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Risk-based prioritization of water main failure using fuzzy synthetic evaluation technique

Muhammad Al-Zahrani, Amin Abo-Monasar and Rehan Sadiq

ABSTRACT

The prioritization of water mains for renewal requires the consideration of their impact on the deterioration of water quality, in addition to their structural integrity and hydraulic capacity. The deterioration of water mains may lead to structural failure that may have grave economic impacts. This paper develops a fuzzy-based decision support system (DSS) to identify the vulnerable locations in water distribution network (WDN) that may cause overall system failure not only to compromise structural integrity, but also include failures related to water quality and hydraulic capacity. The developed DSS was applied to Al-Khobar WDN located in the eastern part of the Kingdom of Saudi Arabia. To achieve the objectives of the study, an aggregate vulnerability index representing the likelihood of system failure was developed using multi-criteria decision models. In addition, the potential impacts in terms of sensitivity index were also evaluated using advanced soft computing methods. Finally, a risk index, based on both vulnerability and sensitivity indices, was developed to help water managers to prioritize the water mains based on the overall risk of failure.

Key words | decision support system, fuzzy logic, risk, vulnerability, water supply system

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INTRODUCTION

Quantifying the risk of water quality failure requires the consideration of a multitude of factors. Physico-chemical and microbial parameters such as residual disinfectant, water temperature, turbidity, coliform and heterotrophic bacteria are regularly monitored in a water distribution network (WDN). Hydraulics data, system integrity data including pipe attributes and site-specific factors are commonly used (Sadiq *et al.* 2007). One of the challenges to quantify risk is related to the available data which are non-commensurate and require a rational aggregation scheme. In addition, many of these required data are sometimes missing or known vaguely only, accordingly, the risk prioritization provides an alternative of a comparative scheme for failure indices.

Risk prioritization is defined as the prioritization based on the relative intensity of what is important to people or the ranking based on consequence, importance, or urgency (EFSA 2012). Risk prioritization develops the ranking based on predefined risk factors, acceptable thresholds, professionals' judgments, and other qualitative measures. This approach can guide decision-makers to propose solution(s) for complex systems under critical conditions as well as help to identify the factors which will have significant impact and consequences on the overall system.

Failure risks may occur due to high vulnerability and sensitivity of the system. Condition of the WDN as well as the surrounding environment plays a vital role in determining the vulnerability of the WDN to potential intrusion. Pipe age, diameter, length, number of breaks, material type, corrosivity of the soil, and the presence of complex transportation systems above the WDN were investigated to study their effect on the overall vulnerability of the system (Sadiq *et al.* 2006; Christodoulou & Deligianni 2010; Deng *et al.* 2011). In addition to the physical factors of the system, operational parameters such as the hydraulics of the system and water quality may increase vulnerability

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risk failure like low/negative pressures in the network and insufficient disinfectants (Sadiq *et al.* 2008; Fares & Zayed 2010). On the other hand, the sensitivity of the system to failure in vulnerable zones depends on end consumer(s) such as population distribution, presence of hospitals, schools, etc. (Francisque *et al.* 2009). However, developing the overall risk of vulnerability and sensitivity of a WDN faces different challenges, such as the high number of factors affecting the WDN, different natures of data (numerical and non-numerical), and quantifying failure risk index. Accordingly, fuzzy rule-based (FRB) methods and analytical hierarchical process (AHP) were used to aggregate different types of data based on predefined standards as well as expert judgment (Khan & Sadiq 2005; Kleiner *et al.* 2006; Halfawy *et al.* 2008; Guney & Sarikaya 2009).

Many studies have been conducted to investigate the risk of failure in water distribution systems (WDSs) using FRB methods. Mamlook & Al-Jayyousi (2003) proposed a decision support system (DSS) for detecting leakage in the WDN using fuzzy set analysis. Sadiq *et al.* (2004a) applied fuzzy-based method to investigate the effect of soil corrosivity on water main deterioration. Using fuzzy-based method, they were able to classify the soil into: virtually not corrosive, slightly corrosive, corrosive, and highly corrosive. Sadiq *et al.* (2004b) proposed a methodology for developing a DSS to quantify failure risk of water quality in WDN caused by aging water mains. In the literature, different approaches have been used by several researchers to investigate risk-based decisions for WDSs (Sadiq & Rodriguez 2004; Sadiq *et al.* 2004c, 2007; Francisque *et al.* 2009; Fares & Zayed 2010).

In general, data of complex systems such as WDNs can be divided to be either precise or imprecise. While the precise data are required by computers to solve problems, imprecise human reasoning is widely used for understanding scientific concepts and theories. These techniques might not be able to solve problems which require high precision, but on the other hand they can provide a preliminary understanding of complex systems and prioritization of risks. In addition, WDN systems are highly complex systems in which the interactions and behavior between their components and surrounding might not be fully controlled and understood. In such cases, fuzzy systems are preferred when fast and approximate solutions are needed, which is the case for risk prioritization of WDN (Ross 2009). Further details about fuzzy systems and their applicability to complex systems are available in the literature (Wang 1999; Ross 2009). Accordingly, fuzzy synthetic evaluation (FSE) was used in this study.

The aim of this study is to develop a DSS for Al-Khobar WDN which can be used for other networks, that can help to identify the regions within the WDN that may be affected by gradual or rapid deterioration of water quality and risk failure in terms of system vulnerability and sensitivity. Factors relevant to system vulnerability, such as hydraulics of the system, structure integrity, and water quality, were investigated in the study, in addition to system sensitivity based on factors like population distribution, standard of living, activities, and distribution of schools and hospitals. These factors were used to develop the overall risk index for Al-Khobar WDN.

PROPOSED FRAMEWORK

The developed DSS based on the proposed framework will be capable of estimating the risk indices for a wide variety of factors affecting the WDN, including water quality, infrastructure, and population distribution as well as human and industrial activities. The DSS is capable of showing daily, monthly, and annual indices for hydraulics, water quality, structure integrity, vulnerability, sensitivity, and risk.

Figure 1 provides the framework for the DSS to determine indices for vulnerability, sensitivity, and risk. The framework consists of five levels or generations of factors aggregated in hierarchical fashion. The top of the pyramid represents the risk that depends on two factors, i.e., vulnerability and sensitivity in the fourth level. These two factors are determined through aggregation of various factors in the lower levels. The factors or attributes in the first and second levels are referred to as ‘input factors’ since their data are directly available or can be derived.

The vulnerability index is calculated using factors related to hydraulics, structural integrity, and water quality pumped through the WDN. For hydraulics, water age, pressure, and velocity are used, whereas for structural integrity, the required data include pipe material, pipe age, water table levels, type of soil surrounding the pipes, pipe breaks,

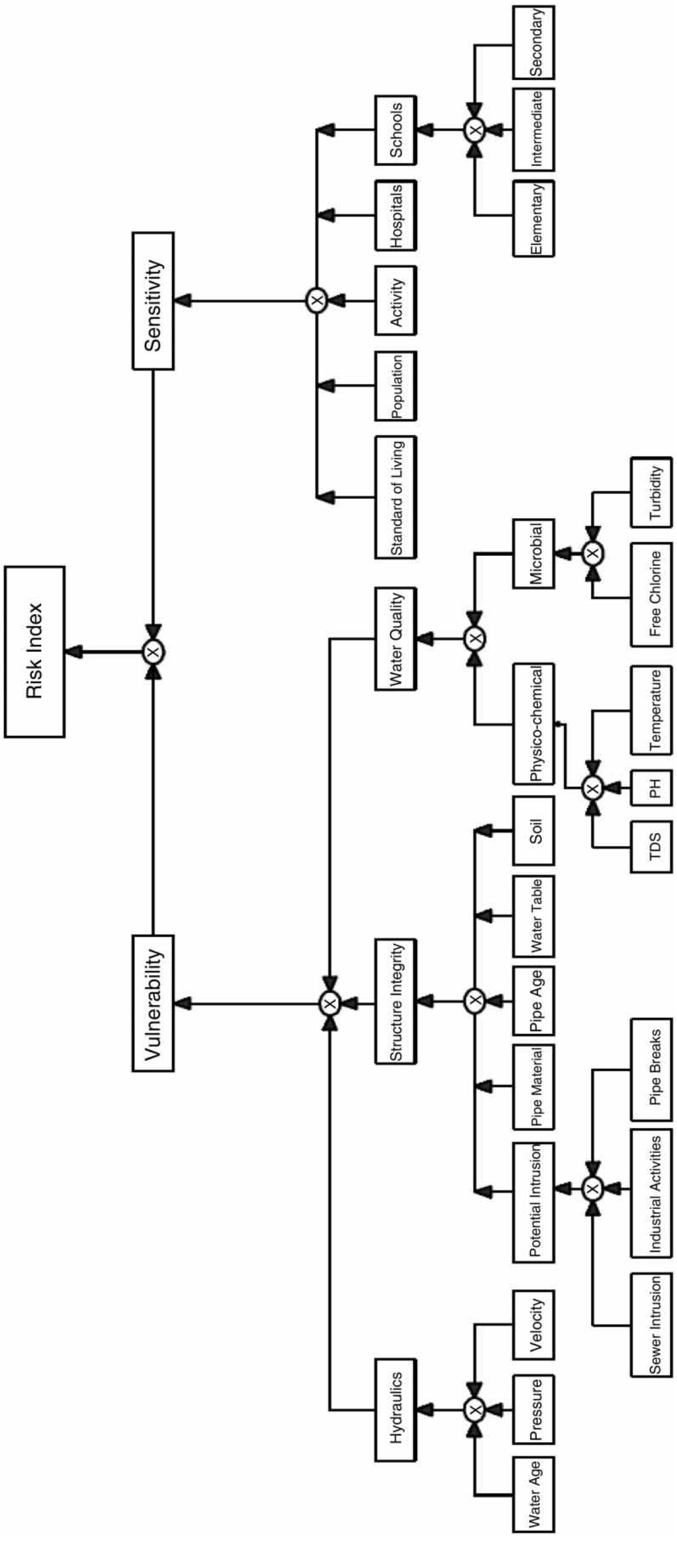

Figure 1 | Risk index for prioritization of water mains.

and potential intrusions from surrounding industrial activities and sanitary systems. For water quality, two sub-factors, including physico-chemical and microbial parameters, are considered in the second level. Each of these factors is further divided into sub-input factors in the first level. Temperature, pH, and total dissolved solids (TDS) are used for the evaluation of physico-chemical water quality, whereas free residual chlorine and turbidity are used for the evaluation of microbial water quality.

The sensitivity index is linked to the presence of certain groups of consumers served by the WDN, who may be harmed seriously if any deterioration of water quality in the WDN occurs. Five input factors, including standard of living, population density, activity, capacity of hospitals and schools in the specified sector are used to characterize sensitivity index.

Each attribute has a fuzzy set which was developed based on the characteristics of the attributes as shown in Figure 2. Table 1 summarizes the fuzzy sets boundaries for all 'level one' attributes. Triangular and trapezoidal fuzzy shapes were used in this study. The attributes' limits, when developing the fuzzy sets, were identified based on the regulatory limits and standards of each attribute published in the literature (AWWA 2002; Sarbatly & Krishnaiah 2007; Francisque et al. 2009; USEPA 2009; WHO 2011) and the operational standards adopted by Al-Khobar WDN authority.

The development of the fuzzy sets, membership functions, and risk indices can be illustrated according to the following four steps.

Fuzzification

Fuzzification is the process by which the attributes with numerical and non-numerical data are converted into a homogenous scale between 0 and 1, by assigning memberships with respect to predefined fuzzy subsets (Lu et al. 2006). Figure 3 can be used to illustrate the fuzzification for TDS, where the input value is 450 ppm (crisp real value). Using triangular membership functions in which their boundaries and structure were constructed using water quality standards and thresholds from literature, crisp TDS values were transformed into fuzzy subsets 'low', 'med', and 'high' and memberships [$\mu_{low}, \mu_{med}, \mu_{high}$].

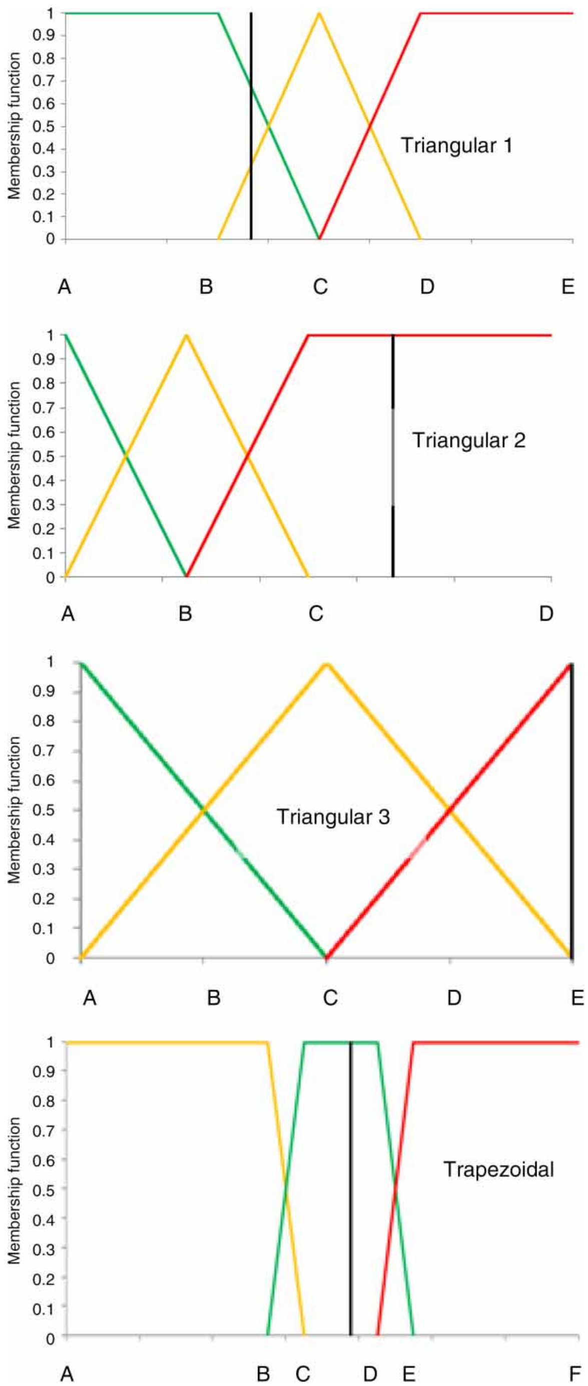

Figure 2 | Shapes of fuzzy sets.

According to the membership functions and fuzzy sets in Figure 3, a TDS value of 450 ppm can be presented after fuzzification as [0.25, 0.75, 0], which implies that the membership of the crisp value (450 ppm) is 0.25 to the

Table 1 | Fuzzy sets' thresholds and types

		Thresholds						
Parameter	**Nature of fuzzy set**	**A**	**B**	**C**	**D**	**E**	**F**	**Type**
TDS	*Data (ppm)*	0	300	500	700	∞		Triangular 1
	Optimal diversions (%)	0	25	50	100			Triangular 2
Temperature	*Data (°C)*	0	20	25	30	100		Triangular 1
	Optimal diversions (%)	0	25	50	100			Triangular 2
pH	*Data*	0	5.5	6.5	8.5	9.5	14	Trapezoidal
	Optimal diversions (%)	0	25	50	100			Triangular 2
Free chlorine	*Data (ppm)*	0	0.2	0.3	1.2	1.3	∞	Trapezoidal
	Optimal diversions (%)	0	25	50	100			Triangular 2
Turbidity	*Data (NTU)*	0	0.5	0.8	1	∞		Triangular 1
	Optimal diversions (%)	0	25	50	100			Triangular 2
Pipe type	Percentage of badness	0	25	50	75	100		Triangular 3
Potential industrial intrusion	Percentage by area	0	25	50	75	100		Triangular 3
Pipe age	Average age	0	20	30	40	60		Triangular 2
Pipe break	Breakage ratio	0	0.25	0.5	0.75	1		Triangular 3
Schools	No. of elementary students	0	709	1,418	2,835	∞		Triangular 1
	No. of intermediate students	0	317	633	1,266	∞		Triangular 1
	No. of secondary students	0	273	546	1,092	∞		Triangular 1
Hospitals	No. of beds	0	40	80	120	160	∞	Triangular 2
Pressure	Nodes with low and high pressure (%)	0	25	50	100			Triangular 2
	Optimal diversions (%)	0	25	50	100			Triangular 2
Velocity	Pipes with low and high velocity (%)	0	25	50	100			Triangular 2
	Optimal diversions (%)	0	25	50	100			Triangular 2
Water age	Nodes with high water age	0	25	50	100			Triangular 2
	Optimal diversions (%)	0	25	50	100			Triangular 2
Population	Population density	0	9,420	18,840	300,000			Triangular 2
Sewer system coverage	Percentage of area not covered by sewer system	0	25	50	75	100		Triangular 3
Water table	Dry-wet pipes (%)	0	25	50	100			Triangular 2

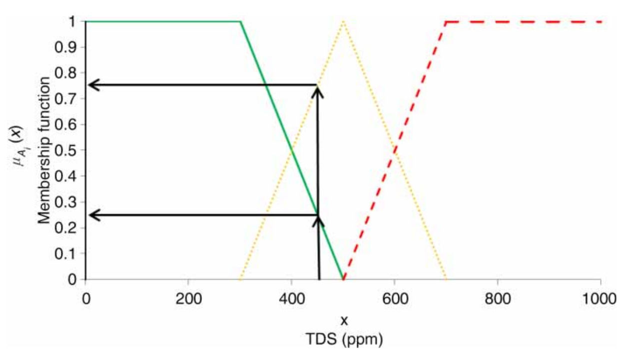

Figure 3 | TDS fuzzy set.

'low' fuzzy subset, 0.75 to the 'med' fuzzy subset, and does not have any membership to the 'high' fuzzy subset (Lu *et al.* 2006). For all child attributes, a similar procedure is applied to develop the fuzzy subsets for each parameter. The parent attribute is developed by aggregating the fuzzified child attributes. Consider a parent attribute with three child attributes A, B, and C that follow the Triangular-1 fuzzy shape such that each child attribute will have three membership functions.

Analytical hierarchical process

Saaty (1982) proposed AHP for decision analysis method. The AHP is a multi-criteria decision-making approach which can be used to solve complex decision problems. The approach uses a multi-level hierarchical structure of objectives, criteria, subcriteria, and alternatives (Saaty 1982, 1990). After developing the hierarchical structure shown in Figure 1, prioritizing the elements, which is an essential component of the AHP, needs to be set to relative importance weights for all attributes in the system. The relative importance of children attributes comprising parent attribute are not equal and, therefore, weighting criteria are required to define the degree of belonging and the effect of each child attribute on its parent attribute. Figure 4 shows a schematic diagram for parent and children attributes. Parent attribute has three children attributes A, B, and C. These children attributes comprise the parent attribute, but may not have equal relative importance, weights, and degree of belonging to the parent attribute. Based on the relative importance of children attributes, a weight for each of the children attributes is defined. These weights are normalized to unity (Chu *et al.* 1979; Sadiq *et al.* 2004b; Francisque *et al.* 2009; Ross 2009).

Saaty (1982) developed a scaling, ranking, and prioritizing scheme for AHP. Table 2 shows the scale for pairwise comparison between elements to determine the relative importance, degree of belongings, and finally, weights for each element.

Recall Figure 4 and assume that there are three child elements A, B, and C. To determine their relative importance, first, the reciprocal matrix should be constructed to show pairwise comparisons between these three elements according to the scale summarized in Table 2.

Table 3 shows the general form of reciprocal matrix, where d, e, and f are relative importance scales ranging from 1 to 9 as presented in Table 2. Suppose element A is more important than element B by scale of d, element A is more important than element C by scale of e, and element B is more important than element C by scale of f. Accordingly, element B is more important than element A by the reciprocal of the importance of A over B, i.e., $(1/d)$ and so on.

Suppose d, e, and f are equal to 4, 6, and 2, respectively, as shown in Table 4. To normalize the matrix, each column entry will be divided by the total of that column as shown in Table 5. Finally, the average of each row of the normalized

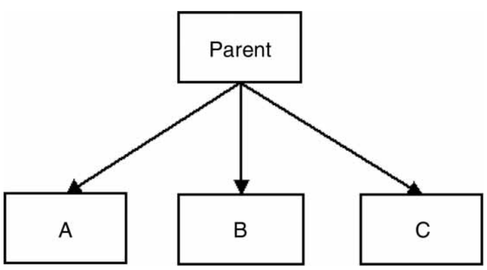

Figure 4 | Parent–child attributes.

Table 2 | Pairwise comparison scale (Saaty 1982, 1990)

Importance	Definition	Explanation
1	Equal importance of both elements	Two activities contribute equally to the objective
3	Weak importance of one element over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance of one element over another	Experience and judgment strongly favor one activity over another
7	Demonstrated importance of one element over another	An element is strongly favored over another and its dominance is demonstrated in practice
9	Absolute importance of one element over another	The evidence favoring one element over another is of highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgments	Comparison is needed between two judgments

Table 3 | General form for reciprocal matrix

Element	A	B	C
A	1	d	e
B	$1/d$	1	f
C	$1/e$	$1/f$	1

Table 4 | Illustration for reciprocal matrix

Element	A	B	C
A	1	4	6
B	1/4	1	2
C	1/6	1/6	1
Column total	1.42	5.50	9.00

Table 5 | Normalization of reciprocal matrix

Element	A	B	C
A	$\frac{1}{1.42}$	$\frac{4}{5.50}$	$\frac{6}{9.00}$
B	$\frac{1/4}{1.42}$	$\frac{1}{5.50}$	$\frac{2}{9.00}$
C	$\frac{1/6}{1.42}$	$\frac{1/2}{5.50}$	$\frac{1}{9.00}$

matrix is calculated to find the weights as follows (Saaty 1982, 1990):

$$W_A = \frac{\frac{1}{1.42} + \frac{4}{5.50} + \frac{6}{9.00}}{3} = 0.70$$

$$W_B = \frac{\frac{1/4}{1.42} + \frac{1}{5.50} + \frac{2}{9.00}}{3} = 0.19$$

$$W_C = \frac{\frac{1/6}{1.42} + \frac{1/2}{5.50} + \frac{1}{9.00}}{3} = 0.11$$

$$W_{\text{Parent}} = \begin{bmatrix} W_A \\ W_B \\ W_C \end{bmatrix} = \begin{bmatrix} 0.70 \\ 0.19 \\ 0.11 \end{bmatrix}$$

Aggregation

Aggregation is the process by which fuzzy sets representing the outputs for each child element $[\mu_{\text{low}}, \mu_{\text{med}}, \mu_{\text{high}}]$ are combined or aggregated to produce a single output for the group of elements (parent fuzzy set output) (MathWorks 2012).

Fuzzy sets produced from fuzzification for all elements (A, B, and C) and weights calculated for each element were used to determine the aggregated fuzzy set for parent group using matrix multiplication (Sadiq & Rodriguez 2004; Francisque *et al.* 2009). For a hierarchical system of a parent attribute with three child attributes, the fuzzy sets for all child elements after fuzzification will be as follows:

$$\begin{bmatrix} \mu^A_{\text{low}} & \mu^A_{\text{med}} & \mu^A_{\text{high}} \\ \mu^B_{\text{low}} & \mu^B_{\text{med}} & \mu^B_{\text{high}} \\ \mu^C_{\text{low}} & \mu^C_{\text{med}} & \mu^C_{\text{high}} \end{bmatrix} \quad (1)$$

Therefore, the parent fuzzy set can be represented by matrix multiplication as:

$$\begin{bmatrix} \mu^{\text{Parent}}_{\text{low}} & \mu^{\text{Parent}}_{\text{med}} & \mu^{\text{Parent}}_{\text{high}} \end{bmatrix} = [\, w_A \quad w_B \quad w_C \,] \times \begin{bmatrix} \mu^A_{\text{low}} & \mu^A_{\text{med}} & \mu^A_{\text{high}} \\ \mu^B_{\text{low}} & \mu^B_{\text{med}} & \mu^B_{\text{high}} \\ \mu^C_{\text{low}} & \mu^C_{\text{med}} & \mu^C_{\text{high}} \end{bmatrix} \quad (2)$$

This parent fuzzy set produced from matrix multiplication in Equation (2) was used in further calculations. This fuzzy set was considered as the parent element in the current level, but was also considered as a child element in the upper level in the AHP, where the same process was repeated until the final risk fuzzy set was produced as indicated in Figure 1.

Defuzzification

The process by which output fuzzy sets $[\mu_{\text{low}}, \mu_{\text{med}}, \mu_{\text{high}}]$ are mapped into crisp value rather than membership function is called defuzzification (Leekwijck & Kerre 1999). It is the opposite of fuzzification; while fuzzification converts crisp values into fuzzy sets, defuzzification uses fuzzy sets to calculate single crisp value (Ross 2009). There are several methods to defuzzify fuzzy sets, such as the first maximum, the last maximum, the mean of the maximum, the center of the area, weighted average, and others. Weighted average method or scoring is preferred by many researchers (Lu *et al.* 1999; Silvert 2000; Francisque *et al.* 2009), especially in environmental applications. According to the weighted average method, to convert the fuzzy sets into crisp value, each fuzzy set will be multiplied by a constant weight and the product summation is the crisp value as follows:

$$\text{Crisp value (Risk Index)} = (a \times \mu_{\text{low}}) + (b \times \mu_{\text{med}}) + (c \times \mu_{\text{high}}) \quad (3)$$

where a, b, and c are weights for each fuzzy set.

In this study, since there are only three fuzzy sets, 'low', 'med' and 'high', weights of 0, 0.5, and 1 were suggested for a, b, and c, respectively (Francisque *et al.* 2009).

One of the objectives of this study was to develop an interactive DSS tool, which can be used by water authorities to prioritize risks in real time. The operator has to update the DSS tool with daily or weekly water quality and hydraulic data to prioritize risks between different regions in the WDN.

APPLICATION OF DSS FOR AL-KHOBAR CITY

Al-Khobar city is located on the eastern coast of Saudi Arabia. It has an area of approximately 64 km^2 with a population of about 457,000 in 2004 and expected to reach 814,000 in 2025 (MEP 2010). This increase in population as well as the comprehensive development has resulted in a tremendous increase in water consumption. Water demand in Al-Khobar city has increased from 35.60 million cubic meters (MCMs) in 1990 to 58.52 MCM in 2002 and is expected to reach 111.95 MCM by the year 2020 (Al-Zahrani 2014).

Al-Khobar city is served with a WDN that covers all urban areas as shown in Figure 5. The total length of the network is approximately 472,652 m. The network consists of pipes with different materials and diameters ranging from as small as 50 mm to a maximum of 1 meter. Figure 6 shows the skeleton for Al-Khobar WDN.

Al-Khobar WDN was divided into several sub-regions in order to prioritize and characterize risk assessment associated with them. Since it is impractical to test water quality at every node in the city, the WDN was divided into different regions using Thessien method based on the locations of the current monitoring stations. It is assumed that water quality within each region is similar to the water quality of the monitoring station. A similar approach was applied by Francisque et al. (2009). The number assigned to each of the sub-regions corresponds to the monitoring station number within the sub-region assigned by Al-Khobar water authority. For example, sub-region 94 is named after monitoring station number 94.

Hydraulics

The WDN was modeled hydraulically and calibrated using WaterGEMS (Bently Systems 2006). More details regarding the network construction, calibration, and simulation can be found in Al-Zahrani (2014). For the sake of DSS development, simulations were performed to estimate three hydraulic variables, namely pressure, velocity, and water age.

In Al-Khobar WDN, there is only one central pumping station and two elevated tanks to maintain operational pressure head in the WDN, which ranges between 5 and 35 m. Al-Khobar water authorities defined the minimum pressure to be not less than 5 m. Figure 7(a) shows the simulated average pressure head for all demand scenarios and patterns from the calibrated hydraulic model of each one of the sub-regions of Al-Khobar WDN. The average maximum pressure varies between 13 and 41 m, while the average minimum pressure varies between 7 and 31 m, as shown in Figures 7(b) and 7(c), respectively. The highest pressure in the city as revealed from the figure occurred at the city center, especially in sub-region 94 and its surroundings, since the main pumping station is located in this sub-region. The results indicate that the pressure decreases for sub-regions away from the center, but it does not violate the minimum

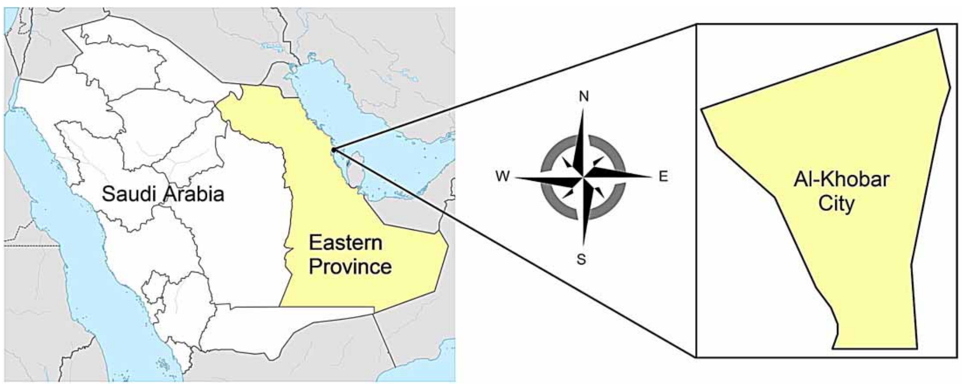

Figure 5 | City of Al-Kohbar, Saudi Arabia.

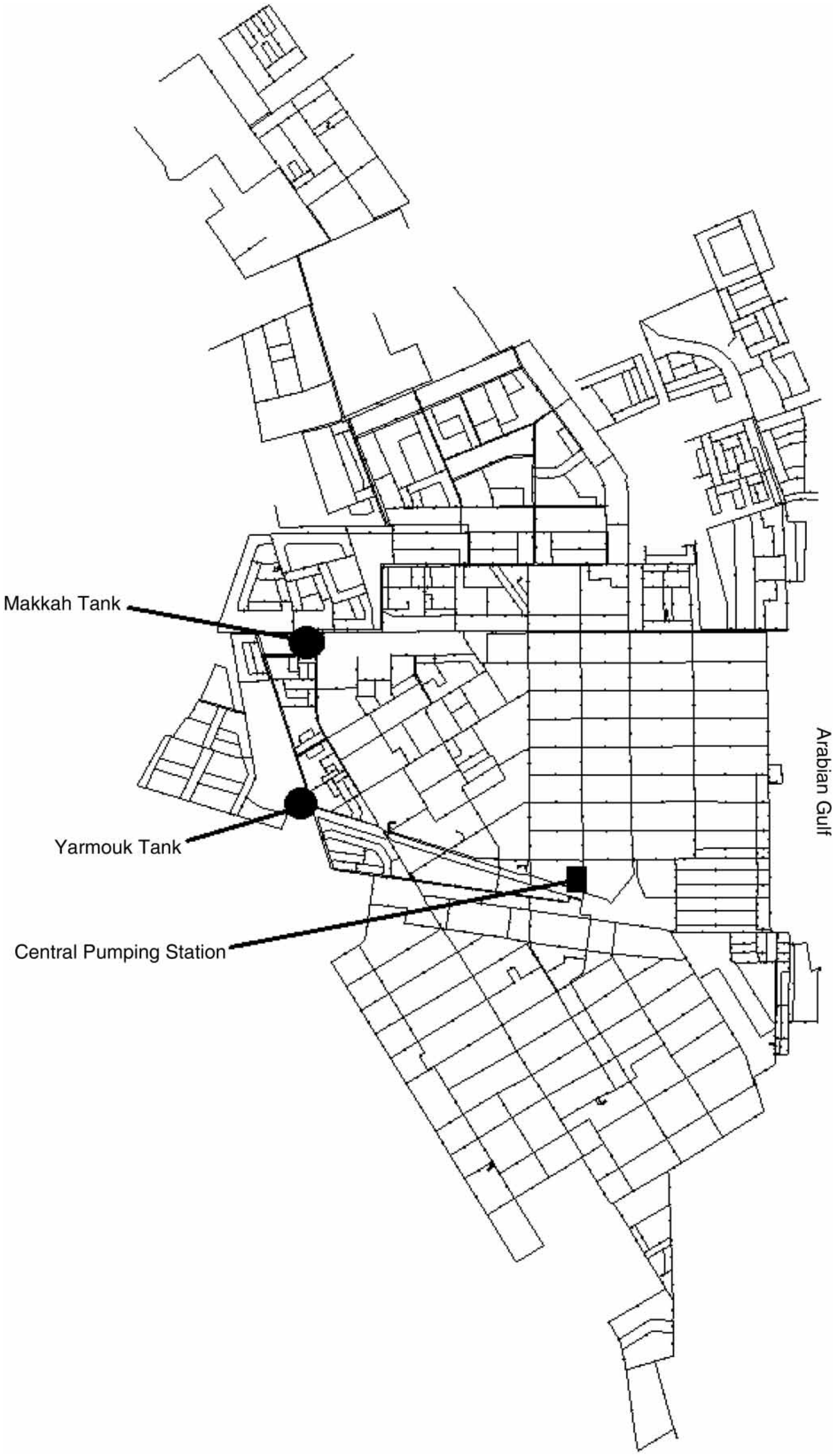

Figure 6 | Skeleton of Al-Khovar WDN.

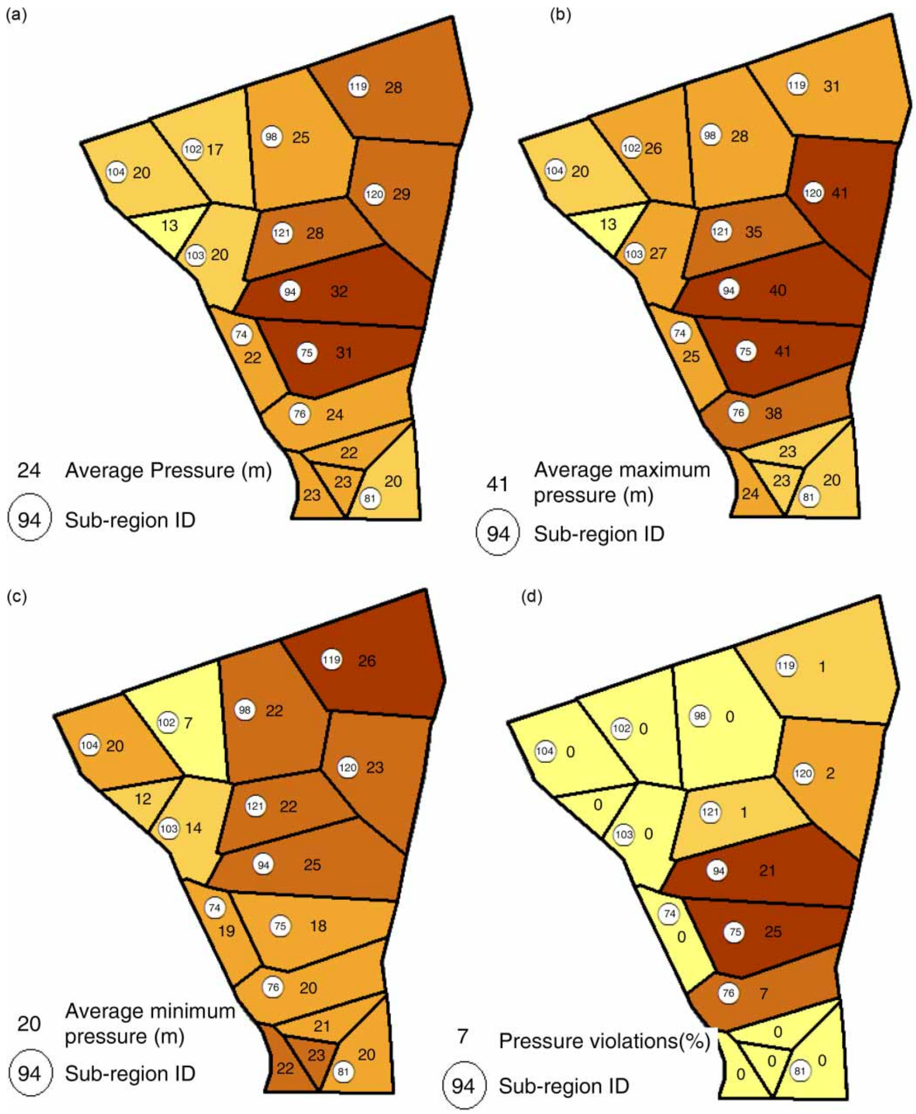

Figure 7 | Pressure head characteristics: (a) average pressure, (b) average maximum pressure, (c) average minimum pressure, and (d) percentage of nodes having pressure violating upper and lower limits.

acceptable pressure set by the water authorities (5 m) as indicated in Figures 7(a) and 7(c). Analysis of the pressure head of approximately 1,000 nodes shows that the percentage of nodes in each sub-region, violating the upper or lower pressure limits, based on all conducted scenarios, was less than 25%. Figure 7(d) shows regional percentages of nodes exceeding the pressure limits. It is clear that the sub-regions surrounding the central pumping station, i.e., sub-region 94, showed the highest percentages of pressure violations. Away from sub-region 94, pressure violations decrease until they reach almost zero in most of the sub-regions.

Similar analysis for both velocity and water age was performed. For the velocity, the results show that most of the pipes violating the recommended velocity range of 0.6 to 1.5 m/s (Gupta 2008) are those having low velocity, indicating that there is a high possibility for sedimentation to accumulate in the pipes due to low velocity. On the other hand, water age is recommended to be less than 1.3 days (AWWA 2002). For Al-Khobar WDN, it was observed that water age was always less than the recommended standard and, accordingly, the percentage of junctions having water age higher than the standard is zero.

Pressure, velocity, and water age represent the hydraulic characteristics of the WDN in the DSS. In general, the analysis indicates that the hydraulic properties for most of the sub-regions are within the acceptable limits. Figure 8(a) shows the risk index for hydraulic properties for all the sub-regions. Sub-regions 75 and 94 show a high hydraulic risk index of 0.80 and 0.75, respectively, while other sub-regions have a hydraulic risk index of less than 0.31. The calculated hydraulic risk index at sub-regions 75 and 94 was found to be high compared to other sub-regions, which is attributed to the existence of the central pumping station in sub-region 94, which increases the pressure head and causes the pressure to violate the recommended limits at these sub-regions and, consequently, increases the hydraulic risks at these sub-regions.

Structure integrity

The structure integrity part of the risk index was developed by aggregating the potential intrusions, pipe materials, pipes age, water table levels, and soil surrounding the pipes, as shown in Figure 1. Al-Khobar water authority has detailed records for the infrastructure and structure integrity factors used in the DSS framework. These records were used as input data for the DSS. Based on the DSS, there are three factors controlling the potential intrusions, i.e., sewer intrusion, industrial intrusion, and pipe breaks. The major factors that have significant influence on the potential intrusion risk index are pipe break ratios and industrial intrusions. The contribution of sewer intrusions to the risk index is almost negligible since the whole city of Al-Khobar is served with a sanitary sewer system, which reduces the chances of sewer intrusion to the minimum level compared to situations where sewage is dumped underground.

In general, the pipe material of Al-Khobar WDN is either asbestos or PVC except for a small portion of the network located north of the city where pipes are made of steel. Cracks and breakages have been widely reported in asbestos pipes in the city. According to Al-Khobar water authority, approximately 65% of the total breaks occurred in asbestos pipes. Asbestos is considered to be a carcinogenic material, although the risk of using it in water pipes is not substantial (Morris 1995). Due to the fact that asbestos is a carcinogenic material, then the higher percentage of asbestos pipes in a sub-region, the higher is the risk index for that region in terms of pipe material attribute.

Pipe material, age, breaks, sanitary coverage, industrial and wastewater intrusions, water table levels, and soil surrounding the pipes provide a clear view about the infrastructural condition of the WDN. Figure 8(b) shows the structure integrity risk index, which ranges between 0.18 and 0.63. As expected, sub-regions in the southern

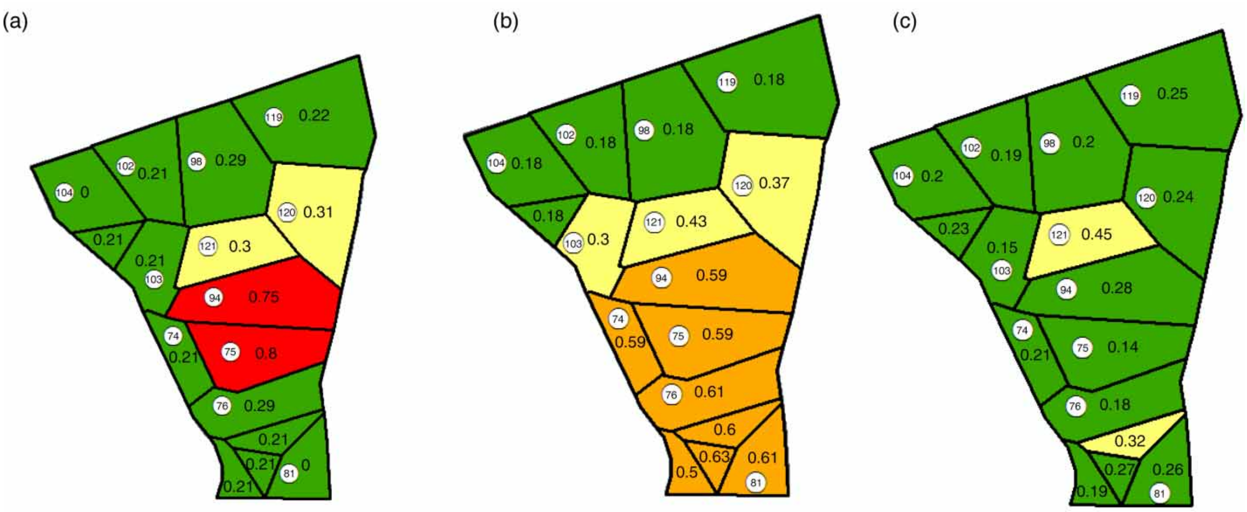

Figure 8 | Risk index for: (a) hydraulic properties, (b) structural integrity, and (c) water quality.

part of the city have a higher risk index compared to the city center and the northern part. Sub-regions in the north, such as 98 and 119, have PVC pipes, relatively newer pipes, low pipe breakage ratio and no industrial activity or potential intrusions (either industrial or wastewater), which explains the relatively low risk in these sub-regions. On the other hand, sub-regions in the south, i.e., 79 and 82, have asbestos pipes, aged pipes, high pipe breakage ratio, and industrial potential intrusions, which explains the higher risk index.

Water quality

In this study, the characteristics of water quality transported in the network, which include physico-chemical and microbial properties, were investigated based on the historical records provided by Al-Khobar water authorities for about ten months (daily records). According to WHO (2011), the TDS concentration exceeds 1,000 ppm, which makes the water significantly and increasingly unpalatable. Furthermore, TDS values higher than 500 ppm resulted in excessive scaling in water pipes. Available TDS data for Al-Khobar WDN indicate low values except for sub-region 81 where the average TDS level is 2,129 ppm, which is the highest throughout the city, since most of the pumped water in this sub-region is groundwater. The central part of Al-Khobar has low TDS level ranging between 250 and 500 ppm. Unlike TDS, pH levels seem to be consistent all over the WDN with values ranging between 7 and 8, which represent the optimal pH level (WHO 2011).

Based on the fuzzy analysis for TDS, pH, and temperature, the distribution of risk index for physico-chemical properties is shown in Figure 9(a). In general, the risk index associated with physico-chemical parameters ranges between 0.11 and 0.31, which is relatively low. Results indicate that sub-regions with relatively high TDS levels are the same sub-regions with relatively high risk in terms of physico-chemical properties.

Microorganisms in drinking water are generally controlled by the injection of disinfectant (usually chlorine) at distribution systems. Residual chlorine was used as an indicator of chlorine level in the network. The optimal level of free chlorine at any location and any time should range between 0.2 and 2 mg/L (WHO 2011). Analysis of free chlorine data indicates that the majority of the sub-regions of Al-Khobar city are within the acceptable limit and no significant violations were observed.

Turbidity is another indicator of water quality. WHO (2011) recommends that the turbidity of water in a WDN should range between 0.1 and 5 NTU, depending on the size of the network and preferably not exceeding 1 NTU

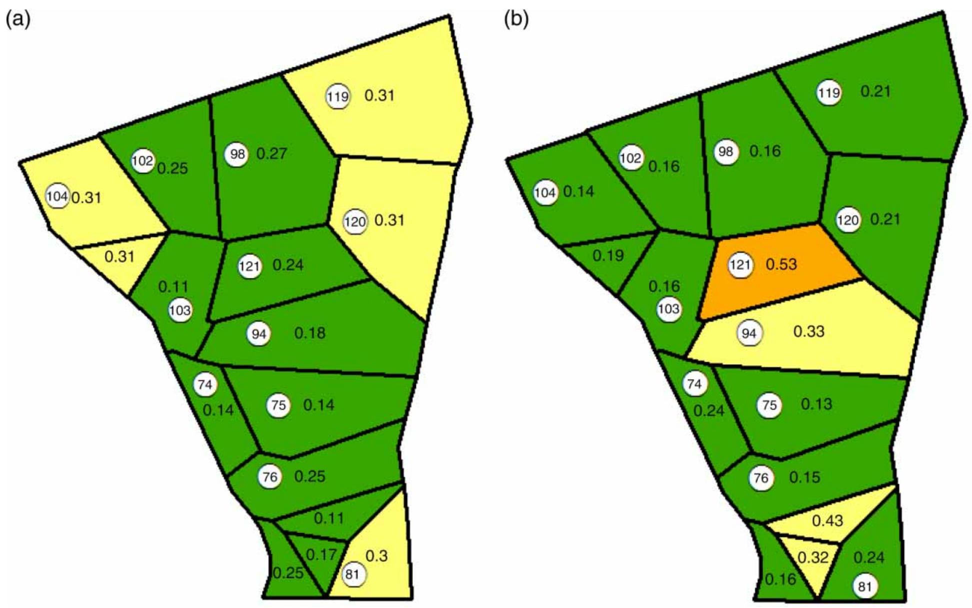

Figure 9 | Risk index for: (a) physico-chemical properties and (b) microbial properties.

(USEPA 2009). In Al-Khobar city, regional turbidity did not exceed 0.29 NTU.

Based on the analysis and aggregation of free chlorine and turbidity, microbial risk distribution was developed. Figure 9(b) shows the microbial risk index for each sub-region. Since turbidity is consistent throughout the city, residual chlorine plays a vital role in controlling the prioritization of risks between sub-regions. It can be seen from Figure 9(b) that the microbial risk index is relatively low. Accordingly, the water quality risk index for each sub-region was aggregated based on the physico-chemical and microbial indices as shown in Figure 8(c). The results show that the regional water quality risk indices range between 0.14 and 0.45, which indicates relatively low risk.

Vulnerability index

The vulnerability of the WDN is identified by aggregating hydraulic properties, water quality, and structural integrity. The aggregation of these factors will develop the vulnerability index for the WDN, as shown in Figure 10(a). As can be revealed from the figure, the vulnerability index ranges between 0.12 and 0.54. The results indicate that most of the sub-regions have moderate to low vulnerability except for sub-regions 75 and 94 which have a relatively high vulnerability.

Major factors affecting vulnerability are hydraulic properties and structure integrity since water quality risk index is low throughout the city. Sub-regions which have high risk due to hydraulic properties and structure integrity, i.e., sub-regions 75 and 94, are the sub-regions in the city center which have high vulnerability. Sub-regions in the north, such as 98 and 102, have low risk in terms of hydraulic properties and structure integrity, which is reflected in the vulnerability index. Sub-regions in the extreme south of the city, such as sub-regions 77 and 82, have low risk index due to hydraulic properties, but they have high risk index due to structure integrity, which explains why vulnerability

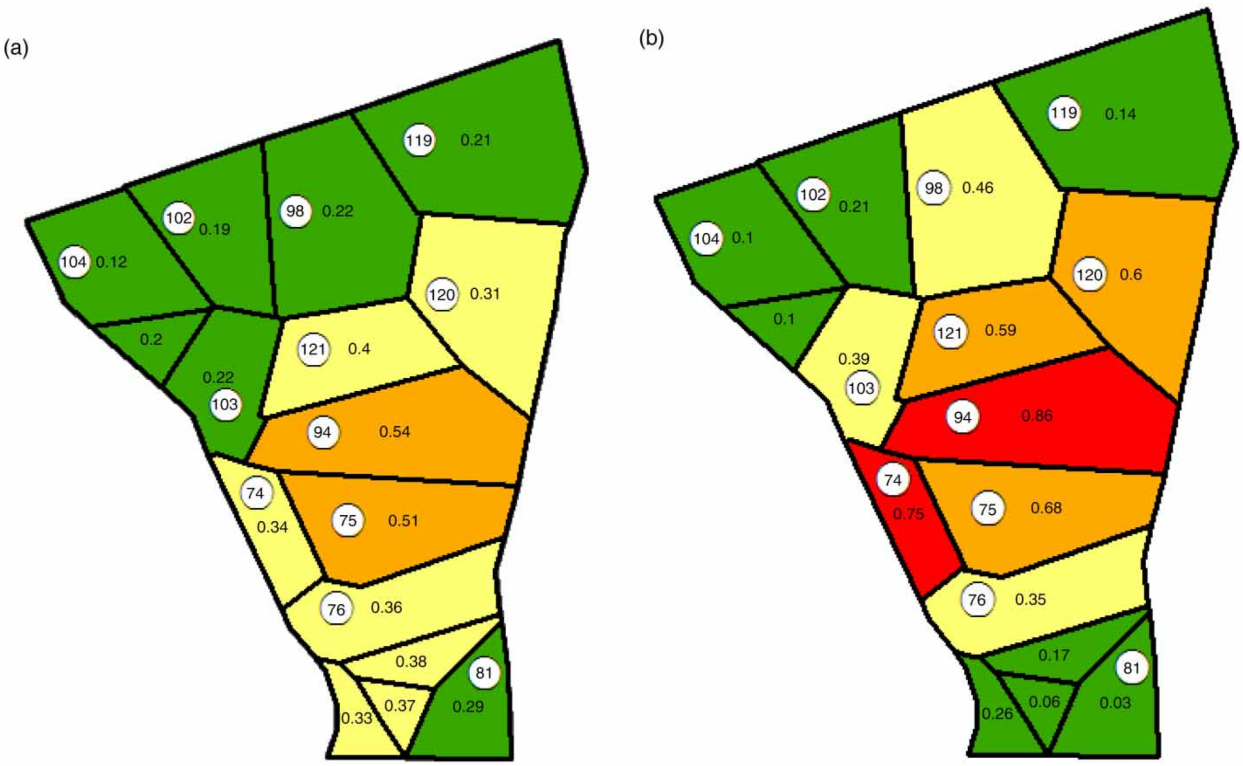

Figure 10 | Al-Khobar WDN indices for: (a) vulnerability and (b) sensitivity.

indices in that zone are higher than northern sub-regions but at the same time less than the sub-regions in the city center.

Sensitivity index

Sensitivity of the sub-region can provide a sense of possible consequences and casualties in the case that anything goes wrong in the WDN. Standard of living, population density, type of activity, number of beds in hospitals, and number of students are measures for regional sensitivity in the case any possible deterioration of water quality, hydraulics, or structure integrity occurs within the WDN. An aggregation of all these factors will determine the sensitivity of each sub-region. Fuzzy methods were used to aggregate these factors to determine sensitivity prioritization for different sub-regions in the city as shown in Figure 10(b). As can be revealed from the figure, sensitivity index was found to range between 0.03 and 0.86. Sub-regions located in the center of the city, such as 74, 75, 94, and 121, are more sensitive to any deterioration of water quality in the WDN. On the other hand, sub-regions in the north and in the south, such as 81, 82, 102, and 119, have the least sensitivity, mainly because they have low population density, low number of students, and a small proportion of residential areas.

Total risk

The overall risk index for each sub-region was developed by aggregating vulnerability and sensitivity indices. Overall risk indices range between 0.11 and 0.70 as shown in Figure 11. In general, the results indicate that northern and southern sub-regions have the least risk index, which is a reflection of the low vulnerability and sensitivity of these sub-regions. Sub-regions in the city center are the most sensitive sub-regions in the city due to the high concentration of population, schools, and residential areas. On the other hand, central regions are also the most vulnerable, especially sub-regions 75 and 94, as shown in Figure 10(a). This explains the relatively high risk in the city center compared to the other sub-regions of the city. Table 6 summarizes the risk indices for all sub-regions in the Al-Khobar network. It is clear that

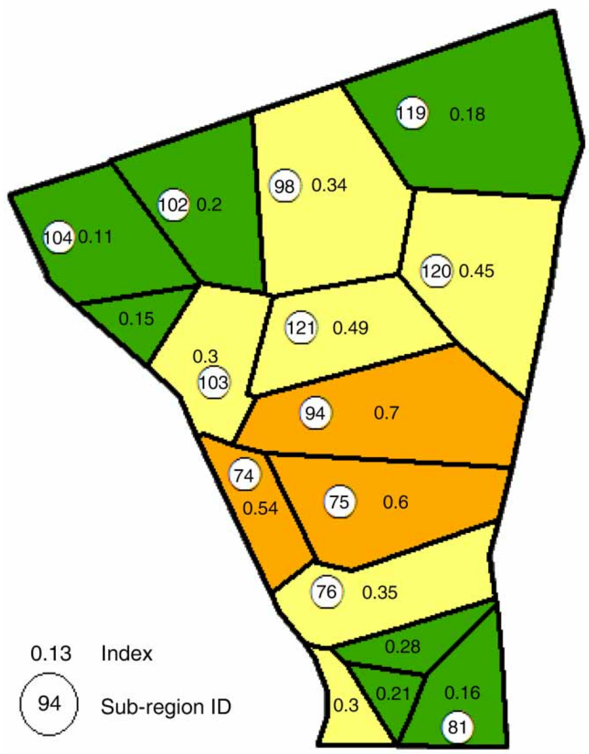

Figure 11 | Total risk index for each sub-region.

sub-regions 75 and 94 have high risk indices, such as pressure index, velocity index, hydraulics index, schools index, activity index, standard of living index, population density index, and, finally, vulnerability and sensitivity indices. On the other hand, sub-regions 102 and 104 have low risk indices for most of the indices. This implies that the total risk index reflects the general condition of each sub-region in terms of hydraulics, structure integrity, water quality, and sensitivity.

As observed in this study, many factors affect the ability of WDN to service the community. The degree of severity or risk of water quality deterioration depends on the vulnerability of the system and the sensitivity of the population. Risk prioritization for the WDN in this study can be of great importance for developing a representative water quality monitoring system for WDNs. One of the main objectives for a monitoring system is to be a 'representative' of the condition of the WDN. Representativeness has been emphasized in the standards, however, no specific criteria have been defined.

Table 6 | Summary of total risk indices for all sub-regions of Al-Khobar city

	Sub-region															
Index	**74**	**75**	**76**	**77**	**79**	**81**	**82**	**94**	**98**	**102**	**103**	**104**	**105**	**119**	**120**	**121**
Physico-chemical	0.14	0.14	0.25	0.25	0.11	0.30	0.17	0.18	0.27	0.25	0.11	0.31	0.31	0.31	0.31	0.29
Microbial	0.24	0.13	0.15	0.16	0.43	0.24	0.32	0.33	0.16	0.16	0.16	0.14	0.19	0.21	0.21	0.53
Water quality	0.21	0.14	0.18	0.19	0.32	0.26	0.27	0.28	0.20	0.19	0.15	0.20	0.23	0.25	0.24	0.45
Intrusion	0.50	0.50	0.55	0.50	0.54	0.55	0.63	0.50	0.00	0.00	0.15	0.00	0.00	0.00	0.24	0.31
Structure integrity	0.59	0.59	0.61	0.59	0.60	0.61	0.63	0.59	0.18	0.18	0.30	0.18	0.18	0.18	0.37	0.43
Water age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.50	0.50
Pressure	0.00	0.99	0.13	0.00	0.00	0.00	0.00	0.91	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.02
Velocity	1.00	0.84	1.00	1.00	1.00	0.00	1.00	0.83	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00
Hydraulics	0.21	0.80	0.29	0.21	0.21	0.00	0.21	0.75	0.29	0.21	0.21	0.00	0.21	0.22	0.31	0.30
Vulnerability	0.34	0.51	0.36	0.33	0.38	0.29	0.37	0.54	0.22	0.19	0.22	0.12	0.20	0.21	0.31	0.40
Schools	0.88	0.94	0.73	0.00	0.32	0.00	0.17	0.61	0.36	0.02	0.49	0.00	0.00	0.00	0.48	1.00
Hospitals	0.00	0.19	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
Activity	1.00	0.92	0.71	1.00	0.76	0.16	0.30	0.74	0.92	0.97	0.60	0.32	0.30	0.60	0.61	0.82
Standard of living	1.00	0.85	0.67	0.70	0.50	0.24	0.16	0.54	0.50	0.50	0.56	0.50	0.50	0.33	0.36	0.50
Population density	0.96	0.75	0.35	0.33	0.20	0.20	0.20	0.97	0.25	0.28	0.46	0.20	0.20	0.26	0.48	0.70
Sensitivity	0.75	0.68	0.35	0.26	0.17	0.03	0.06	0.86	0.46	0.21	0.39	0.10	0.10	0.14	0.60	0.59
Total risk	0.54	0.60	0.35	0.30	0.28	0.16	0.21	0.70	0.34	0.20	0.30	0.11	0.15	0.18	0.45	0.49

Developing a monitoring system that considers vulnerability and sensitivity risks may lead to a representative monitoring system that diagnoses the WDN from different aspects.

SUMMARY AND CONCLUSIONS

In this study, a DSS was developed to prioritize regional risk for any WDN. The model considered 19 variables from different categories including water quality and hydraulic properties, in addition to factors such as structure integrity of the WDN and regional sensitivity based on the distribution, population density, income rates, activities in each region, and the presence of public service like schools and hospitals. FSE, AHP, and FRB methods were used to develop the DSS.

The DSS was applied to Al-Khobar WDN in Saudi Arabia. The study showed that the central parts of the city have high total risk indices compared to regions in the north and south of the city. Central regions have the maximum population density and are mainly residential areas, which make them sensitive regions for any water quality deterioration. In addition, the vulnerability of the system at the central regions is higher compared to other regions in the WDN. However, the vulnerability at regions in the south is relatively higher than regions in the north of the city. High vulnerability in the central regions occurred due to the water quality distributed, hydraulics and structure integrity, and infrastructure of the system. The hydraulic index for central regions was high due to the high pressure in these regions since they are close to the main pumping station. In addition, structure integrity, including pipe age, materials and breakage ratios is relatively low for regions in the center and south. Therefore, risk indices due to structural integrity were found to be high in these regions.

The results of this study show that the highest and lowest regional risk indices were 0.65 and 0.13, respectively. Risk indices can be reduced by improving the conditions of one or more of the factors contributing to the overall risk, such as the structure integrity of the WDN.

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