Water Supply

Water Supply Vol 22 No 3, 3044 doi: 10.2166/ws.2021.415

Flexible and deterministic household water saving under water demand uncertainty: existing water distribution system and sanitary sewer perspectives

Innocent Basupi

Climate Change Division, Botswana Institute for Technology Research and Innovation, Maranyane House, Plot 50654, Machel Dr, Gaborone, Botswana
E-mail: ibasupi@yahoo.co.uk; ibasupi@bitri.co.bw

ABSTRACT

An integrated method that evaluates conflicting hydraulic performances of water distribution systems (WDSs) and sanitary sewers (SSs) considering water-saving schemes (WSSs) under fixed (deterministic) or uncertain water demands was formulated. WSSs considered include household water-saving fixtures and appliances whose water flows impact water distribution system (WDS) and sanitary sewer (SS) hydraulic performances in different ways. In the proposed flexible approach, a multi-objective optimisation problem was formulated and solved considering trade-offs of three objectives: (1) maximisation of the average cost savings (2) maximisation of the average WDS resilience index and (3) minimisation of the average SS self-cleansing velocity deficit factor. The decision variables include water-saving fixture and appliance capacities that are applied in a deterministic or flexible manner at a household level. The constraints include WDS and SS hydraulic requirements together with decision bounds of the available water-saving scheme capacities. The non-dominated sorting genetic algorithm was used to obtain trade-off solutions. This method was demonstrated in the corresponding WDS and SS network subsystems of Tsholofelo extension in Gaborone, Botswana. The results indicate that WSSs lead to visibly conflicting WDS and SS hydraulic performances. Moreover, considering the uncertainty inherent in water demand and the corresponding planning and management of WDSs and SSs provides more sustainable solutions as demand uncertainties unveil.

Key words: Monte Carlo simulation, optimisation, sanitary sewers, water demand uncertainty, water distribution system, water saving schemes

HIGHLIGHTS

- Performances of WSSs and water networks have been analysed considering water demand uncertainty.
- A method that considers trade-offs between water network hydraulics amidst WSSs has been articulated.
- Deterministic and flexible applications of WSSs have been examined.
- Considering demand uncertainty provides appropriate and more sustainable management of integrated water systems.

INTRODUCTION

Uncertainty is inevitable in the planning and management of water systems especially under the influence of the continuously changing urban demographics. In this regard, water demand uncertainty renders water supply and demand management interventions uncertain. The uncertainty inherent in water demand requires counteractive interventions that would promote sustainable supply of water, collection, and treatment of wastewater generated downstream. Therefore, development of novel approaches that would turn challenges into opportunities for sustainable water supply and management of water and wastewater networks becomes more relevant. Another challenge is the planning of water-saving schemes (WSSs) that clearly interact with both water distribution systems (WDSs) and sanitary sewers (SSs). WSSs impact each of the water networks differently due to different hydraulic principles applied in their designs and operations. Traditionally, water reticulation and wastewater networks have always been designed as separate entities. However, because of the technical sustainability required in existing networks, they would require trade-offs of hydraulic performances amid water-saving initiatives. Existing WDS nodal pressures would be enhanced by reduction of water demand (Basupi *et al.* 2014) caused by WSSs while such reduction may prevent the sanitary sewer (SS) pipe flow velocities from meeting the required self-cleansing flow velocity (Penn *et al.* 2013a, 2013b). The pipe flows conveyed by SSs are much impacted considering that their flows are only dependent on water consumption in connected households (Bailey *et al.* 2019). It is therefore important to investigate and obtain deterministic or flexible WSSs for sustainable WDSs and SSs in holistic approaches under uncertain water demands, accordingly.

Various sources of uncertainty in water infrastructure require appropriate interventions. In this respect, uncertainty in the design and performance analysis parameters is considered as the major source of uncertainty in engineering work (Hosseini & Ghasemi 2012). Researchers have incorporated uncertainty in the design of WDSs (Basupi & Kapelan 2015; Marques *et al.* 2015) and WDS booster chlorination (Basupi & Nono 2019; Nono & Basupi 2019) where uncertainty was countered by robustness or flexibility. While robustness is mainly the ability of a system to minimise failure due to perturbations, flexibility may include changeability of the system in response to the unveiling conditions. Robustness studies can be categorised into two groups, i.e., those that develop robustness indicators and those that propose robustness frameworks from which robust solutions in planning, design, operation, and management are derived (Jung *et al.* 2019). Over the years, more studies (e.g., Giustolisi *et al.* 2009; Sun *et al.* 2011; Kang & Lansey 2012; Perelman *et al.* 2013; Puccini *et al.* 2016; Nono & Basupi 2019; etc) have generally explored robustness in water network designs than those that introduced flexibility to cope with uncertainty (e.g., Basupi & Kapelan 2015; Marques *et al.* 2015; Basupi & Nono 2019).

Considering water demand uncertainty in WDSs, Perelman *et al.* (2013) proposed a non-probabilistic robust counterpart approach as an optimisation method under uncertainty. This method is a deterministic equivalent of the stochastic problem of optimal design or rehabilitation of WDSs. Other methods such as the fuzzy approaches have also been employed to incorporate uncertainty in WDS operations and analyses (Ostojin *et al.* 2011; Tsakiris & Spiliotis 2017). In another approach, Basupi & Kapelan (2015) developed a flexible intervention approach to counteract the effects of uncertain water demand. Their method revealed that there is value in flexibility that can be derived from uncertainties. In a similar study, Marques *et al.* (2015) incorporated flexibility in terms of spatial development of WDSs. From a different perspective, Basupi & Nono (2019) integrated uncertainty in the design of chlorine disinfection booster stations considering WDS supply paths and water demands as sources of uncertainty.

While several studies (e.g., Hosseini & Ghasemi 2012; Austin *et al.* 2014; Duque *et al.* 2016; Bailey *et al.* 2019) have considered sewer designs and analyses, only a few have considered uncertainty. For example, Hosseini & Ghasemi (2012) proposed a flexible fuzzy model for analysis of SS hydraulic performances. However, in both WDS and SS studies, demand management has not been considered as an intervention that controls uncertainty in the context of integrated operations of WDSs and SSs despite that uncertainty being controllable by demand management (De Neufville 2004).

In addition to cost savings resulting from water savings studied previously, WDS hydraulic benefits that can be measured in terms of nodal hydraulic pressures or resilience have also been observed (see Basupi *et al.* 2014). The potential benefits from water conservation cannot be fully realised without adjustments in network operation (Zhuang & Sela 2020). These benefits, however, may come at a cost in terms of water quality (McKenna *et al.* 2018; Zhuang & Sela 2020). Resilient WDSs are desirable in cases of uncertain system failures. To obtain resilient WDSs whose performances are determined by the resilience index (e.g., Todini 2000; Prasad & Park 2004; Baños *et al.* 2011), nodal water demands should be managed and/or system components should be upgraded. On the other hand, existing SSs would need adequate flows to meet the minimum self-cleansing velocity requirement for which they were designed. Evaluating the impact of WSSs on the performances of existing SSs needs to be explored, for example, Penn *et al.* (2013b) analysed the impact of a few WSSs on an existing SS while Basupi (2019) synchronised a wide range of WSSs in SS designs. These network issues need a more integrated, system view that focuses on both sustainability and resilience of infrastructure design (Minsker *et al.* 2015). While cost saving and WDS resilience index have been used before to inform solutions in water systems, a self-cleansing velocity deficit factor, which can measure the hydraulic behavior of any SS, is proposed in this study. The aim of this paper is to develop a method that analyses the existing WDS and SS conflicting hydraulic performances and obtain appropriate (deterministic or flexible) household WSS solutions considering the deterministic or uncertain water demands, accordingly.

This paper is organised as follows: after this introduction, a novel method that can consider fixed water demands and alternatively incorporate water demand uncertainty in a multi-objective optimisation problem is articulated. Flexible interventions and system performance indicators that would correspond to different levels of uncertainty are explained. Next, the method is demonstrated in real-life WDS and SS networks. The deterministic and flexible solutions obtained are analysed and discussed and conclusions are finally drawn.

METHODOLOGY

Source of uncertainty

The main source of uncertainty considered in the method presented in this section is water demand. This uncertainty is quantified using the Monte Carlo sampling technique with known (or assumed) statistical parameters such as the mean (average) and the standard deviation or variance. This stochastic approach can accommodate sampling techniques other than Monte Carlo simulation. With system demand assumed to follow the Gaussian (normal) distribution (Figure 1), the sampled demands are categorised into three divisions that represent the two tails of the distribution and the middle region whose boundary limits depend on the confidence level considered. Note that categories of demands in Figure 1(a) represent the alternative and null hypotheses. Moreover, sampled demands are assumed to increase or decrease proportionately at a nodal level. Therefore, the sampled system demands are allocated to demand nodes proportionally (i.e., equal percentage) in respective networks before effecting the impact of any water-saving scheme (WSS) as well as performing consequent model runs and evaluations.

Water consumption at WDS demand nodes is a function of water-use appliances and fittings, which are interventions considered for sustainability in this study. WSS intervention options considered in this study include various capacities of washing machines, dish washers, toilets, showerheads, kitchen and basin taps, and bathtubs as shown in Table 1. While US water-use proportions were adopted for realistic analysis, the aggregated tapwater-use proportion was allocated to kitchen and basin taps according to the UK kitchen and basin tap water-use ratio (POST 2000). As opposed to the common

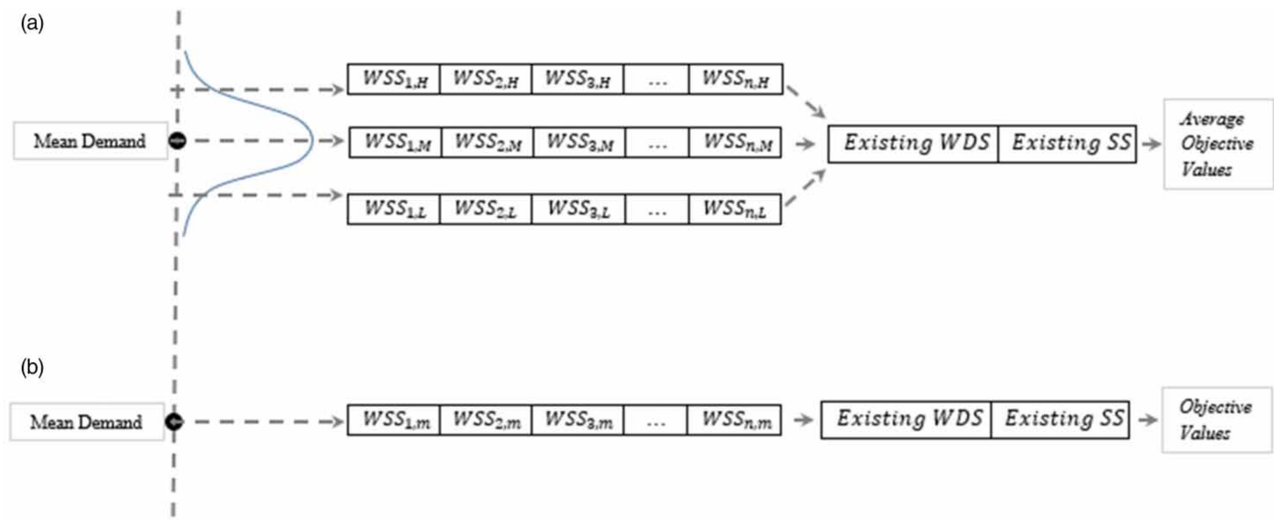

Figure 1 | Uncertain water demand and fixed water demand together with the corresponding (a) flexible and (b) deterministic water-saving applications.

Table 1 | Summary of possible WSS capacities and water-use proportions used in the integrated water system evaluations (Alliance for Water Efficiency 2016; EPA 2008)

WSS component	Capacities	Water-use proportion (%)
Toilet (WC)	6.06; 4.85; 4.16 (litres/flush)	26.7
Showerhead (SH)	0.16; 0.13; 0.09; 0.05 (litres/second)	16.8
Bath (B)	192.5; 149 (litres)	1.8
Washing machine (WM)	628; 495; 428; 374 (litres/cycle/m^3)	21.7
Dishwasher (DW)	18.9; 16.1; 15.7; 13.2 (litres/cycle)	1.4
Kitchen tap (KT)	0.14; 0.08 (litres/second)	9.8
Basin tap (BT)	0.14; 0.09; 0.08; 0.06 (litres/second)	5.9

Note: Other water consumptions not attributed to the WSSs listed in this table include outdoor use (2.2%) and leakages (13.7%).

conventional interventions and objectives that were largely considered in the literature, the current approach presents conflicting hydraulics and combines flexibility with demand management to control and cope with water demand uncertainty.

Performance indicators

Economic costs and benefits

The performances considered in this study are the economic benefits or cost savings that are achieved by applying WSS interventions. These cost savings are dependent on water and energy savings together with respective costs. Water and energy cost implications of household WSSs and water networks are basically determined from the total water-use efficiency. The efficiency of a single household water-use product is estimated relative to the known standard product, i.e., the difference between the capacity of a standard product and an efficient one is divided by the capacity of the standard product and expressed as a percentage (%). Therefore, the water-saving efficiency (η_{syst}) of the entire system is estimated as follows:

$$\eta_{\mathrm{syst}} = \sum_{i=1}^{n_{\mathrm{n}}} \frac{Q_i}{Q_{\mathrm{syst}}} \eta_{i,\mathrm{wss}} \tag{1}$$

$$\eta_{i,\mathrm{wss}} = \sum_{k=1}^{n_{\mathrm{wss}}} f_{k,\mathrm{wss}} \times \left(\frac{K_{k,\mathrm{std}} - K_{k,\mathrm{wss}}}{K_{k,\mathrm{std}}} \right) \times 100 \tag{2}$$

where n_{n} is the total number of WDS demand nodes; Q_i is the demand at the i-th node with standard products; $\eta_{i,\mathrm{wss}}$ is the total efficiency (%) of WSSs at the i-th node; wastewater flows into SSs are functions of WSSs applied at WDS demand nodes; n_{wss} is the number of WSSs at the i-th node; $f_{k,\mathrm{wss}}$ is the fraction of water use attributed to the k-th water-use product considered; and $K_{k,\mathrm{std}}$ and $K_{k,\mathrm{wss}}$ are the standard and efficient capacities of the water-use products considered. The total system demand (Q_{syst}) is estimated as follows:

$$Q_{\mathrm{syst}} = \sum_{i=1}^{n_{\mathrm{n}}} Q_i \tag{3}$$

Worth noting is that the inflows into the SS would be less than Q_{syst} due to water-saving efficiency, i.e., $Q_{\mathrm{syst}}(1 - \eta_{\mathrm{syst}})$, which is also reduced by any household water activities/events that consume and reduce inflows at the nodes of the sanitary sewer. This study estimates costs of water and wastewater treatment requirements together with costs of WSS water use, which are used for evaluating the capital and operational cost savings as follows:

$$C_{n,\mathrm{cap}} = AK^B \tag{4}$$

where $C_{n,\mathrm{cap}}$ is the cost of the n-th water or wastewater treatment facility; A and B are positive parameters that are determined by observed data; K is the capacity in flow units. Operating cost components are as follows:

$$C_{k,\mathrm{op}} = C_{\mathrm{u,e}} E_k + C_{\mathrm{u,w}} V_{\mathrm{w},k} \tag{5}$$

$$C_{n,\mathrm{op}} = C_{\mathrm{u,e}} E_n \tag{6}$$

where $C_{k,\mathrm{op}}$ and $C_{n,\mathrm{op}}$ are the WSSs' and networks' (WDS and SS) operating energy costs due to the running of equipment, heating and water treatment associated with the k-th and the n-th interventions, respectively; $C_{\mathrm{u,e}}$ and $C_{\mathrm{u,w}}$ are the unit costs of energy and water associated with the k-th WSS and n-th network interventions, respectively; E_k and E_n are the corresponding energy components of the k-th WSS and n-th network interventions; $V_{\mathrm{w},k}$ is the volume of water used by the k-th WSS component. The energy required for heating water (E_k) that is apportioned according to water use by fixtures and appliances is estimated in kWh using the following equation:

$$E_k = \frac{mc\Delta T}{3.6 \times 10^6 \eta} \tag{7}$$

where m is the mass (kg) of water that requires heating. Well-documented proportions of WSS components that use hot water are needed to estimate m and ratios (e.g. equal use) between cold and hot water use for each component; c is the specific heat capacity of water (J/kg/°C); ΔT is the desirable change in water temperature (°C); and η is the efficiency of the heating system that is used. The constant in the equation is a factor that converts joules to kWh. For systems based on water demand, capital ($S_{n,\mathrm{cap}}$) and annual operational cost savings ($S_{k,\mathrm{op}}$ and $S_{n,\mathrm{op}}$), are functions of the use of specific WSSs, overall system water-saving efficiencies for the network treatment facilities, and costs due to standard water system components are calculated as follows:

$$S_{n,\mathrm{cap}} = C_{n,\mathrm{cap}}\left(\frac{\eta_{\mathrm{syst}}}{100}\right) \tag{8}$$

$$S_{k,\mathrm{op}} = C_{k,\mathrm{op}}\left(\frac{\eta_{k,\mathrm{wss}}}{100}\right) \tag{9}$$

$$S_{n,\mathrm{op}} = C_{n,\mathrm{op}}\left(\frac{\eta_{\mathrm{syst}}}{100}\right) \tag{10}$$

In general, cost savings (S) are equivalents of the differences between the costs and/or losses that would be incurred assuming no water efficient measures applied (C) and the corresponding costs with efficient measures (C_{wss}) as follows:

$$S = C - C_{\mathrm{wss}} \tag{11}$$

The total cost saving of WSSs (S_{t}) resulting from one water demand scenario under uncertainty is expressed as follows:

$$S_{\mathrm{t}} = \sum_{i=1}^{n_n}\sum_{j=1}^{n_{\mathrm{h}}}\sum_{k=1}^{n_{\mathrm{wss}}} S_{k,\mathrm{op}} + \sum_{n=1}^{n_{\mathrm{wn}}}(f_{\mathrm{c_r},n}.S_{n,\mathrm{cap}} + S_{n,\mathrm{op}}) \tag{12}$$

$$f_{\mathrm{c_r},n} = \frac{r(1+r)^{n_{\mathrm{d},n}}}{(1+r)^{n_{\mathrm{d},n}} - 1} \tag{13}$$

where n_{h} is the total number of households and/or any other entities in the catchments of the WDS demand nodes that need WSSs; $f_{\mathrm{c_r},n}$ is the capital recovery factor, which is used to express capital cost savings as equivalent annual worth (McGhee 1991); r is the interest rate for the investment; $n_{\mathrm{d},n}$ is the design period (lifespan) of the n-th WDS or SS component under consideration; n_{wn} is the total number of WDSs and SSs considered. Therefore, the average total cost saving ($S_{\mathrm{t,av}}$) due to all the sampled water demands is expressed as follows:

$$S_{\mathrm{t,av}} = \frac{\sum_{s=1}^{n_{\mathrm{s}}} S_{\mathrm{t},s}}{n_{\mathrm{s}}} \tag{14}$$

where n_{s} is the total number of samples; $S_{\mathrm{t},s}$ is the S_{t} of the s-th sample. In this approach, all costs/benefits are added regardless of cost ownership because the approach used is a holistic method, which considers the general cost to society. Even though the focus is mainly on the selection of WSSs, the operational cost savings on the existing WDS and SS networks are included here because they are subsequent effects caused by the implementation of WSSs.

Water distribution system and sanitary sewer hydraulics

The ever-increasing water demands in WDSs make the capability of the system to react and overcome stress conditions relevant. This capability can be enhanced by WSSs because lower demands increase WDS nodal pressures, which are variables that would also enhance WDS resilience. Accordingly, the WDS hydraulic indicator considered in this approach is the resilience index (RI), which is estimated as a function of nodal pressures according to Todini (2000) as follows:

$$RI = \frac{\sum_{i=1}^{n_{\mathrm{n}}} q_i(h_i - h_{\mathrm{req},i})}{\sum_{r=1}^{n_{\mathrm{r}}} Q_r H_r + \sum_{j=1}^{n_{\mathrm{p}}}\left(\frac{P_j}{\gamma}\right) - \sum_{i=1}^{n_{\mathrm{n}}} q_i h_{\mathrm{req},i}} \tag{15}$$

where q_i corresponds to the flow of the i-th node; h_i is the available piezometric head; $h_{\mathrm{req},i}$ is the minimum required head; Q_r is the r-th reservoir flow; H_r is the reservoir head; P_j is the pump power; γ is the specific weight of water; n_{p} is the number of WDS pumps; n_{r} is the number of reservoirs. The large number of demand scenarios considered in this method suggests that the average resilience index (RI_{av}) for the flexible solutions should be calculated as follows:

$$RI_{\mathrm{av}} = \frac{\sum_{s=1}^{n_{\mathrm{s}}} RI_s}{n_{\mathrm{s}}} \tag{16}$$

where RI_s is the resilience index corresponding to a sampled demand scenario. EPANET 2.0 (Rossman 2000) WDS hydraulic solver is used to obtain network flows and pressures that are used to compute resilience and determine constraint violations. The minimum resilience across a 24-hour simulation is used to make decisions. Note that other WDS resilience measures would be applicable in this method, for instance, the network resilience and the modified resilience indices presented by Prasad & Park (2004) and Jayaram & Srinivasan (2008), respectively. While there are several methods for determining WDS resilience, this paper presents the results obtained using the Todini (2000) resilience index because conflicting hydraulics, uncertainty and flexibility issues are the main focal points rather than the most appropriate resilience measure.

The SSs are evaluated in terms of the proposed self-cleansing velocity deficit factor ($\bar{v}_{\mathrm{d}}$), which is a system performance measure obtained by averaging the accumulated pipe flow velocity deficits (v_{d}) in all the simulation intervals and across all the sewer pipes considered as follows:

$$v_{\mathrm{d}} = \begin{cases} \sum_{i=1}^{n_{\mathrm{c}}} \sum_{j=1}^{n_{\mathrm{sim}}} \left(\frac{v_{\mathrm{req},i} - v_{i,j}}{v_{\mathrm{req},i}} \right) & (v_{\mathrm{req},i} - v_{i,j}) > 0 \\ 0, & (v_{\mathrm{req},i} - v_{i,j}) \leq 0 \end{cases} \tag{17}$$

$$\bar{v}_{\mathrm{d}} = \frac{v_{\mathrm{d}}}{n_{\mathrm{sim}} \cdot n_{\mathrm{c}}} \tag{18}$$

With several samples and the corresponding $\bar{v}_{\mathrm{d},s}$ (i.e., $\bar{v}_{\mathrm{d}}$ for the s-th sample) the average is therefore calculated as follows:

$$\bar{v}_{\mathrm{d\_av}} = \frac{\sum_{s=1}^{n_{\mathrm{s}}} \bar{v}_{\mathrm{d},s}}{n_{\mathrm{s}}} \tag{19}$$

where n_{c} is the number of pipes considered; n_{sim} is the number of simulation intervals; $v_{\mathrm{req},i}$ is the required minimum flow velocity in the i-th sewer conduit and $v_{i,j}$ is the instantaneous velocity in the i-th sewer conduit at the j-th simulation interval. The EPA SWMM 5.0 (Rossman 2004) sewer hydraulic model should be run (i.e., simulation) over a defined period (e.g., 24 hours) while storing pipe flow velocities at specified intervals (i.e., values of $v_{i,j}$) that are used to determine the self-cleansing velocity deficit factor and constraint violations. The maximum value from the stored values over the entire simulation is referred to as $v_{\mathrm{max},i}$ in constraint calculations. The conduits considered in this formulation may also include upstream pipes with fewer house connections and lower wastewater inflows.

The SS hydraulic solver is very slow compared with the WDS hydraulic solver for the same time steps. The whole model run includes the WDS extended period simulation (24 hours) and SS kinematic wave routing. Therefore, repetitive simulations that include many solutions and SS hydraulic computations over many samples make the already computationally expensive optimisation process almost impossible. To counteract this issue in an existing SS problem with a demand pattern, simulations are performed with many demand samples while storing the values of the corresponding $\bar{v}_{\mathrm{d}}$ and constraint violations prior to the optimisation process. Subsequently, a scatterplot (i.e., self-cleansing velocity deficit factor vs water demand) is produced, followed by the fitting of a curve as shown in Figure 2 to obtain a performance model for the SS hydraulics considered, given levels of demands. It should be noted that the resultant performance model relationship seems to be not physically based. The use of the fitted curve saves time in the subsequent optimisation process. For instance, by using a quad-core computer with a 3.2 GHz processor, typical computations for a single candidate solution take about 0.19 and 58 seconds

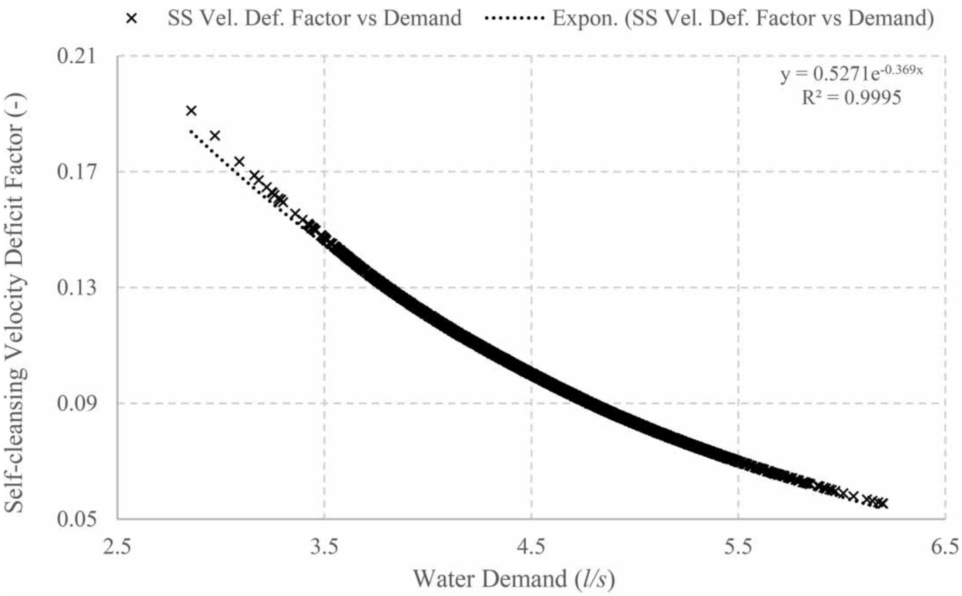

Figure 2 | A typical hydraulic performance curve for a sanitary sewer.

for deterministic and flexible hydraulic simulations of the existing Tsholofelo subsystems presented in the case study section, respectively. The corresponding deterministic and flexible simulations using the relationship model shown in Figure 2 take 0.003 and 0.862 seconds, respectively.

Deterministic and flexible solution configurations

The evaluations of interventions (variables) considering uncertain water demands are performed in a flexible approach (Figure 1(a)). Figure 1(b) illustrates the deterministic evaluation approach that has been widely used in the literature. The main difference between the deterministic and the stochastic approaches is that one demand scenario (or state), which is the mean (average), is used to evaluate the deterministic solutions while all samples are evaluated in the flexible approach using appropriate interventions depending on demand levels. However, in both cases, interventions are evaluated in terms of cost savings, WDS resilience index, and the SS self-cleansing velocity violation factor, which are subsequently traded-off in the optimisation process. The flexible approach has separate streams for the evaluations of three categories of demands considered. In Figure 1(a), subscripts H, M, and L (i.e., in $WSS_{n,\mathrm{H}}$, $WSS_{n,\mathrm{M}}$, and $WSS_{n,\mathrm{L}}$) represent flexible WSS interventions that correspond with higher, medium and lower water demand than the mean (i.e., indicated by subscript m in the $WSS_{n,\mathrm{m}}$ notation), which is associated with the deterministic approach as shown in Figure 1(b). Many performances for different levels of demands are obtained, hence average objective values are used to evaluate flexible solutions. With intervention arrangements and demand scenarios depicted in Figure 1(a), WSS solutions are determined simultaneously in all the alternative streams. Figure 3 shows schematic links of WDS, WSS, and SS components. These components were previously put together with the normal distribution curve of uncertain water demands in Figure 1.

Optimisation problem formulation

The combinations of interventions are many with varying ranges of cost savings, and hydraulic and environmental implications. Therefore, the three conflicting objectives of this combinational problem are the maximisation of the average cost savings and average resilience index while minimising the average self-cleansing velocity deficit factor. Higher pressures in WDSs are obtained by keeping lower flows (demands) in the networks, thereby compromising the SS pipe flow velocity requirements. The opposite would happen if SS pipe flow velocity requirements were highly met. Furthermore, higher household cost savings arise because of WSSs that promote lower flows, which conflicts with SS pipe flow velocity requirements. Including network water treatment benefits (cost savings) resulting from the application of WSSs may complicate the problem further.

This integrated system optimisation is subject to the following constraints:

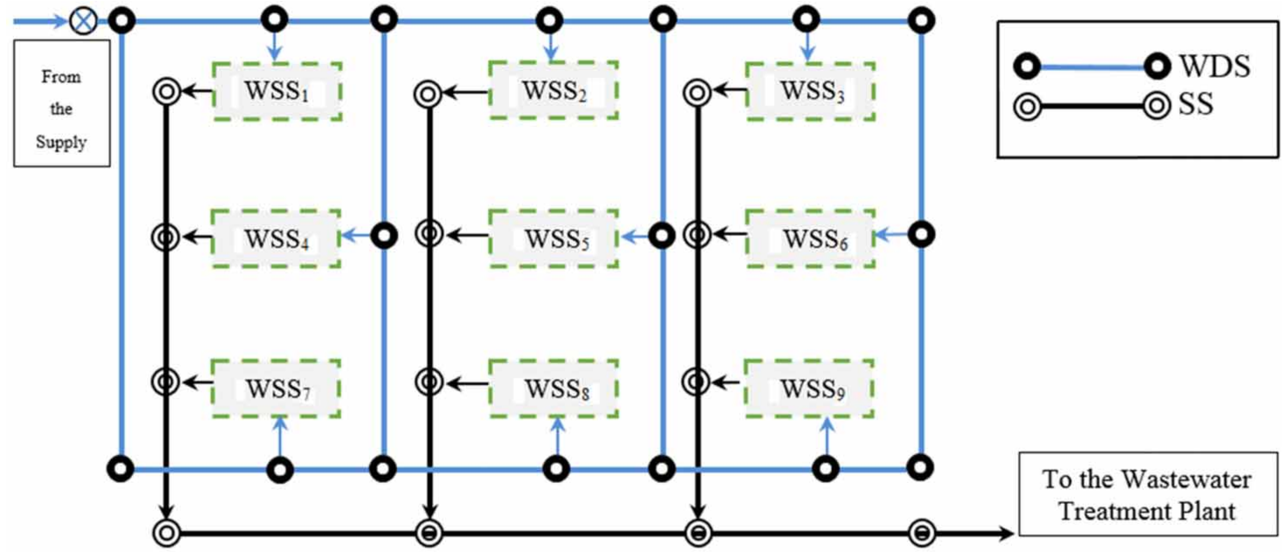

Figure 3 | Schematic illustration of the linkages between the existing water distribution system, sanitary sewer, and respective water-saving scheme locations.

WDS hydraulic model constraint:

$$h_{\mathrm{av},i} \geq h_{\mathrm{req},i} \quad (i = 1, \ldots, n_{\mathrm{n}}) \tag{20}$$

SS hydraulic model constraints:

$$\text{(i)} \;\; v_{\mathrm{av\_max},i} \geq v_{\mathrm{req},i} \quad (i = 1, \ldots, n_{\mathrm{c}}) \tag{21}$$

$$\text{(ii)} \;\; \frac{d_{\mathrm{av},i}}{D_{\max,i}} \leq FDR_{\max,i} \quad (i = 1, \ldots, n_{\mathrm{c}}) \tag{22}$$

Decision variable constraints:

$$D_j \in D \quad (j = 1, \ldots, n_{\mathrm{d}}) \tag{23}$$

where $h_{\mathrm{av},i}$ is the average of the actual head of the i-th WDS node; $v_{\mathrm{av\_max},i}$ is the average of $v_{\max,i}$ in the i-th sewer conduit; n_{c} is the number of sewer conduits; $d_{\mathrm{av},i}$ and $D_{\max,i}$ are the average flow depth and the maximum flow depth (i.e., pipe diameter) in the i-th conduit, respectively; $FDR_{\max,i}$ is the maximum allowed flow depth ratio in the i-th conduit; D_j is the value of the j-th discrete decision variable; D is a discrete set of available WSS capacities; and n_{d} is the number of decision options. The decision variables are selected from a set of available water-saving fitting and appliance capacities that are then applied appropriately to all WDS and SS nodes. In the evaluation process, the governing equations for water flows such as the energy and mass balance are satisfied by hydraulic solvers.

Solution method

In the proposed method, the well-known NSGA-II optimisation algorithm (Deb *et al.* 2002) linked to EPANET 2.0 (Rossman 2000) and the SWMM 5.0 (Rossman 2004) network hydraulic solvers is used to search for solutions to the formulated problem. Genetic algorithms have been widely used due to their abilities to identify near-optimal solutions in many complex combinational problems including WDSs, WSSs, and SSs (e.g., Penn *et al.* 2013a; Wu *et al.* 2013). NSGA-II applies optimisation processes such as initialisation of population, evaluation of objective functions, selection, crossover, and mutation in the search process until optimal solutions are obtained. A computer program that implements NSGA-II, runs hydraulic simulators (EPANET 2.0 and SWMM 5.0), and performs all necessary computations in the C programming language was developed. The computer program interprets the deterministic or flexible solution constituents and writes their implications in the WDS and SS input files before performing 24-hour simulations of the networks while storing the respective hydraulic parameters. The genetic algorithm parameters used in the specific case study considered here include a population of 100, which was allowed to evolve over 700 generations. The solutions for both strategies were obtained and confirmed by performing multiple independent model runs with different seeds.

CASE STUDY

Tsholofelo extension water distribution system and sanitary sewer

The method presented in this study has been demonstrated on the subsystem of Tsholofelo extension WDS and the corresponding SS in Gaborone, Botswana. The models for these networks were built using data collected from the Water Utilities Corporation of Botswana. The problem formulation presented in this study uses only a portion of the larger Tsholofelo extension water distribution and sanitary sewer systems.

Figure 4 shows WDS and SS subsystems that were used for demonstrating the proposed approach. These WDS and SS systems should serve about 320 dwellings/properties in a low-density development area. The WDS considered is made up of 24 demand nodes, 28 pipes and a representative supply. A representative reservoir that meets the hydraulic requirements in the most upstream node (water inlet) given the water demands in the existing system was used to simulate the inflows. At the node, specific WSS product capacities available on the market as shown in Table 1 were the options (decision variables) considered for selection. Standard capacities were also considered in the selection process. The existing SS consists of 113 inflow nodes (manholes) and 122 links (pipes) of 160 mm diameter. The basic assumption is that all household sewer pipes connect and discharge inflows into the immediate manholes.

Data and assumptions

The mean water demands were deduced from WUC (2014) and the respective existing network to evaluate and select WSSs in the holistic approach proposed in this study. The mean demands used in this case satisfied Equations (20)–(22). The degree of confidence considered for the network demand is 95%. An appropriate water demand pattern adopted from WUC (2014) was considered in the evaluations. Ninety percent (90%) of the overall water used was assumed to be equal to the wastewater

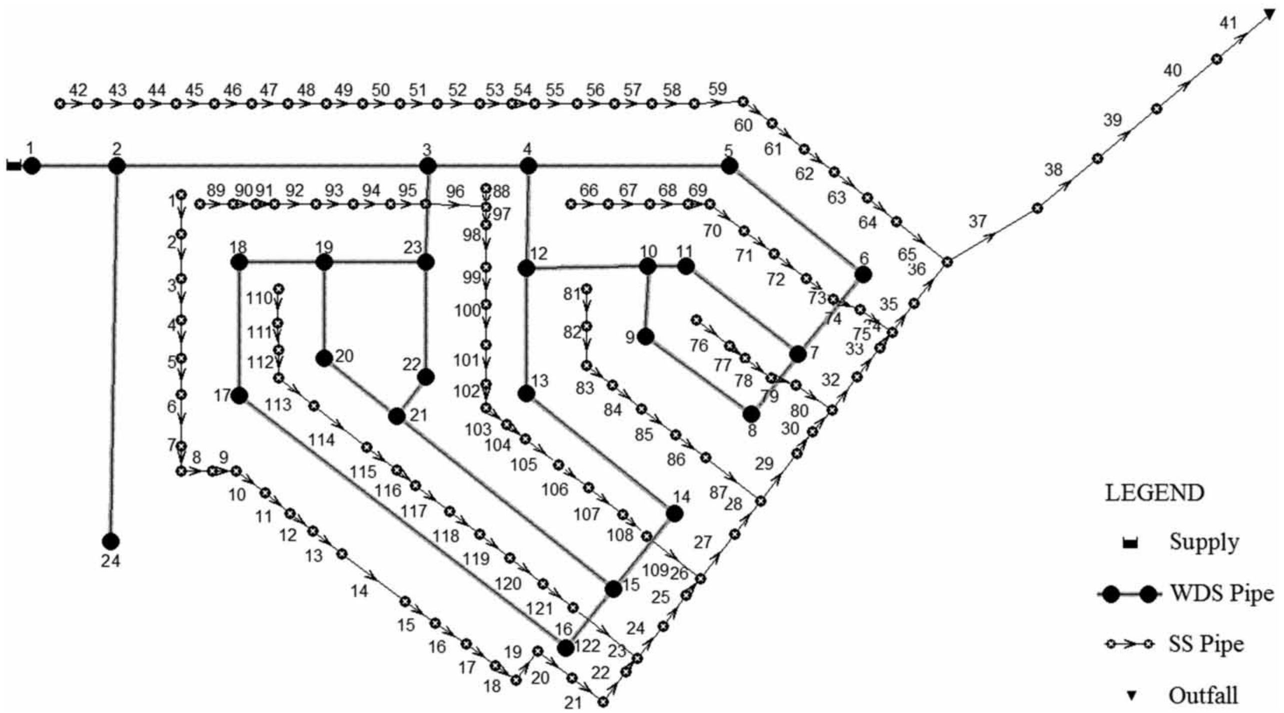

Figure 4 | Skeletonised subsystems of the Tsholofelo extension water distribution and sanitary sewer networks.

generated in the households. WDS technical aspects include meeting the minimum nodal pressure requirement of 15 metres with reference to the ground level. It is assumed that each household has two toilets and basin taps while water-use appliances and other fittings (SH, B, WM, DW and a KT) are single in each household. The technical requirements of the SS include meeting the self-cleansing velocity of 0.6 m/s at least once a day and the maximum flow depth ratios of 0.4 for pipe diameters of more than 375 mm and 0.5 otherwise (Department of Sanitation and Waste Management 2003). These aspects were used as constraints that the SS should not violate to be considered feasible. For solutions that were obtained under uncertain demands, average values were compared with the requirements to compute constraint violations, accordingly.

Key assumptions that are needed to quantify energy and expenses of water systems include an electric water heater efficiency of 0.75, specific heat capacity of 4,190 J/kg/°C, and a desired change in temperature of 40 °C. With hot water used through taps and showers, cold and hot water uses in the households are assumed to be equal. The water and wastewater treatment plant energy requirements per unit water of 0.371 kWh/m^3 and 0.505 kWh/m^3 (EPRI 2002) were used to estimate the cost of water and wastewater treatment and the associated cost savings due to water savings, respectively. The energy used by WMs and DWs was calculated using the energy calculator from the US Department of Energy (2015). The cost of energy and bills paid by consumers for water in unit prices of \$0.12/kWh and \$2.2/m^3, respectively, were also obtained from the energy calculator mentioned here. The cost data for energy were also obtained from the US Department of Energy (2015).

The capacity increment costs of both water and wastewater treatment plants needed to determine treatment cost savings were calculated according to Chenery (1952). An interest rate of 5% and water treatment facility design period of 50 years were used to determine cost components considered in this study. For sensible comparisons, the online inflation calculator (CoinNews Media Group LLC 2015) was used to convert all the costs in different years to a common year. The US federal standards (Alliance for Water Efficiency 2014) and the available water-saving products on the market were used to estimate the potential water-saving efficiencies of WSSs. The WSS capacities and the water-use proportions of household water-use components used in the evaluations are shown in Table 1.

RESULTS AND DISCUSSION

The flexible results obtained in this study were obtained using 300 Monte Carlo samples of demands while the deterministic solutions were obtained for the average demand before they were also subjected to uncertain demands. Note that prior to the first comparative analysis, both flexible and deterministic solutions were re-evaluated in the same manner using 5,000 water demand samples for sensible comparisons. Comparative attributes of the proposed deterministic and flexible solutions were revealed in this study. For better visualisation and comprehension, Figures 5–7 present three paired dimensions of tradeoffs resulting from the three objectives considered. Further details corresponding to solutions shown in Figures 5–7 and solution sensitivities to different demand scenarios (low, mean, high) are presented in Tables 2–5, respectively. Selected solutions 1–3 and solutions A–C are comparative in terms of WDS resilience or SS self-cleansing velocity deficit factor, i.e., comparative solutions selected are either resilience-equivalent (or similar) or they have equivalent (or similar) SS self-cleansing velocity deficit factor.

Figure 5 compares the implementation of WSSs considering the average WDS resilience index and the average SS self-cleansing velocity deficit factor. The results in Figure 5 reveal that the relationship between the WDS resilience index and the SS self-cleansing velocity deficit factor is mostly linear for both intervention strategies. A conflict of network hydraulic performances evidently exists between the WDS resilience index and the SS self-cleansing velocity deficit factor. This observation means that the more desirable levels of WDS resilience index adversely translate to undesirable levels of SS self-cleansing velocity deficit factor. The tradeoff resulting from the simultaneous improvement of the WDS and the SS hydraulic measures is visibly small, which is attributable to the narrow range of the resilience and self-cleansing velocity deficit factor determined by the WDS and SS networks considered. The WDS resilience indices are generally high with a narrow range (about 0.979 to 0.982) attributable to the magnitude of the mean water demand derived for the system, network characteristics, and the WSS fixture and appliance capacities used as intervention options.

Flexible WSS solutions generally outperform the deterministic solutions in terms of WDS resilience for equivalent SS self-cleansing velocity deficit factor because of their appropriate implementation according to different magnitudes of uncertain water demands. In this regard, the flexibility effect would be more with a wider variety of intervention options (combinations) at each demand node. The performances of tradeoff solutions with high average self-cleansing velocity deficit factor and high

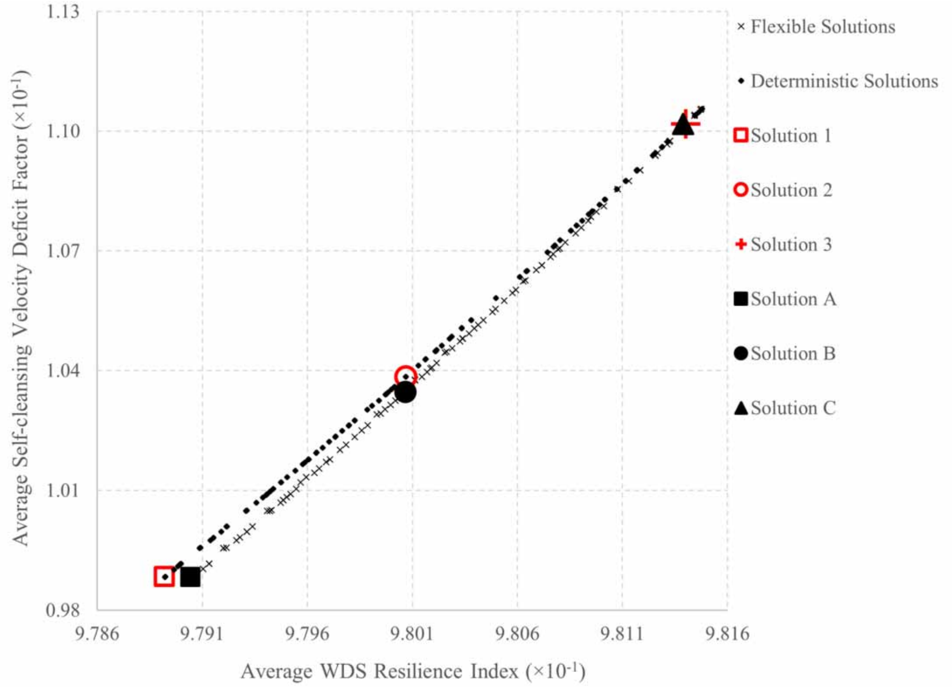

Figure 5 | Comparative WDS–WSS–SS performances in terms of the average WDS resilience index and the average SS self-cleansing velocity deficit factor.

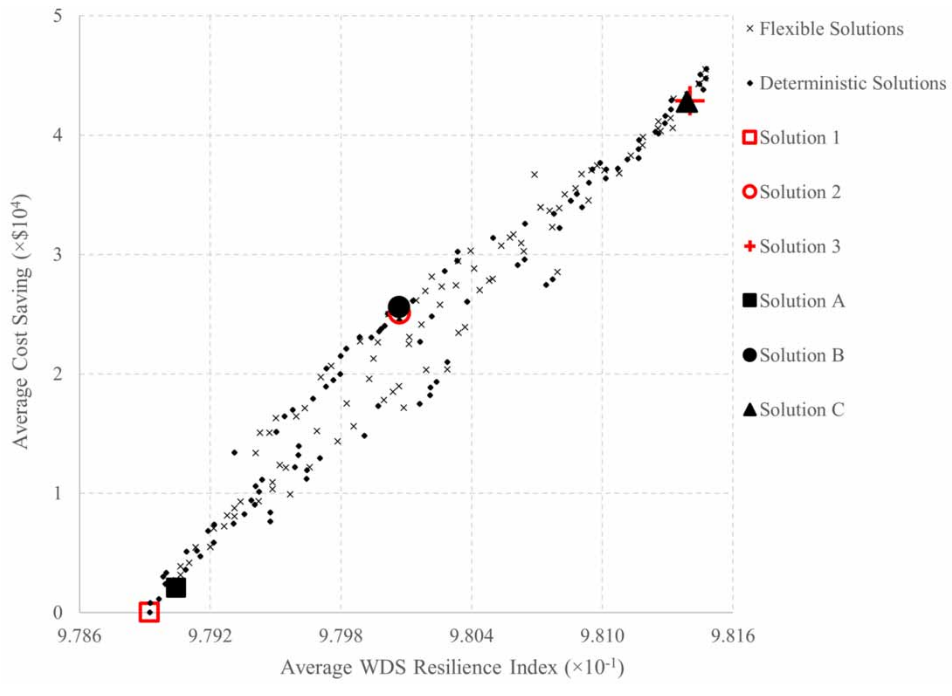

Figure 6 | Comparative WDS–WSS–SS performances in terms of the average WDS resilience index and the average cost-saving.

average WDS resilience are similar, for example, solutions 3 and C hydraulic performances are similar. This observation suggests that there would be a smaller effect of flexible responses to uncertain water demand with the increase in water-use efficiency while the self-cleansing velocity deficit factor would be worsening.

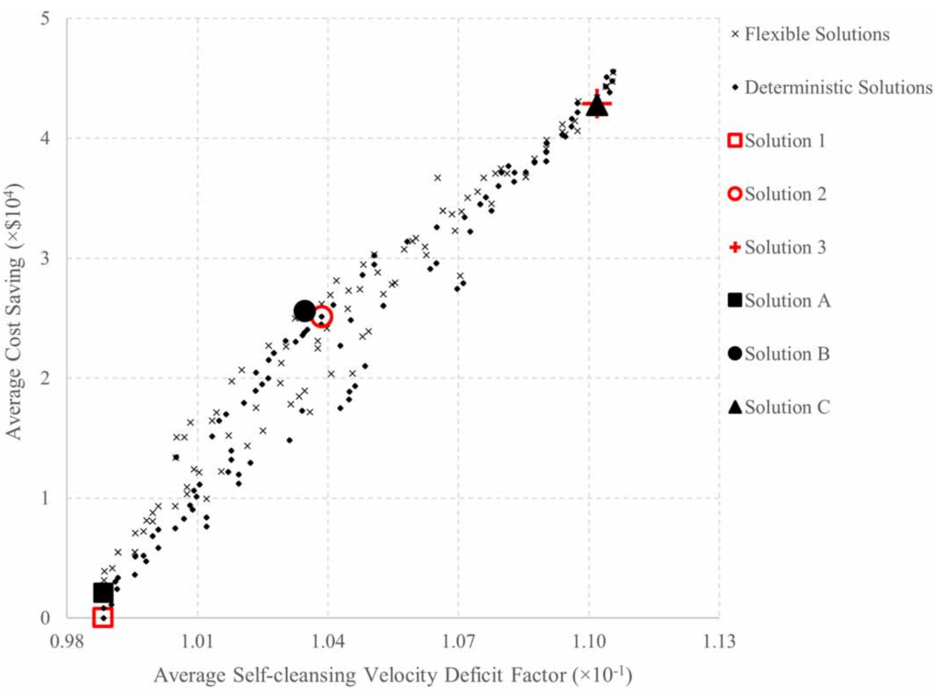

Figure 7 | Comparative WDS–WSS–SS performances in terms of the average SS self-cleansing velocity deficit factor and the average cost-saving.

Table 2 | Details of WDS–WSS–SS performances for selected WSS solutions

		Water-saving scheme capacities[a]		Average objective values	
Solution approach	**Solution**	**WC, SH, B, WM, DW, KT, BT**	**Cost saving ($\times$\$$10^4$)**	**WDS RI ($\times10^{-1}$)**	**SS velocity deficit factor ($\times10^{-1}$)**
Deterministic	1	6.06; 0.16; 193; 628; 18.9; 0.14; 0.14	0.000	9.789	0.988
	2	6.06; 0.05; 193; 495; 15.7; 0.14; 0.14	2.512	9.801	1.039
	3	4.16; 0.05; 193; 374; 18.9; 0.08; 0.14	4.287	9.814	1.102
Flexible	A	4.16; 0.05; 193; 374; 13.2; 0.14; 0.06			
		6.06; 0.16; 193; 628; 18.9; 0.14; 0.14	2.073	9.790	0.988
		4.16; 0.05; 149; 428; 13.2; 0.14; 0.08			
	B	4.16; 0.05; 149; 374; 13.2; 0.08; 0.06			
		6.06; 0.09; 149; 428; 13.2; 0.14; 0.09	2.560	9.801	1.035
		4.16; 0.05; 149; 374; 13.2; 0.08; 0.06			
	C	4.85; 0.05; 149; 374; 13.2; 0.08; 0.06			
		4.16; 0.05; 193; 374; 18.9; 0.08; 0.14	4.278	9.814	1.102
		4.16; 0.09; 149; 374; 13.2; 0.08; 0.08			

[a]Units are as indicated in Table 1.

Figure 6 indicates that even though solutions may have the same effect in terms of SS self-cleansing velocity deficit factor or WDS resilience index, cost savings may differ as indicated by the scattered patterns in Figures 6 and 7. For example, solutions 1 and A demonstrate this observation. This observation is attributable to water efficiency contributed by a wide range of WSSs with different water and energy costs that determine cost savings. The graph in Figure 6 also indicates clearly that the increase of cost savings would also lead to higher WDS RI values, which are both desirable effects. A similar effect is observable in Figure 7 where cost savings are plotted against the SS self-cleansing velocity deficit factor. In this graph, resilient equivalent solutions may have different average cost savings and self-cleansing velocity deficit factors. This observation reveals that cost savings were achieved at the expense of the SS hydraulic performance. Overall, considering integrated water management, flexibility in the implementation of household water-savings, and conflicts between WDS and SS hydraulic performances

Table 3 | Sensitivity of the selected solutions when subjected to the low water demand scenario

	Total performance			Change from the average value (%)		
Solution	Cost saving ($\times\$10^4$)	WDS RI ($\times10^{-1}$)	SS velocity deficit factor ($\times10^{-1}$)	Cost saving	WDS RI	SS velocity deficit factor
1	0.000	9.864	1.382	0.00	0.761	39.84
2	2.167	9.871	1.438	−13.75	0.720	38.50
3	3.637	9.880	1.509	−15.17	0.671	36.92
A	3.669	9.879	1.504	77.03	0.906	52.15
B	3.881	9.880	1.513	51.60	0.813	46.21
C	3.615	9.878	1.497	−15.49	0.657	35.83

Table 4 | Sensitivity of the selected solutions when subjected to the mean (average) water demand scenario

	Total performance			Change from the average value (%)		
Solution	Cost saving ($\times\$10^4$)	WDS RI ($\times10^{-1}$)	SS celocity deficit factor ($\times10^{-1}$)	Cost saving	WDS RI	SS velocity deficit factor
1	0.000	9.792	0.981	0.000	0.032	−0.713
2	2.506	9.804	1.032	−0.246	0.031	−0.652
3	4.276	9.817	1.095	−0.275	0.029	−0.581
A	0.000	9.792	0.981	−100	0.020	−0.713
B	2.448	9.803	1.028	−4.382	0.022	−0.656
C	4.276	9.817	1.095	−0.052	0.030	−0.581

Table 5 | Sensitivity of the selected solutions when subjected to the high water demand scenario

	Total performance			Change from the average value (%)		
Solution	Cost saving ($\times\$10^4$)	WDS RI ($\times10^{-1}$)	SS velocity deficit factor ($\times10^{-1}$)	Cost saving	WDS RI	SS velocity deficit factor
1	0.000	9.705	0.692	0.00	−0.856	−30.00
2	2.848	9.722	0.735	13.35	−0.807	−29.22
3	4.920	9.740	0.790	14.75	−0.752	−28.28
A	4.509	9.737	0.780	117.5	−0.549	−21.12
B	5.210	9.741	0.793	103.5	−0.607	−23.31
C	4.587	9.737	0.779	7.22	−0.787	−29.26

amidst water demand uncertainty, would holistically improve the sustainability of water systems. Even though the deterministic strategy also trades-off cost savings, WDS RI, and SS self-cleansing velocity deficit factor, its WSS solutions would potentially underperform in terms of SS self-cleansing velocity deficit factor for equivalent WDS resilience compared with flexible WSSs. The alternative comparison would also provide similar results, i.e., comparing solutions in terms of WDS resilience for equivalent SS self-cleansing velocity deficit factor.

Table 2 displays details of the selected WSS solutions (capacities) and the corresponding objective values. In confirmation, WDS average RI and SS average self-cleansing velocity deficit factor evidently increase with the rise of cost saving in both intervention strategies. Solution A, which has the same average SS self-cleansing velocity deficit factor as solution 1 (i.e., 0.988×10^{-1}), illustrates combinations of interventions selected in the middle path that are identical to those of solution 1. This observation agrees with the fact that solution 1 was obtained using the mean demand, which falls in the same category whose demands were used to evaluate combinations of WSSs that are in the middle of solution A during the optimisation process. With the same average SS self-cleansing velocity deficit factor in solutions 1 and A or equivalent resilience in solutions 2 and B but obtaining more average cost savings from solutions A and B, respectively, this suggests that the effective implementation of WSSs according to demand levels may add value. On the other hand, solutions C and 3 that have equivalent WDS resilience (i.e., 9.814×10^{-1}) and SS self-cleansing velocity deficit factor (i.e., 1.102×10^{-1}) would achieve similar cost savings. However, solutions such as A and C have alternative paths with different combinations of WSSs, which would be appropriately implemented in cases of demands that are above or below the specified limits. For instance, the BT capacities of 0.06 and 0.08 litres/second would be implemented at the top and bottom of solution A while the alternative middle WSS combination contains a BT of 0.14 litres/second, respectively. As for resilience-equivalent solutions (e.g., solutions 2 and B), the trend may not be the same as that of solutions 1 and A and similar average values are caused by the necessary adjustments of interventions in the solution envelope. In addition to the flexibility provided by the interventions that correspond to appropriate demand categories (or levels), the size of possible WSS combinations would enhance the value of flexibility.

Further analyses of comparable solutions were performed by subjecting selected solutions to different water demand scenarios to determine the sensitivity of solutions in terms of the performance indicators considered. Selected solutions were analysed using three levels of demands corresponding to the mean demand and the limits of the 96% confidence interval, which are used as low and high demands. The extreme levels should be outside the 95% confidence interval whose limits are used to decide which solution path to evaluate in the flexible strategy, thereby ensuring that all the alternative paths are considered in the sensitivity analysis. The performances of solutions were compared with those resulting from many samples as shown in Table 2. The results in Table 3 show that with low water demands, the solution's WDS RI and the SS self-cleansing velocity deficit factor would increase while the negative signs for some cost savings indicate reduction. The mean water demand scenario causes smaller increments in WDS RI as shown in Table 4. In addition, cost saving and the SS self-cleansing velocity deficit factor would decrease slightly, except for the non-existent cost savings in solutions 1 and A. These observations are expected considering that the uncertain water demands were sampled around the mean value assuming a normal distribution. In constrast to low and mean demands, the high water demand would completely present the opportunity to increase cost savings for deterministic and flexible approaches with the latter providing more potential as provided in Table 5. However, the WDS RI would in turn reduce slightly while the SS self-cleansing velocity deficit factor would desirably reduce.

Among the three performance indicators considered, the selected deterministic water systems proved to be most sensitive to water demand uncertainty in terms of the SS self-cleansing velocity deficit factor across all the demand scenarios and least sensitive in terms of the WDS RI. Flexible solutions seem to be most sensitive in terms of cost savings, particularly when subjected to extreme demands (low and high). With low water demand for both intervention strategies, cost saving would reduce by about 13.2%–15.2%, in the selected deterministic solutions but up to 77% increase in the selected flexible solutions would be achievable. WDS RI and the SS self-cleansing velocity deficit factor would increase by approximately 0.66%–0.91% and 35.8%–52.2% across solutions, respectively. As for the mean demand scenario, cost savings and the SS self-cleansing velocity deficit factor would, across the selected solutions, reduce by approximately 0.05%–100% (i.e., with 100% caused by zero savings in solution A) and 0.58%–0.71% while the WDS RI would slightly increase by about 0.02%–0.03% across solutions, respectively. On the other hand, with high water demand, cost savings increase by up to 14.8% and 117.5% for deterministic and flexible strategies, respectively. In this case, WDS RI and the SS self-cleansing velocity deficit factor would reduce by approximately 0.55%–0.86% and 21%–30% across solutions, respectively. Therefore, in the context of water networks, flexible WSSs would readily provide appropriate solutions for corresponding levels of demand as water demands unveil while deterministic WSS solutions would be fixed and likely to miss opportunities presented by the unveiling demands. The insights provided by the methodology presented in this study would holistically inform water system managers to implement the most beneficial WSS interventions at suitable times that are determined by levels of water demands.

CONCLUSIONS

This study developed a method for household WSS application in the context of water demand uncertainty considering the conflicting objectives of existing WDSs and SSs. A WSS, WDS, and SS problem was formulated and solved with three conflicting objectives: maximising the WDS resilience index and the cost savings while minimising the SS self-cleansing velocity deficit factor using a genetic algorithm. This holistic method, which applies deterministic and flexible solution strategies, was demonstrated on WDS and SS subsystems of Tsholofelo extension in Gaborone, Botswana.

With data and assumptions made in the application of this method, the results indicated that considering interacting water systems and uncertainty in WSS planning and management is important. In this regard, deterministic strategies in the Tsholofelo water network subsystems would underperform in terms of resilience for equivalent SS self-cleansing velocity deficit factor compared with the flexible approaches despite similarly trading-off cost savings, WDS RI, and SS self-cleansing velocity deficit factor. Furthermore, flexible WSSs would readily provide appropriate solutions (i.e., appropriate efficiency and cost savings) for corresponding levels of demands as they unveil while deterministic WSS solutions would be fixed and likely to miss opportunities presented by unveiling demands.

From another perspective, both deterministic and flexible WDS–WSS–SS integrated strategies are sensitive to changes in water demands. Deterministic systems were found to be sensitive to different levels of demands in terms of the SS self-cleansing velocity deficit factor, cost savings, and the WDS RI, in this descending chronological order while flexible ones are potentially more sensitive in terms of cost savings. With lower water demand in the system (i.e., at the lower limit of the 96% confidence limit), analyses indicated that cost saving would reduce by about 13.8%–15.2% in the selected deterministic solutions while up to 77% increase in the selected flexible solutions would also be achievable. In addition, WDS RI and the SS self-cleansing velocity deficit factor would increase by approximately 0.66%–0.91% and 35.8%–52.2% across the selected solutions, respectively. As for the mean demand scenario, cost savings and the SS self-cleansing velocity deficit factor would reduce by approximately 0.05%–100% (i.e., 100% occurring where there are no cost savings in the sensitivity analysis) and 0.58%–0.71% while the WDS RI would slightly increase by about 0.02%–0.03% across the selected solutions, respectively. In contrast, with high water demand, cost savings increase by up to 14.8% and 117.5% for deterministic and flexible strategies, respectively. In this case, WDS RI and the SS self-cleansing velocity deficit factor would reduce by approximately 0.55%–0.86% and 21%–30% across solutions, respectively.

The method developed in this study should be tested with different data, conditions, assumptions, intervention options, and objectives to extend the scope of its application and enhance the value of flexibility in other water networks that present different complexities. To counteract the computational limitation posed by the SS hydraulics, the method can be extended by applying a combination of more sophisticated solution and sampling techniques, which would enable the implementation of uncertainty in the joint designs and/or selection of all the water systems considered in this study.

ACKNOWLEDGEMENTS

The author is grateful to the Water Utilities Corporation of Botswana for availing Tsholofelo water distribution and sanitary sewer system data that supported this study. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CONFLICT OF INTEREST

There is no conflict of interest associated with this study.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

REFERENCES

Alliance for Water Efficiency 2014 *National Efficiency Standards and Specifications for Residential and Commercial Water-Using Fixtures and Appliances*. Alliance for Water Efficiency/Koeller & Co.

Alliance for Water Efficiency 2016 Indoor Water Use. Available from: https://www.home-water-works.org/indoor-use (accessed 3 May 2021).

Austin, R. J., Chen, A. S., Savić, D. A. & Djordjević, S. 2014 Quick and accurate Cellular Automata sewer simulator. *Journal of Hydroinformatics* **16** (6), 1359–1374.

Bailey, O., Arnot, T. C., Blokker, E. J. M., Kapelan, Z., Vreeburg, J. & Hofman, J. A. M. H. 2019 Developing a stochastic sewer model to support sewer design under water conservation measures. *Journal of Hydrology* **573**, 908–917.

Baños, R., Reca, J., Martínez, J., Gil, C. & Márquez, A. L. 2011 Resilience indexes for water distribution network design: a performance analysis under demand uncertainty. *Water Resources Management* **25**, 2351–2366.

Basupi, I. 2019 Integrating water-saving schemes in the design of sanitary sewers. *Water and Environment Journal* **34** (4), 536–549.

Basupi, I. & Kapelan, Z. 2015 Flexible water distribution system design under future demand uncertainty. *Journal of Water Resources Planning and Management* **141** (4), 04014067.

Basupi, I. & Nono, D. 2019 Flexible booster chlorination: design and operation for water distribution systems under uncertainty. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* **5** (4), 04019012.

Basupi, I., Kapelan, Z. & Butler, D. 2014 Reducing life-cycle carbon footprint in the (re)design of water distribution systems using water demand management interventions. *Urban Water Journal* **11** (2), 91–107.

Chenery, H. B. 1952 Overcapacity and acceleration. *Econometrica* **20** (1), 1–28.

CoinNews Media Group LLC 2015 Inflation Calculator: Money's Real Worth over Time. Available from: http://www.coinnews.net/tools/cpi-inflation-calculator.

Deb, K., Pratap, A., Agarwal, S. & Meyarivan, T. 2002 A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* **6** (2), 182–197.

De Neufville, R. 2004 Uncertainty management for engineering systems planning and design. In: *Engineering Systems Symposium*, MIT, Cambridge, MA, USA.

Department of Sanitation and Waste Management 2003 *Botswana National Wastewater and Sanitation Planning and Design Manual: Part 2a – Gravity Sewer Systems*. Ministry of Environment, Wildlife and Tourism, Gaborone, Botswana.

Duque, N., Duque, D. & Saldarriaga, J. 2016 A new methodology for the optimal design of series of pipes in sewer systems. *Journal of Hydroinformatics* **18** (5), 757–772.

Electric Power Research Institute, EPRI 2002 *Water and Sustainability: U.S. Electricity Consumption for Water Supply & Treatment – The Next Half Century*, Topical Report (1006787). EPRI, Palo Alto, CA, USA.

EPA 2008 *Indoor Water Use in the United States*. WaterSense, EPA. Available from: https://www.epa.gov/watersense.

Giustolisi, O., Laucelli, D. & Colombo, A. F. 2009 Deterministic versus stochastic design of water distribution networks. *Journal of Water Resources Planning and Management* **135** (2), 117–127.

Hosseini, S. M. & Ghasemi, A. 2012 Hydraulic performance analysis of sewer systems with uncertain parameters. *Journal of Hydroinformatics* **14** (3), 682–696.

Jayaram, N. & Srinivasan, K. 2008 Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing. *Water Resources Research* **44**, W01417.

Jung, D., Lee, S. & Kim, J. H. 2019 Robustness and water distribution system: state-of-the- art review. *Water* **11**, 974.

Kang, D. & Lansey, K. 2012 Scenario-based robust optimization of regional water and wastewater infrastructure. *Journal of Water Resources Planning and Management* **139** (3), 325–338.

Marques, J., Cunha, M. & Savić, D. A. 2015 Multi-objective optimization of water distribution systems based on a real options approach. *Environmental Modelling & Software* **63**, 1–13.

McGhee, T. J. 1991 *Water Supply and Sewerage*, 6th edn. McGraw-Hill, New York, USA.

McKenna, A., Silverstein, J., Sharvelle, S. & Hodgson, B. 2018 Modeled response of wastewater nutrient treatment to indoor water conservation. *Environmental Engineering Science* **35** (5), 437–446.

Minsker, B., Baldwin, L., Crittenden, J., Kabbes, K., Karamouz, M., Lansey, K., Malinowski, P., Nzewi, E., Pandit, A., Parker, J., Rivera, S., Surbeck, C., Wallace, W. A. & Williams, J. 2015 Progress and recommendations for advancing performance-based sustainable and resilient infrastructure design. *Journal of Water Resources Planning and Management* **141** (12), A4015006.

Nono, D. & Basupi, I. 2019 Robust booster chlorination in water distribution systems: design and operational perspectives under uncertainty. *Journal of Water Supply: Research and Technology – AQUA* **68** (6), 399–410.

Ostojin, S., Mounce, S. R. & Boxall, J. B. 2011 An artificial intelligence approach for optimizing pumping in sewer systems. *Journal of Hydroinformatics* **13** (3), 295–306.

Penn, R., Friedler, E. & Ostfeld, A. 2013a Multi-objective evolutionary optimization for greywater reuse in municipal sewer systems. *Water Research* **47**, 5911–5920.

Penn, R., Schütze, M. & Friedler, E. 2013b Modelling the effects of on-site greywater reuse and low flush toilets on municipal sewer systems. *Journal of Environmental Management* **114**, 72–83.

Perelman, L., Housh, M. & Ostfeld, A. 2013 Least-cost design of water distribution systems under demand uncertainty: the robust counterpart approach. *Journal of Hydroinformatics* **15** (3), 737–750.

POST 2000 *Water Efficiency in the Home*, Post Note 135 (March). Parliamentary Office of Science and Technology, 7 Millbank, London, UK.

Prasad, T. D. & Park, N.-S. 2004 Multiobjective genetic algorithms for design of water distribution networks. *Journal of Water Resources Planning and Management* **130** (1), 73–82.

Puccini, G. D., Blaser, L. E., Bonetti, C. A. & Butarelli, A. 2016 Robustness-based design of water distribution networks. *Water Utility Journal* **13**, 13–28.

Rossman, L. A. 2000 *EPANET 2 Users Manual*. US Environmental Protection Agency , Washington, DC, USA.

Rossman, L. A. 2004 *Stormwater Management Model User's Manual. SWMM5.0*. US Environment Protection Agency, Washington, DC, USA.

Sun, S., Khu, S.-T., Kapelan, Z. & Djordjević, S. 2011 A fast approach for multiobjective design of water distribution networks under demand uncertainty. *Journal of Hydroinformatics* **13** (2), 143–153.

Todini, E. 2000 Looped water distribution networks design using a resilience index based heuristic approach. *Urban Water* **2**, 115–122.

Tsakiris, G. & Spiliotis, M. 2017 Uncertainty in the analysis of urban water supply and distribution systems. *Journal of Hydroinformatics* **19** (6), 823–837.

US Department of Energy, Office of Energy Efficiency & Renewable Energy 2015 Energy- and Cost-Savings Calculators for Energy-Efficient Products. Available from: http://www.energy.gov/eere/femp/energy-and-cost-savings-calculators-energy-efficient-products (accessed 22 November 2015).

Wu, W., Maier, H. R. & Simpson, A. R. 2013 Multiobjective optimization of water distribution systems accounting for economic cost, hydraulic reliability and greenhouse gas emissions. *Water Resources Research* **49** (3), 1211–1225.

WUC 2014 *Gaborone Water Supply MasterPlan Update 2010; Pre-Investment Study, Final Report*. Water Utilities Corporation, Francistown, Botswana.

Zhuang, J. & Sela, L. 2020 Impact of emerging water savings scenarios on performance of urban water networks. *Journal of Water Resources Planning and Management* **146** (1), 04019063.

First received 4 August 2021; accepted in revised form 17 November 2021. Available online 6 December 2021