to fine tune parameters through experimentation. • <u>Test networks:</u> (1) Simplified model of a WDS of Sopron, Hungary.
75. Broad et al. (2010) SO Optimal operation of WDSs for a planning horizon of 25 years using ANN and GA.	<u>Objective (1):</u> Minimise (a) the energy costs for operating pumps (net present value (NPV) over 25 years), (b) capital costs of new chlorinators, (c) maintenance costs of existing and new chlorinators (NPV over 25 years), (d) costs of chlorine (NPV over 25 years), (e) penalty costs for violating min pressure, (f) penalty costs for violating residual chlorine concentrations. <u>Constraints:</u> (1) Min pressure at nodes, (2) min allowable residual chlorine concentration. <u>Decision variables:</u> (1) Tank trigger levels to control pumps, (2) chlorine dosing rates.	<u>Water quality:</u> Chlorine. <u>Network analysis:</u> ANN (process-driven, EPS) as a substitute for a hydraulic simulation model in order to provide savings in computational expenses; EPANET to train ANN. <u>Optimisation method:</u> GA.	• Extension of the paper by Broad et al. (2005) catering for more complex WDSs inclusive of water quality considerations. • The metamodelling approach taken is to create several ANNs, one for each output (pressure, energy consumed, chlorine residual, etc.), as opposed to a single ANN with several outputs. The approach taken is because “calibrating an ANN model for a single output generally improves predictive performance”. • Time horizon is 700 hours (i.e. max water age in the test network), cyclic 24-hour demand patterns are used, a hydraulic time step is 1 hour, water quality time step is 6 minutes. • The results show that for the test network, some degree of skeletonisation of the ANN model is required to achieve suitably accurate metamodels. • The best solution found represents a saving of 14% compared with the current operating regime with an estimated NPV of $1.56 million. ANN-GA run time was 1.4 hours compared to estimated EPANET-GA run time of over 1,000 days. • <u>Test networks:</u> (1) WDS in Wallan (over 1700 nodes), Victoria, Australia
76. Gibbs et al. (2010a) SO Optimal operation of a real WDS including costs of pumping and disinfecting water using GA.	<u>Objective (1):</u> Minimise (a) the pump operating costs (energy consumption charge; demand charge included by constraint (1)), (b) costs of dosing calcium hypochlorite tablets in reservoirs, (c) penalty costs for violating constraints. <u>Constraints:</u> (1) Peak electricity demand bound, (2) min chlorine concentration, (3) min	<u>Water quality:</u> Chlorine (first order decay). <u>Network analysis:</u> EPANET (EPS). <u>Optimisation method:</u> GA.	• Total chlorine is used as a surrogate for the chloramine, because only total chlorine measurements were available to calibrate the model. • First the hydraulic model is calibrated, after which the chlorine decay model is added. The ‘triangular distribution’ model of calcium hypochlorite tablet dosing influence on the total chlorine concentration is developed. • The daily demand is forecast assuming it will be the same as the previous days demand obtained from SCADA.

	water level in reservoirs, (4) volume deficit in reservoirs at the end of the simulation period, (5) min flow from one of the water storages to the treatment plant. Decision variables: (1) Reservoir trigger levels to control pumps, (2) yes/no decisions for dosing calcium hypochlorite tablets in the reservoirs.		• Five different control periods over the day are used, these were derived from the electricity daily tariff. • Four different scenarios are used in optimisation: with varying initial reservoir water levels, and with or without water quality constraints. For scenarios without water quality constraints, time horizon is 24 hours. For scenarios with water quality constraints, time horizon is 57 hours to observe the influence of the tablet dosing in the network. • The solutions found can save up to 30% compared to the real operation of the system. Also it identified the allowing reservoir levels to be lower overnight, more pumping can be shifted to off-peak period. • Test networks: (1) Woronora WDS, Sydney, Australia.
77. Gibbs et al. (2010b) SO Comparison of GA parameter setting methods in optimal operation of drinking WDSs.	Objective (1): Minimise (a) the mass of chlorine added to the system at six possible locations. Constraints: (1) Min/max chlorine concentrations at nodes. Decision variables: (1) Mass of chlorine injected at each dosing point.	Water quality: Chlorine. Network analysis: EPANET (EPS). Optimisation method: GA.	• The paper compares six GA calibration methods. Method 1: parameterless GA, method 2: convergence due to genetic drift, method 3: GA with typically/commonly used parameter values, methods 4-6: all the previous methods in a self-adaptive framework. In methods 1-3, crossover and mutation are fixed, whereas in methods 4-6 they self-adapt. • Results: All methods consistently located better solutions than the typical GA parameter values, indicating the importance of identifying suitable values for a particular case. Furthermore, methods with fixed parameter values generally located better solutions than methods with self-adapting values. • Test networks: (1) Cherry Hill-Brushy Plains portion of the South Central Connecticut Regional Water Authority network (incl. 34 nodes), U.S. (data same as in (Boccelli et al. 1998)).
78. Kang and Lansey (2010) SO Optimal operation of drinking WDSs in real-time combining optimal settings of valves and chlorine booster injection doses to improve water quality using GA.	Objective (1): Minimise (a) the excess chlorine residuals at the consumer nodes, (b) penalties for violating constraints. Objective (2): Minimise (a) the total mass of injected chlorine at sources/boosters, (b) as above. Constraints: (1) Min/max chlorine concentrations at nodes, (2) min/max pressure head at nodes, (3) min/max tank water level, (4) volume deficit at tanks at the end of the decision period posed as limit on tank water level. Decision variables: (1) Source water chlorine injection concentrations, (2) booster chlorine injection concentrations, (3) control valve	Water quality: Chlorine. Network analysis: EPANET (EPS, and steady state to predict system pressure). Optimisation method: GA.	• Extension of the paper by Kang and Lansey (2009) including four operation cases. Case 1: Disinfectant supplied at a WTP with a constant injection rate. Case 2: Varied disinfectant injection rate. Case 3: Three additional booster stations with varied injection rates. Case 4: Additionally considers valve operation. • Time horizon is 24 hours which is acquired by four real-time runs performed every 6 hours. Nodal demands vary in space/time, hydraulic behaviour is non-periodic. • Pump operation schedules are assumed to be given. • A warm up simulation period is used for water quality analysis in order to obtain better initial concentrations. • Because demands do not change rapidly, solutions obtained on previous days can be used as initial solutions on the next runs, which saves time and provides better solutions as opposed to starting with a fully random initial population.

	settings (% of valve closure). Note: Two SO models, each including one objective.		• Results: Objectives (1) and (2) can be used equally as they are directly correlated. Using valves improves water quality by reducing disinfectant contact time and preventing slow moving water within the looped system. However, it can deteriorate water quality in tanks by increasing its residence times. A booster station is necessary for the nodes which are directly affected by water from tanks. • Test networks: (1) Medium-sized WDS with 1 WTP, 5 pumps and 3 booster stations (incl. 67 nodes).
79. Ostfeld et al. (2011) SO Optimal operation of multiquality WDSs including chemical water stability due to blended desalinated water using GA.	Objective (1): Minimise (a) the pumping costs, (b) water treatment costs. Constraints: (1) Min pressure head at the consumer nodes, (2) min and max CCPP limits at the selected nodes, (3) max pH at the selected nodes, (4) tank volume deficit at the end of simulation. Decision variables: (1) Scheduling of the pumping units (binary), (2) alkalinity level required at each of the desalination treatment plants (real).	Water quality: Total dissolved solids (TDS), alkalinity, temperature, acidity, calcium, CCPP, pH. Network analysis: EPANET (EPS), STASOFT4 (Loewenthal et al. 1988). Optimisation method: OptiGA (Salomons 2001).	• Aspect of chemical water instability, which can be a result of mixing desalinated water with surface and/or groundwater, is included in the optimal operation of WDSs. Chemical water stability is quantified through CCPP representing the precise potential of a solution to precipitate (or dissolve) $CaCO_3$. • Solution scheme links 3 components, GA (OptiGA), EPANET and STASOFT4. EPANET simulates TDS, alkalinity, temperature, acidity, calcium as conservative parameters, STASOFT4 simulates CCPP and pH. Time horizon is 24 hours. • The intensive computational effort is highlighted, which needs to be addressed in further research. • Test networks: (1) Two-loop network with 3 sources (incl. 6 demand nodes) (Ostfeld and Salomons 2004), (2) EPANET Example 3 (incl. 94 nodes) (USEPA 2013).
80. Bagirov et al. (2012) SO Optimal pump operation with explicit and implicit pump scheduling using grid search with Hooke-Jeeves method.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for violating constraint (4). Constraints: (1) Min/max water level at storage tanks, (2) volume deficit at storage tanks at the end of the scheduling period, (3) min/max pressure at nodes, (4) consecutive pump start/end run times, (5) limits on downstream pressure trigger values. Decision variables: (1) Pump start/end run times, (2) downstream pressure trigger values to control pumps.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Grid search with Hooke-Jeeves method.	• The optimisation problem is formulated to combine explicit and implicit pump scheduling into one optimisation model. Explicit pump schedules are represented by the start/end run times of pumps, while implicit pump schedules are represented by downstream pressure trigger values. • For explicit pump scheduling, the number of pump switches is limited a priori. For implicit pump scheduling, the number of pump switches, which is dependent on a difference between downstream pressure trigger values, can be defined by a user. • Time horizon is 24 hours, two energy tariffs are used. • Test networks: (1) Small water distribution network (incl. 13 nodes) (Van Zyl et al. 2004).
81. Bene and Hos (2012) SO Optimal pump operation to fill a reservoir using series of the local optima (SLO) technique.	Objective (1): Minimise (a) the pump energy costs to fill a reservoir. Constraints: Not specified. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on, for each time interval).	Water quality: N/A. Network analysis: Simplified hydraulics. Optimisation method: SLO technique.	• A problem of filling a reservoir using a variable speed pump is considered. Artificial but qualitatively proper performance curves are used. The time to fill up the reservoir is unbounded. Two scenarios are analysed: infinitely large reservoir and finite reservoir. • The method developed is based on sequentially updating the operating point corresponding to instantaneous minimal energy consumption,

			which is calculated analytically. • SLO technique is compared to the multipurpose global optimisation solver SBB (GAMS 2014). Results show that SLO technique gives similar results with significantly less computational effort. • Test networks: (1) System with a source, a pump, a pipe network (representing losses), an upper reservoir and a node in which the consumption is concentrated.
82. Giustolisi et al. (2012) MO Optimal operation of WDSs including the non-revenue water costs due to leakage and pump operating costs using GA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) cost of non-revenue water (water losses) due to leakage. Objective (2): Minimise (a) the constraint (1), (b) the constraint (2), (c) the constraint (3). Constraints: (1) Min pressure for sufficient service expressed as the number of times in which it is not satisfied, (2) tank volume deficit at the end of simulation, (3) min tank levels as the number of times in which it is not satisfied, (4) max tank levels, (5) global mass balance in each tank during an operating cycle. Decision variables: (1) On/off statuses (binary) of pumps (and gate valves). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: Generalised steady-state model, where EPS is performed as a sequence of steady state simulation runs. Optimisation method: WDNetXL (Giustolisi et al. 2011) using optimised multi-objective genetic algorithm (OPTIMOGA) (Laucelli and Giustolisi 2011).	• Demand-driven analysis is used to calculate pressures, pressure-driven analysis is used to calculate water losses. • Time horizon is 24 hours divided into 1-hour intervals, with a varied energy tariff. • During optimisation process, if three constraints on min and max tank levels and min nodal pressure are not satisfied, the computation of EPS is stopped to reduce the computational burden. • Three scenarios for water leakage are considered, where water losses are 10%, 20% and 40% of the daily volume of customer demands. Also, the case of only pumping cost is compared to the case of pumping and water loss cost. • It was found out that pump energy costs and water losses due to leakage are conflicting objectives. Minimization of just pump energy costs moves the pumping to the night time when the pressures in the system are higher and thus more leakage occurs. When cost of non-revenue water is introduced, more pumping occurs during the day time and leakage reduces. • It was found that non-revenue water cost dominates the energy cost of pumping water, although the unit volume cost of water is assumed rather low. Therefore, it could be a better practice to pump during the day time in order to control leaks. • Test networks: (1) Network with 1 reservoir, 3 pumps, 1 tank (incl. 30 nodes).
83. Gleixner et al. (2012) SO Optimal pump operation using MINLP.	Objective (1): Minimise (a) the cost of purchasing water at the sources, (b) the pump operating costs (energy consumption charge). Constraints: (1) Min/max flows through pumps, (2) max pump head, (3) min/max flows through valves, (4) min/max flows through pipes, (5) min/max pressure at junctions, (6) pressure at sources is fixed. Decision variables: (1) On/off pump statuses (binary), (2) flow direction through valves	Water quality: N/A. Network analysis: Explicit mathematical formulation (steady state). Optimisation method: SCIP solver (Achterberg 2009) using branch and bound method for general MINLP problems.	• The aim is to find epsilon-globally optimal solution. • Problem specific presolving steps are used to reduce size and difficulty of the model. These steps include merging subsequent pipes, contracting pipe-valve sequences, etc. • A distinction is made between so called real and imaginary flows. Head levels at nodes without water (caused by a closed valve or inactive pump) and flow induced by these heads according to Darcy-Weisbach equation are said to be imaginary as opposed to real. Therefore, Darcy-Weisbach equation is enforced only between real nodes.

	(binary), (3) indicator whether node is real (binary), (4) flows in pipes (continuous).		• Two scenarios are tested: the first with all tanks half full, the second with certain tanks set to their minimum levels. • It is demonstrated that defined optimisation problems can be solved to global optimality in short running times in order of seconds. • Test networks: (1) Small network with 1 reservoir, 4 tanks, 12 pumps and 6 valves (incl. 20 nodes), (2) large network with 15 reservoirs, 11 tanks, 55 pumps and 9 valves (incl. 62 nodes).
84. Selek et al. (2012) SO Optimal pump operation using micro GA with constraint handling using neutrality.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge; demand charge included by constraint (6)). Constraints: (1) Min/max reservoir volumes, (2) volume deficit in reservoirs at the end of the scheduling period, (3) limit on the number of pump switches for well pumps (variable speed pumps), (4) max pump capacity, (5) min/max water volume delivered from wells, (6) upper energy limit. Decision variables: (1) Pump flows (integer for fixed speed pumps, continuous for variable speed pumps).	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: Micro GA with constraint handling using neutrality.	• Extension of the paper by Bene et al. (2010) including detailed description of constraint handling using neutrality. • Neutrality principle is that individuals in the same partition (rather than each individual) are assigned the same fitness value, so they do not dominate each other, thus have equal probability to propagate through generations. The advantage of neutrality is to achieve a good tradeoff between exploitation and exploration. • Time horizon is 24 hours divided into 1-hour intervals. Initial flow rates are determined by operators and serve as input for optimization algorithm. • The methodology is compared to constraint handing using penalty approach, Powell's method (Powell and Skolnick 1993) and Deb's method (Deb 2000). All are incorporated into a micro GA. • The results indicate that in terms of pump operating costs there is marginal improvement over the other methods, however there is a significant improvement of 37.6% in the speed. • Test networks: (1) WDS of Sopron, Hungary.
85. Arai et al. (2013) SO Optimal operation of drinking WDSs using ISM and multipurpose fuzzy LP.	Objective (1): Minimise total energy consumption for (a) water treatment at treatment plants, (b) supplying water from treatment plants, (c) water distribution from supply stations. Objective (2): Minimise (a) water quality distance. Constraints: (1) Max treatment capacity of WTPs, (2) the total water volume flowing into a reservoir must not exceed its volume, (3) the total water volume flowing into a distribution area must satisfy its demand. Decision variables: (1) Water volumes. Note: One SO model combining both objectives.	Water quality: Total organic carbon (TOC). Network analysis: ISM (Warfield 1982) as a substitute for a hydraulic simulation model. Calculates (yearly) volumes. Optimisation method: LP, multipurpose fuzzy LP (Zimmermann 1978).	• Decision variables represents water volumes to be supplied via WTPs and supply stations. • Two optimisation requirements were adopted to account for water quality; the amount of organic substances contained in water and the distance travelled by water containing TOC should be minimal. • First, hierarchisation of the WDS is performed using ISM. Second, each objective is minimised separately using LP. Third, multipurpose fuzzy LP is used, where linear membership functions are applied to normalise and combine both objectives. By introducing a supplementary variable, multipurpose fuzzy LP problem is converted into a standard LP problem. • Tradeoff between total energy consumption and water quality is obtained. It is commented that results are affected by the shape of membership function. • Test networks: (1) WDS including 11 WTPs, 9 supply stations and 10 water distribution districts.

86. Bagirov et al. (2013) SO Optimal pump operation with start/end run times of pumps as decision variables using grid search with Hooke-Jeeves method.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). (b) penalty costs for violating constraint (4). Constraints: (1) Min/max water level at storage tanks, (2) volume deficit at storage tanks at the end of the scheduling period, (3) min/max pressure at nodes, (4) consecutive pump start/end run times. Decision variables: (1) Pump start/end run times, (2) binary indicator showing whether the pump is on or off at the initial time interval.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Grid search with Hooke-Jeeves method.	• The proposed methodology significantly reduces the number of decision variables in the pump scheduling optimisation problem. • Time horizon is 24 hours, two energy tariffs are used. • The number of pump switches is limited a priori. • First, a set of pump schedules is generated using grid. Second, hydraulic simulator EPANET is used to check the feasibility of the schedules. Third, the modification of Hooke-Jeeves method is applied to improve the feasible schedules. The algorithm iterates between EPANET and Hooke-Jeeves method. Last, the local solutions identified are ranked, and the solution with the lowest objective function value is selected. • Test networks: (1) EPANET Example 3 (incl. 94 nodes) (USEPA 2013), (2) Small water distribution network (incl. 13 nodes) (Van Zyl et al. 2004).
87. Bene et al. (2013) SO Optimal pump operation using approximate dynamic programming (ADP).	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the number of pump switches. Constraints: (1) Max power output of power supplies, (2) min/max flow from wells, (3) limit on the number of operating points of well pumps, (4) min/max limits for the exploited water for wells, (5) min/max reservoir volumes. Decision variables: (1) Pump flows (discrete for fixed speed pumps, continuous for variable speed pumps). Note: Two SO models, each including one objective.	Water quality: N/A. Network analysis: 'Flow only' model (EPS) (Cembrano et al. 2000). Optimisation method: ADP.	• A modified approach to DP is used. The method is based on two key ideas. First, the network is split into smaller parts in order to reduce the state and action space of the solvable submodels compared to the original one. Second, the state space of the WDS is further reduced to the key reservoirs. • It is noted that due to the hilly terrain of the test network, the water level variations in the reservoirs and friction losses are negligible compared to geodetic heights, so the operating point of the pumps can be determined in advance, hence there is no need for hydraulic simulation during the optimisation process. • Time horizon is 24 hours divided into 1-hour intervals. • Nine test cases with different initial water volumes of the reservoirs are defined. • The results are compared with GA and 6 other general purpose deterministic solvers available from (NEOS 2014). The benefits and drawbacks of these methods are highlighted. • Test networks: (1) WDS of Sopron, Hungary.
88. Fanlin et al. (2013) SO Optimal location and injection rates of booster disinfectant stations for drinking WDSs using matrix based algorithm.	Objective (1): Maximise (a) the coverage of the booster disinfection stations to the target nodes, which have a disinfection deficiency problem (so called 'target cases'). Objective (2): Minimise (a) the disinfection injection rate. Constraints: (1) Positive injection rate, (2) lower/upper concentration limits at nodes. Decision variables: (1) Number of booster	Water quality: Chlorine (first order decay). Network analysis: EPANET (EPS) in the set up phase, linear superposition in the solution phase. Optimisation method: Matrix based algorithm.	• The aim is to improve the current disinfection state of the network. • The solution procedure consists of two phases as follows. (1) Set up phase: EPANET is used to determine 'target cases'. The candidate set of booster stations is, instead of subjectively selected, narrowed down to the disinfection weak points with the aid of the hydraulic calculation by particle backtracking algorithm (PBA) (Shang et al. 2002). (2) Solution phase (approached as a two-step single optimisation problem): Optimisation is performed based on matrix calculations (so called 'coverage matrix') using the principle of linear superposition. If

	disinfection stations, (2) locations of booster disinfection stations, (3) injection rate (flow paced). Note: One SO model as a two-step single optimisation problem.		more than one solution with maximum coverage is obtained, minimisation of the injection rates is performed. • It is assumed that the number of booster stations is known before the optimisation of locations and injection rates. After each optimisation, the number is increased by one and in the end a tradeoff is observed between the number of booster stations and improvement of the water quality in the network. • Hydraulic cycle is 24 hours divided into 1-hour monitoring intervals. • Results show that adding booster disinfection stations to 0.1% of nodes can satisfy the chlorine residual at about 97.5% of total nodes. • Test networks: (1) WDS in Beijing (incl. 3339 nodes), China.
89. Giacomello et al. (2013) SO Optimal pump operation in real-time using a hybrid method where LP is combined with a greedy algorithm (LPG).	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min pressure at nodes, (2) min/max tank water levels, (3) recovery of water levels in tanks at the end of the scheduling period, (4) constant reservoir levels. Decision variables: LP: (1) Hourly flow rates in all network pipes and pumps, (2) heads at all network nodes; Greedy algorithm: (1) hourly pump statuses for the pumps which are still on (i.e. open) after the execution of the LP method.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Hybrid LPG method.	• Time horizon is 24 hours divided into 1-hour intervals. • Two stage optimisation method is used. Firstly, the optimisation model is linearised and LP applied to find a near optimal solution. Secondly, all the linearisation is removed and the greedy local search algorithm coupled with EPANET explores the vicinity of identified solutions to improve them. This allows obtaining the solutions in a computationally efficient way. • For the Anytown network, the best solution found is compared to the previously obtained solution using GA (Vamvakeridou-Lyroudia et al. 2005). The optimal pumping costs are slightly lower than in the previous study, with computation time of 4 seconds. • For the Richmond network, GA was implemented for a comparison. The best solution found is 1.6% more expensive than the best solution by GA, however, it is found only in 23 seconds compared to 90 minutes by GA. • Test networks: (1) Anytown network (incl. 19 nodes) (Walski et al. 1987), (2) Richmond WDS (incl. 41 nodes), UK.
90. Kougias and Theodossiou (2013) MO Optimal pump operation considering both energy and demand charges using HSA.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the quantity of pumped water. Objective (3): Minimise (a) the electric energy peak consumption (demand charge). Objective (4): Minimise (a) the number of pump switches Constraints: (1) Min/max water levels in storage tanks, (2) volume deficit at storage tanks at the end of the scheduling period (final discharges equal to ±10% of the daily	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: MO-HSA and Poly-HSA.	• Time horizon is 24 hours divided into 1-hour intervals. • Modifications to a single objective HSA are made to cater for a MO case, which results in MO-HSA and the development of Poly-HSA. The algorithms are evaluated using standard multi-objective test functions (Zitzler et al. 2000). • The performance of MO-HSA and Poly-HSA is evaluated using three performance metrics: C-metric, diversity metric - Δ and the hypervolume indicator. • Two penalty functions are used to handle constraints. The first penalty adds a constant value to the objective function for the solutions which violate tank water levels. The second penalty ensures that the solutions cover the ±10% range of the daily demand. Thus, the second penalty

	demand). Decision variables: (1) Pump statuses. Note: Two MO models, the first including objectives (1), (2), (3), the second objectives (1), (2), (4).		adds an extra cost to the objective function, analogous to the distance from the defined range. • Test networks: (1) Operational pumping field, Paraguay.
91. Kurek and Ostfeld (2013) MO Optimal operation of drinking WDSs including costs of pumping, water quality considerations and costs of tanks using SPEA2.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the evaluation function of disinfectant concentrations at monitoring nodes (including tanks). Objective (3): Minimise (a) the water age for all nonzero demand nodes. Objective (4): Minimise (a) the costs of tanks. Constraints: (1) Pressure at nodes, (2) tank volume surplus/deficit at the end of simulation, (3) storage reliability constraint to guarantee a sufficient amount of stored water at any time. Decision variables: (1) Pump speeds (real), (2) disinfectant concentrations at treatment plants (real), (3) tank diameters (integer). Note: Two MO models, the first including objectives (1), (2), (4), the second objectives (1), (3), (4).	Water quality: Water age and disinfectant (i.e. chlorine). Network analysis: EPANET (EPS). Optimisation method: SPEA2 (Zitzler et al. 2001).	• Extension of the paper by Kurek and Ostfeld (2014) including additional objectives such as water age and tank costs. • Variable speed pumps are considered. • Two optimisation problems are solved, each includes a different water quality measure, the first chlorine concentrations and the second water age. • The costs of tanks vary with the location and diameter. • Time horizon is 24 hours divided into 1-hour intervals. • 'Balanced' solution is selected according to the utopian mechanism (Miettinen 1999). • It was found out that operation of the tanks is significantly different for two optimisation problems. In the first problem with chlorine concentrations, water levels in tanks nicely fluctuate. Whereas in the second problem with water age, water levels in tanks fluctuate much less or are almost constant. This operation for the second problem is caused by exclusion of tanks from the objective (3) where only nonzero demand nodes are considered. • Test networks: (1) EPANET Example 3 (incl. 94 nodes) (USEPA 2013).
92. Price and Ostfeld (2013a) SO Optimal pump operation with linearised Hazen-Williams (H-W) head-loss equation using LP.	Objective (1): Minimise (a) the annual pump operation cost, (b) flow change penalty. Constraints: (1) Tank volume water balance closure over the optimisation period, (2) min/max tank water levels, (3) min/max pressure heads at nodes, (4) max total head at pumping stations. Decision variables: (1) Pipe flow rates, (2) total pump heads.	Water quality: N/A. Network analysis: Explicit mathematical formulation (unsteady state). Optimisation method: COIN-OR (COIN-OR 2014) using branch and cut LP method.	• The paper deals with the linearization of H-W equation for subsequent use in LP optimisation model. • Time horizon is 1 year or 1 week. • The methodology is based on a water balance model with no hydraulic equations (no head-loss equations). The model is extended to include the H-W equation, which is partitioned into two sub-equations. The first sub-equation represents the constant part of the H-W equation dependent only on pipe geometry. The second sub-equation represents the linearisation of the nonlinear flow $Q^{1.852}$ as a linear equation, subject to linearisation coefficients. These two sub-equations are then combined into one linear H-W head-loss equation. • The linearisation algorithm is developed. At each iteration of the optimisation algorithm, linearization coefficients are updated. The advantage of the proposed methodology is short solution times. • Test networks: (1) Basic WDS with 1 pump (incl. 2 nodes), (2) complex WDS with 3 pressure zones (incl. 15 nodes).

93. Price and Ostfeld (2013b) SO Optimal pump operation with linearised H-W head-loss and leakage equations using LP.	Objective (1): Minimise (a) the annual pump operation cost, (b) source cost penalty, (c) flow change penalty. Constraints: (1) Max pump station flow rate, (2) water leakage equation, (3) flow change constraint, (4) min/max water tank volumes, (5) min/max heads at nodes, (6) max total head at pumping stations. Decision variables: (1) Pipe flow rates, (2) leakage at nodes, (3) total pump heads.	Water quality: N/A. Network analysis: Explicit mathematical formulation (unsteady state). Optimisation method: GAMS/CLP (COIN-OR 2014).	• Improved version of the iterative linearization method (Price and Ostfeld 2013a) is proposed. • H-W head-loss equation, water leakage equation and pump energy consumption equation are linearised. Water leakage is pressure-dependent. • Time horizon is 1 week divided into 1-hour intervals. • Fixed speed pumps are not handled because their inclusion would transform the original smooth NLP problem into a discrete mixed integer programming (MIP) problem. • The flow change penalty is introduced to all iteration steps to prevent solution oscillation, which occurs between two similar solutions in the final iteration steps and prevents convergence. It was found out that flow change penalty helps to reach the optimal solution in less iteration steps. • Several scenarios (cases) are analysed, constraints are increasingly implemented into scenarios. • Test networks: (1) Complex WDS with 3 pressure zones (incl. 15 nodes).
94. Ghaddar et al. (2014) SO Optimal pump operation using Lagrangian decomposition with improved limited discrepancy search (ILDS) algorithm.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Upper bound for pipe flows, (2) pump must be on for the water to flow in the corresponding pipe, (3) min/max tank water levels, (4) nonnegativity for pipe flows, (5) min length of time for a pump to be on, (6) min length of time for a pump to be off, (7) max number of pump switches, (8) no deficit in tanks at the end of simulation period. Decision variables: (1) Pipe flows, (2) pipe headlosses, (3) node pressures, (4) pump statuses (binary, 0 = pump off, 1 = pump on).	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Lagrangian decomposition combined with ILDS.	• Lagrangian decomposition, which is a relaxation, breaks the original problem into smaller subproblems. Due to the relaxation of the original problem, the solutions of the subproblems may not be feasible for the original problem. Therefore, a heuristic ILDS is used to find feasible solutions. ILDS provides an upper bound on the optimal objective function value, while the Lagrangian relaxation provides a lower bound, so the proposed approach provides solutions of guaranteed quality. • The approach is compared with the MILP relaxation of the original MINLP problem, which is solved by CPLEX. • Time horizon is 24 hours, and the decisions to turn a pump on or off are made at 30 minute intervals. • Two electricity pricing schemes are used. First, fixed day/night scheme; second, dynamic scheme with prices changing every 30 minutes. • The results show that the ILDS can find better solutions than CPLEX in significantly less time. Optimised pump schedules typically lead to decrease in tank water levels. • Impact of electricity pricing schemes on pump operating costs is evaluated. Dynamic pricing results in up to 34% of cost reduction. • Test networks: (1) Small network with 1 reservoir, 2 pumps, 2 tanks (incl. 1 node), (2) Poormond network (incl. 47 nodes) adapted from

			Richmond network.
95. Goryashko and Nemirovski (2014) SO Optimal pump operation with demand uncertainty using LP.	Objective (1): Minimise (a) the pump operating costs (including two components: energy consumption charge and the price of water). Constraints: (1) Bounds on tank levels, (2) bound on pump capacity, (3) bound on source capacity. Decision variables: (1) The amount of water pumped into the system during time interval.	Water quality: N/A. Network analysis: Explicit mathematical formulation/ EPANET (EPS). Optimisation method: MOSEK software (MOSEK 2014) using LP.	• The original problem of minimization of pumping cost is simplified to a LP problem, in which the demands are treated as uncertain. To cater for demand uncertainty, the robust counterpart methodology is employed, which involves obtaining the ‘worst-case’ cost over all possible data from the ‘uncertainty set’, ensuring that all the constraints are satisfied for all realisations of the demands. Using the robust counterpart methodology, the uncertain LP model is converted to a linearly adjustable robust counterpart. Results obtained are referred to as linear robust optimal (LRO) policy. • Time horizon is 24 hours divided into 1-hour intervals. • The obtained LRO policy with the uncertainty level set to 20% is tested in EPANET to ensure appropriate hydraulic behaviour. For testing purposes, the demands were perturbed in EPANET. The results show that the warnings in EPANET (negative pressure etc.) start appearing when the perturbations become as large as 50%. • Test networks: (1) Anytown network (incl. 19 nodes) (Walski et al. 1987) with modifications.
96. Ibarra and Arnal (2014) SO Optimal pump operation using parallel programming techniques and MIP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Min/max operational tank volumes, (2) the number of start/stop events of the pumps. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on during a time interval), (2) special binary variables A_i and P_i to model start/stop events of the pumps (they are used to reduce the number of start/stop events).	Water quality: N/A. Network analysis: Explicit mathematical formulation, simplified hydraulic equations (unsteady state). Optimisation method: COIN-OR libraries (COIN-OR 2014) using branch and bound method and demand prediction.	• The optimisation problem is formulated as a MIP problem. • Time horizon is 24 hours. • Near real-time optimal pump scheduling is proposed based on demand forecast. Demand forecast is determined every hour for the next 24 hours and the next 7 days using seasonal autoregressive integrated moving average (SARIMA) (Makridakis et al. 2008) models from statistical time series theory. • Parallel programming is implemented on both shared and distributed memory multiprocessors. Stochastic scenario tree evaluation and multisite problems (multiple networks controlled from a single control centre) are solved. • Test networks: (1) WDS of Granada, Spain.
97. Hashemi et al. (2014) SO Optimal pump operation considering variable speed pumps using ACO.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Volume deficit in tanks at the end of the simulation period. Decision variables: (1) Pump speeds for each interval.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: Ant system iteration best (AS_{ib}) algorithm.	• Time horizon is 24 hours divided into 1-hour intervals. • Sensitivity analysis to find the best performing values of AS_{ib} stochastic parameters is performed. • For the Richmond network, the results with single speed pumps are compared to the results with variable speed pumps. Cost savings of about 10% are obtained for the network with variable speed pumps. • For the Anytown network, the size of search space is reduced using two approaches, ‘Replacing reservoir’ (RR) and ‘In-station scheduling’ (ISS). RR involves replacing one of the pumping stations by the reservoir and optimising head and flow supplied by that

			reservoir. Decision variable is the water level. ISS involves transforming obtained heads and flows to a pump schedule. Search space is reduced more than 10^{38} times. • Test networks: (1) Simplified Richmond WDS (incl. 13 nodes) (Van Zyl et al. 2004), (2) optimised design of the Anytown network (incl. 22 nodes) (Murphy et al. 1994).
98. Kurek and Ostfeld (2014) MO Optimal operation of drinking WDSs including pumping cost and water quality objectives using SPEA2.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Minimise (a) the evaluation function of disinfectant concentrations at monitoring nodes. Constraints: (1) Pressure at nodes, (2) tank volume surplus/deficit at the end of simulation, (3) storage reliability constraint to guarantee a sufficient amount of stored water at any time. Decision variables: (1) Pump speeds (real), (2) disinfectant concentrations at treatment plants (real). Note: One MO model including both objectives.	Water quality: Disinfectant (i.e. chlorine). Network analysis: EPANET (EPS). Optimisation method: SPEA2 (Zitzler et al. 2001).	• Variable speed pumps are considered. • Time horizon is 72 hours divided into 1-hour intervals. Only the last 24 hours are used to evaluate the values of objective functions and constraints in order to minimise the effect of initial conditions. • Tradeoffs between energy consumed by pumps and water quality are obtained: more energy consumed by pumps results in better water quality, conversely, limiting the amount of energy consumed by pumps results in deterioration of water quality. • Sensitivity analysis is performed to test the change in energy tariffs to the solution, indicating the higher use of pumps during cheap tariff. • Introduction of the storage reliability constraint (3) caused the algorithm to reduce the volume of water stored. Sensitivity analysis is performed to test the change in volume of water stored to the solution. The increase in volume of water stored cased the increase in energy consumed by pumps and deterioration of water quality. • Test networks: (1) Anytown network (incl. 16 nodes) (Walski et al. 1987), (2) EPANET Example 3 (incl. 94 nodes) (USEPA 2013).
99. Mala-Jetmarova et al. (2014) MO Optimal operation of regional multiquality WDSs including pumping cost and water quality objectives using NSGA-II.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for violating constraints. Objective (2): Minimise (a) the deviations of the actual constituent concentrations from the required values, (b) as above. Constraints: (1) Min pressure at customer demand nodes, (2) min/max water levels at storage tanks, (3) volume deficit in storage tanks at the end of the scheduling period. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on during a time interval). Note: One MO model including both objectives.	Water quality: Conservative parameter. Network analysis: EPANET (EPS). Optimisation method: NSGA-II.	• Tradeoffs between water quality and pumping costs are explored using 14 scenarios, which reflect different water quality conditions in source reservoirs. Time variability for source water quality as well as customer requirements is introduced. • Time horizon is 24 hours divided into 1-hour intervals. • It was discovered that for the majority of the scenarios, there is a tradeoff with a competing nature between the objectives. It was also discovered that the problem can be reduced, in certain instances, to a single-objective problem. This outcome is dependent upon the water quality configuration of the system (i.e. how source water qualities relate to customer water quality requirements), and upon system operational flexibility. • Some particular conclusions are drawn for both a WDS with multiple water sources and a WDS with a single water source, which suggest how changes in source water qualities or customer water quality requirements may impact on system operation. • Test networks: (1) Network with 3 sources (incl. 9 nodes) (Ostfeld and

			Salomons 2004; Ostfeld et al. 2011), (2) Anytown network (incl. 19 nodes) (Walski et al. 1987).
100. Price and Ostfeld (2014) SO Optimal pump operation including leakage using LP.	Objective (1): Minimise (a) the annual pump operation cost, (b) sum of the penalty variable given by the discrete pump operation constraint (3), (c) flow change penalty. Constraints: (1) Max pump station flow rate, (2) water leakage equation, (3) discrete pump operation constraint, (4) flow change constraint, (5) min/max water tank volumes, (6) min/max heads at nodes, (7) max total head at pumping stations. Decision variables: (1) Pipe flow rates, (2) leakage at nodes, (3) total pump heads.	Water quality: N/A. Network analysis: Explicit mathematical formulation (unsteady state). Optimisation method: GAMS/CLP (COIN-OR 2014).	• Extension of the papers by Price and Ostfeld (2013a) and Price and Ostfeld (2013b) including a discrete pump operation algorithm which encourages continuous pump operation over time without frequent pump switching. • Time horizon is 1 month, 1 week or 1 day divided into 1-hour intervals. • Iterative LP is used, which iteratively introduces a discrete pump operation constraint into the optimisation model encouraging the pump to work for the whole time interval. The iterative process calculates an index, which is high for the pumping intervals with high flow rates and low energy consumption. The constraint is introduced to the pumping interval with the highest index. The model is reevaluated at each iteration, with constraints being removed from intervals which failed the constraint (due to water balance or water head constraints) and added to new intervals with a high index. The process stops when all the time intervals have been covered. • For a small test network, the methodology is compared to a complete enumeration, with the optimal cost being within 0.2% of the global minimum. For more complex networks, several scenarios are analysed including changes in tank volumes, nodal head constraints, presence /absence of leakage etc. • Test networks: (1) Basic WDS with 1 pump (incl. 2 nodes), (2) complex WDS with 3 pressure zones (incl. 15 nodes), similar to Price and Ostfeld (2013b), (3) large network with 5 pressure zones (incl. 75 nodes).
101. Reca et al. (2014) SO Optimal pump operation of irrigation systems using LP.	Objective (1): Minimise (a) the annual pump operating costs (energy consumption charge). Constraints: (1) Max pumping capacity of each pumping system for each period, (2) min/max storage capacity, (3) restriction on a total pumped volume to prevent volume deficit at storages in the final period, (4) nonnegativity constraints on variables. Decision variables: (1) Water volumes pumped for each pumping system in each price discrimination period.	Water quality: N/A. Network analysis: Explicit mathematical formulation (unsteady state), with the operating points confirmed by EPANET. Optimisation method: Revised simplex method.	• The optimisation problem is formulated as a LP problem. • The model is aimed to help decision makers identify which energy tariff structures are more economical and determine optimal pumping policies. Three electricity tariff structures which differ in the number of tariff periods, prices in each period and their daily and annual distribution are examined. • Test network consists of 15 submerged pumps which lift water from 3 groups of wells, and 3 booster stations which deliver water to the network. The system is simplified as follows. Each group of wells is replaced by one equivalent pump, the joint operation of every well group and its associated booster station is modelled as two pumping systems in series, hourly demands are estimated from daily demands using a daily mean demand pattern.

			• Two operating scenarios are compared: pump stations operating simultaneously or independently. Independent operation proves to be more energy efficient. • Test networks: (1) Irrigation WDS, Almeria, Spain.
102. Wu et al. (2014a) SO Optimal operation of parallel pumps to achieve their best operating point using GA.	Objective (1): Minimise (a) pump power. Constraints: (1) Min/max rotational speed ratios, (2) min/max flow rates for each pump, (3) head of each pump greater than demanded head. Decision variables: (1) Pump rotational speed, (2) valve positions.	Water quality: N/A. Network analysis: N/A. Optimisation method: GA.	• The aim is for pumps to operate as close as possible to the designed conditions at their maximum efficiency. • Results indicate that control valves help improve efficiency and reliability of a single pump. However, valve throttling losses cause a significant decline in efficiency in the system of parallel pumps. • Test networks: (1) Two identical parallel pumps, (2) multiple parallel pumps with different characteristics.
103. Wu et al. (2014b) SO Optimal disinfectant dosing rate in chloraminated drinking WDSs using ANN and GA.	Objective (1): Minimise (a) maximum absolute relative error for the total chlorine and free ammonia levels. Constraints: (1) Lower/upper bounds of ammonia dosing rate, (2) the target value for total chlorine, (3) the target value for free ammonia. Decision variables: (1) Ammonia dosing rate at the source.	Water quality: Chloramine, chlorine, ammonia. Network analysis: ANN (data-driven, EPS) to forecast both total chlorine and free ammonia levels. Optimisation method: GA.	• Objective is to control total chlorine and free ammonia levels to be close to their desired levels. • Water in the test network is used for both agricultural and domestic purposes. • There is no process-based hydraulic/water quality model for the test network. Therefore, a data-driven ANN model is developed to forecast both total chlorine and free ammonia levels. Data for the development of the ANN model was gathered from the SCADA system and was converted into hourly average values. • Time horizon is 5 days (120 hours). • It is demonstrated that model predictive control system for a chloraminated WDS can potentially provide additional information to water quality operators on dosing rate control. • Test networks: (1) Goldfield and agricultural water system, Perth, Australia.
104. Kim et al. (2015) SO Optimal pump operation using DP.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Constraints: (1) Max daily pumping capacity, (2) min/max limit for reservoir storage capacity, (3) min/max limit for pipe conveyance from pump station to reservoir. Decision variables: (1) Pump schedules.	Water quality: N/A. Network analysis: Not specified (EPS). Optimisation method: CSUDP program (Labadie 1999) using DP.	• Time horizon is 24 hours. Electricity tariff varies with the time of the day and the seasons. • Four pump operating scenarios are tested. These include the inclusion of standby pumps and different demands, demand patterns and electricity tariff. • Results demonstrate that operating standby pumps together with existing pumps is more effective due to taking a full advantage of low electricity tariff. Optimised pump schedules represent cost savings of 6.3% compared to the current mode of operation, and cost savings of 19.2% while using standby pumps. • Test networks: (1) YangJu, Korea.
105. Mala-Jetmarova et al. (2015) MO Optimal operation of regional	Objective (1): Minimise (a) the pump operating costs (energy consumption charge), (b) penalty costs for violating constraints.	Water quality: Turbidity, salinity. Network analysis:	• Optimal operation is analysed using 6 network scenarios, which represent different water quality conditions in 2 source reservoirs in terms of turbidity and salinity levels. These water quality conditions as well as

multiquality WDSs including pumping cost and two water quality objectives using NSGA-II.	Objective (2): Minimise (a) the turbidity deviations from the allowed values, (b) as above. Objective (3): Minimise (a) the salinity deviations from the allowed values, (b) as above. Constraints: (1) Min pressure at customer demand nodes, (2) min/max water levels at storage tanks, (3) volume deficit in storage tanks at the end of the scheduling period. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on during a time interval). Note: One MO model including all objectives.	EPANET (EPS). Optimisation method: NSGA-II.	different customer types were adapted from a real system titled the Wimmera Mallee Pipeline, western Victoria, Australia. • Time horizon is 5 days (120 hours) divided into 1-hour intervals. • It was discovered that 2 types of trade-offs, competing and noncompeting, exist between the objectives and that the type of trade-off is not unique between a particular pair of objectives for all scenarios. The nature of a trade-off between pumping costs and water quality objectives, and between multiple water quality objectives, can be categorized by consistent water quality (CWQ) or inconsistent water quality (IWQ) sources. These sources are identified based on the relationship between water quality conditions in source reservoirs and customer water quality requirements. • Proposed methodology can assist in long-term operational planning for optimal pump and water quality control. • Test networks: (1) EPANET Example 3 (incl. 94 nodes) (USEPA 2013).
106. Odan et al. (2015) MO Optimal pump operation in real-time including demand forecasting and system operational reliability using AMALGAM.	Objective (1): Minimise (a) the pump operating costs (energy consumption charge). Objective (2): Maximise (a) operational reliability. Constraints: (1) Min pressure at any network node, (2) tank water levels at the end of the scheduling period, (3) max number of pump switches, (4) occurrence of hydraulic simulation errors and negative pressures. Decision variables: (1) Pump statuses (binary, 0 = pump off, 1 = pump on). Note: One MO model including both objectives.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: AMALGAM (Vrugt and Robinson 2007).	• Operational reliability objective is represented by four alternative measures: (i) entropy, (ii) modified resilience index, (iii) min reservoir level, (iv) surplus head. • Demand forecasting is performed 24 hours ahead using the hybrid dynamic neural network (DAN2-H) (Odan and Reis 2012). • To reduce the search space, decision variables are combined applying relative time control triggers (Lopez-Ibanez et al. 2011). • Time horizon is 24 hours divided into 1-hour intervals. The optimization is performed every hour for the next 24 hours, with only the first hour pump schedule being implemented. Optimised pump schedules are postprocessed to ensure that nominated number of pump switches is not exceeded. • Real-time data from the SCADA system is used for optimisation and optimal pump schedules implemented back via SCADA. • The reliability measures based on minimum reservoir level and surplus head seem most suitable for real-time pump scheduling. The results demonstrate 13% of energy cost savings compared to historical system operation. • Test networks: (1) Araraquara WDS (incl. 1236 nodes), São Paulo, Brazil.
107. Stokes et al. (2015a) MO Optimal pump operation including greenhouse gas (GHG) emissions using NSGA-II.	Objective (1): Minimise (a) the pump operating costs (as the cost of electricity). Objective (2): Minimise (a) the GHG emissions associated with the use of electricity from fossil fuel sources for pumping purposes.	Water quality: N/A. Network analysis: EPANET (EPS). Optimisation method: NSGA-II.	• Different emission factors (EFs), majority of them time-varying, are used. These include actual 1-year EF, average EF, estimated 24-hour EF curve, and modified estimated 24-hour EF curve including various amounts of renewable energy generated. Sensitivity analysis of 6 scenarios with different EFs is performed.

	Constraints: (1) Min pressure at network nodes, (2) min total volume of water pumped into each district metered area. Decision variables: (1) Pump schedules (integer). Note: One MO model including both objectives.		• Time horizon of 7 days or 1 year is used dependent on the scenario. • Results indicate that (i) optimal solutions can be significantly affected by time-varying EFs, (ii) estimated 24-hour EF curves can be used to accurately replace actual EFs, and (iii) the amount of renewable energy generated can affect the magnitude of EF time variations, thus optimal solutions. • Test networks: (1) D-Town network (incl. over 350 demand nodes) (Salomons et al. 2012).
Note: *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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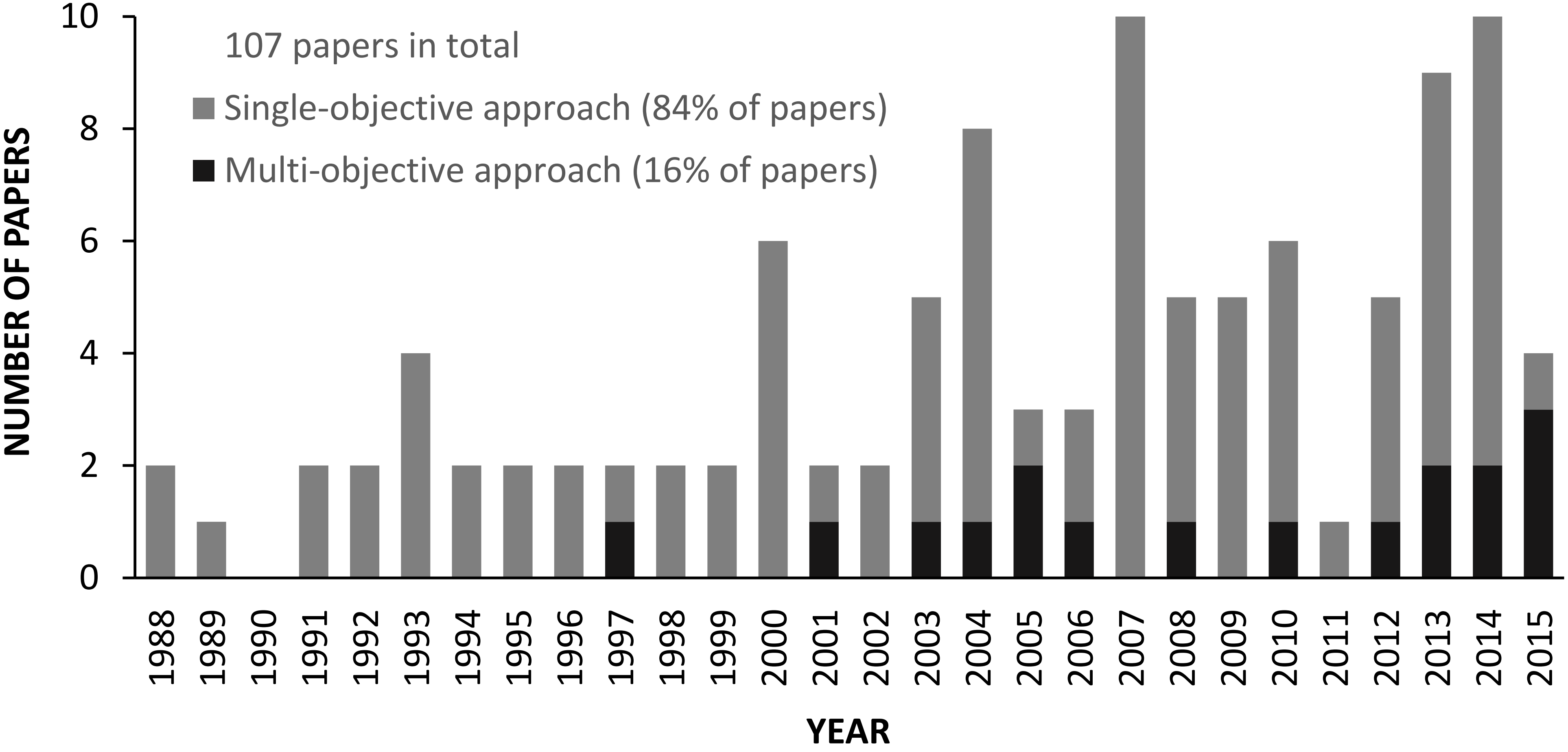
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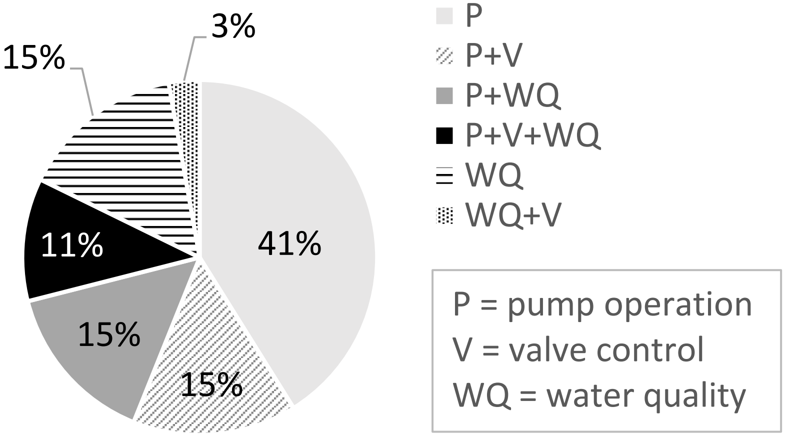
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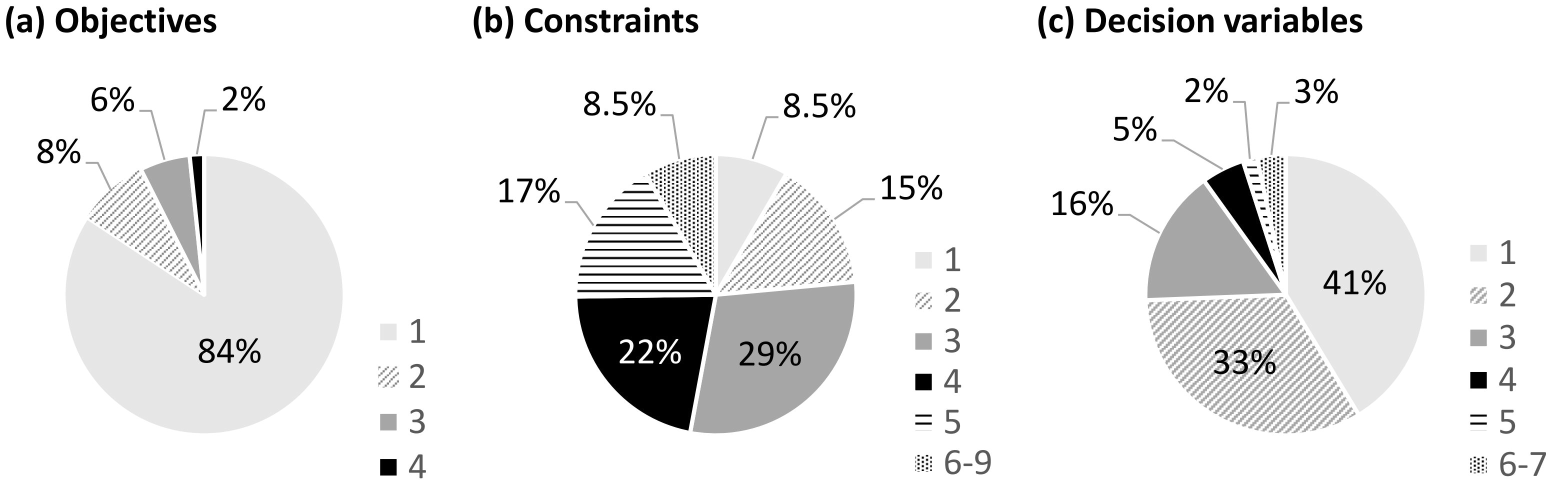
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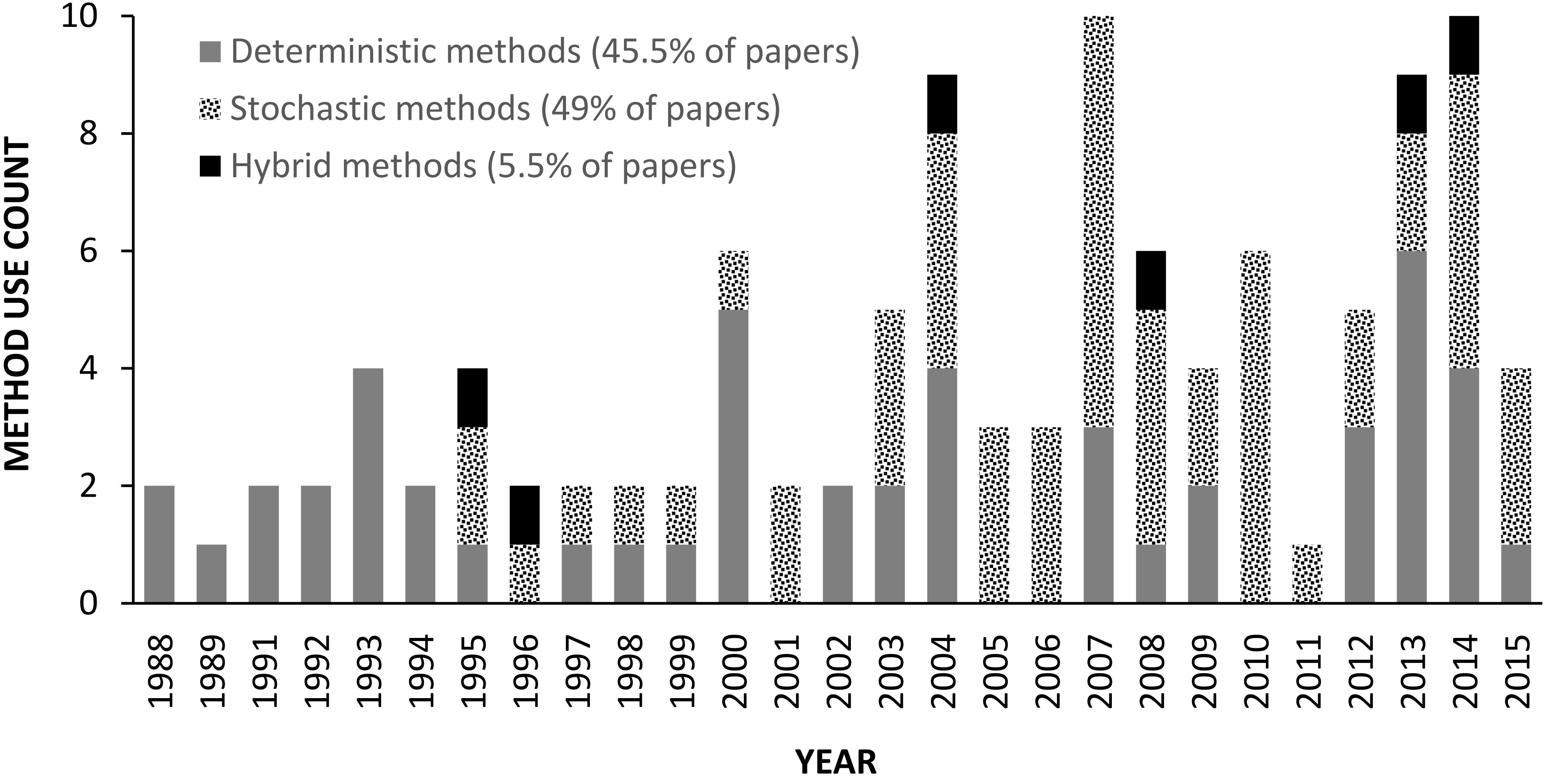
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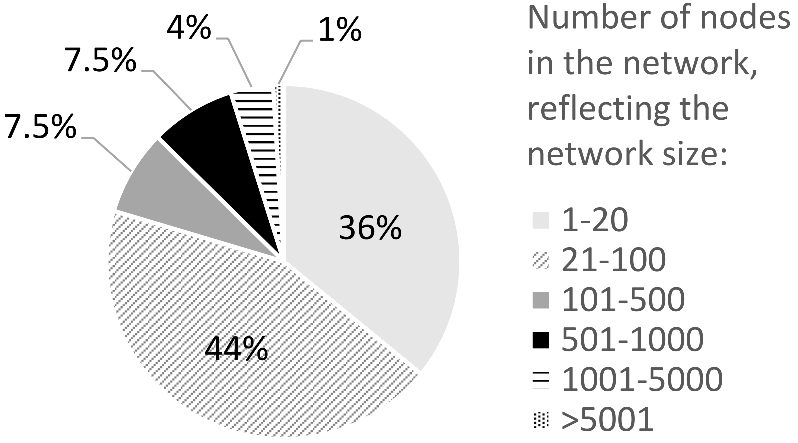
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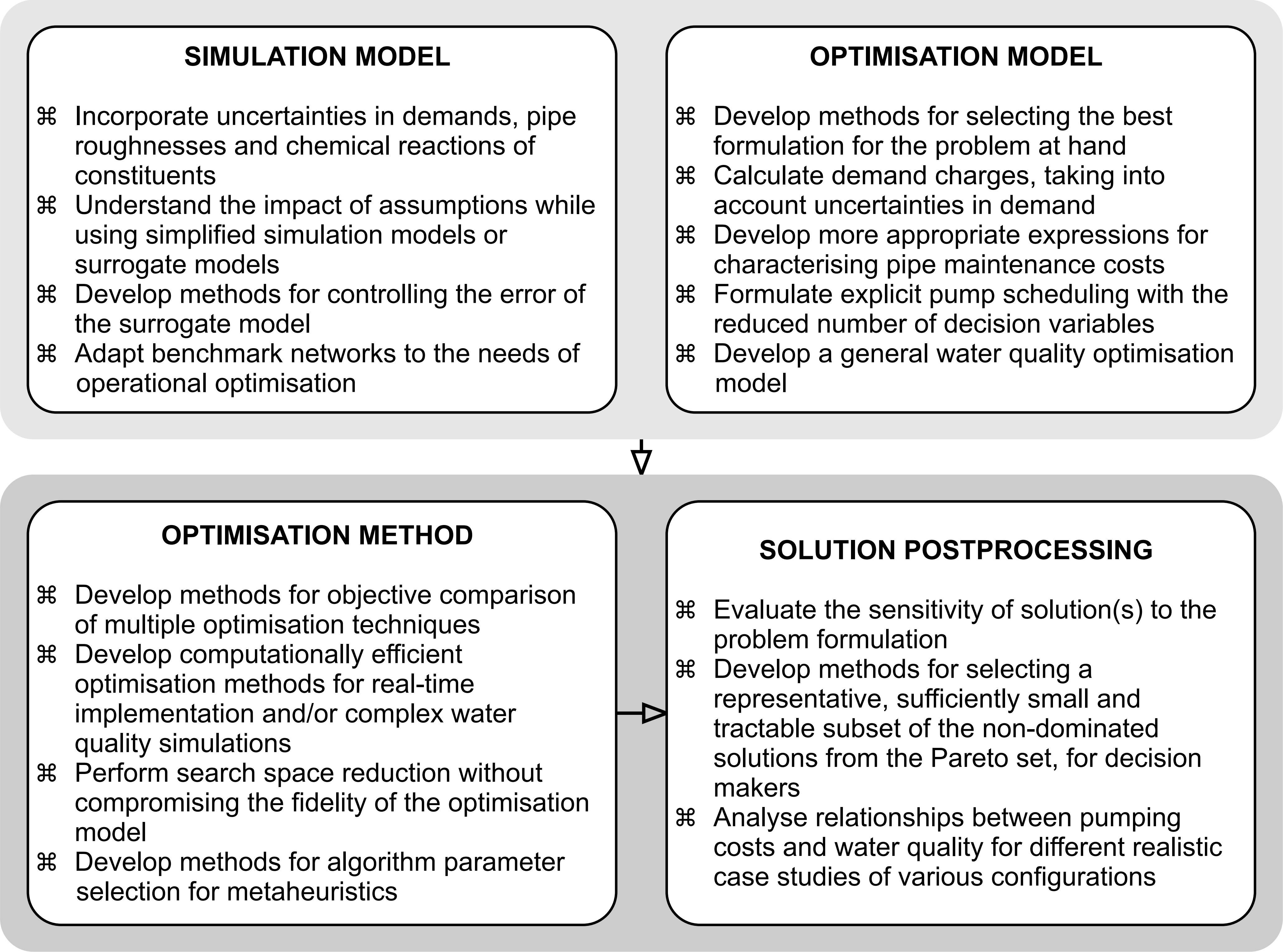

SIMULATION MODEL

- Incorporate uncertainties in demands, pipe roughnesses and chemical reactions of constituents
- Understand the impact of assumptions while using simplified simulation models or surrogate models
- Develop methods for controlling the error of the surrogate model
- Adapt benchmark networks to the needs of operational optimisation

OPTIMISATION MODEL

- Develop methods for selecting the best formulation for the problem at hand
- Calculate demand charges, taking into account uncertainties in demand
- Develop more appropriate expressions for characterising pipe maintenance costs
- Formulate explicit pump scheduling with the reduced number of decision variables
- Develop a general water quality optimisation model

OPTIMISATION METHOD

- Develop methods for objective comparison of multiple optimisation techniques
- Develop computationally efficient optimisation methods for real-time implementation and/or complex water quality simulations
- Perform search space reduction without compromising the fidelity of the optimisation model
- Develop methods for algorithm parameter selection for metaheuristics

SOLUTION POSTPROCESSING

- Evaluate the sensitivity of solution(s) to the problem formulation
- Develop methods for selecting a representative, sufficiently small and tractable subset of the non-dominated solutions from the Pareto set, for decision makers
- Analyse relationships between pumping costs and water quality for different realistic case studies of various configurations

Highlights

- A review of operational optimisation of water distribution systems is provided.
- Future challenges were identified, despite the large body of existing literature.
- Universally agreed formulation of an operational optimisation problem is needed.
- Algorithm performance for a particular problem requires improved understanding.
- A method for selecting only one solution for a real system needs to be developed.