Robust booster chlorination in water distribution systems: design and operational perspectives under uncertainty
Denis Nono and Innocent Basupi

ABSTRACT

Booster chlorination designs have been widely based on predefined (deterministic) network conditions and they perform poorly under uncertainty in water distribution systems (WDSs). This paper presents a scenario-based robust optimisation approach which was developed to obtain booster chlorination designs that withstand uncertain network operations and water demand conditions in the WDSs. An optimisation problem was formulated to minimise mass injection rates and the risk of chlorine disinfection. This problem was solved by a non-dominated sorting genetic algorithm (NSGA-II). The proposed approach was demonstrated using the Phakalane network in Botswana. The results present robust booster chlorination (RBC) designs, which indicate the number of boosters, locations and injection rates in the network. The performance of RBC designs evaluated under uncertainty reveals lower risks of chlorine disinfection compared to deterministic-based designs. The proposed approach obtains booster chlorination designs that respond better to uncertainty in the operations of WDSs.

Key words | optimisation, robust booster chlorination, scenario analysis, uncertainty, water distribution systems

LIST OF ABBREVIATIONS

BDR | booster dosing rate
BL | booster location
DBC | deterministic booster chlorination
MIR | mass injection rate
NCOI(s) | network configuration and operational intervention(s)
NSGA-II | non-dominated sorting genetic algorithm II
PRVs | pressure reducing valves
RBC | robust booster chlorination
RCD | risk of chlorine disinfection
TP-DR | treatment plant dosing rate
WD(s) | water demand(s)
WD-E | water demand-estimated
WD-H | water demand-higher
WD-L | water demand-lower
WDS(s) | water distribution system(s)

INTRODUCTION

Water distribution system (WDS) parameters (e.g. water demand (WD) and pipe roughness coefficients), water quality parameters (e.g. chlorine decay rate) and operational interventions are highly uncertain with time. The changes in demography, climate, socioeconomic developments, system age, mechanical failures, operations, repairs and maintenance requirements are key drivers for uncertainty in WDSs. These uncertainties may hinder effective performances of WDSs over time and therefore understanding how they affect the design and operation of WDSs is very essential. Booster chlorination is one of the practical techniques that are used to mitigate the risk conditions such as insufficient or excessive chlorine residuals at remote parts of the network or near water treatment plants, respectively. These are the challenges that are associated with the conventional disinfection approaches. Over the past two
decades, booster chlorination problems have been expressed widely by a range of deterministic mathematical formulations to optimise booster chlorination designs in WDSs. However, deterministic approaches are known for providing solutions that are suboptimal or infeasible because they ignore uncertainties in WDSs (Watkins & McKinney 1997).

Earlier efforts that addressed uncertainties in WDS designs performed model and parameter sensitivity analysis (Hutton et al. 2012). However, sensitivity analysis only quantifies the consequences of uncertainty, but does not reduce or control them (Watkins & McKinney 1997). Robust optimisation based on scenario analysis is considered as one of the suitable approaches that deal with uncertainty in many fields of studies including the design of water supply infrastructures (Kang & Lansey 2012a). Some previous studies have applied robust optimisation in WDS designs (Kapelan et al. 2005; Babayan et al. 2007; Giustolisi et al. 2009; da Conceição Cunha & de Oliveira Sousa 2010). For instance, Kapelan et al. (2005) developed a multi-objective optimisation problem to minimise total costs of designs and to maximise robustness of WDS designs considering future water consumption and pipe roughness coefficients as sources of uncertainty. Similarly, Giustolisi et al. (2009) developed a robust optimisation method to design WDSs under uncertain water demands (WDs) and pipe roughness as a multi-objective problem formulated to minimise costs and maximise hydraulic reliability. The optimisation problems involved were solved using a non-dominated sorting genetic algorithm II (NSGA-II). A related study by Carr et al. (2006) presented a robust optimisation model for contaminant sensor placement under uncertain attack weights and population in WDSs. Various sources of uncertainty have been considered by the aforementioned robust WDS optimisation studies, but they do not include operational interventions and WDSs, simultaneously. In addition, water quality-driven solutions that address problems associated with uncertainties inherent in operations and WDs have not been explored explicitly and to a greater extent.

Further researchers such as Kang & Lansey (2012a, 2012b) proposed scenario-based uncertainty analysis and robust optimisation approaches for multistage planning of water and wastewater infrastructure under uncertain WD over a long-term planning horizon. These authors formulated the optimisation problems to minimise the economic (capital, operational, management and regret) costs. In another effort, Jung et al. (2014) addressed the shortcomings associated with the chance-constrained and reliability-based models by introducing a robustness index. Moreover, Puccini et al. (2016) found that robust-based designs display better performances in cases of pipe bursts than those based on the resilience index. Using linear programming, Goryashko & Nemirovski (2014) proposed a robust optimisation method for optimising daily operations of pumping stations under uncertain WDs with a single objective formulated to minimise the total pumping energy costs. More recently, Choi et al. (2018) proposed a framework in order to improve robustness of WDSs using an optimal valve installation approach. Many water supply researchers (e.g., Kapelan et al. 2005; Zhou & Hu 2009; Basupi & Kapelan 2014) have considered WD as the main source of uncertainty in their respective studies. In this regard, Basupi & Kapelan (2014) and Kapelan et al. (2005) mainly focused on designs of WDS components rather than the operation and management of existing systems. Despite the fact that previous studies have taken into account several uncertainties and robustness indices, other critical uncertainties inherent in WDS configuration, operational interventions, WD and water quality issues (chlorination) are yet to be explored simultaneously.

WDs are known to vary with time and locations in WDSs. Network operational aspects, such as pumping schedules, storage (capacity and refilling cycles), pressure and flow regulations (valve settings) may require changes over time to meet the prevailing customers’ demands. Variations in WD, network configuration and network operation affect water age and chlorine residuals; hence, robust booster chlorination (RBC) designs in WDSs are necessary. Long delays and changing demands in WDSs render disinfection goals difficult to achieve without modelling. The fundamental component of a system disinfectant model is the bulk water decay model (Fisher et al. 2016). In this regard, Fisher et al. (2012) assert that a suitable general model of chlorine decay in the transported bulk water is an essential component for efficiently modelling chlorine concentration in distribution systems. In addition, accurate modelling of chlorine concentrations throughout a drinking water system needs sound mathematical descriptions of decay mechanisms in bulk water and at pipe walls (Fisher et al. 2017).

The aim of this study is to develop a RBC design approach and compare its results with the commonly used
deterministic booster chlorination (DBC) design method in terms of the mass injection rate (MIR) and the risk of chlorine disinfection (RCD). This RBC design incorporates uncertainties inherent in WD, network configurations and operational interventions in order to minimise the MIR and the RCD in WDSs. The outcomes are novel RBC solutions with MIR–RCD trade-offs that enable WDSs to withstand eventualities posed by the aforementioned examples of uncertainties. The remaining sections of this paper present a brief background, followed by the methodology and the application of the proposed RBC approach in the Phakalane water distribution network found in Gaborone city, Botswana.

**METHODOLOGY**

**Uncertainty scenarios and RBC solutions**

Scenario planning is one of the powerful ways used by researchers to incorporate uncertainties in water distribution network designs (da Conceição Cunha & de Oliveira Sousa 2010). The sources of uncertainty considered in this study are network configuration and operational interventions (NCOIs), together with WDs. It is worth noting that the procedure proposed here is not restricted to the aforementioned sources of uncertainty. The method can similarly account for other sources of uncertainty such as that of the chlorine decay rate, which can be very sensitive to temperature as indicated by researchers such as Fisher et al. (2012). NCOIs are here referred to as combinations of network configurations (i.e., possible ways water can be transmitted to the storage reservoirs in the network from the treatment plant) and operational interventions (i.e., possible ways water can be delivered at different times to the network from the storage reservoirs). It is assumed that WDs vary at the same relative rate (percentage, %) in all the nodes within the entire network. If the number of NCOIs is $n_c$, the uncertain scenarios of NCOIs and WDs can be represented as shown in Figure 1(a). Notation WD-E represents the estimated or projected WD at the nodes of the network model. WD-H and WD-L represent the possible and different values of WDs above or below the WD-E in the network, respectively. In other words, WD-H and WD-L each generally represent numerous states of WDs. In this study, fewer corresponding values of WD-H and WD-L can be derived by arbitrarily increasing or decreasing the nodal WD in the network model with some percentages. Therefore, the total number of scenarios that can be obtained is equal to the number of branches of the scenario tree in Figure 1(a).

The decision variables and bounds considered in the RBC optimisation are the number of boosters, locations and injection rates at the treatment plants and chlorine booster stations. If $n_b$ is the number of potential booster stations, the booster locations ($I$) and their respective injection rates ($u$) in the network are presented as arrays of values ($I_1$, $I_2$, …,$I_n$) and ($u_1$, $u_2$, …,$u_n$), respectively. If the number of network scenarios is equal to $n_s$, the RBC solutions can be illustrated as shown in Figure 1(b). The objective-1 to objective-$n_s$ represent the MIR and the RCD for the respective scenarios. The overall objectives for the RBC solutions are the minimised expected MIR and RCD failures. The MIR is directly associated with the cost of chlorine disinfection in WDSs, while other costs of a booster station are not considered as variables.

The RBC design approach presented in this paper is compared with the widely used DBC design approaches (Prasad et al. 2004; Behzadian et al. 2012), which assume that there are no uncertainties in both NCOIs and the WD of the network. The solutions for DBC are obtained for the current/existing NCOI under the estimated (mean) WD as shown in Figure 1(c). The overall objective values for the DBC solutions are the minimised MIR and RCD.

**Problem formulation**

A multi-objective problem for the proposed RBC was formulated to minimise the expected MIR and the expected RCD for uncertain scenarios as expressed by the following equations:

\[
\text{Expected MIR} = \sum_{s=1}^{n_s} P_s \cdot \text{MIR}_s 
\]

\[
\text{Expected RCD} = \sum_{s=1}^{n_s} P_s \cdot \text{RCD}_s 
\]

\[
\text{MIR} = \sum_{j=1}^{n_m} \sum_{k=1}^{n_b} u_k^j \cdot Q_k^j 
\]

\[
\text{RCD} = \sum_{j=1}^{n_m} P_j e_j 
\]
where $n_s$ is the number of scenarios; $n_b$ the number of chlorine booster stations; $P_s$ the probability of occurrence of a scenario $s$; MIR$_s$ the mass injection rate that corresponds to scenario $s$; RCD$_s$ the risk of chlorine disinfection that corresponds to scenario $s$; $u^i_k$ the injection rate (mg/L) leaving the chlorine booster location $i$ at an injection period $k$; $Q^i_k$ the total outflow rate (L/s) from the booster location $i$ at the injection period $k$; $n_m$ the number of monitoring nodes (all the nodes are considered as the monitoring nodes); $P_j$ the probability that a monitoring node $j$ has unacceptable chlorine residual (i.e., $<0.3$ mg/L or $>0.6$ mg/L) expressed in terms of the monitoring time steps as shown in Equations (5) and (6); $\epsilon_j$ the consequences associated with having unacceptable chlorine residual in the monitoring node $j$. The consequences are expressed in terms of the WD at the nodes with chlorine residuals within the unacceptable range as shown in Equation (7). Note that consequences can be expressed in other quantities.

$$
P_j = \frac{\sum_{m=1}^{t+n_b-1} \gamma^m_j}{T}$$  \hspace{1cm} (5)

$$
\gamma^m_j = \begin{cases} 
0 & \text{if } c^\text{min}_j \leq c^m_j \leq c^\text{max}_j \\
\Delta t & \text{otherwise}
\end{cases}
$$  \hspace{1cm} (6)

$$
\epsilon_j = \frac{\sum_{m=1}^{t+n_b-1} q^m_j}{Q}
$$  \hspace{1cm} (7)
where \( n_h \) is the number of hydraulic time steps (monitoring time steps); \( t \) the start time in the steady periodic chlorine residual concentration at the monitoring node; \( \gamma_j^m \) the monitoring time step \( m \) at node \( j \) when chlorine residuals are unacceptable; \( T \) the total monitoring time step per hydraulic cycle; \( \Delta t_h \) the length of monitoring time step; \( c_j^{\min} \) and \( c_j^{\max} \) are the lower (0.3 mg/L) and upper (0.6 mg/L) chlorine residual limits at the monitoring node \( j \), respectively; \( q_j^m \) the WD at the monitoring node \( j \) at hydraulic time step \( m \) with unacceptable chlorine residual; \( Q \) the total WD in the network; \( c_j^m \) the chlorine residual concentration at the monitoring node \( j \) and monitoring time step \( m \) given by the following equation:

\[
 c_j^m = \sum_{i=0}^{n_h} \sum_{k=1}^{n_j} \alpha_{ij}^{km} \gamma_k^j
\]

where \( \alpha_{ij}^{km} \) is the response coefficient at monitoring node \( i \) due to chlorine injection at chlorine booster location \( j \) for injection time \( k \) and monitoring period \( m \). The response coefficients are determined by running the hydraulic and water quality models for a unit injection rate at the booster stations. The residual concentration \( c_j^m \) at the monitoring nodes is obtained by summing up individual responses due to injections according to the principle of linear superposition (Boccelli et al. 1998). In this regard, the proposed systematic robust approach is general and would accommodate any more sophisticated principles other than the linear superposition.

**Solution evaluations and optimisation**

The candidate solutions are evaluated by simulation–optimisation processes using the EPANET (Rossman 2000) and NSGA-II (Deb et al. 2002) models. To evaluate the candidate solutions, an EPANET hydraulic and water quality solver is first used to generate the response coefficients at the monitoring nodes for each NCOI and the outflow rate from potential booster locations. To generate the response coefficients, a long-term water quality simulation is run for unit injection rates at each potential booster location one at a time until steady chlorine residual concentrations are obtained at the monitoring nodes. The response coefficients for each NCOI and the outflow rates at each booster location for the last day (24 h) are stored and used in the NSGA-II optimisation, thus reducing the computational time. It is acknowledged that the use of a standard EPANET water quality solver may present shortcomings. For example, its use in systems of lined pipes introduces some level of uncertainty (Fisher et al. 2017). However, the demonstration of the worth of the proposed procedure is comparative (deterministic versus robust solutions). In other words, the value of the proposed method would be valid despite the modelling tools used due to the commonality of the uncertainty introduced by such tools. The emphasis of the results of this study is the general approach that can improve performances (hydraulic and water quality) of WDSs under uncertain conditions rather than the accuracy of water quality parameters. The NSGA-II optimisation obtains pareto-optimal solutions by applying processes such as encoding, population initialisation, evaluation, and genetic operation (selection, crossover, and mutation).

**CASE STUDY**

**Network descriptions and uncertainty scenarios**

The proposed method is tested on the Phakalane water distribution network (Figure 2), which is part of the larger Gaborone city network in Botswana. The network was skeletonised into 319 pipes of various diameters, 232 junctions, a reservoir at the treatment plant, two ground tanks, an elevated tank, two pumps, and two pressure reducing valves (PRVs). The network has three existing disinfection locations, one at the treatment plant and the other two are at booster locations 1 and 2 but are not functional. In addition to the existing booster locations 1 and 2, seven other booster locations 3, 4, 5, 6, 7, 8, and 9 are proposed for optimisation as shown in Figure 2. To select booster locations 3–9, the hydraulic and water quality simulations were performed with the relevant demand pattern to identify areas with inadequate chlorine residuals. The potential booster locations were then proposed along the pipe mainlines which supply water to the areas with inadequate chlorine residuals.

In this case study, seven possible options of network configurations and operational interventions in the Phakalane network are considered as presented in Table 1. Two
network configurations are proposed and they include (refer to Figure 2):

1. Water transmission to ground tank 2 from the treatment plant via ground tank 1 (i.e., the current configuration without configuration B).

2. Water transmission to ground tank 2 from the treatment plant directly without going via ground tank 1 (a planned configuration, i.e., the broken line).

The operational interventions with different options for storage (in terms of capacity, locations and refilling cycles) and pressure regulations (valve setting) are proposed as described in Table 1. The NCOIs can be interpreted as follows: NCOI-1 is the use of network configuration A (as defined above) with the operational intervention that delivers water to the network directly from ground tank 1 via the PRV during the day and from ground tank 2 (i.e. at full capacity) via the elevated tank at night. All other NCOIs can be interpreted in a similar manner. Note that NCOI-1 is the current/existing NCOI that is used to transmit and deliver water to the Phakalane network.

For each of the NCOIs, only one value of uncertain high WDs (i.e. WD-H) and one for uncertain low WDs
(i.e. WD-L) are considered to reduce computation time. Many values of WD-H and WD-L can be considered because they are continuous variables, but the computation time would be extremely high. A total of 14 uncertain scenarios were obtained using the scenario tree shown in Figure 1(a). The demonstrative values of WD-H and WD-L were obtained by a 50% arbitrary increase and decrease of estimated (mean) WDs (WD-E), respectively. Due to the lack of operational data, all the seven NCOIs were assumed to have equal likelihood to occur and assigned the same probability of 0.143 (1/7) for demonstration purposes. Similarly, the WD-H and WD-L were assumed to have equal probabilities of occurrences equal to 0.5 (1/2) assuming normal distribution around the mean value. The probability of occurrence for each uncertain scenario is computed by multiplying the probabilities of the NCOI and the respective WD-H and WD-L as shown in the branches of the scenario tree.

Data and assumptions

The network data required for the hydraulic simulation that generates the flow rate for the chlorine decay model were obtained from various sources (e.g. network drawings, contour maps, Google maps, engineering tables and water billing records). The data required for water quality simulation that obtains chlorine residuals were chlorine dosing rate, bulk decay and wall decay coefficients. The chlorine dosing/injection rates at the treatment plant were obtained from the monitoring records of the Botswana water utilities corporation and they range between 1.0 and 3.0 mg/L. The injection rates refer to the concentration of chlorine residual leaving the treatment plant going into the network. The bulk decay coefficient considered is 0.888 per day which was estimated by the bottle test experiment and the wall decay coefficient was assumed to be zero (insignificant). The recommended range of chlorine residual used in this study is 0.3–0.6 mg/L according to Botswana water quality standards (Central Statistics Office 2009). The lower and upper bounds of the decision variables used in the optimisation are 0–9, 0.3–8 mg/L and 0.2–0.6 mg/L for booster locations, treatment plant and booster station injection rates, respectively. The hydraulic and water quality/chlorine decay models were assumed to be properly calibrated and the principle of linear superposition was used to determine the chlorine residual concentration at the monitoring nodes (Prasad et al. 2004; Behzadian et al. 2012). NSGA-II was run with a population of 100 and 1,000 generations (considered adequate from trial runs). Three independent optimisation runs with different initial seeds were performed and the best Pareto fronts are shown and discussed in the section ‘Results and Discussions’. Each optimisation process was terminated when the specified number of generations was reached.

RESULTS AND DISCUSSION

The non-dominated solutions (designs) for the multi-objective optimisation problem of RBC are compared with the

<table>
<thead>
<tr>
<th>NCOIs</th>
<th>Network configurations</th>
<th>Operational interventions</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCOI-1</td>
<td>A</td>
<td>Water is delivered to the network directly from ground tank 1 via the PRV during the day and from ground tank 2 operating at full capacity via the elevated tank at night</td>
</tr>
<tr>
<td>NCOI-2</td>
<td>A</td>
<td>Water is delivered to the network directly from ground tank 1 via the PRV during the day and from ground tank 2 operating at half capacity via the elevated tank at night</td>
</tr>
<tr>
<td>NCOI-3</td>
<td>A</td>
<td>Water is delivered to the network from ground tank 2 operating at full capacity via the elevated tank during the day and at night</td>
</tr>
<tr>
<td>NCOI-4</td>
<td>A</td>
<td>Water is delivered to the network from ground tank 2 operating at half capacity via the elevated tank during the day and at night</td>
</tr>
<tr>
<td>NCOI-5</td>
<td>A</td>
<td>Water is delivered to the network directly from ground tank 1 via the PRV during the day and at night</td>
</tr>
<tr>
<td>NCOI-6</td>
<td>B</td>
<td>Water is delivered to the network from ground tank 2 operating at full capacity via the elevated tank during the day and at night</td>
</tr>
<tr>
<td>NCOI-7</td>
<td>B</td>
<td>Water is delivered to the network from ground tank 2 operating at half capacity via the elevated tank during the day and at night</td>
</tr>
</tbody>
</table>
common DBC solutions. The RBC solutions were obtained under the uncertain NCOI and WD scenarios driven by the expected MIR and the expected RCD. The DBC solutions were obtained under the current/existing NCOI (i.e. NCOI-1) and the estimated (mean) WD (WD-E) scenario driven by desirable levels of MIR and RCD.

The robust solutions were re-evaluated in the current/existing NCOI and estimated WD scenario in terms of the MIR and the RCD, so that they can be comparable with the deterministic solutions as shown in Figure 3. Solutions A–C and A1–C1 selected from Figure 3 are examples of comparable (equivalent or similar values of RCD) RBC and DBC designs, respectively. Note that these solutions appear in italics in the graphs. Table 2 shows the details of the selected solutions in terms of the variables and the objective values. Column 2 in Table 2 shows the optimal injection rates at the treatment plant. Columns 3–14 present the booster locations and their respective injection rates, while columns 15 and 16 show the objective values (MIR and RCD). A zero for booster location and hence a zero-injection rate in Table 2 mean that no booster station was selected.

It can be observed from Figure 3 that most deterministic solutions slightly outperform robust solutions (in terms of both the RCD and the MIR) under the current NCOI (i.e. NCOI-1) and estimated WD. Comparisons of robust and deterministic solutions, which have equivalent or similar values of RCD, indicate that deterministic solutions have slightly lower values of MIR. Similarly, comparing robust and deterministic solutions, which have equivalent or similar values of MIR, it can be seen that deterministic solutions have slightly lower values of RCD. For instance, the MIR of deterministic solution C1 is 16.1 kg/day, which is slightly lower than that of robust solution C (16.5 kg/day) at an equivalent RCD of 0.018 (Figure 3 and Table 2). It should be noted that the deterministic solutions were obtained for the current NCOI under the estimated WD and therefore are expected to outperform robust solutions which are obtained for many scenarios with different NCOIs and WDs. This effect suggests that deterministic solutions for any specific scenario would be the best solutions if the network considered would not change in terms of operations (i.e., fixed).

The selected robust and deterministic solutions presented in Table 2 indicate that at least two chlorine booster stations are required in addition to injection at the treatment plant to effectively reduce the RCD (i.e. the volume of water with unacceptable chlorine residual) in the case study network. The number, locations and injection rates of the

Table 2 | Selected robust and deterministic solutions (booster design options) showing decision variables and objective values

<table>
<thead>
<tr>
<th>Selected solution</th>
<th>Decision variables</th>
<th>Objective values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TP-DR</td>
<td>BL1</td>
</tr>
<tr>
<td>A</td>
<td>0.300</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0.300</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>0.300</td>
<td>0</td>
</tr>
<tr>
<td>A1</td>
<td>0.300</td>
<td>0</td>
</tr>
<tr>
<td>B1</td>
<td>0.300</td>
<td>4</td>
</tr>
<tr>
<td>C1</td>
<td>0.300</td>
<td>0</td>
</tr>
</tbody>
</table>

TP-DR, treatment plant dosing rate; BL, booster location; BDR, booster dosing rate; MIR, mass injection rate; RCD, risk of chlorine disinfection.
booster stations in robust solutions differ from those of the deterministic solutions. For instance, robust solution C presents a booster design with two booster stations at locations 2 and 9 (see Figure 2) that have injection rates of 0.440 and 0.202 mg/L, respectively. On the other hand, deterministic solution C1 presents a booster design with three boosters at locations 2, 3 and 6 that have injection rates of 0.325, 0.200 and 0.210 mg/L, respectively. The booster design options (e.g. solutions C and C1) are also located in the areas, which receive inadequate chlorine residuals under conventional disinfection.

Robust booster designs would maintain better levels of chlorine residuals in the network even when any of the alternative operations (NCOIs) are used due to eventualities such as cut-offs during maintenance, rehabilitation and repair of a section of the network. For example, a need for repair or maintenance work on the direct transmission line to ground tank 2 (Figure 2) may arise. In this case, the alternative NCOI-5 (Table 1), which supplies water to the network from the treatment plant to ground tank 1, can be used. For this alternative route, any comparable robust solutions will accommodate the change better than the deterministic solutions. Deterministic solutions would compromise chlorine residuals more than robust solutions in this alternative route. For example, risk comparative robust solution C with booster locations at 2 and 9 would maintain chlorine residuals in the network better than the corresponding deterministic solution C1 with booster locations at 2, 3 and 6, when the alternative NCOI-5 is used.

The performances of the robust and deterministic booster solutions were then compared by subjecting these solutions to uncertain scenarios that lead to extreme or intermediate performances. Figure 4 shows the comparison of robust and deterministic solutions when subjected to (a) and (b) uncertain scenarios that lead to extreme performances and (c) and (d) uncertain scenarios that lead to intermediate performances.
solutions to the uncertain network scenarios. The re-evaluations that lead to results shown in Figure 3 were followed by re-evaluations of both robust and deterministic solutions using all the 14 uncertain scenarios obtained with the guidance of Figure 1(a). Thereafter, uncertain scenario 5 (with NCOI-3 under WD-H) and scenario 8 (with NCOI-4 under WD-L) that led to extreme performances were selected for comparisons of deterministic and robust solutions as shown in Figure 4(a) and 4(b). Note that scenarios 5 and 8 are used because they lead to extreme performances of solutions, which are the most concerns that would be addressed using the robust chlorine booster designs. Additionally, uncertain scenario 13 (with NCOI-7 under WD-H) and scenario 14 (with NCOI-7 under WD-L) were randomly selected from other remaining uncertain scenarios (i.e., which do not lead to extreme performances) in order to demonstrate further, the performances of the robust and deterministic booster designs under uncertain network scenarios as shown in Figure 4(c) and 4(d). Note that any other uncertain scenarios could be used for similar comparisons. The details of the effects of the aforementioned uncertain scenarios on performances of the selected solutions are presented in Table 3.

The results in Figure 4(a)–4(d) indicate that robust solutions clearly outperform the deterministic solutions in terms of both the RCD and the MIR. The RCD values of the selected robust solutions (e.g., A–C) are lower than the RCD values of their corresponding deterministic solutions (e.g., A¹–C¹). For instance, in scenario 5 (Figure 4(a)), the RCD for selected robust solution C is 0.027 while for the corresponding selected deterministic solution C¹ is 0.167 (see Table 3). In scenario 14 (Figure 4(d)), the RCD for the selected robust solution C is 0.319, while for the corresponding selected deterministic solution C¹ is 0.680.

The above evaluation of the robust and deterministic solutions indicates that robust booster designs provide better adaptation to uncertain NCOIs and WDs than deterministic booster designs. The fact that deterministic booster designs are obtained for specific NCOI under the estimated WDs (WD-E) made them have limited adaptability (i.e., rigid) to adjust to other uncertain NCOIs and WDs in the network. Although both robust and deterministic booster stations may be located in the areas which receive inadequate chlorine residuals in the network, their injection rates are different (e.g. solutions C and C¹ in Table 2). The injection rates of robust booster stations that are located at the upstream of the main water distribution network (e.g., booster location 2 in Figure 2) are higher than those of the corresponding deterministic booster stations. For instance, the injection rate at booster location 2 in the robust solution C is 0.440 mg/L, which is higher than that of the corresponding booster location 2 in the deterministic solution C¹ (0.325 mg/L). The higher injection rates in robust booster designs increase the MIR and hence reduce the RCD more than lower injection rates found in deterministic booster designs.

It can also be observed from Figure 4 that the RCD values for robust solutions in the uncertain NCOI under high WDs (i.e., scenarios 5 and 13) are generally lower than those under low WDs (i.e., scenarios 8 and 14), respectively. For instance, the RCD for robust solution C in scenario 13 is only 0.12, whereas in scenario 14 the RCD is 0.319 (Table 3). These results imply that robust booster designs would perform better in the uncertain NCOIs under high WDs than low WDs. This is attributed

<table>
<thead>
<tr>
<th>Method</th>
<th>Selected solutions</th>
<th>Scenario 5</th>
<th>Scenario 8</th>
<th>Scenario 13</th>
<th>Scenario 14</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MIR</td>
<td>RCD</td>
<td>MIR</td>
<td>RCD</td>
</tr>
<tr>
<td>Robust</td>
<td>A</td>
<td>14.7</td>
<td>0.811</td>
<td>3.2</td>
<td>0.886</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>15.8</td>
<td>0.406</td>
<td>3.5</td>
<td>0.670</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>16.9</td>
<td>0.027</td>
<td>3.9</td>
<td>0.442</td>
</tr>
<tr>
<td>Deterministic</td>
<td>A¹</td>
<td>14.5</td>
<td>0.815</td>
<td>3.1</td>
<td>0.959</td>
</tr>
<tr>
<td></td>
<td>B¹</td>
<td>15.5</td>
<td>0.541</td>
<td>3.4</td>
<td>0.877</td>
</tr>
<tr>
<td></td>
<td>C¹</td>
<td>16.4</td>
<td>0.167</td>
<td>3.8</td>
<td>0.850</td>
</tr>
</tbody>
</table>
to the fact that the RCD is inversely proportional to the MIR, which is directly proportional to the WD in the network.

This study has demonstrated that the RBC designs based on the scenario analysis of the uncertain network interventions and WD can improve chlorine residuals under uncertainty conditions in the WDSs. Water suppliers and decision makers can use the proposed RBC approach to plan for booster designs that would desirably accommodate alternative network operations that are used to respond to network uncertainties in an attempt to meet the supply of safe drinking water. Provided that any WDS such as the Phakalane network would require routine changes in its operations, the RBC design approach developed in this paper would be most applicable and beneficial.

CONCLUSIONS

The RBC designs presented in this study were compared with the commonly used DBC designs in terms of the MIR and the RCD using the Phakalane network as a case study. The conclusions were drawn from the results as follows:

1. The risks associated with chlorine disinfection in RBC designs (location, number and the injection rate) are lower than those of the DBC designs, if they are operated under different network conditions (i.e., uncertain WD, network configurations and operational interventions). This therefore means that under WDS uncertainties, the RBC designs outperform the corresponding DBC designs.

2. However, under specific (i.e., fixed) network conditions, the risks associated with chlorine disinfection and the MIR for the DBC designs are lower than those of the RBC designs, which are obtained under uncertain network conditions. Therefore, DBC designs outperform RBC designs if they are operated under specific (fixed) network conditions for which they were designed. This suggests that deterministic solutions for any specific scenario would be the best solutions if the condition of the network considered would not change (i.e., fixed).

3. When any of the alternative network interventions is adopted due to eventualities such as cut-offs during the maintenance, rehabilitation and repair of a section of the network, RBC designs would maintain better levels of chlorine residuals in the WDSs. Therefore, the RBC designs would offer more adaptability to uncertain WDs and operational interventions in WDSs.

4. An increase in WD also increases the flow rate and the chlorine demand in WDSs. These changes affect the performances of DBC designs more than the robust ones. The risks of chlorine disinfection for RBC designs under uncertain network operational interventions with high WDs are lower than those with low WDs. Similarly, network operational interventions may either increase or decrease water age in WDSs which affects chlorine residuals. In this regard, DBC designs would also be negatively affected more than RBC designs.

It is acknowledged that the RBC design method was demonstrated with few uncertain scenarios on a small network. Therefore, further application of the proposed approach on bigger networks with many uncertain scenarios using other techniques that quantify and represent uncertainty such as sampling methods (e.g., Monte Carlo and Latin Hypercube) is recommended to extend the method.

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CONFLICT OF INTEREST

There is no conflict of interest.

REFERENCES

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