Sensitivity analysis for water supply input parameters of the CLARA simplified planning tool using three complementary methods

Atekelt Abebe Ketema and Guenter Langergraber

ABSTRACT

Three sensitivity analysis methods based on derivative, screening and regression are applied to the CLARA simplified planning tool (CLARA-SPT) estimating life cycle cost (LCC) of water supply systems. Derivative-based and standard regression coefficient methods are used to address parameter prioritization and Morris screen method for parameter fixing. The study investigated sensitivity of 26 parameters through three feasible water supply alternatives. The results revealed the importance of all global parameters: period of consideration, net interest rate and expected annual growth rate, for the LCC of all alternatives. The analysis identified ten technological parameters as non-influential, which can be fixed to a certain value. In contrast, two internally fixed parameters (i.e., chlorine dosage and alum dosage) are determined to be important; hence, these parameters need to be available for planners for reasonable cost estimation. Except for period of consideration, all parameters have low standard deviation (σ) value that indicates linear correlation of alternatives' LCC with input parameters and/or insignificant interaction among parameters. This study is valuable for further development of the CLARA-SPT in order to simplify it and to provide guidance for the tool user on the importance of specific input parameters.

Key words | CLARA simplified planning tool, important parameter, life cycle cost, non-influential parameter, water supply alternatives

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ACRONYMS

CLARA-SPT	CLARA simplified planning tool
LCC	life cycle cost
OAT	one parameter at a time
RV	residual value
SA	sensitivity analysis
SRC	standardized regression coefficient
TC	total cost

INTRODUCTION

Environmental decision support tools usually face a problem of conceptualization, uncertainty effect of input parameters on the intended output, over-parameterized and poor result predation, which possibly mislead the decision-making process (Huang & Liu 2008; Sun *et al.* 2012). One way to achieve performance assessment of a model is by applying sensitivity analysis (SA) to examine how the uncertainty of model input parameters influences the efficiency of the model estimation (Saltelli *et al.* 2008). The selection of a specific SA method is highly influenced by the main objective of the study, the complexity of the model and the computational time and cost. Often, simple and computationally less expensive SA methods are preferred for models with many input parameters.

According to Saltelli *et al.* (2000), SA is classified as local, screening and global methods. Relatively local and screening methods that apply the principle of changing one parameter at a time (OAT) are computationally cheaper than global SA methods; whereas, global SA is the most

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efficient and reliable method that explores the entire parameter space (Homma & Saltelli 1996; Saltelli *et al.* 2004).

This study addresses the following two objectives of SA (Saltelli *et al.* 2008):

1. Parameter prioritization (PP): to identify the most important input parameters that have the greatest potential for uncertainty of the model output, thereby more certainty is demanded.
2. Parameter fixing (PF): to determine non-influential input parameters that do not cause significant variability on the model outputs. These parameters can be fixed to a certain average value in their acceptable boundaries.

Three complementary SA methods are selectively applied to assess input parameters sensitivity for the uncertainty of proposed water supply alternatives' life cycle cost (LCC). The engaged techniques are derivative-based, standard regression coefficient (SRC) and Morris screening SA methods. Derivative-based and SRC are used for PP and Morris screening for PF (Neumann 2012).

The CLARA simplified planning tool (CLARA-SPT) was launched in February 2014 and is used to estimate LCC of water supply and/or sanitation alternatives. The tool was developed for five African countries: Burkina Faso, Ethiopia, Kenya, Morocco and South Africa (Lechner *et al.* 2014). Because the tool was developed recently, sensitivity of water supply systems' LCC has not yet been assessed. Conducting SA should contribute to determining conceptualization gaps and potential improvements of the tool (Farr 2011). In this regard, the main focus of this study relies on assessing the sensitivity of CLARA-SPT to identify important and non-influential water supply input parameters for prioritizing and fixing them, respectively.

METHODS

Study area description

The SA of water supply system's LCC computation through CLARA-SPT was tested for one of the nine urban districts of Bahir Dar city named Hidar-11. Bahir Dar city is located at the south of Lake Tana, 11 ° 38′ north latitude and 37 ° 15′ east longitude (MUDHCo 2014). The mean annual precipitation, temperature and aquifer hydraulic conductivity of the area ranges from 1,103 to 1,336 mm, 22 to 29 °C and 0.06 to 19 m/day (W/Yohannes 2010; Wondmagegne *et al.* 2012).

The estimated population size of Hidar-11 district is about 24,600 in 2014 based on a population of 18,890 in 2008 (TCE 2009) and 4.5% annual population growth rate of the city (CSA 2008). Hidar-11 district is geographically bounded by the river Abay (i.e., a cross boundary river) on the west and Lake Tana on the north-west side (Figure 1).

Bahir Dar's existing water supply system that comes from springs and boreholes is evaluated to be insufficient and unreliable. This is because of water shortage, an aged distribution network, system management problems and frequent electricity power interruption. Currently, the city water supply authority, which is responsible for planning, designing, constructing and operating the water supply system, is exploring additional water supply sources to solve the water shortage problem. As a result, Lake Tana is identified as a potential source to satisfy the ever growing water demand of the city. Users are responsible for their house connection fee, monthly water bill and to maintain the quality of the water at the household level.

Case study model set-up

A reconnaissance survey of the intervention area confirms the presence of alternative water supply sources: spring, borehole and lake at an approximate distance of 20.7, 8.0 and 6.3 km from the district, respectively. The three feasible alternatives are proposed to satisfy the water demand of the projected population size of about 60,000 in 2034 (20 year planning horizon). Alternatives were labelled as Alt-1, Alt-2 and Alt-3 for a system sourced from the borehole, lake and spring, respectively. Each alternative comprises the appropriate set of technologies under water source, water purification and water distribution functional groups. This example deliberately excluded the costs of individual house connections, since the service provider is not accountable for such expense, rather users are. Involved technologies in the three alternatives are shown in Figure 2, while detailed information of each technology can be seen in the Supporting material (available online at http://www.iwaponline.com/jws/064/126.pdf).

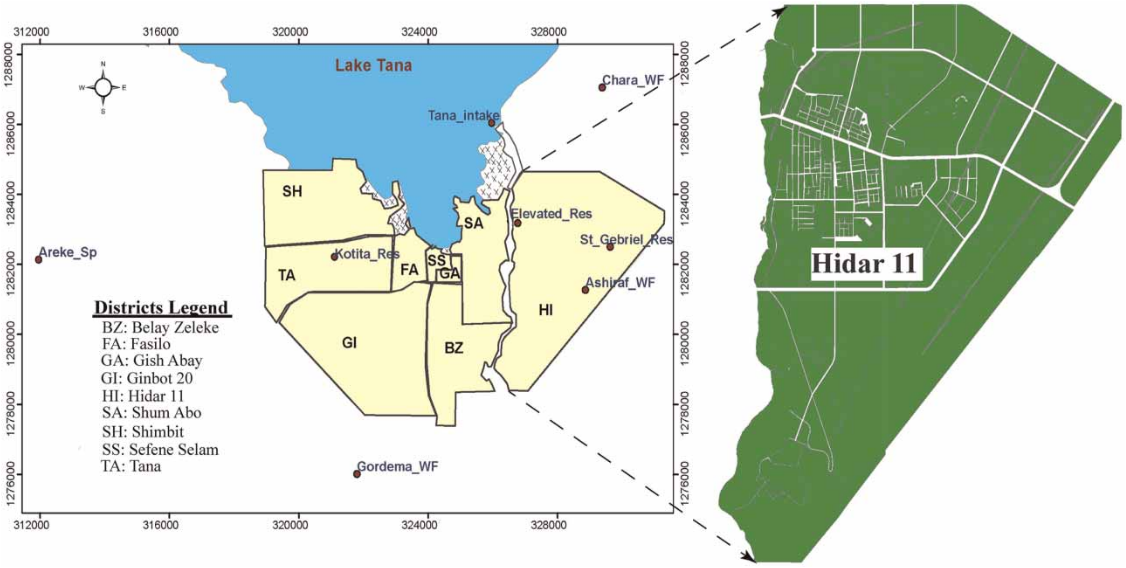

Figure 1 | Bahir Dar city: location of nine districts, selected well fields (WF), spring (SP) and Lake Tana; and reservoirs (Res) for Hidar-11 district.

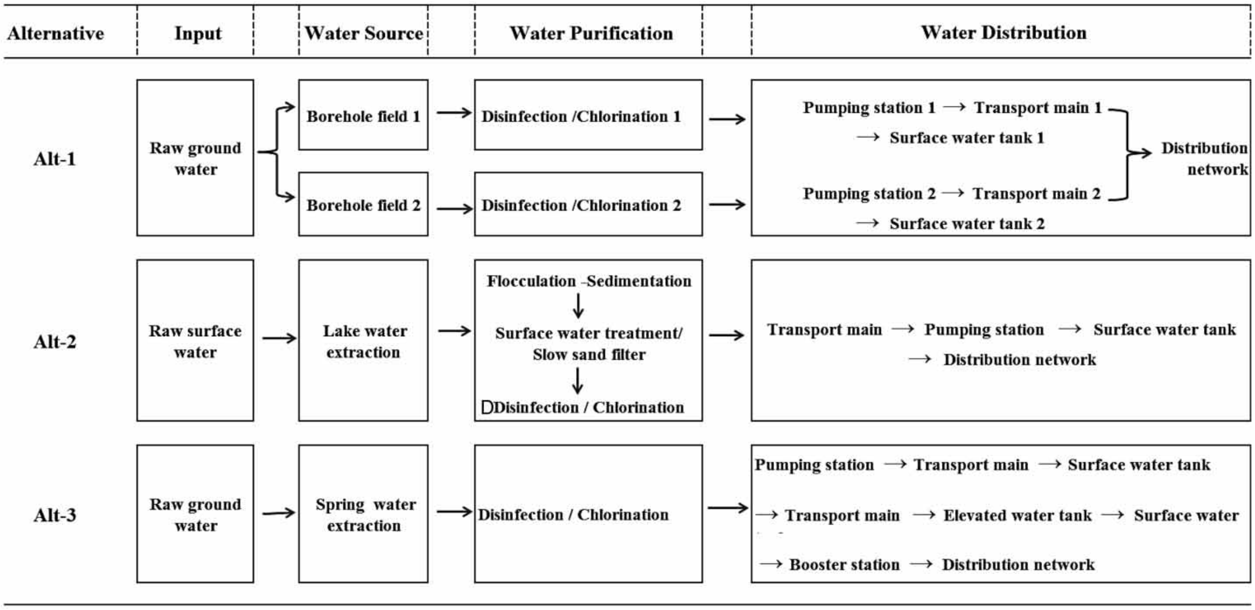

Figure 2 | Proposed water supply system alternatives.

CLARA-SPT working principle

The CLARA-SPT is designed to estimate and compare LCC of water supply and/or sanitation systems. The water supply part of the tool comprises: water source, water purification and water distribution functional groups (Casielles Restoy *et al.* 2014). The very first step of LCC computation using CLARA-SPT is to wisely insert all input parameters for each alternative. Consequently, the tool calculates LCC components (i.e., initial investment cost, operation and maintenance cost, reinvestment cost and residual value (RV)) of each and every technology embedded in the alternatives. This is followed by linearly aggregating the net present value of technologies' cost component to alternatives' respective LCC component. Since a 20 year planning horizon is considered, the remaining asset value of each infrastructure after 20 years of service is taken as the RV of the systems.

Global parameters of CLARA-SPT (Table 1) are designed to influence the cost of all technologies. However, technological parameters mainly influence the cost of affiliated technology; whereas, internal-technological parameters are design assumptions of technologies, which are internally fixed into certain values.

The system capacity is the main design parameter of the water supply system. For example, for a 20 year period, all systems are designed for 12,615 m^3/d capacity, while the capacity rises to 19,591 m^3/d for a period of 30 years. Therefore, when one changes the value of the period of consideration, it is required to change the system capacity (i.e., daily demand or flow rate) simultaneously. For this case study, the maximum daily demand is taken as the system capacity, which is estimated based on the Ethiopia

Table 1 | Input parameters label, description, unit and variation range

Label	Description	Unit	Range of value
Global parameters			
X1	Period of consideration	Year	5–30
X2	Net interest rate	%	1.5–6.5
X3	Expected annual growth	%	1.5–7.5
User-technological parameters			
X4	Ground water depth	m	10–80
X5	Number of boreholes	Number	9–30
X6	Number of disinfection plants	Number	1–26
X7	Number of pumping stations	Number	4–40
X8	Pressure head	m	20–320
X9	Trench depth	m	0.6–2
X10	Pipe length	m	1,000–45,300
X11	Number of surface water tanks	Number	2–24
X12	Number of lake water extractions	Number	3–25
X13	Pump head at intake	m	12–60
X14	Number of flocculation sedimentation plants	Number	1–25
X15	Number of surface water treatment plants	Number	1–25
X16	Number of spring water extraction chambers	Number	7–5
X17	Hydraulic conductivity	m/s	1.2E-5–2.5E-4
X18	Water tank elevation	m	2–20
X19	Borehole diameter	inch	8 and 20
X20	Kind of disinfectant	–	$Ca(OCl)_2$, Na(OCl) and Cl_2 gas
X21	Pump installation	–	Surface and sub-surface
X22	Kind of flocculant	–	Alum, ACH and ferric sulphate
X23	Number of water lines	Number	1–2
Internal-technological parameters			
X24	Diameter distribution	%	30–70% small; 10–50% middle; 0–40% large
X25	Chlorine dosage	mg/l	1.2–3
X26	Alum dosage	mg/l	15–60

design guideline (MOWRD 2002). For details of calculation refer to the Supporting material (online at http://www.iwaponline.com/jws/064/126.pdf).

SA techniques

SA of the case study involves 26 parameters: three global parameters, 20 user-technological and three internal-technological parameters (Table 1). Five of the technological parameters (i.e., borehole diameter, kind of disinfectant, pump installation, type of flocculent and number of water lines) are categorized as qualitative/subjective parameters. Their influence was assessed using Equation (1), by which the relative cost change (Δ_{rr}) of the alternative from its base value is computed

$$\Delta_{rr} = \frac{Y(X_i) - Y(X)}{Y(X)} \tag{1}$$

where $Y(X)$ is the respective alternative base output at the reference value of X, and $Y(X_i)$ is the alternative output obtained after changing the input parameter from the existing qualitative options in the tool.

Sensitivity of the remaining 21 quantitative parameters was evaluated using derivative-based, SRC and Morris screening methods.

Derivative-based method

The derivative-based SA is a commonly applied method using first-order partial differentiation of the dependent variable Y, with the function of input parameter $X_i(X_1, X_2, X_3, \ldots, X_n)$. In this method, the sensitivity of Y (i.e., alternative's total cost (TC) and RV) was assessed by changing OAT, while keeping all other parameters constant at the base value. Parameter perturbation at ±5, ±10, ±15 and ±20% from the base value of X_i was tested. According to Saltelli *et al.* (2000), the derivative-based sensitivity coefficient S_{d_i} is estimated by Equation (2)

$$S_{d_i} = \frac{\partial Y}{\partial X_i}\left(\frac{X_i}{Y}\right) \tag{2}$$

The quotient X_i/Y is used to normalize the unit effect of the derivative. For a small change of the ith input parameter, the partial derivative can be approximated as a fraction of finite difference of output value to the change of input parameter. In this regard, Equation (2) can be approximated by the ratio of percentage change of Y to percentage change of X_i (Equation (3)), assuming that Y is linear (Hamby 1994)

$$S_{d_i} = \frac{\%\Delta Y}{\%\Delta X_i} \tag{3}$$

To compute S_{d_i} for K number of input parameters, minimum simulation number $N = K + 1$ is required.

SRC method

The working principle of regression-based SA method is random selection of input parameters to execute a Monte Carlo simulation so as to find out a multivariate linear function with the output parameter (Equation (4)). Here, the magnitude of statistically significant regression coefficients are used to estimate SA indices of corresponding input parameters. To remove the unit difference of input and output parameters, standardization of regression coefficients is needed (Kutner *et al.* 2005). The SRC of a parameter (β_i) calculated by Equation (5), is taken as the sensitivity index of the associated parameter, if the coefficient of determination R^2 is greater than 0.70 (Saltelli *et al.* 2004). The greater value of R^2 shows linearity and absence of input parameters' interaction (Haahtela 2010).

$$Y = b_0 + \sum_{i=1}^{K} b_i X_i \tag{4}$$

$$\beta_i = b_i \frac{\sigma_{X_i}}{\sigma_Y} \tag{5}$$

where Y is the dependent output parameter obtained after regression analysis of K number of input parameters ($X_1, X_2, X_3, \ldots, X_K$) and N number of simulations, b_0 is the aggregated error factor (intercept) of the regression equation, b_i is the coefficients or slope of X_i, (σ_{X_i}) and (σ_Y) are the standard deviations of X_i and Y, respectively.

Literature recommended ranges of N from 500 to 1,000 irrespective of input parameter numbers (Saltelli *et al.* 2008).

In this paper, sensitivity of the 21 quantitative parameters was assessed by conducting 987 simulations.

Morris screening method

The fundamental principle of the Morris screening method relies on the concept of elementary effect of input parameters on the model result (Morris 1991). It measures sensitivity of large numbers of parameters through partitioning of the parameters space at low computational cost (Saltelli *et al.* 2004). The method is mainly used to identify non-influential parameters to address parameter fixing objectivity of SA. The elementary effect of the *i*th parameter $d_i(X_i)$ represents the relative difference between the tool output obtained after parameter perturbation by Δ, $Y(X_1, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_K)$, and the base output $Y(X)$ for the given reference input parameter value (Equation (6)).

$$d_i(x_i) = \frac{[Y(X_1, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k) - Y(X)]}{\Delta} \quad (6)$$

where $X_1, \ldots, X_{i-1}, X_i, X_{i+1}, \ldots, X_K$ are parameters sampled from K dimensional, P-level grid parameter space. As $d_i(X_i)$ depends on the location of the random sample, R numbers of replicate runs for each parameter are summarized by mean (μ_i) and standard deviation (σ_i) to obtain sensitivity indices of each parameter (Morris 1991). μ_i measures the overall influence of the *i*th parameter on the output uncertainty, while σ_i assesses non-linearity and/or interaction of the parameter with others. When the model is non-monotonic the value of μ_i is affected by negative and positive values of d_i, which leads the values to cancel each other out. To avoid this effect, Campolongo *et al.* (2007) suggested referring to the mean of the absolute value $d_i(X_i)$ instead of μ_i to calculate the sensitivity index($\mu_i *$) of a specific parameter (Equation (7)).

$$\mu_i^* = \frac{1}{R}\sum_{i=1}^{R} |d_i(X_i)| \quad (7)$$

According to Morris (1991), the required number of simulations is estimated by $N = R \times (K + 1)$, where R ranges from 4 to 10 and K is the number of input parameters. In this study, eight replicates of each quantitative input parameter varying OAT by ±10, ±20, ±30 and ±40% from their base values were tested. Therefore, for the 21 quantitative parameters a total of $N = 8 \times (21 + 1) = 176$ model simulations were performed.

Cut-off value setting for parameter categorization

In this study, a 5% of significant level (i.e., 95% confidence level) was chosen to classify non-influential parameters (Frey & Patil 2002). The assumption is that economic value difference of alternatives that fall within a ±5% margin can be considered approximately identical economic options. Hence, the parameter with $\mu_i * < 0.05$ *or* $| \Delta_{rr} | < 0.05$ is categorized as a non-influential parameter that can be fixed to a certain value. For parameter prioritization, a 10% significant level was selected, i.e., alternatives having more than 10% economic value deviation are considered as distinguished options. Therefore, the parameter with $|\Delta_{rr}| \text{ or } |S_{d_i}| \text{or} |\beta_i| \geq 0.1$ is classified as important. Sensitivity indices that range between 0.1 and 0.05 represent still sensitive parameters, which are neither so important to prioritize nor non-influential to fix them (Hamby 1994).

RESULTS AND DISCUSSION

SA results of all 26 input parameters for alternatives' TC and RV are presented in this section. Positive values of the derivative-based index (S_{d_i}) indicate that an increase of the parameter leads to a rise of the output value, while negative values indicate the inverse effect.

Global parameters SA

The relative significance level of the global parameters *X1* (consideration period), *X2* (net interest rate) and *X3* (expected annual growth rate) for alternatives' TC and RV are presented in Table 2. Both derivative-based and SRC methods confirmed the importance of all global parameters ($|S_{di}|$ and $|\beta_i| > 0.1$) except *X3* for alternatives' RV. The negative sensitivity index of *X2* shows the decrease of the alternative's present economic value with the rise of net

Table 2 | Global parameters' sensitivity indices for alternatives' TC and RV

	Alt-1				**Alt-2**				**Alt-3**			
Label	S_d	β	μ^*	σ	S_d	β	μ^*	σ	S_d	B	μ^*	σ
TC												
X1	**1.722**	**0.827**	1.585	***0.306***	**1.711**	**0.877**	1.767	*0.393*	**1.531**	**0.829**	1.553	***0.292***
X2	**– 0.328**	**– 0.262**	0.329	0.027	**– 0.353**	**– 0.201**	0.353	0.029	**– 0.316**	**– 0.246**	0.317	0.026
X3	**0.366**	**0.328**	0.367	0.029	**0.394**	**0.252**	0.394	0.031	**0.352**	**0.274**	0.352	0.028
RV												
X1	**– 1.453**	**– 0.835**	1.500	***1.041***	**– 1.114**	**– 0.200**	1.456	*1.812*	**– 1.017**	**– 0.575**	0.811	***0.254***
X2	**– 0.773**	**– 0.435**	0.776	0.092	**– 0.773**	**– 0.460**	0.776	0.092	**– 0.773**	**– 0.660**	0.776	0.092
X3	0.084	0.053	0.461	0.037	0.093	0.061	0.461	0.037	0.091	0.096	0.461	0.037

Grey highlighted and bold: important; bold italic: non-linearity and/or parameter interaction.

interest rate. Similarly, longer consideration period (*X1*) clearly has the consequence of further devaluing the system's RV (Jovanovic 1999; Pearce *et al.* 2006). Highest standard deviation (σ) of parameter *X1* for both TC and RV indicates the presence of significant non-linearity and/or interaction with other parameters.

Technological parameters SA

Qualitative parameters SA

Results in Table 3 show non-influential effect of *X21* (pump installation type) for both TC and RV of all alternatives ($\Delta_{rr} < 0.05$). Similarly, *X20* (kind of disinfectant) and *X22* (kind of flocculent) did not have any effect on the RV of alternatives. This is because these parameters are hardly associated with alternatives' infrastructure cost contribution on the system's RV. However, their main influence on the alternative's operation and maintenance cost result in an un-neglected effect of *X20* ($\Delta_{rr} \geq 0.05$) and significant effect of *X22* ($\Delta_{rr} \geq 0.1$) for respective alternative's TC. Parameter *X19* (borehole diameter) was found to be important for Alt-1 TC ($\Delta_{rr} \geq 0.1$) and sensitive for its RV ($0.1 \geq \Delta_{rr} \geq 0.05$). This can be explained by the fact that a larger diameter for drilling needs is more costly than a smaller diameter. Parameter *X23* (number of water lines), either one or two water lines, was also determined to be important for Alt-2 TC. The amount of discharge flow per water line is affected and influences the pipe diameter and thus the TCs.

Table 3 | Qualitative parameters relative sensitivity indices for alternatives' TC and RV

Label	**TC**			**RV**		
	Δ_{rr}**-Alt-1**	Δ_{rr}**-Alt-2**	Δ_{rr}**-Alt-3**	Δ_{rr}**-Alt-1**	Δ_{rr}**-Alt-2**	Δ_{rr}**-Alt-3**
X19	**0.100**			0.051		
X20	0.075	0.072	0.086	*0.000*	*0.000*	*0.000*
X21	*0.002*	*0.002*	*0.004*	*0.012*	*0.010*	*0.012*
X22		**0.108**			*0.000*	
X23		**0.158**			*0.010*	

Light grey highlighted and bold: important; dark grey highlighted and italic: non-influential parameter.

Derivative-based SA indices of quantitative parameters

The results obtained from derivative-based SA for alternatives' TC are shown in Figure 3. The vertical distance from the horizontal axis refers to the importance of the parameter. Parameter *X8* (pressure head) was detected as the most important parameter for all alternatives' TC and RV. Because the relative share of pumping station costs is highest for Alt-3 (54%) its influence on Alt-3 TC is higher than on Alt-1 and Alt-2 TCs (36 and 37% of TC are pumping station costs for Alt-1 and Alt-2, respectively). Moreover, *X10* (pipe length) was found to be important for all alternatives' TC and RV. The result also shows the importance of *X25* (chlorine dosage) only for alternatives' TC but not for RV, since infrastructure cost of alternatives has never been influenced by *X25*. Parameter *X4* (ground water depth)

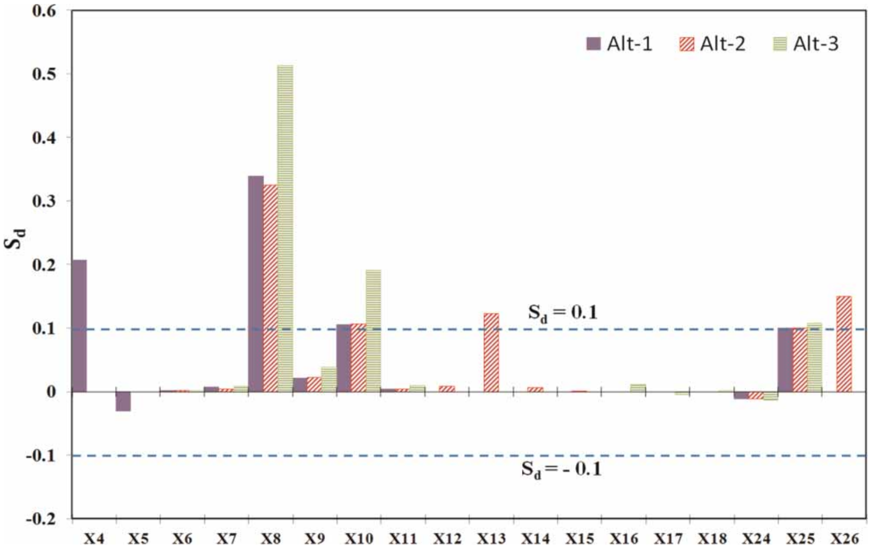

Figure 3 | Derivative-based SA of quantitative user-technological parameters for Alt-1, Alt-2 and Alt-3 TC.

was classified as an important parameter, since the LCC of borehole development largely depends on drilling depth of the well (Jagals & Rietveld 2011). On the other hand, *X5* (number of boreholes) and *X9* (trench depth) were found to be important for RV of related alternatives, but not for their respective TC. The reason might be either their influence is more governed by capital costs, or the hosting technologies of these parameters (i.e., borehole, transport main and/or distribution network) have longer lifetimes than 20 years of consideration. For TC of Alt-2, X13 (pump head at intake) and *X26* (alum dosage) were identified to be important parameters but not for RV. This is due to the substantial effect of *X13* on Alt-2 operation and maintenance costs and overshadows its effect on capital cost, whereas *X26* is totally an operation-related parameter.

SRC-based SA indices of quantitative parameters

The coefficients of determination R^2 of Alt-1, Alt-2 and Alt-3 TC are 0.98, 0.93 and 0.97 and thus >0.70, respectively.

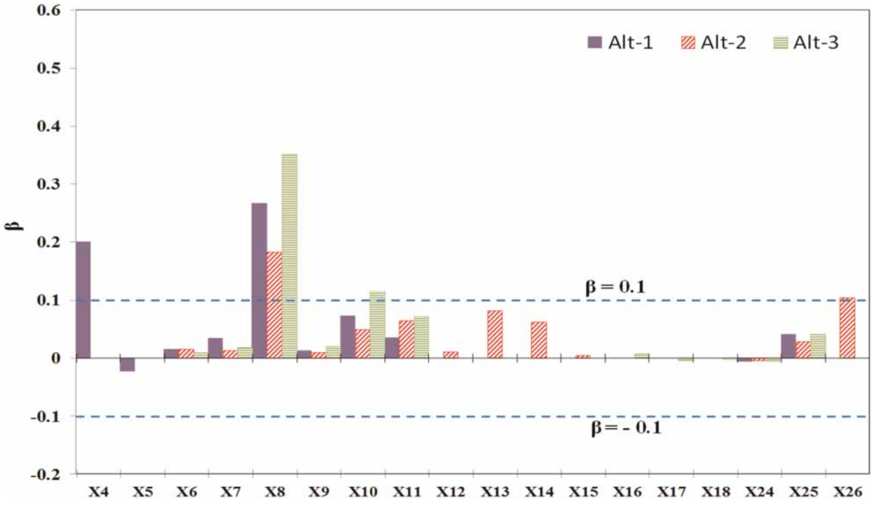

Figure 4 | SRC-based SA of quantitative user-technological parameters for Alt-1, Alt-2 and Alt-3 TCs.

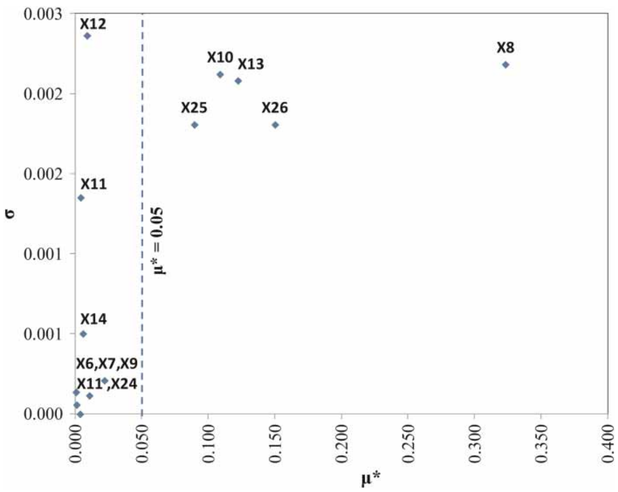

Figure 5 | Morris screening relative sensitivity $\mu*$ versus linearity σ for Alt-2 TC.

This indicates the validity of SRC sensitivity measure and high degree of linearity for all alternatives' TC. The method was also valid for RV of Alt-1 and Alt-3, where R^2 is 1.00 and 0.99, respectively. However, it was found to be invalid for RV of Alt-2, since estimated $R^2 = 0.34$. The result obtained from SRC confirmed the importance of *X8*, *X4* and *X26* for the TC of related alternatives (Figure 4 and Table 4). Parameter *X10* (pipe length) was determined to be important only for TC of Alt-3 despite its involvement in all alternatives. The reason is that the presence of longest transport main (20.7 km) in Alt-3 resulted in a relatively higher cost share of 9% than 2% for 8.0 km and 3% for a 7.5 km long transport main of Alt-1 and Alt-2, respectively. However, *X10* was classified as an important parameter for RV of all alternatives, since 50 year lifetimes of pipes leaves considerable RV in the system at the end of 20 years.

Unlike the derivative-based method, SRC result showed the importance of *X11* (number of surface water tanks) and

Table 4 | SA results of alternatives' TC

	Alternatives' TC											
	Alt-1				**Alt-2**				**Alt-3**			
Label	S_d	β	μ*	σ	S_d	β	μ*	σ	S_d	β	μ*	σ
X4	**0.207**	**0.201**	0.209	0.005								
X5	−0.030	−0.023	*0.038*	0.019								
X6	0.002	0.015	*0.002*	0.000	0.002	0.015	*0.002*	0.000	0.002	0.009	*0.002*	*0.000*
X7	0.007	0.034	*0.008*	0.002	0.004	0.013	*0.004*	0.001	0.008	0.018	*0.009*	0.003
X8	**0.339**	**0.267**	0.339	0.001	**0.325**	**0.182**	0.323	0.002	**0.513**	**0.352**	0.513	0.002
X9	0.021	0.013	*0.021*	0.000	0.022	0.010	*0.022*	0.000	0.039	0.020	*0.039*	0.000
X10	0.105	0.073	0.105	0.000	**0.107**	0.050	0.109	0.002	**0.192**	**0.115**	0.192	0.000
X11	0.004	0.035	*0.004*	0.000	0.004	0.064	*0.004*	0.000	0.009	0.072	*0.010*	0.000
X12					0.008	0.011	*0.009*	0.002				
X13					**0.123**	0.082	0.123	0.002				
X14					0.007	0.062	*0.006*	0.001				
X15					0.001	0.004	*0.001*	0.000				
X16									0.012	0.007	*0.012*	0.000
X17									−0.004	−0.005	*0.004*	0.001
X18									0.002	−0.002	*0.002*	0.000
X24	−0.011	−0.005	*0.011*	0.000	−0.011	−0.004	*0.011*	0.000	−0.013	−0.005	*0.013*	0.000
X25	**0.100**	0.041	0.093	0.002	**0.100**	0.028	0.090	0.002	**0.108**	0.041	0.108	0.002
X26					**0.150**	**0.104**	0.150	0.002				
	PP		*PF*		*PP*		*PF*		*PP*		*PF*	

Light grey highlighted and bold: important; dark grey highlighted and italic: non-influential.

X7 (number of pumping stations) for RV of Alt-1, and *X11* for RV of Alt-3.

Morris screening SA indices of quantitative parameters

The calculated mean value of parameter absolute elementary effects μ^* (abscissa) was plotted against the standard deviation σ (ordinate) of the parameter elementary effect for Alt-2 TC (Figure 5). From these figures we can clearly observe the relative sensitivity (μ^*) of qualitative user-technological parameters and their linearity effect (σ). The value of μ^* was used to determine non-influential parameters. The results in Tables 4 and 5 reveal the non-influential effect of *X6* (number of disinfectant plants), *X7* (number of pumping stations) and *X11* (number of surface water tanks) for all alternatives' TC and RV. Whereas *X9* (trench depth) and *X24* (diameter distribution), which are capital cost items, were identified to be non-influential for all alternatives' TC but not for RV. This can be explained by the fact that the 50 years' lifetime of water distribution networks and transport mains leaves substantial RV in the system at the end of 20 years of consideration. In line with this, a previous study finding of small water supply systems agreed the independence of distribution system's TC on the pipe diameter, since the capital cost of pipe sizes used in the small system are relatively constant (Jagals & Rietveld 2011).

Parameter *X5* (number of boreholes) involved only in Alt-1, was found to be non-influential for TC but not for RV. On the other hand, *X12* (number of lake water extractions), *X14* (number of flocculation-sedimentation plants) and *X15* (number of surface water treatment plants) only involved in Alt-2, are determined to be non-influential for both TC and RV. From Alt-3 specific parameters, *X16*

Table 5 | SA results of alternatives' RV

	Alternatives' residual value											
	Alt-1				**Alt-2**				**Alt-3**			
Label	S_d	β	μ^*	σ	S_d	β	μ^*	σ	S_d	β	μ^*	σ
X4	**0.137**	**0.100**	0.137	0.002								
X5	**0.128**	**0.178**	0.131	0.005								
X6	0.002	0.002	*0.002*	0.000	0.002	−0.067	*0.002*	0.000	0.001	0.011	*0.001*	0.000
X7	0.029	**0.136**	*0.032*	0.013	0.012	−0.003	*0.017*	0.012	0.010	0.093	*0.017*	0.014
X8	**0.140**	0.077	0.140	0.000	**0.156**	0.091	0.157	0.002	**0.121**	**0.102**	0.121	0.001
X9	**0.140**	0.060	0.140	0.000	**0.174**	0.078	0.174	0.000	**0.150**	0.097	0.150	0.000
X10	**0.306**	**0.148**	0.306	0.000	**0.375**	**0.186**	0.385	0.009	**0.357**	**0.265**	0.357	0.000
X11	0.022	**0.152**	*0.025*	0.002	0.025	−0.149	*0.028*	0.002	0.029	**0.336**	*0.033*	0.003
X12					0.018	0.017	*0.020*	0.004				
X13					0.014	0.030	*0.014*	0.000				
X14					0.010	0.079	*0.010*	0.000				
X15					0.001	−0.011	*0.001*	0.000				
X16									0.030	0.053	*0.030*	0.000
X17									−0.009	−0.013	*0.010*	0.002
X18									0.008	0.012	*0.008*	0.000
X24	−0.074	−0.025	0.074	0.000	−0.085	−0.030	0.085	0.000	−0.050	−0.026	0.050	0.000
X25	0.000	0.000	*0.000*	0.000	0.000	0.000	*0.000*	0.000	0.000	0.000	*0.000*	0.000
X26					0.000	−0.009	*0.000*	0.000				
	PP		***PF***		***PP***		***PF***		***PP***		***PF***	

Light grey highlighted and bold: important; dark grey highlighted and italic: non-influential.

Table 6 | Summary of parameter prioritization and parameter fixing

Important (parameter)		**Non-influential (parameter fixing)**	
Global parameters			
X1[a,b]	Period of consideration		
X2[a,b]	Net interest rate		
X3[a]	Expected annual growth rate		
User-technological parameters			
X4[a]	Ground water depth	***X6***	Number of disinfectant plant
X5[b]	Number of borehole	***X7***	Number of pumping station
X8[a,b]	Pressure head	***X11***	Number of surface water tank
X9[b]	Trench depth	***X12***	Number of lake water extraction
X10[a,b]	Pipe length	***X14***	Number of flocculation sedimentation plant
X13[a]	Pump head at intake	***X15***	Number of surface water treatment plant
X19[a,b]	Borehole diameter	***X16***	Number of spring water extraction chamber
X20[a]	Kind of disinfectant	***X17***	Hydraulic conductivity
X22[a]	Kind of flocculant	***X18***	Water tank elevation
X23[a]	Number of water line	***X21***	Pump installation
Internal parameters			
X25[a]	Chlorine dosage	***X24***	Diameter distribution
X26[a]	Alum dosage		

[a] Denotes alternatives' TCs.
[b] Denotes alternatives' RVs.

(number of spring water extractions), *X17* (hydraulic conductivity) and *X18* (water tank elevation) were classified as non-influential.

It is well understood that *X25* (chlorine dosage) and *X26* (alum dosage) are operation cost items, thus both parameters are categorized as non-influential for alternatives' RV, but not for TC, where operation costs are included.

The low σ value of all technological parameters indicates the linear behaviour and no significant interaction of parameters for all alternatives' TC and RV (Tables 4 and 5).

Parameter prioritization and parameter fixing

If the parameter is classified as non-influential by Morris sensitivity indices (μ_i*), it is unlikely to be identified as an important parameter both by derivative-based and SRC sensitivity methods (Saltelli *et al.* 2008). Sensitivity indices obtained from this study were also able to prove this agreement. For a parameter to be classified as a prioritized parameter, it is enough to be identified as important either by the derivative-based or SRC method (Table 6). A parameter with low importance according to factors of prioritization does not necessarily imply the parameter to be non-influential (factor fixing). Parameter *X24* (diameter distribution) was seen to be neither important nor non-influential for all alternatives' RV (Table 5).

In general, by applying the three complementary SA methods, one internal and 10 user-technological parameters were identified as non-influential. While the analysis determined two internally fixed (i.e., chlorine dosage and alum dosage), three global and ten user-technological parameters were classified as important parameters for the LCC of water supply system.

CONCLUSIONS

Even if the result found from the three methods shows some discrepancy, reasonable input parameter sensitivity classification has been achieved by complementing the methods.

Relatively, the Morris screening method gave a better overview about parameter non-linearity and/or interactions than derivative-based or SRC methods. Parameter non-linearity/interaction is found to significantly contribute to the uncertainty of the tool output. During water supply system planning the highest attention should be placed on the accuracy of the important parameters' value. Special care is also needed for the selection of period of consideration because it interacted with most of the other parameters.

From the CLARA-SPT SA results, input parameters *X17* (hydraulic conductivity), *X18* (water tank elevation), *X21* (pump installation) and all other non-influential parameters can be fixed to a certain value without causing any significant influence on the LCC of water supply systems (Table 6). By doing this, it is possible to reduce the number of unknown variables which will help to further simplify the CLARA-SPT in the future.

In contrast, *X25* (chlorine dosage) and *X26* (alum dosage) were identified to be important, while the CLARA-SPT internally fixed them into 2 mg/l and 30 mg/l, respectively. Therefore, these two parameters should be made available as accurate values to make realistic LCC estimation of water supply systems.

In general, this study clearly shows the level of sensitivity of water supply input parameters that contributes to further improvement of CLARA-SPT computational efficiency.

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