DECISION SUPPORT SYSTEM FOR RISK AND WATER QUALITY MANAGEMENT IN WATER DISTRIBUTION NETWORK

BY

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To everyone looking for his compass in this life.

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LIST OF ABBREVIATIONS

AC	:	Asbestos
AHP	:	Analytical Hierarchical Process
CT	:	Coverage Threshold
CWS	:	Contamination Warning System
DCM	:	Demand Coverage Method
DSS	:	Decision Support System
EPS	:	Extended Period Simulation
EWS	:	Early Warning System
FRB	:	Fuzzy Rule-Based
FSE	:	Fuzzy Synthetic Evaluation
GIS	:	Geographic Information System
MCDM	:	Multi-Criteria Decision Making
MCM	:	Million Cubic Meter
MIP	:	Mixed Integer Programming
MS	:	Monitoring Stations
PMS	:	Potential Monitoring Station
TDS	:	Total Dissolved Solids
TMD	:	Total Monitored Demand
WDN	:	Water Distribution Networks

ABSTRACT

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Delivering water in sufficient quantity and acceptable quality is the main objective of water distribution networks (WDN) and at the same time is the main challenge. WDN risk assessment is gaining importance worldwide due to the wide range of factors that could alter the operation of WDN and the scarcity of data of some of these parameters. Some of these factors are relevant to water quality, quantity and the condition of the infrastructure itself. The deterioration of water quality in the WDN leads to failure at the water quality level, which can be critical because it is closest to the point of delivery and there are virtually no safety barriers before consumption. This research developed a decision support system (DSS) to identify the risk, vulnerable and sensitive locations in WDN that may lead to overall system failure caused by deterioration, insufficient and/or critical conditions of water quality, quantity and infrastructure, respectively. In addition, using water demand and the identified risk, vulnerable and sensitive locations, water quality monitoring system was developed.

To achieve the objectives of this research, an aggregate vulnerability index, representing likelihood of system failure, was developed using multi-criteria decision models. Similarly, the potential impacts (consequences) in terms of sensitivity index were evaluated. Advanced soft computing methods including fuzzy synthetic evaluation (FSE) and fuzzy rule-based (FRB) were used to develop these indices. In addition, a risk index

based on both vulnerability and sensitivity indices was developed, and Geographic Information System (GIS) was used for data display. Other tools, such as WaterGEMs (for hydraulic simulations of distribution network) and (fuzzy-based) techniques were implemented for the prioritization of regions based on risk, vulnerability and sensitivity in distribution network. Optimization techniques including mixed integer programming (MIP) and multi-criteria decision making (MCDM) were used to develop water quality monitoring system.

The developed DSS was applied to a local water distribution network (Al-Khobar WDN) to study the vulnerability and sensitivity of the network and recommend a suitable risk management strategy, which was used to manage, control and/or reduce the overall risk of failure of the network.

ملخص الرسالة

الاسم الكامل: أمين علي أبو منصر

عنوان الرسالة: نظام دعم القرارات للمخاطر و إدرة جودة المياه في شبكة توزيع المياه

التخصص: الهندسة المدنية و البيئية

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إن الهدف الأساسي و التحدي الرئيس عند ضخ المياه في شبكات التوزيع هو أن تكون هذه المياه كافية من ناحية الكمية و مقبولة من ناحية الجودة كذلك. يكتسب علم تقييم المخاطر لشبكات توزيع المياه مزيدا من الأهمية على مستوى العالم و ذلك لتعدد الأسباب التي قد تؤثر في تشغيل شبكات التوزيع إضافة إلى شح البيانات لبعض العوامل المؤثر في شبكات التوزيع. بعض هذه العوامل لها علاقة بجودة المياه و كميته و كذلك حالة البنية التحتية لشبكة التوزيع. إن تدهور جودة المياه في شبكات التوزيع سيؤدي إلى فشل في توزيع المياه حسب الجودة المرجوة، والذي سيكون خطرا و حرجا خاصة أنه لا توجد حماية لمستخدمي الشبكة في حال تلوث المياه أثناء التوزيع. في هذا البحث تم تطوير نظام دعم القرارات - (Decision Support System (DSS لتقييم المخاطر و قابلية الإصابة و الحساسية لمختلف المناطق في شبكة توزيع المياه و التي قد تؤدي لفشل عام لنظام التوزيع ناتج عن تدهور جودة المياه و عدم كفاية المياه و حالة البنية التحتية للشبكة. إضافة إلى ما سبق، فقد تم استخدام عامل الطلب على المياه إضافة إلى المخاطر و قابلية الإصابة و الحساسية لتطوير نظام لمراقبة جودة المياه.

و لتحقيق هذه أهداف هذا البحث، فإنه تم تطوير مؤشر لقابلية الإصابة، و الذي يمثل إحتمالية فشل نظام التوزيع و ذلك باستخدام نماذج اتخاذ القرار متعددة المعايير. كما تم تطوير مؤشر الحساسية والذي يبين التأثير المتوقع. كما تم استخدام أساليب الحوسبة الناعمة (Soft computing methods) مثل (Fuzzy Synthetic Evaluation-FSE) و كذلك (Fuzzy Rule-Based-FRB) لتطوير هذه المؤشرات.

بالإضافة لما سبق، فقد تم تطوير مؤشر للمخاطر مبني على مؤشرا القابلية للإصابة و الحساسية، و تم استخدام نظم المعلومات الجغرافية (GIS) لعرض هذه المؤشرات. كما تم استخدام أدوات أخرى مثل (WaterGEM) لتمثيل المحاكاة الهيدروليكة لشبكة توزيع المياه و الطرق الضبابية (fuzzy-based) لفرز المناطق حسب الأولوية في الخطورة و قابلية الإصابة و الحساسية في شبكة التوزيع.

كما تم استخدام الطرق المثلى (Optimization techniques) مثل برمجة الأعداد الصحيحة المختلطة و طريقة اتخاذ القرار متعددة المعايير لتطوير النظام الأمثل لمراقبة جودة المياه. تم تطبيق (DSS) على شبكة المياه في مدينة الخبر بالمملكة العربية السعودية لدراسة قابلية الإصابة و الحساسية لشبكة المياه إضافة إلى الإدارة اللإستراتيجية للمخاطر على الشبكة للتحكم و/أو تقليل المخاطر الكلية الناتجة عند فشل الشبكة.

CHAPTER 1

INTRODUCTION

Studying the history of all great civilizations shows that these civilizations established their kingdoms, empires and communities in places where there were plenty of water. Ancient Egypt, Roman Empire, Ottoman Empire and others proved the vital role of water for any community to develop. At those times, water was carried from rivers and lakes to the cities using animals. The dream was to have access to water for each civilian in his own house instead of going regularly back and forth to the source of water. In the royal city of Knossos in Greece during the period between 1700 and 1400 B.C., simple water distribution systems were used to supply palaces with water. Terracotta aqueduct transported water from springs to the city (Mays, 2010). During the period between 300 B.C and 100 A.D., the Romans constructed aqueduct systems (Walski et al., 2003; Bavusi et al., 2004) which were used to deliver water from sources to cities, towns, baths and private houses. The aqueducts were either elevated open channels or pipes buried underground. This system could be considered as one of the oldest water distribution networks (WDN). Table 1.1 shows the historical key events which developed WDN to the industry available today.

Nowadays, the main function of WDN compared to ancient distribution systems is still the same but with much more complex components, objectives and technologies. Modern

Table 1.1 Historical development of water distribution networks' infrastructure and modeling (Walski et al., 2003)

Date	Event
1500 B.C.	First water distribution pipes were used in Crete
250 B.C.	Archimedes principle was developed
100	Roman aqueducts
1455	Cast iron was used for the first time as pipes in Germany
1732	Pitot invented velocity-measuring device
1738	Bernoulli published the energy principle
1770	Chezy developed head loss relationship
1843	St. Venant developed equations of motion
1845	Darcy-Weisbach head loss equation was developed
1883	Laminar/Turbulent flow distinction was explained
1906	Hazen-Williams equation was developed
1936	Hardy Cross method was developed
1960s and 70s	Earliest pipe network digital models were created
1970s	Early attempts to optimize water distribution design
1980s	Water Quality Modeling was first developed
2001	Water security awareness increased
2002	Integration with GIS

WDNs consist of thousands of pipes, links, junctions, pumps, tanks, reservoirs, valves, etc. Each component has a specific role in controlling the distribution of water through the network. Unlike the ancient distribution networks, the recent increase in living standards has introduced new challenges to water authorities. Nowadays, quantity of water is not the only issue considered when pumping water through the network, but also transporting and delivering water to end consumers with an acceptable quality is another issue that the water authority should consider. Modern WDNs are required to deliver “drinking water” to cities, houses, hospitals, daycare centers, schools, industries and all running activities.

Before pumping water through the WDN, it goes through a complex process of treatment (in water treatment plants) to ensure that pumped water is meeting the acceptable quality standards assigned by the governmental agencies. Treatment of drinking water depends on different factors such as quality of raw water (surface water and/or ground water), application of appropriate treatment technology/disinfection and monitoring of treated/finished water within the WDN (Hall and Szabo, 2009).

Once the water leaves the treatment plant, there are usually no defensive lines that could protect consumers from any deterioration of water quality due to any unexpected consequence. These consequences might be gradual such as the variation of chlorine levels or rapid such as contamination caused by intentional criminal or terrorist attacks. There are many factors that could directly or indirectly affect water quality within the WDN. Some of these factors are relevant to the infrastructure of the system such as pipe materials, age and breaks. Some are related to the operational practices of the network such as water age in the network. In the state of Wisconsin in the US, tens of deaths were reported, 4000 hospitalized and more than 400,000 people suffered from health consequences due to waterborne outbreak in Milwaukee city in 1993. It took two weeks to know that these casualties were caused by degradation of water quality in the WDN due to deficiencies during the treatment process prior to pumping of water to the WDN (Murray et al., 2005). To prevent, control and/or reduce any potential deterioration of water quality and to ensure that the WDN is functioning the way it should be, constant and comprehensive assessment and monitoring of the WDN should be established.

Risk assessment is considered as a tool to identify threats, analyze vulnerability and risks, and determine measures for WDNs to enhance and improve the system's safety and reliability (Li, 2007). Recently, risk assessment has been gaining vital importance from governments and environmental protection agencies such as the American and UK governments and the U.S. Environmental Protection Agency (USEPA). In 1996, the American administration established the President's Commission on Critical Infrastructure Protection (PCCIP) for protecting the infrastructure and guaranteeing its operation if exposed to any threats (Clinton, 1996). Water supply systems (or WDN) are considered as one of these infrastructures. In 2002, The Federal Public Health Security and Bio-terrorism Preparedness and Response Act (Bio-terrorism Act) was passed to evaluate the vulnerability of water supply systems. Accordingly, water authorities serving 3,300 or more individuals were required to establish a vulnerability assessment for their systems. In addition, the U.S. Environmental Protection Agency (USEPA) requires these water authorities to conduct and submit a security assessment (Li, 2007).

Routine monitoring in a WDN aims to ensure a safe and reliable supply of drinking water with 'acceptable' quality. Many guidelines and best practices have been developed in the past for effective water quality monitoring in WDN (Kwietniewski and Sudol, 2002; Sudol and Kwietniewski, 2005). Water quality in the WDN can be described by specific microbiological, physico-chemical and aesthetic attributes of the water. These attributes are generally maintained within a desirable range by predefined upper and/or lower limits (Maier, 1999). Generally, water quality regulations and guidelines (WHO, 1993; Health Canada, 2004; USEPA, 2004) require a specific number of samples to be taken, e.g. at the point of entry, the 'center' and at the 'extremity' of the network, but the choice of selecting a specific location remains an arbitrary process. In addition, these guidelines indicate that the sampling locations should guarantee a maximum representativeness of the actual condition of water quality, while on the other hand, there were no clear guidelines or procedures to achieve this goal. Practicality, accessibility, important buildings, presence of schools, hospitals and areas with high population densities are the factors considered when selecting the monitoring locations in the WDN and in the judgment of a decision maker, without following any formal specific criteria (Francisque et al., 2009).

CHAPTER 2

LITERATURE REVIEW

Delivering water to each point in a city through WDN is a complex process starting from collecting water from its sources then treating it from possible contaminants and/or odour and finally pumping it through the WDN to the point of use. Many factors impact the quality and quantity of water delivered through the WDN. Some of these factors lack sufficient data to be used for precise risk and statistical analysis either because of the difficulty in obtaining adequate data due to the expensive tests and measuring techniques and/or due to the limited data provided by the water authorities. In a situation where data about the system are scarce as described above, determining specific failure indices for the system becomes a difficult task. Instead, risk prioritizations (ranking) is another alternative which provides a comparative scheme for failure indices between different regions in the city.

2.1 Risk Prioritization and Decision Making

The concept of risk helped humanity to see the future as a mirror reflection of past events. The modern concept of risk started in the Hindu-Arabic numbering system, but the extensive study started in the Renaissance era. In the period between 1654 and 1760, most of the tools used today in decisions, choice and risk management were developed (Bernstein, 1996). The modern development of risk analysis started when scientists were interested to study the health impacts due to the exposure of humans to chemicals

(Thompson et al., 2005). "Risk" has many definitions which depend on the way of understanding the concept itself. There is no agreement about the definition of risk (Aven, 2012). The word 'risk' comes from the Italian word 'risicare', which means 'to dare' (Bernstein, 1996), but originally the word has Arabic roots. It is believed that the word ricisum in Latin was derived from the Arabic word 'rizq', in which one of its senses means fortune, luck, destiny and chance (Aven, 2012). It is not possible to list all the definitions of risk but a general expression for risk is the exposure to the possibility of loss, damage, injury or other adverse or unwelcome circumstance, or a chance or situation involving such a possibility (Oxford, 2011). International Organization for Standardization (ISO) defined risk as 'the effect of uncertainty on objectives, whether positive or negative' (ISO 31000, 2009). Table 2.1 shows several potential definitions of "Risk".

Quantifying the risk for possible threats and hazards is defined as risk assessment. According to the United States Environmental Protection Agency (USEPA), risk management is the process which evaluates how to protect public health. Simply, qualitative and quantitative ranking of risks is determined by risk assessment and the action to be taken to control and/or reduce risk is "risk management" (USEPA, 2012).

Risk assessment, prioritization and management have been used extensively in different engineering and environmental applications (Wallnerström, 2008; Francisque et al., 2009; EFSA, 2012). Risk prioritization or simply priority is defined as the relative intensity of what is important to people (Saaty, 1987) or in other words, the rank, consequence, importance or urgency (EFSA, 2012).

Table 2.1 Summary of potential definitions of Risk (Aven, 2012)

No.	Definitions
1	Expected value (loss)
2	Probability of an (undesirable) event
3	Risk is measurable uncertainty
4	Risk is uncertainty
5	Risk is potential/possibility of a loss
6	Risk is the potential for realization of unwanted, negative consequences of an event
7	Risk is probability and scenarios/consequences/severity of consequences
8	Risk is event or consequence
9	Risk is consequences/damage/severity + uncertainty
10	Risk is the effect of uncertainty on objectives

Risk prioritization gains its importance from its ability to compare relative risks of different potential threats from different factors and parameters affecting the system. In addition, risk prioritization builds the ranking based on predefined risk factors, safety acceptable thresholds, professionals' judgments and qualitative measures (EFSA, 2012). This approach can guide and help decision makers to concentrate in the solution of the most urgent and critical conditions and enlighten them about the factors which will have greater impact and consequences on the overall system. On the other hand, it determines what is and what is not important when it comes to taking a decision from potential alternatives rather than studying the probability of likelihood which is provided by traditional probabilistic analysis. Some of the factors which have an effect on the system cannot be defined probabilistically due to lack of complete representation and data, but they can be described in terms of priorities and importance (Saaty, 1987). The ability of this approach to classify and rank risks based on its importance and consequences set risk prioritization as an important component of risk management (EFSA, 2012), especially when it comes to decision making for complex systems such as WDN.

WDN may be affected by many factors, some of which are relevant to the structure of the system, operational practices or conditions surrounding its environment. Haimes and Horowitz (2004) defined vulnerability as 'the manifestation of the inherent states of the system (e.g., physical, technical, organizational, cultural) that can be exploited by an adversary to harm or damage the system. In the last decade, especially after 9/11, several studies concentrated on the vulnerability of infrastructure systems such as electrical, gas and water systems (Apostolakis and Lemon, 2005). For WDN, the efforts were focused on determining risks involved in delivering water due to the possible threats and consequences that people might suffer if anything went wrong during the transmission of water. The sensitivity of the WDN to different factors increases the dimension of the problem and encouraged the researchers to investigate the suitable techniques that will aid decision makers in taking proper actions.

Risk prioritization for infrastructure systems is relatively new. This scientific area started developing in the last ten years, influenced by the idea of protecting the systems from terrorist attacks. Several techniques were used for quantifying and prioritizing risk such as fuzzy-based methods, Analytical Hierarchical Process (AHP) and optimization as discussed below.

2.2 Fuzzy-based Techniques

Fuzzy-based methods have been used extensively in engineering applications such as assessing air pollution, environmental impacts, and risk prioritization for public services such as water, sewer and electricity (Khan and Sadiq, 2005; Kleiner et al., 2006; Halfawy et al., 2008; Guney and Sarikaya, 2009).

Examining different scenarios and alternatives in order to evaluate, control and/or reduce risks is a major application of fuzzy set theory. Some of these applications are focusing on the optimal operational practices due to rapid increase in growth in transportation and basic services like water and electricity in developing countries such as China and India. In Yantze city in China, there was a need for determining the suitable transportation route for containers (Zhang and Xiao, 2003). Along the Changjiang river, containers transportation faces a conflict of interests due to the need to deliver containers in different amounts, low costs and shorter durations through three possible alternatives: road, river sail and rail. Using fuzzy analysis, researchers discovered that using road is preferred if the distance was not long and the number of containers was small, otherwise, delivering containers through river is generally preferred. Similarly, China is having a rapid electrical demand growth which puts the authorities in a challenge of allowing private sectors in the country to invest in the power industry. Liang et al. (2006) developed a decision support system using fuzzy techniques and AHP to enable decision makers to define the suitable attractive investors who will not violate the environmental and energy policy regulations, damage the national community, minimize monopoly power and support competitive markets. In southern Haryana in India, groundwater in 15 villages was classified as desirable, acceptable or non-acceptable after testing the physico-chemical water quality parameters using fuzzy synthetic evaluation (Dahiya et al., 2007). In 2006, a fuzzy model was developed by Ghosh and Mujumdar to minimize the risk of water quality deterioration in a river system. After evaluating risks using fuzzy set theory, policies required to minimize risks were derived using optimization techniques. Additional applications for fuzzy set theory and AHP in ranking risk and evaluating likelihood of failure in different fields are presented in Table 2.2.

2.3 Fuzzy Applications in WDN

In relevance to WDN, fuzzy techniques were applied for determining the optimal design and evaluating the infrastructure of the system and quality of the water transported.

Mamlook and Al-Jayyousi (2003) proposed a decision support system for detecting leakage in the WDN using fuzzy set analysis. They characterized the zones in the WDN into three fuzzy sets: leakage, possible leakage and no leakage using pipe characteristics

Table 2.2 Applications of Fuzzy set theory and AHP (other than WDN)

Researcher(s)	Objective(s)	Technique(s)
(Lu et al., 1999)	Identifying water quality in Fei-Tsui Reservoir in China	Fuzzy Synthetic Evaluation and AHP
(Chang et al., 2001)	Assessing water quality and developing water quality index for Tseng-Wen River in Taiwan	Fuzzy Synthetic Evaluation
(Haiyan, 2002)	Assessing environmental quality including air, soil and water	Fuzzy Comprehensive Assessment
(Sadiq et al., 2004c)	Evaluation of soil corrosivity levels surrounding main pipes in the WDN	Fuzzy-Based Methods
(Strobl et al., 2006)	Methodology development for identifying the critical sampling locations within a watershed	Fuzzy Logic
(Dahiya et al., 2007)	Analyzing and classifying groundwater quality	Fuzzy Synthetic Evaluation
(Nobre et al., 2007)	Developing vulnerability and risk indices for groundwater quality	Fuzzy Hierarchical Model
(Wang et al., 2008)	Evaluation of water quality in Naoli River	Fuzzy Synthetic Evaluation
(Bin and Xingpeng, 2010)	Assessing the ecological and environmental impacts	Fuzzy Synthetic Evaluation
(Islam et al., 2011)	Leak detection in WDN	Fuzzy Algorithms

in the network and operational demand patterns. In 2004(c), Sadiq et al. studied, evaluated and ranked soil corrosivity surrounding WDN based on the soil and WDN mains characteristics to predict deterioration of WDN mains. Using fuzzy-based method, they were able to classify the soil into: virtually not corrosive, slightly corrosive, corrosive and highly corrosive. One year later, a combined approach for optimal design for WDN was presented by Vamvakeridou-Lyroudia et al. (2005) who combined fuzzy set functions and genetic algorithm to obtain the optimal design with a reduced cost for the WDN. Vamvakeridou-Lyroudia et al. (2006) extended the approach more by adding AHP to include the relative importance of the components of the WDN in the multi-objective design process to minimize the cost and maximize the benefits.

2.4 Optimization of Monitoring Stations Locations

In 1990 and 1992, Lee and Deininger stepped up the first serious move in trying to develop a scientific criteria to determine representative water quality monitoring locations by developing coverage method concept and using integer programming. The set of monitoring stations that maximize water coverage is defined as the optimal monitoring stations for that WDN. If 50% of water in node X is originally coming from node Y, then it is said that setting monitoring station at X will cover demands at Y and X (Lee, 1990; Lee and Deininger, 1992).

New approach was introduced by Kumar et al. (1997) to locate water quality monitoring stations in WDN. It was stated that integer programming approach which was developed by Lee and Deininger (1990, 1992) is highly cumbersome and complex to deal with the size and dimensionality as the network increases. The new approach was based on the hydraulics of the network assuming a steady state condition and satisfying mass balance equation all around the network. Similar to original coverage method, the concepts of fractional demands, demand coverage and the assumption that water quality deteriorates as water flows downstream the network were adopted. In addition, the proposed procedure started by analyzing the network hydraulically and determining the ratio of each demand in every node from the total demand (water fraction matrix). Based on the coverage criteria of 60%, coverage matrix was constructed. In the coverage matrix, the nodes with maximum coverage demand were chosen as potential monitoring stations. For the network presented in the study, four stations were selected with demand coverage of 66.2% of the total demand. To validate their results, the analysis was repeated for the same network using the original coverage method developed by Lee and Deininger (1990, 1992), and showed that the same four stations were selected as the optimum with the same amount of demand coverage.

The coverage method developed by Lee and Deininger (1990, 1992) was suitable for monitoring gradual and internal contamination events. A methodology for monitoring accidental contamination was developed by Kessler et al. (1998). Unlike the original coverage method which does not consider the accidental contaminant intrusion in the system, the new approach tries to determine the optimal monitoring locations to detect the contaminant faster (in time) before a specific quantity of water is consumed within the distribution network, or what is called “level of service”. Hydraulic characteristics of the network were simulated by EPANET to calculate average flows and velocities. The shortest paths of flows from each node were determined and used to construct the pollution matrix which determines the detection domain of pollution and coverage domain of water demand at each node. Pollution matrix was used to select the least number of monitoring locations which will cover all the demand at the nodes and at the same time has the ability to detect any potential pollution at any node within the specific level of service. The study showed that the volume of water consumed before detecting the pollution (level of service) can be reduced by increasing the number of monitoring stations. However, increasing the number of monitoring stations will increase the cost and, therefore, the decision maker has to make a tradeoff between the number of optimal monitoring stations and the level of service required on one side and total cost on the other side.

In 1999, Harmant et al. improved the objective function developed by Lee and Deininger (1990, 1992). Harmant et al. (1999) suggested that to increase the representativeness of the monitoring stations in the WDN, demand coverage is not sufficient and additional factors have to be considered. The researchers argued that using water demand fractions (coverage) alone will result in selecting the "stagnant area" far away from the water sources in order to maximize demand coverage during optimization. On the other hand, these stagnant areas will have high residence and retention times (water age), which makes them the worst locations for monitoring water quality and does not represent the quality of the network. Harmant et al. (1999) suggested to consider water age and pipe diameters as variables during the process of finding the most representative and optimal monitoring locations in the network since most of the reactions such as bacterial growth and disappearance of chlorine are functions of these variables. Water demand, water age and pipe diameters were the three variables which controlled the selection of optimal monitoring locations, and each variable was given different weight (priorities) which reflects its importance in the optimization procedure.

In the 1990s, studies tend to increase the representativeness of water monitoring stations using demands and physical characteristics of the networks. It was until 2001, when Woo et al. incorporated quality parameters in the selection process in conjunction with Extended Period Simulation (EPS). In this approach, a contaminant was assumed to exist in water, in which monitoring stations should monitor the levels of this contaminant. Woo et al. (2001) improved the coverage method presented by Lee and Deininger (1990, 1992) and assumed deterioration of water quality in the network with time and distance from the source. By using the coverage matrix and adding a potential contaminant to the objective function, “representative” water quality monitoring stations were located. The additional quality variable added by Woo et al. (2001) can represent a potential contaminant or even residual chlorine available in the WDN.

Traditionally, integer and mixed integer programming optimization techniques were used for locating optimal monitoring stations. Al-Zahrani and Moied (2001 and 2003) used genetic algorithm to locate optimal locations for monitoring stations using coverage method developed by Lee and Deininger (1990, 1992) assuming steady demands. Water fraction matrix and demand coverage matrix were constructed assuming the deterioration of water quality downstream the network. Genetic algorithm was used to maximize water demand coverage for different scenarios. To validate the approach, Al-Zahrani and Moied (2003) applied Genetic Algorithm to distribution networks presented by Lee and Deininger (1992) and Kumar et al. (1997). For both cases, Genetic Algorithm approach was able to locate the same optimal locations for monitoring stations in those networks.

In 2004, Tryby and Uber developed a new approach for selecting optimal water quality monitoring stations. Unlike previous researchers who considered water demand in the network as the key parameter, Tryby and Uber assumed water age to be the only factor which affects the selection of monitoring stations. Water ages were generated using simulation software and presented in a histogram showing the frequency of occurrences of water ages simulated. A mixed integer programming optimization technique was used to minimize the number of "potential" monitoring stations for each bin (range of water age in the histogram). The monitoring stations are considered optimal if the cumulative sample histogram constructed using the water age data from the selected monitoring stations was able to simulate the "actual" cumulative total histogram. In addition, Tryby and Uber (2004) admitted that the complexity of the approach increases as the number of binary variable used in the mixed integer programming increases.

Sandia National Laboratories, the Environmental Protection Agency (EPA) and other researchers (Hart et al., 2007) developed a sensor placement optimization tool (SPOT) which is an optimization tool used to minimize the public health hazards by assuming the occurrence of contamination threat at different locations in the WDN and locating optimal locations for contamination sensors' placement considering demand coverage and water age. Studies used this approach and the tool showed that it was possible to select monitoring locations inside the water distribution system and at the edges, which makes it suitable for tracer tests and for real-time monitoring sensors' placement (Boccelli and Hart, 2007; Liu et al., 2011).

In 2012, Liu et al. presented a modification for a flaw in demand coverage method. The key concept behind the conventional demand coverage method is to use accumulative demand in nodes to determine coverage of demand. According to this procedure, it will give acceptable solutions for specific steady demand patterns while not taking into consideration the temporal distribution of demands in unsteady hydraulic situations. In real life systems, extended period simulations and temporal effect of demand are important factors controlling the WDN. To make the conventional demand coverage method simulate real situations, a Demand Coverage Index (DCI) was developed. After performing several hydraulic simulations for different demand patterns, nodes are ranked based on the demand it covers. Simply, DCI represents the ratio of the Total Demand Coverage (TDC) to the Accumulative Demand Coverage Ranking (ADCR) for the nodes. In addition to considering maximum demand coverage and temporal effect in selecting optimal nodes, this modification provides a tool for selecting optimal nodes – even if nodes have equal demand coverage – based on the number of times the nodes were considered as representative for different demand patterns. By maximizing the DCI, optimal locations for monitoring stations can be determined. Liu et al. (2012) demonstrated their approach using genetic algorithm. This study showed that the conventional demand coverage method was not able to prioritize between nodes having the same amount of demand coverage if only one of them has to be chosen. While for the modified technique, the selection was based on the demand coverage in addition to the accumulative ranking of coverage demand which reflects the temporal effect in an extended period simulation and ratio of coverage in different demand scenarios and patterns.

Gradual or internal water quality degradation is not exclusively the only source threatening the water supply systems. Accidental and/or on-purpose actions such as terrorist or criminal attacks are possible factors that have been taken seriously by many researchers, especially after 9/11. How would a contaminant act in the network? How effectively can a monitoring system detect this sudden and rapid action? What are the effects of detection delay time on the population? All these questions and others were raised.

Monitoring strategies based on extracting data from monitoring stations in regular time bases may not be sufficient to detect rapid and sudden contamination events. This kind of events generally has a higher risk due to its higher concentration, which consequently threatens a higher portion of population. Construction of Early Warning System (EWS), also known as Contaminant Warning System (CWS), and installing real-time monitoring sensors could be a suitable option to decrease the portion of population affected, decrease the exposure time and decrease operational costs compared to conventional monitoring practices. Studying the transport and fate of contaminants in the WDN is essential to increase the reliability of the system and produce extremely important information, which will help in the creation of efficient EWS.

Bahadur et al. (2003) predicted the contaminant transport of accidental event in the distribution network in order to determine the optimal monitoring locations. This approach tends to minimize the contamination threat, mainly in locations with higher population density. Accordingly, the importance of ranking and prioritizing of monitoring stations based on availability of schools, hospitals and high population densities was emphasized.

In 2004, Berry et al. developed a general integer programming-based framework for sensor placement. The target was to minimize the number of population affected by contaminant caused by an attack at a specific location in the network by minimizing the amount of contaminated water consumed prior to detection. The developed approach assumed that the contaminant will flow in a discrete pattern and is flowing at the same velocity of the flow. The study showed that minimum consumed volume of contaminated water prior to detection can be achieved if all nodes were considered as potential attack locations and with no time limitations for the attackers (can strike day or night). Although this approach was complex, it raised the attention to important unsolved concerns such as how to determine the appropriate number of population consuming water from a specific node taking into consideration the mobility of people during day and night times. Berry et al. (2005a) conducted another study with a different approach, where they studied the application of real-time monitoring sensors in water distribution systems. Unlike the studies where judgments were based on minimizing contaminated water consumption or determining the minimum path of contaminant, this study proposed a different objective which depends on minimizing the percentage of population at risk due to sudden contamination attack. The attack scenario was given a specific probability distribution at different locations on the network based on several factors such as experts' opinions and terrorists' prior knowledge of the network. Using Mixed Integer Programming (MIP), the number of population consuming water from a specific node was considered as a weighting factor for that node. Also, the study assumed that the number of population is not always proportional to water demands. Obviously, as the number of monitoring sensors increased, population's percentage at risk decreased. It was discovered that the optimal locations for monitoring stations have little sensitivity to the variation of population even by a factor of 25%.

Watson et al. (2004) proposed a multi-objective optimization approach based on the optimization formulation developed by Berry et al. (2005a). The study compared locating monitoring stations using multi-objective and single objective optimization. Five objectives were used for the multi-objective optimization: minimizing exposed population, minimizing detection time of contaminant, minimizing contaminated water consumed, minimizing the number of times the system fails to detect a contaminant, and minimizing the length extent that contaminant would reach in pipelines. In addition to the multi-objective optimization, a single objective optimization was performed using each one of the previously listed objectives independently. The study assumed the ability of locating monitoring stations at nodes as well as any pipe. The results showed that there is no correlation between the different objectives, in other words, reaching an optimal solution for one objective does not lead to optimal solution for the other objectives. Furthermore, the study showed that locating monitoring stations at nodes rather than pipes led to optimal solutions in all examined cases, while failed to reach optimal solution when pipes were considered as potential locations for monitoring stations/sensors. The study emphasized that running a tradeoff analysis between several objectives would lead to a better optimization rather than trying to find the 'best' solution for each objective which may cause dramatic failure to other objectives. In addition, complexity of this approach was obvious; the researchers were able to obtain optimal solution using multi-objective approach for a small network but failed for a medium sized network. In 2006, Huang et al. proposed to determine the optimal monitoring locations based on multi-objective setting using genetic algorithm. Four objectives were set for this study: minimize detection time, population affected prior to detection, expected water demand prior to detection, in addition to maximizing the detection likelihood. Minimizing population at risk and contaminated water consumed were considered as one objective since the population was assumed to be strongly correlated to water demand. This approach seems to be promising but involves complex ranking procedures and intensive database construction prior to using genetic algorithm for locating optimal monitoring sensors in the distribution system.

By the year 2005, many approaches and optimization techniques with different formulations were presented and proposed to find optimal locations for sensors' placement, decreasing population at risk, decreasing contaminated water consumed…etc. Integer programming was widely used in this field. Berry et al. (2005b) raised a concern about the effect of integer programming formulation on the final optimization outcome. The researchers examined static and dynamic programming, in which dynamic programming takes into consideration the contaminant dilution and spread with time, while static programming assumes the constant behavior of contaminant in different time steps (extended period simulation). It was shown that dynamic programming could reach optimal solutions while static programming reached near optimal solutions and the results of the two were close in most cases. Care must be taken when choosing which model to use, although dynamic performance is better but it significantly increases the complexity of the problem, especially for real networks, and requires high-end workstations, which raises a question whether the additional improved accuracy is worth going through this complex procedure.

Based on Red-Blue teams concept developed in the 19th century, Grayman et al. (2005 and 2006) presented an exercise simulating the expected consequences of a "red" team trying to contaminate the water distribution network without significant knowledge of the network, and a "blue" team of water experts trying to locate monitoring sensors to minimize the effect of red team's attack. Red team members tend to select injection points which will cause severe contamination, such as nodes following water sources and pumps, while blue team members tried to select locations which will cover most of the network's demand. An optimization model was then developed using genetic algorithm to maximize the detection likelihood of pollution, given the allowable water volume consumed prior to detection, fixed number of proposed contaminant injection locations and fixed number of monitoring locations. Five scenarios were tested in the study, where delay time before detection was considered, adding more monitoring sensors, limiting injection locations and increasing the allowable water volume consumed prior to detection. The results indicated that detection likelihood decreased as detection delay time increased and when contaminant's injection was considered to vary with time (uniform variation). On the other hand, the detection likelihood increased as more monitoring sensors were added to the network, reducing the potential injection locations, and when the allowable water volume consumed was increased prior to detection.

Several techniques were also developed to locate the optimal monitoring station/sensors locations such as Robust Optimization (Carr et al., 2006; Watson et al., 2009) and Bayesian Belief Network (Murray et al., 2010). For Robust Optimization, intensive research and development is required before adopting it due to its high complexity, which limits it to small distribution networks rather than for real networks. Similarly, application of Bayesian Belief Network has to be studied more since some assumptions may not reflect the real world problem such as assuming normality.

Some studies also used different key parameters other than water demand (traditional demand coverage approach) such as water age (Tryby and Uber, 2004). Although this approach was able to simulate the trend of the cumulative total histogram, but excluding important variables like water demand and assuming that water age is the only factor controlling the selection of monitoring stations, it needs to be tested with caution using complex systems with frequent change in demand patterns.

In literature, frameworks for DSS considering vulnerability and sensitivity in the WDN are relatively new. However, the most comprehensive framework (Francisque et al., 2009) did not include important factors such as pressure and velocity of the water at different zones in the WDN for developing vulnerability index. Similarly, sensitivity factors such as population distribution, standard of living and activities in the city were not investigated as well. In this study, these factors were studied and the framework developed by Francisque et al. (2009) was improved by considering these factors. The developed DSS for risk, vulnerability and sensitivity index considers a wide range of factors affecting water quality in WDN including hydraulics, water quality, structure integrity and sensitivity.

On the other hand, typical water demand and water quality characteristics (such as water age) were used to determine the optimal locations of monitoring stations. Factors such as infrastructure of the WDN, hydraulic characteristics and sensitivity factors including population distribution, standard of living, activities in the city and distribution of hospitals and schools have not been used for developing monitoring systems at WDN despite of their importance. In this study, a monitoring approach was developed which takes into consideration water demand, water quality and hydraulic characteristics at the WDN as well as infrastructure of the system and sensitivity of different zones in the city.

2.5 Research Objectives

The aim of this research was to develop a decision support system (DSS) that can help identify zones within WDN that may be affected by gradual or rapid deterioration of water quality. Factors relevant to water quality, quantity and network's infrastructure were considered in the study. Specifically, the study aimed to:

i) Develop a diagnostic tool for the assessment of WDN by aggregating diverse data including pipe material, age, diameter, history of breakage, average pressure, history of velocity and flow regimes, and surrounding soil conditions.

ii) Evaluate the current condition of the WDN by estimating the likelihood of system risk and identifying vulnerable and sensitive locations in the WDN by considering the hydraulics, water quality, structure integrity and sensitivity in the WDN.

iii) Perform a risk-based prioritization (ranking) of locations (water mains) in the WDN and present the results spatially using GIS.

iv) Determine the optimal monitoring locations (sampling) in the network that will be the most representative of the actual water quality in the WDN, which will be used for controlling and/or reducing risk.

v) Select the most prudent and effective alternative for risk control using the Decision Support System (DSS).

CHAPTER 3

METHODOLOGY

Level of uncertainty associated with a system is related to its complexity. Uncertainty arises as a result from incomplete understanding of known relationships among various entities, and randomness in the mechanisms governing the process. Typical complex systems such as WDN consist of numerous interacting components. Modeling of highly complex non-linear dynamic systems requires methods that combine human knowledge and experience. When significant historical data exist, model-free methods such as artificial neural networks can provide insights into cause-effect relationships and uncertainties through data learning (Ross, 2009). In cases where historical data are scarce and/or available information are ambiguous and imprecise, soft computing techniques can provide a framework to handle such as relationships and uncertainties. Such techniques include probabilistic and evidential reasoning (Dempster-Shafer theory), fuzzy logic and evolutionary algorithms (Makropoulos and Butler, 2004). Methods based on fuzzy sets provide simple but logical solutions to complex problems where data uncertainties are major impediment. In this research, fuzzy synthetic evaluation (FSE) and fuzzy-based methods (FRB) were used to develop the DSS for WDN. On the other hand, prioritizing and zonal ranking for risks associated with water delivery through WDN, raises the concerns for increasing the protection and security of the WDN. Securing WDN from water quality deterioration caused by expected events such as sewer intrusions or high chlorine doses due to human error is essential. In addition, the WDN should be secured also against intentional and unexpected criminal and terrorist threats such as injecting hazardous contaminants into the WDN to cause fast and severe casualties. This national security objective can be achieved by increasing the representativeness and efficiency of the monitoring system of the WDN, which will be built on prior knowledge of the different risk levels in the WDN developed by the Decision Support System (DSS).

This research developed a DSS tool that can assist decision makers to quantify the regional risks based on vulnerability of the WDN and sensitivity (or potential consequences) in case of failure of the system to deliver water in acceptable quality. A wide number of factors were considered in the analysis, which include water quality, quantity and infrastructure of the system. Based on the evaluation of the current risks in the WDN using the DSS, optimization techniques such as integer/mixed programming were used to determine the optimal monitoring locations for the WDN. The optimal monitoring stations will be more representative of the actual water quality condition of the WDN, which will aid the decision makers to execute effective actions to control risks accompanying water delivery to customers. The developed model will be applied on Al-Khobar WDN to investigate the reliability and security of the network.

The development of the DSS requires an aggregation of measurable and non-measurable factors to estimate vulnerability, sensitivity and risk at specific points in the WDN using routinely collected data. Due to the complexity of the problem, an index-based approach using FSE and FRB was used to describe vulnerability, sensitivity and risk. An estimate of risk at a given location in the WDN will provide a representative value for a predefined geographical region. A region represents an influence zone in which the values of all contributing factors are assumed to be fixed. Once risk values are determined in various sectors of the WDN, they can be ordered, ranked or prioritized based on vulnerability, sensitivity and/or risk values.

Figure 3.1 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 risk (fifth level) that depends on two factors, i.e. vulnerability and sensitivity in the second level. These two factors are determined through aggregation of various factors in the previous levels. The factors or attributes in the first and second levels (Figure 3.1) are referred to as 'input factors' if 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 and potential intrusions from surrounding industrial activities and sanitary system. 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.

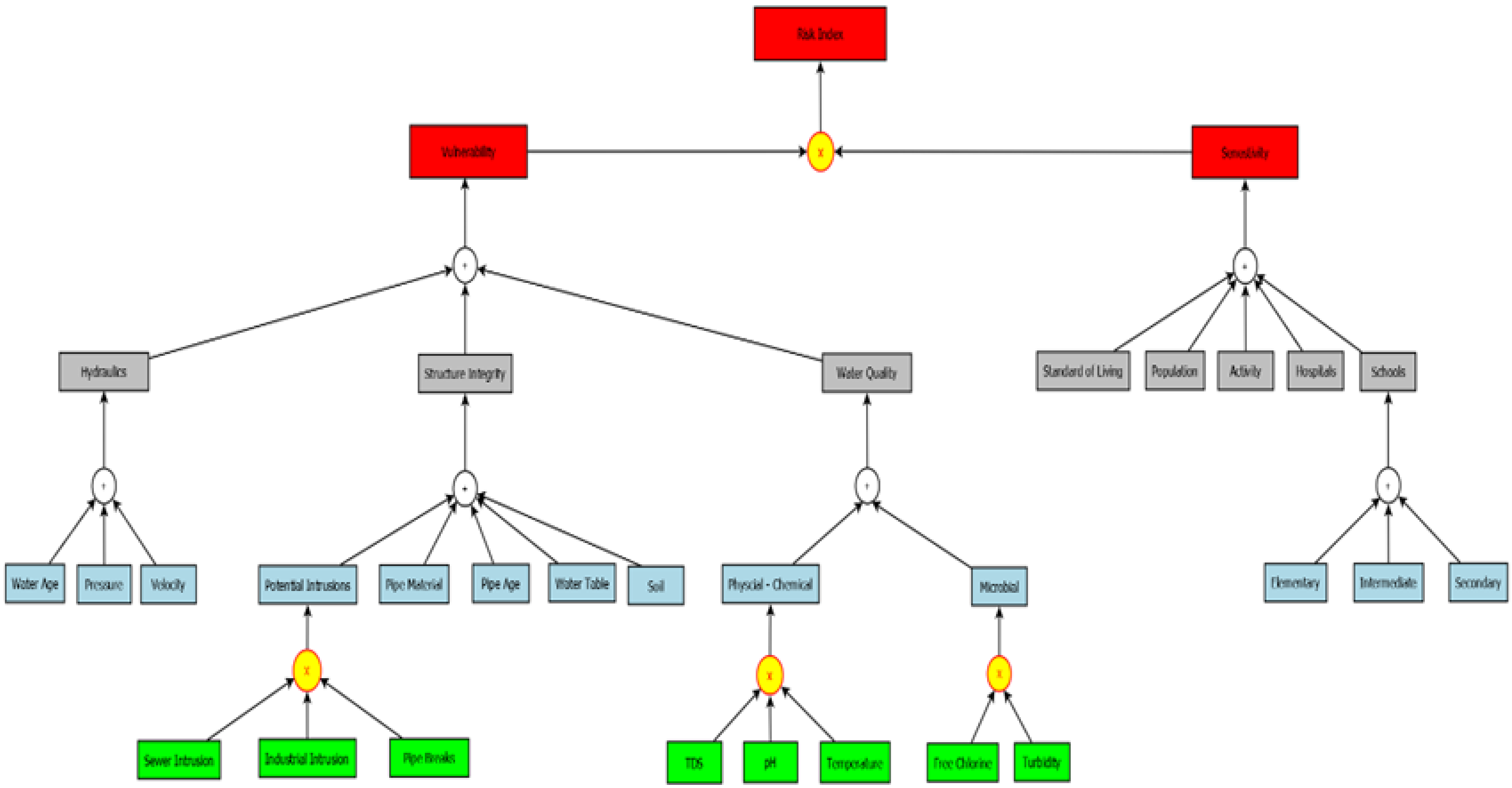


Figure 3.1 Proposed risk index for prioritization of water mains

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.

The developed DSS tool can be applied to evaluate the condition of any WDN. Based on the evaluation of risks accompanying the delivered water through the WDN, optimization techniques were used to locate the optimal monitoring stations for the WDN. The optimal monitoring stations will be more representative of the actual condition of the WDN, which can help decision makers to control and/or reduce the risk associated with water delivered to the end consumers.

To accomplish the objectives of this study, it was divided into five main phases. Table 3.1 shows the five phases and summarizes the tasks involved to achieve the research objectives.

3.1 Risk Assessment Module (Phase I)

The analysis in Phase I represents a risk assessment at a single point in the WDN. Two types of fuzzy-based methods were used in the analysis. Vulnerability and sensitivity indices were determined using fuzzy synthetic evaluation (FSE), which is primarily a fuzzy-based method that uses linearized weighting scheme for aggregation. Risk index was evaluated from vulnerability and sensitivity indices. Fuzzy rule-based (FRB) technique (a non-linear method) was used to develop several parameters as will be

Table 3.1 Mapping of phases and tasks to achieve objectives

Objectives	Phases	Tasks
1,2	**Risk Assessment Module (Phase I)**	i) Collection of pipe, surrounding location, hydraulics and water quality data. ii) Development of fuzzy-based algorithms to make inferences. iii) Assessment of risk (also vulnerability and sensitivity indices) at a given location.
2,3	**Hydraulic Module (Phase II)**	iv) Development of a database for the network under investigation. v) Integration of database with fuzzy algorithm proposed in a “risk assessment module”. vi) Display risk at various locations in a WDN.
3,4	**Optimization Module (Phase III)**	vii) Development of the optimization objective function and constraints. viii) Determine the optimal monitoring locations based on water quality, quantity and infrastructure of the network.
2,3,4	**Display Module (Phase IV)**	ix) Development of a GIS model to display the risk, vulnerability and sensitivity for different zones within the WDN. x) Locate the optimal monitoring points using the GIS model.
5	**Risk Management Module (Phase V)**	xi) Selection of the most prudent and effective alternative for risk control using the Decision Support System (DSS).

explained in this chapter. These indices were developed for different sub-regions in the WDN based on the local data for each sub-region (Francisque et al., 2009). Based on the locations of existing water quality monitoring stations, Thiessen method was used to divide the WDN into different sub-regions. For each sub-region, a risk assessment module was developed.

3.1.1 Fuzzy systems

In general, information can be classified into precise and imprecise data. While the precise data are required by computers to solve problems, imprecise human reasoning is widely used for understanding scientific concepts and theories. The use of reasoning in complex problems is the core of fuzzy logic concept. This technique might not be able to solve problems which need very high precision but on the other hand, not all problems need high precision such as controlling traffic at intersections, preliminary understanding of complex systems and prioritization of risks (Ross, 2009). A drawback for using systems which depend on precise data increases the cost and efforts needed for establishing and developing these systems compared to systems which need less precision. Exploiting the tolerance for imprecision is required for professionals working with complex systems. Complex system problems which require decision making can be managed when formulated imprecisely to make rational decisions in uncertain and imprecise environments, which are difficult to solve by traditional approaches since these approaches do not exploit the tolerance for imprecision. Fuzzy logic and other soft computing methods mimic the human mind abilities of reasoning to formalize complex problems (Zadeh, 1994).

Traditionally before the nineteenth century, scientists considered uncertainty as a figure that should be avoided by any means necessary. After the development of probability theory, the effect of uncertainty was taken into consideration to strengthen models in terms of solving problems as well as quantifying uncertainty. Zadeh developed in 1965 fuzzy sets theory which challenged classical probability theory and introduced a thorough ground for understanding and looking at uncertainty (Klir and Yuan, 1995; Ross, 2009).

Although the word "fuzzy" in English language means blurred, imprecise or vague, this should not prevent researchers from using it. Fuzzy systems may be characterized as fuzzy, but the theory itself is precise. Fuzzy systems theory can be justified as follows (Wang, 1999):

i- Complexity of real world problems makes it impressively difficult for precise methodologies. Accordingly, approximations (or fuzziness) must be used to obtain reasonable models. Generally speaking, all engineering theories are approximations of the real world in one way or another. Most of the real systems are non-linear and conventional approaches work hard to linearize them in order to get the best approximation.

ii- Due to the massive use of information, human judgments and knowledge are gaining more importance. There is a need for a technique which can smoothly and systematically merge human judgments and knowledge into engineering systems as well as mathematical models. This justification shows the uniqueness of fuzzy systems theory and presents it as an independent branch of engineering.

Several characteristics of fuzzy systems make it a robust and practical approach for problems that involve decision making, such as (Ross, 2009):

1. Fuzzy systems are universal approximators (Wang, 1992; Buckley, 1993; Kosko, 1994; Castro, 1995; Castro and Delgado, 1996; Ross, 2009). Universal approximators are explained as the ability to uniformly approximate continuous functions, such as algebraic functions, to any degree of accuracy on compact sets. In the 1990s, fuzzy systems were applied in different fields such as control design and decision making, but some were curious about it since it has not been approved mathematically (Castro and Delgado, 1996). These claims encouraged researchers to prove the effectiveness of fuzzy systems by showing and proving its ability of being universal approximators (Wang, 1992; Buckley, 1993; Kosko, 1994; Castro, 1995; Castro and Delgado, 1996; Ross, 2009). This ability originated from the similarities between algebra and the structure of fuzzy systems. While algebraic function maps input variable into output variable, fuzzy systems do the same but by mapping a group of inputs to a group of outputs, with an advantage for fuzzy systems since it deals with numerical and non-numerical quantities.
2. The important ability of fuzzy systems to work with new and complex systems even if it did not have an existing formulation or even if the effects of the tested systems are observed. This important feature opens the door for using fuzzy systems for a wide variety of untested new complex systems that consider human conditions, social, political, risk, and economic systems.

3. For cases where precise solutions are not required or maintaining higher precision costs more in terms of finances and efforts, fuzzy systems could be the suitable technique. Similarly, fuzzy systems can be very efficient if used for approximating fast solutions in decision making, setting initial solutions for numerical methods, reducing computational cost and/or when dealing with scarce, vague, ambiguous or unknown input data records.
4. For conventional modeling and analysis, first, models are created and formulated based on prior assumptions and then uncertainties encountered in each input or output variable are considered. The strength of fuzzy systems is that system's structure is actually formulated using inputs and outputs which already take uncertainties into consideration.

Ross (2009) generalized major applications of fuzzy systems in conditions involving high complex systems with lack of full understanding of its behavior, and in conditions where approximate but fast solutions are needed (which is the case for risk assessment of WDN). Fuzzy systems are classified as shallow reasoning method. If the behavior of a system can be observed and predictions are possible using observed data without the need for investigating and fully understanding the physical processes behind the system, then this system can be classified as shallow. On the other hand, if the system is using the observed data to study the mechanisms or physical processes of how these data were produced, then this is called deep model. For simple problems, it is usually easier to use deep models to solve them, especially if the physical processes are already known and mathematically formulated, while for new and complex systems, using shallow models such as fuzzy systems is preferred. Before moving deep to fuzzy systems, FSE and FRB system, the major components of fuzzy systems are introduced first.

3.1.2 Fuzzy sets

In 1965, Zadeh introduced for the first time the concept of fuzzy sets which deal with imprecision and/or uncertainty. Fuzzy sets are also defined as mathematical tools used to deal with fuzziness of the real world (Cai, 1996; Li, 2007). According to the concept developed by Zadeh, fuzzy sets are divided into different subsets which are often called fuzzy subsets or fuzzy numbers. These fuzzy subsets are assigned to linguistic variables such as “high”, “med”, “low”, “large”, “fast”…etc., in which each of these subsets represents human knowledge that can be “fuzzy”, imprecise and vague when it comes to setting a specific definition and boundaries to these words. A fuzzy set can be represented by A_i, which shows the relationship between imprecise/uncertain quantity x and a membership function $\mu_{A_i}(x)$. Membership function $\mu_{A_i}(x)$ ranges between 0 and 1, where zero means an absolute confidence that x does not belong to fuzzy set A_i. Similarly, if $\mu_{A_i}(x)$ equals 1, this implies that x belongs to fuzzy set A_i with an absolute confidence.

Intermediate values between 0 and 1 show the confidence that x belongs to A_i (Kleiner et al., 2005). Suppose Figure 3.2 shows a fuzzy set for TDS level in water. There are three fuzzy subsets (or fuzzy numbers), low, med and high. If TDS in water is 200 ppm, then it is said that TDS level has a membership of 1 to “low” fuzzy subset, and if the level is 800 ppm, then it is said that TDS level has a membership of 1 to “high” fuzzy

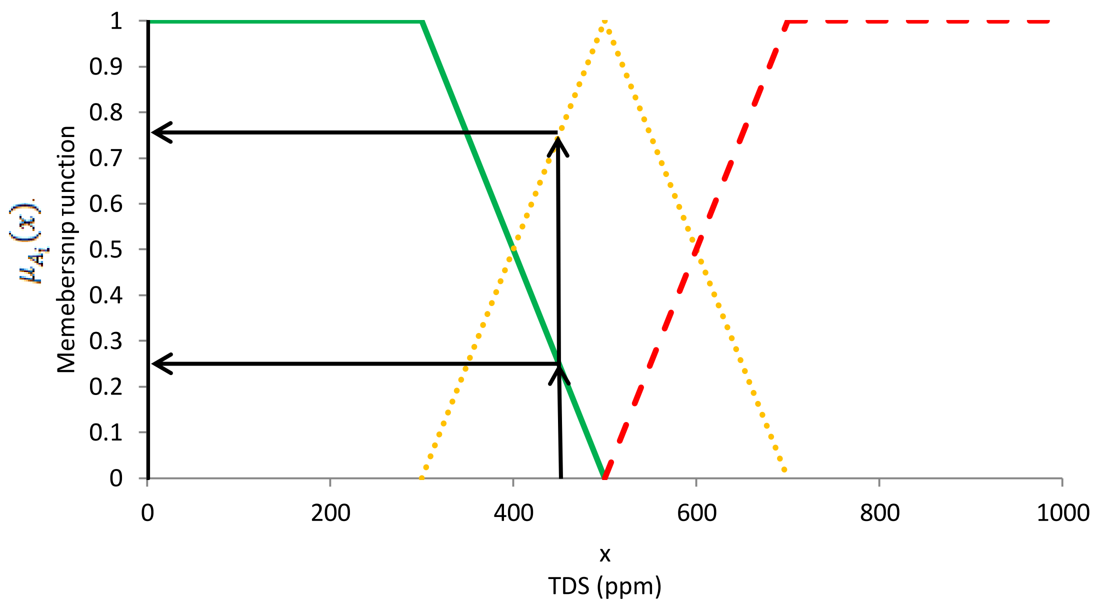


Figure 3.2 TDS fuzzy set

subset. If TDS level is 450 ppm, then it is said that TDS level has a membership of 0.25 to "low" fuzzy subset and 0.75 to "med" fuzzy subset. Accordingly, fuzzy set is an extension to set theory where *x* is or not a member of set A_i (Kleiner et al., 2005).

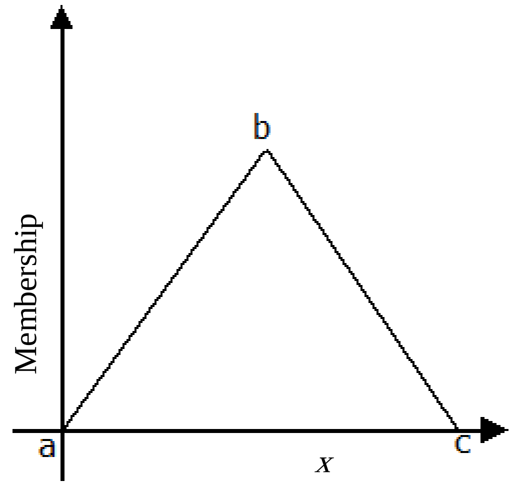
3.1.3 Fuzzy subsets (numbers)

Fuzzy subsets are special cases of fuzzy sets. Each fuzzy set contains several fuzzy subsets. Generally, there are several membership functions used for fuzzy subsets, such as triangular, trapezoidal and Gaussian. There is a strong debate in literature discussing the criteria on how membership functions' shape should be assumed for a specific parameter. Actually, the locations or boundaries of the membership function (points *a, b*, *c* and *d* in Figure 3.3) have more significant effect on the final outcomes of the function compared to the shape of the membership function (Li, 2007; Ross, 2009). Usually, positioning of membership functions depends on standards for the parameter under study and expert's knowledge.

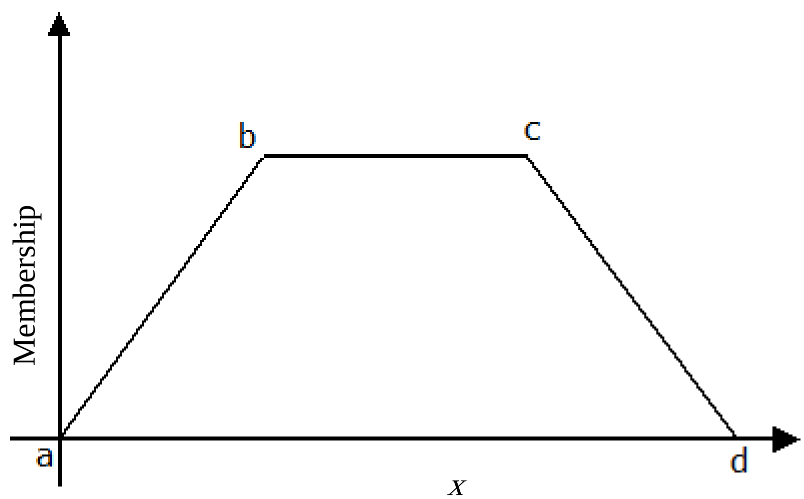
3.1.4 Fuzzy synthetic evaluation

There are two main points of interests for a decision maker to focus on (Maes and Faber, 2004; Ross, 2009):

a. Operational decisions in which best actions are taken to minimize hazards, and/or
b. Future strategic decisions to maintain maximum protection or benefits.



(a)



(b)

Figure 3.3 Membership functions:

(a) Triangular and (b) Trapezoidal

FSE method is one of the most widely used Multi-Criteria Decision Making (MCDM) techniques in environmental engineering and water quality modeling (Chang et al., 2001; Francisque et al., 2009). From its name, two essential characteristics of the approach can be defined, which are: it deals with decision making under uncertainty and fuzziness and consists of different components that are evaluated and aggregated together or synthesized into an aggregation form. Since FSE is a fuzzy-based method, variables used as inputs for decision making can be of numeric or non-numeric types. Natural linguistics can be used to evaluate inputs such as "low", "med" and "high" (Ross, 2009).

FSE is used to quantify and estimate indices for vulnerability, sensitivity and risk. Hydraulics of the system, structure integrity and water quality indices can also be estimated based on FSE. Following are the required steps which need to be considered when constructing FSE (Chang et al., 2001; Sadiq and Rodriguez, 2004; Sadiq et al., 2004(d); Khan and Sadiq, 2005; Francisque et al., 2009):

- Development of hierarchical framework,
- Development of membership functions and fuzzification,
- Defining weights,
- Aggregation,
- Defuzzification and prioritization of risk.

Detailed descriptions of each of the above steps are presented in the following paragraphs.

3.1.4.1 Development of hierarchical framework

Saaty (1982) proposed the use of Analytical Hierarchical process (AHP) for setting and estimating priorities and ranks for different children attributes. This approach is widely accepted and adopted in various engineering applications (Lu et al., 1999; Khan et al., 2002; Sadiq and Rodriguez, 2004; Sadiq et al., (2004a and 2004d, 2007); Khan and Sadiq, 2005; Ishizaka and Labib, 2009; Francisque et al., 2009; Moazami and Muniandy, 2010).

AHP simplifies human natural decision making process and applies it effectively in complex systems and frameworks without increasing the complexity of the problem. Simply, AHP breaks down complex unstructured systems into its basic components and arranges and orders these parts into hierarchy order. These components (or attributes) are arranged in hierarchical order in which they are given weights – or degree of relative importance – based on their degree of belonging and effect on parent attributes. Consequently, judgments are made on how each attribute affects the final outcome (Saaty, 1982). This technique is a flexible decision making approach which has several interesting features such as (Saaty, 1982; Saaty and Vargas, 2000):

- Enables professionals to improve their judgment and understanding as well as refine previous problems' definitions.
- It does not urge consensus but synthesizes representative outcome from diverse judgments.
- It gives decision makers the ability to determine relative priorities and degree of belongings and let them make their choice between alternatives based on their goals.

- Provides an overall index or estimate of the desirability or risk of each alternative.
- Consistency of judgments used to determine priorities and weights is guaranteed.
- Its hierarchical structure mimics human natural ability to sort elements into levels.
- Capable of dealing with interdependence of elements in the systems.
- Solves problems using deductive integration.
- It can be used for direct resources allocation, benefit/cost analysis, resolves conflicts, designs and optimizes the systems.

There are three main concepts featuring AHP (Saaty, 1982; Saaty, 2008):

1- Hierarchical structure and decomposition, which means breaking the problem into separate elements.
2- Priority setting, which is the ranking of elements based on their relative importance and degree of belonging.
3- Logical consistency, which ensures that judgments and ranking used for determining priorities are consistent.

The hierarchical structure that was used in the DSS for WDN is shown in Figure 3.1. The key index for that structure is risk, which is the parent of the entire structure. This structure is an improvement of the hierarchical structure which was developed by Francisque et al. (2009). The system comprises four levels, where each level has several parameters (attributes or elements). The first level contains vulnerability and sensitivity, which are children elements for parent attribute “risk”. The second level contains two children groups, one for parent attributes “vulnerability” and “sensitivity” as shown in Figure 3.1. The third level has four children groups for parents: hydraulics, structure integrity, water quality, and schools' capacity. The fourth level contains three children attribute groups for parent attributes: potential intrusion, physico-chemical and microbial parameters as shown in Figure 3.1.

3.1.4.2 Development of membership functions

Fuzzification can be defined as a process by which measurable and non-measurable input data are transformed into a homogenous scale (0-1), or the process of changing crisp values into fuzzy (Francisque et al., 2009; Ross, 2009). One of the main characteristics of fuzzy sets is their ability to consider and deal with uncertainty in decision making process. Since many parameters are not actually deterministic and they have different levels of uncertainties due to measurements, human errors or approximate methodologies are used to obtain data. Parameters can be classified as fuzzy and represented by membership functions if the uncertainty encountered is caused by imprecision, vagueness and ambiguity (Ross, 2009).

Triangular (TENs), Gaussian and trapezoidal (ZENs) fuzzy subsets (fuzzifiers) are usually used to fuzzify input data (Lee, 1996; Wang, 1999; Sadiq, 2004a and 2004d; Francisque et al., 2009). Using these fuzzy subsets, real input data, regardless of its type, can be mapped to fuzzy sets. In addition to its ability of transforming data into a membership function of a scale ranging from 0 and 1, fuzzifiers are used to simplify computations during the fuzzy inference machine process and eliminate noise that may be available and could corrupt input data. When membership functions in the fuzzy IF-THEN rules are Gaussian or rectangular, then Gaussian and rectangular fuzzifiers can simplify computational analysis during the fuzzy inference process (Wang, 1999). Figure

3.2 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 [$\mu_{low}, \mu_{med}, \mu_{high}$]. According to the membership functions and fuzzy sets in Figure 3.2, 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 “Low” fuzzy subset, 0.75 to the “Med” fuzzy subset and does not have any membership to the “High” fuzzy subset.

3.1.4.3 Defining weights

The general framework for DSS presented in Figure 3.1 shows that 32 parameters and attributes are distributed into four levels which are further subdivided into several parent-child relationships. Parent attributes are determined by defining weights for each ‘child’ attribute comprising that parent attribute or sometimes called ‘degree of belonging’ to parent attribute (Chu et al., 1979). Relative importance of children attributes comprising parent attribute are not equal and, therefore, weighting criteria is required to define the degree of belonging and effect of each child attribute to its parent attribute. Figure 3.4 shows a schematic diagram for parent and children attributes. Parent attribute has three children 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. After developing the AHP structure shown in Figure 3.1, prioritizing the elements – which is an essential component of AHP – needs to be set to maintain judgment consistency. Table 3.2 shows the scale for pairwise comparison between elements to determine the relative importance, degree of belongings and, finally, weights for each element.

Recall Figure 3.4 and assume that there are three children 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 3.2.

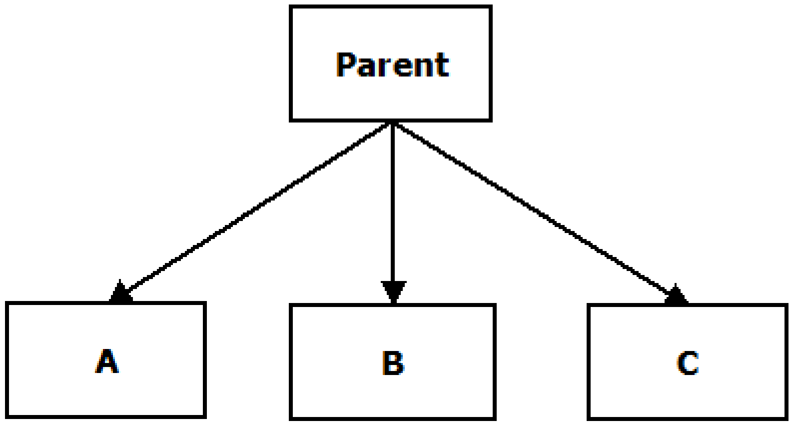


Figure 3.4 Parent-child attributes

Table 3.2 Pairwise comparison scale (Saaty, 1982; Saaty, 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 3.3 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 3.2. 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. $\left(1/_{d}\right)$ and so on.

Suppose *d*, *e* and *f* are equal to 4, 6 and 2, respectively, as shown in Table 3.4. To normalize the matrix, each column entry will be divided by the total of that column as shown in Table 3.5. Finally, the average of each row of the normalized matrix is calculated to find the weights as follows:

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

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

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

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

Table 3.3 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 3.4 Illustration for reciprocal matrix

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

Table 3.5 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	$\frac{1/6}{1.42}$	$\frac{1/2}{5.50}$	$\frac{1}{9.00}$

There is another method for approximating weights, by summing each row and then normalize it with respect to the total sum to obtain weights w_i for each element as shown below (Francisque et al., 2009):

$$W_{Parent\_approximation} = \begin{bmatrix} W_A \\ W_B \\ W_C \end{bmatrix} = \begin{bmatrix} 0.69 \\ 0.20 \\ 0.11 \end{bmatrix}$$

The difference between the two methods in calculating weights is negligible, but for elements more than three, the approximation may lack accuracy, therefore, using the first method is preferred (Saaty, 1982).

Before using these weights, scale and priorities in the reciprocal matrix, it should be tested for consistency. In decision making problems, creating a consistent judgment is important to avoid taking decisions based on judgments with low consistency that may appear to be random (Saaty, 1982; Saaty and Vargas, 2000; Saaty, 2008). There are several methods by which measuring and maintaining consistency is made. Two methods are presented as follows:

i. Equating method

Recall the reciprocal matrix in Table 3.4. There are three priorities (judgments) from experts for that matrix d_{ex}, e_{ex} and f_{ex}. According to the assumed relative importance, the following relations can be made:

$$\mathrm{B} = d\mathrm{A} \Rightarrow \mathrm{A} = \frac{\mathrm{B}}{d} \tag{3.1}$$

$$\mathrm{C} = e\mathrm{A} \Rightarrow \mathrm{A} = \frac{\mathrm{C}}{e} \tag{3.2}$$

$$\therefore \frac{\mathrm{B}}{d} = \frac{\mathrm{C}}{e} \tag{3.3}$$

or,

$$C = \frac{e}{d}\mathrm{B} \tag{3.4}$$

and since,

$$C = f\mathrm{B} \tag{3.5}$$

∴ regardless of the actual value of f_{ex}, for priorities to be ***<u>consistent</u>***, f must be equal to:

$$f_{\square} = \frac{e_{\square}}{d_{\square}} \tag{3.6}$$

therefore,

$$f_{eq} = \frac{e_{ex}}{d_{ex}} \tag{3.7}$$

where f_{eq} is the equated priority and f_{ex} is the actual experts' priority,

$$f_{eq} \neq f_{ex} \tag{3.8}$$

So, priorities should be equated as shown above to maintain consistency, where f_{eq} will be used to replace the actual experts' priority f_{ex}. Accordingly, weights for the illustrative example will be:

$$W_A = \frac{\frac{1}{1.42} + \frac{4}{5.67} + \frac{6}{8.50}}{3} = 0.70$$

$$W_B = \frac{\frac{1/4}{1.42} + \frac{1}{5.67} + \frac{2}{8.50}}{3} = 0.20$$

$$W_C = \frac{\frac{1/6}{1.42} + \frac{1/2}{5.67} + \frac{1}{8.50}}{3} = 0.10$$

$$W_{Parent} = \begin{bmatrix} W_A \\ W_B \\ W_C \end{bmatrix} = \begin{bmatrix} 0.70 \\ 0.20 \\ 0.10 \end{bmatrix}$$

where modified reciprocal matrix is presented in Tables 3.6 and 3.7.

This method is applicable when the difference between experts' judgments or priorities (f_{ex}) and equated priority (f_{eq}) is small. If the difference is significant, consistency ratio method (C.R.) can be used.

ii. Consistency Ratio (*C.R.*)

In real applications, it is sometimes difficult to get consistent priorities or judgments from experts. Therefore, the key issue here is not being consistent, but it is whether the consistency level is accepted or not. For the matrix in Table 3.8,

$$f_{ex} \neq \frac{e_{ex}}{d_{ex}}$$

Table 3.6 Illustration for modified reciprocal matrix

Element	A	B	C
A	1	4	6
B	$1/4$	1	3/2
C	$1/6$	$2/3$	1
Column Total	1.42	5.67	8.50

Table 3.7 Normalization of modified reciprocal matrix

Element	A	B	C
A	$\frac{1}{1.42}$	$\frac{4}{5.67}$	$\frac{6}{8.50}$
B	$\frac{1/4}{1.42}$	$\frac{1}{5.67}$	$\frac{1.5}{8.50}$
C	$\frac{1/6}{1.42}$	$\frac{1/2}{5.67}$	$\frac{1}{8.50}$

Table 3.8 Inconsistent priorities and weights

Element	A(0.70)	B(0.19)	C(0.11)
A	1	4	6
B	$1/4$	1	2
C	$1/6$	$1/2$	1

Therefore, the priorities are inconsistent and they should be tested using *C.R.* to check the consistency level. Saaty (1982) proposed to multiply the element's weight for the inconsistent priorities by the relative priority of that element as shown in Table 3.6. Consistency ratio is defined as:

$$C.R. = \frac{C.I.}{R.I.} \tag{3.9}$$

where:

C.R. = Consistency Ratio

R.I. = Random Consistency Index

C.I. = Consistency Index, which is defined as:

$$C.I. = \frac{\lambda_{max} - n}{n - 1} \tag{3.10}$$

where:

$\lambda_{max} =$ is the average of dividing the row totals in the matrix shown in Table 3.9 by inconsistent weights

$n =$ number of elements

Weights for inconsistent priorities are considered "consistent" if the *C.R.* is less than 10%. Table 3.10 shows sets of values where each value is an average random consistency index (*R.I.*) derived from a sample of randomly generated reciprocal matrices using scale priorities presented in Table 3.2 (Saaty and Vargas, 1994). For the case discussed here, n = 3 and from Table 3.10, *R.I.* is equal to 0.52.

Table 3.9 Inconsistent matrix after multiplication

Element	A	B	C	Row Total
A	0.70	0.76	0.66	2.12
B	0.18	0.19	0.22	0.59
C	0.12	0.10	0.11	0.33

Table 3.10 Average Random Consistency Index (R.I.)

n	1	2	3	4	5	6	7	8	9	10
R.I.	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Therefore, from the matrix in Table 3.9 and Equations (3.9) and (3.10):

$$[Row\ totals] \div [Inconsistent\ weights] = [\lambda]$$

$$\begin{bmatrix} 2.12 \\ 0.59 \\ 0.33 \end{bmatrix} \div \begin{bmatrix} 0.70 \\ 0.19 \\ 0.11 \end{bmatrix} = \begin{bmatrix} 3.03 \\ 3.12 \\ 3.00 \end{bmatrix}$$

$$\lambda_{max} = \frac{3.03 + 3.12 + 3.00}{3} = 3.05$$

$$C.I. = \frac{3.05 - 3}{2} = 0.025$$

$$C.R. = \frac{0.025}{0.52} = 0.048$$

Therefore, since *C.R.* is less than 0.1, the inconsistency was ignored and the original weights were considered consistent.

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

3.1.4.4 Aggregation

Aggregation is the process by which fuzzy sets representing the outputs for each parameter or element (child element) [$\mu_{low}, \mu_{med}, \mu_{high}$] are combined or aggregated to produce a single output for 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 and Rodriguez, 2004; Francisque et al., 2009).

For hierarchical system presented in Figure 3.4, fuzzy sets for all child elements after fuzzification will be as follows:

$$\begin{bmatrix} \mu_{low}^{A} & \mu_{med}^{A} & \mu_{high}^{A} \\ \mu_{low}^{B} & \mu_{med}^{B} & \mu_{high}^{B} \\ \mu_{low}^{C} & \mu_{med}^{C} & \mu_{high}^{C} \end{bmatrix} \tag{3.11}$$

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

$$\begin{bmatrix} \mu_{low}^{Parent} & \mu_{med}^{Parent} & \mu_{high}^{Parent} \end{bmatrix} = \begin{bmatrix} w_A & w_B & w_C \end{bmatrix} \times \begin{bmatrix} \mu_{low}^{A} & \mu_{med}^{A} & \mu_{high}^{A} \\ \mu_{low}^{B} & \mu_{med}^{B} & \mu_{high}^{B} \\ \mu_{low}^{C} & \mu_{med}^{C} & \mu_{high}^{C} \end{bmatrix} \tag{3.12}$$

This parent fuzzy set produced from matrix multiplication in Equation (3.12) was used in further calculation. This fuzzy set was considered as 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 3.1.

3.1.4.5 Defuzzification

The process by which fuzzy sets [μ_{low}, μ_{med}, μ_{high}] are converted to representative crisp value is called defuzzification (Wang, 1999; Francisque et al., 2009). 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 maximum, the center of area, weighted average and others. Weighted average method or scoring is preferred by many researchers (Lu et al., 1999; Silvert, 2000; Sadiq and Rodriguez, 2004; 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:

$$\text{Crisp value (Risk Index)} = (a \times \mu_{low}) + (b \times \mu_{med}) + (c \times \mu_{high}) \qquad (3.13)$$

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). For the fuzzy set representing low risk (μ_{low}), it is acceptable to neglect this risk and assign a zero to weight a, because low risk implies high safety and secure system. Similarly, for the fuzzy set representing high risk (μ_{high}), weight c should be entirely considered since it represents the situation with highest risk and lowest security level. Fuzzy set representing moderate risk (μ_{med}) represents the midway or the mean between low and high risk, therefore, assigning 0.5 to b is logically accepted.

3.1.5 Fuzzy Rule-Based (FRB)

For the parameters and elements used in the AHP, basic assumption of independence of children elements was made. This can be accepted for most of the elements presented in Figure 3.1, but there are few elements that have some sort of dependence or interrelations between them which cannot be ignored.

FRB is used to aggregate dependent child elements using IF-THEN rules based on the knowledge of experts. One of the most common approaches for merging human knowledge into engineering processes using artificial intelligence mechanisms is the IF-THEN rules in the form of (Ross, 2009):

<u>IF premise (antecedent), THEN conclusion (consequent)</u>

IF-THEN rules are classified to be the heart of fuzzy systems. These rules characterize human knowledge, such as classifications and/or judgments, and engineering facts using continuous membership functions (Wang, 1999). Although this approach may look simple, it is very effective and has many applications. Suppose a hydraulic engineer is required to control water pressure in the WDN using pumping power, so that pressure is acceptable all over the network. Actions that should be taken by the engineer can be controlled using IF-THEN rules as follows:

IF pressure is low, THEN apply more pumping power

IF pressure is medium, THEN apply moderate pumping power

IF pressure if high, THEN apply less pumping power

The words “low”, “medium”, “high”, “more”, “moderate” and “less” are defined and characterized using membership functions. Using IF-THEN rules, typical membership function can be constructed between pressure and pumping power as presented in Figure 3.5 which shows the membership function for “low” fuzzy set only, where the horizontal and vertical axes represent the power needed and membership values, respectively.

The challenging step is using all these rules and membership functions to construct a single system. Different fuzzy systems have different approaches for combining rules and membership functions. Generally, major combining approaches for fuzzy systems that are commonly used are: (1) pure fuzzy systems, (2) Mamdani fuzzy systems, (3) Sugeno fuzzy systems and (4) fuzzy systems with fuzzifier and defuzzifier (Wang, 1999; Guney and Sarikaya, 2009).

General framework for pure fuzzy systems is represented in Figure 3.6, where A and B represent inputs and outputs, respectively. The fuzzy interface engine combines IF-THEN rules from input fuzzy sets to output fuzzy sets. The drawback of this approach is the use of natural language words for its input and output fuzzy sets, which is not applicable for all engineering problems that have numeric values and variables.

Mamdani and Sugeno fuzzy systems allow the consequent part of the fuzzy rules (THEN) to be in mathematical form. These approaches are weighted average, which means that different rules can be given different weights based on their importance and effect on the output. The general framework for Mamdani and Sugeno methods is presented in Figure 3.7. The main problem with these two approaches is the consequent part of the fuzzy rules which cannot anymore represent human knowledge since it is a mathematical formulation. In addition, the fuzzy system becomes rigid with limited freedom to apply different fuzzy logic principles. Fuzzy systems with fuzzifiers and defuzzifiers present the advantages of pure, Mamdani and Sugeno fuzzy systems without suffering from the drawbacks of the original methods. Real values and variables are transformed into fuzzy sets using fuzzifiers for inputs and after the analysis, fuzzy sets are transformed into real

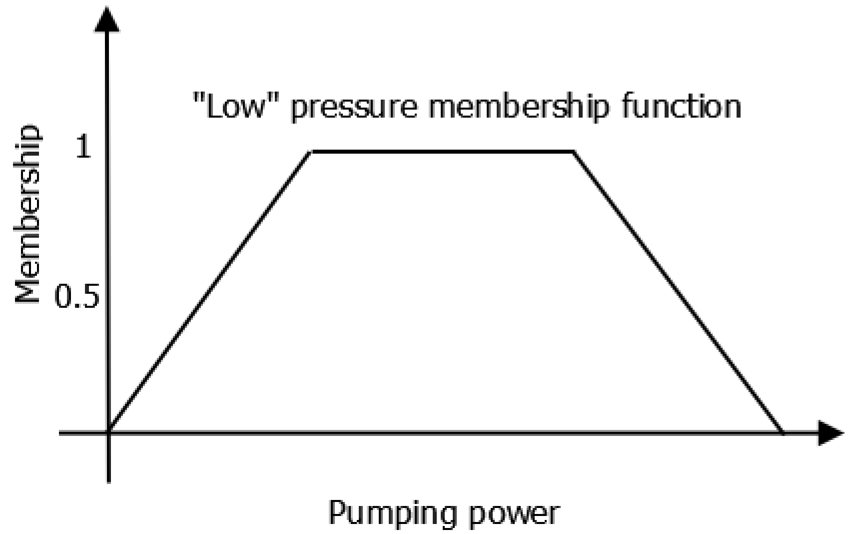


Figure 3.5 Membership function for “low” class

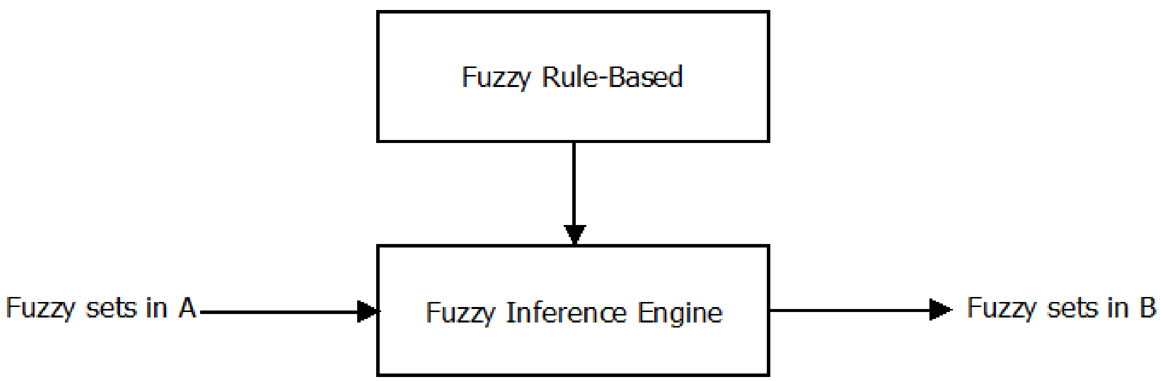


Figure 3.6 Pure fuzzy system’s framework

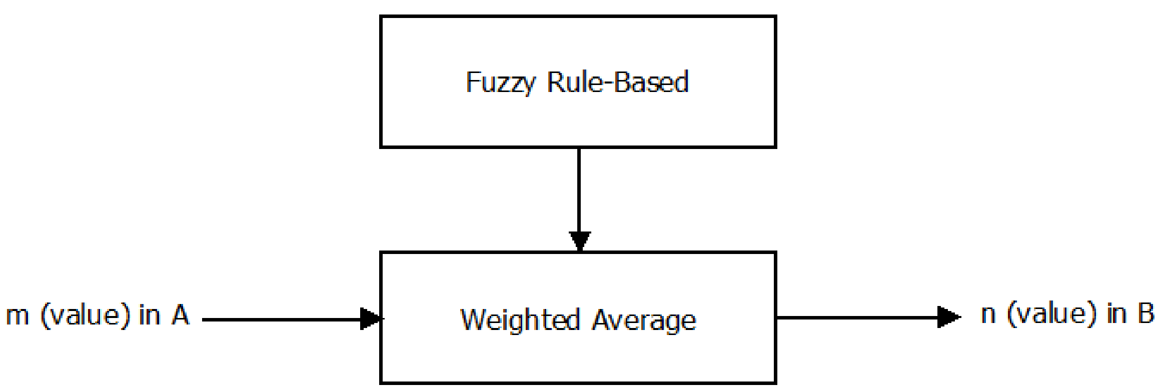


Figure 3.7 Mamdani and Sugeno systems’ framework

values and variables using defuzzifier for outputs as was explained in detail regarding FSE. This approach gives the ability to use a wide range of data types from linguistic classes and natural language words to numerical variables (Wang, 1999) and, accordingly, this approach was used in this research. Figure 3.8 shows the general framework for this fuzzy system. In this study, fuzzifier and defuzzifier used for FSE were exactly the same. The change was only in the aggregation process.

The element groups with $\oplus$ sign in Figure 3.1, imply that the groups' elements were considered independent of each other, and aggregated crisp values for the parent element were determined using weighted average method as discussed previously. Element groups with $\otimes$ sign indicate that elements in these groups are somehow dependent or related to each other. Thus, the IF-THEN FRB rules were used for aggregation instead of the weighted average method to ensure that relations among elements were considered.

For groups such as hydraulics, potential intrusion, physico-chemical and microbial, a single representative value for elements such as pressure, pH, TDS…etc., was considered when using FSE. This representative value is usually the arithmetic mean. In order to reflect the variation and range of data from this representative value, two penalty factors were added to these elements. Adding such penalty would increase the risk index in case there is a significant diversion in the data records from representative value or from the optimal acceptable range of the considered factor. Diversion fuzzy sets and relevant element fuzzy sets were aggregated using FRB to produce fuzzy sets which consider risk due to violation of the hydraulic or environmental standards as well as the risk caused by significant diversion of data from the representative value used in the analysis.

To illustrate the application of FRB, suppose pH fuzzy sets are:

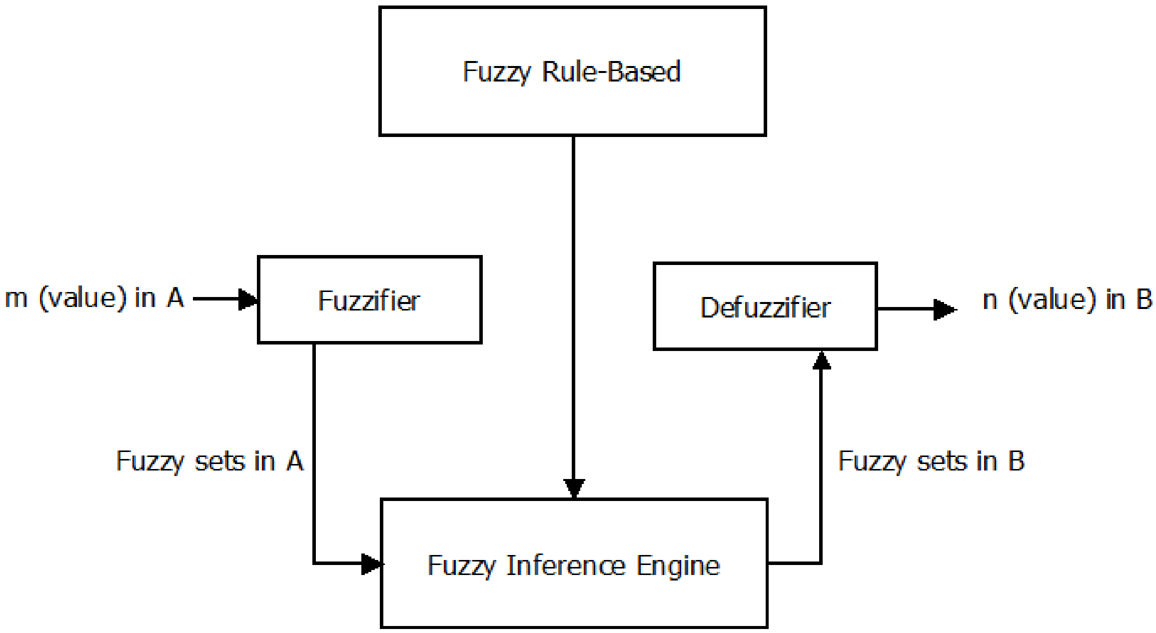


Figure 3.8 Framework for systems with fuzzifiers and defuzzifiers

$$\left[\mu_{low}^{pH} \quad \mu_{med}^{pH} \quad \mu_{high}^{pH}\right]$$

and the diversion (penalty) fuzzy sets are:

$$\left[\mu_{low}^{pH-D} \quad \mu_{med}^{pH-D} \quad \mu_{high}^{pH-D}\right]$$

Consider the following as the IF-THEN rules controlling the relation between pH risk and diversion risk:

IF pH level is LOW and diversion is LOW, THEN LOW

IF pH level is LOW and diversion is MED, THEN LOW

IF pH level is LOW and diversion is HIGH, THEN MED

IF pH level is MED and diversion is LOW, THEN MED

IF pH level is MED and diversion is MED, THEN MED

IF pH level is MED and diversion is HIGH, THEN HIGH

IF pH level is HIGH and diversion is LOW, THEN HIGH

IF pH level is HIGH and diversion is MED, THEN HIGH

IF pH level is HIGH and diversion is HIGH, THEN HIGH

These rules are represented in Table 3.11.

Aggregated new fuzzy sets for pH can be written as:

$$\left[\quad \mu_{low} = \quad \mu_{low}^{pH} \times \mu_{low}^{pH-D} + \ \mu_{low}^{pH} \times \mu_{med}^{pH-D} \quad \right]$$

$$\left[\quad \mu_{med} = \quad \mu_{med}^{pH} \times \mu_{low}^{pH-D} + \ \mu_{med}^{pH} \times \mu_{med}^{pH-D} + \mu_{low}^{pH} \times \mu_{high}^{pH-D} \quad \right]$$

$$\left[\quad \mu_{high} = \quad \mu_{med}^{pH} \times \mu_{high}^{pH-D} + \mu_{high}^{pH} \times \mu_{low}^{pH-D} + \ \mu_{high}^{pH} \times \mu_{med}^{pH-D} + \mu_{high}^{pH} \times \mu_{high}^{pH-D} \quad \right]$$

Table 3.11 Fuzzy rule-based for pH

		pH level		
		LOW	MED	HIGH
Diversion	LOW	LOW	MED	HIGH
	MED	LOW	MED	HIGH
	HIGH	MED	HIGH	HIGH

where $[\mu_{low} \quad \mu_{med} \quad \mu_{high}]$ is the final fuzzy set for pH which considers risk from pH level and diversion from representative value or optimal range.

3.2 Hydraulic Module (Phase II)

In this phase, a database for Al-Khobar WDN was prepared that will provide the necessary information for the fuzzy algorithms developed in "risk assessment module". Risk assessment was performed for predefined nodes in the WDN. Hydraulic simulation model WaterGEMS was used to generate spatial hydraulic data risk assessment module.

WaterGEMS is the newer edition of the well-known hydraulic model WaterCAD, developed by Bentley Systems (2006). WaterGEMS is a hydraulic and water quality model for WDN in which it provides the ability for designing, simulating, operating and managing WDNs. The model is capable of analyzing steady, extended period simulations, water age, fire-flow analysis and many other features. The model was used in many case studies either for modeling WDN, leak detections, demands and nearly all aspects related to hydraulic modeling (Bentley Systems, 2013). In addition to its powerful hydraulic modeling features, WaterGEMS is compatible with ArcGIS, which allows the modeler to geospatially model water systems using GIS (Meadows and Walski, 2001).

3.3 Optimization Module (Phase III)

In this module, the water quality monitoring stations will be selected following the demand coverage approach. Generally, the method is based on simple concept which states that downstream nodes with maximum demand are considered potential monitoring stations and nodes upstream are considered "covered" by these potential monitoring stations under specific conditions. Details of this approach can be found at Lee and

Deininger (1992). The developed coverage matrices based on the demand coverage approach were used to identify the optimal locations for MSs using the optimizations models which will be developed in chapter 4.

3.4 Display Module (Phase IV)

GIS was used extensively all over the study to display regional indices at the WDN. All the maps generated in this study were developed by GIS model. In addition, it was used to divide the city into sub-regions using Theissen method as will be discussed in the model development chapter (Chapter 4).

3.5 Risk Management Module (Phase V)

In this module, the contribution of each factor on the overall risk was studied and quantified using multi-criteria decision making (MCDM). In addition, the sensitivity of each factor on the overall risk, vulnerability and sensitivity of the system was investigated using Monte Carlo simulation.

CHAPTER 4

DSS Tool and Optimization Model Development

In this research, Decision Support System (DSS) tool and optimization model were developed. The DSS tool was developed using FSE and FRB to prioritize risks in any WDNs. On the other hand, the optimization model was developed to maximize monitored demand in the WDN by selecting optimal locations for MSs. The details of these tool and model are discussed in the following sections.

4.1 DSS Tool Development

The DSS tool was developed to prioritize risk between different sub-regions within the WDN. For this purpose, the WDN has to be divided into sub-regions in order to quantify and characterize risk assessment associated with them. Thessien method was applied to divide the WDN into sub-regions based on the existing monitoring stations using ArcGIS package which was used for the zoning process.

The DSS tool was developed based on FSE and AHP. Figure 3.1 shows the general framework for the developed DSS. Risk indices for sub-regions were determined by the aggregation of different components (or attributes) in AHP. According to the framework of the DSS, there are four levels in this system, each level is presented in different color. Level one (green) is considered as child attributes for level two (blue), and while level two are the parent attributes for level one, they are at the same time child attributes for level three (gray), and so on. Child attributes were aggregated together using FSE to determine the risk index for the parent attribute.

Each attribute has a fuzzy set which was developed based on the characteristics of the attribute, for example, the developed fuzzy set for TDS is shown in Figure 4.1. The boundaries for low, med and high membership functions are based on TDS standards presented in literature which define low, med and high levels of TDS. For attributes where there are no predefined boundaries or standards, or when there is no experts' agreement about the classification of the attribute, logical approximations and/or averages of existing standards were used to generalize the boundaries for the attributes. Table 4.1 summarizes the fuzzy sets boundaries for all "level one" attributes. Shapes of different fuzzy sets are shown in Appendix B. Triangular and trapezoidal fuzzy shapes were used in this study. Note that boundaries for population density and distribution of students shown in Table 4.1 are for the case study in this research. Equations (4.1) and (4.2) show how these boundaries were developed.

When dealing with large data records, limiting the analysis to representative values (such as mean or median) for each attribute may not be wise, especially for attributes with high diversity in data. Therefore, in addition to the fuzzy sets developed for defining the risk boundaries based on the representative value of the attribute, additional fuzzy sets such as "representative diversions percentage" and "optimal diversions percentage" were added for some of the attributes as discussed in Chapter 3. Instead of quantifying the risk based only on a single representative value (average), which might be too rough to reflect the variations of the entire data record, the diversity of the entire field data from the "representative value" and "optimal standards" was considered too. These fuzzy sets can

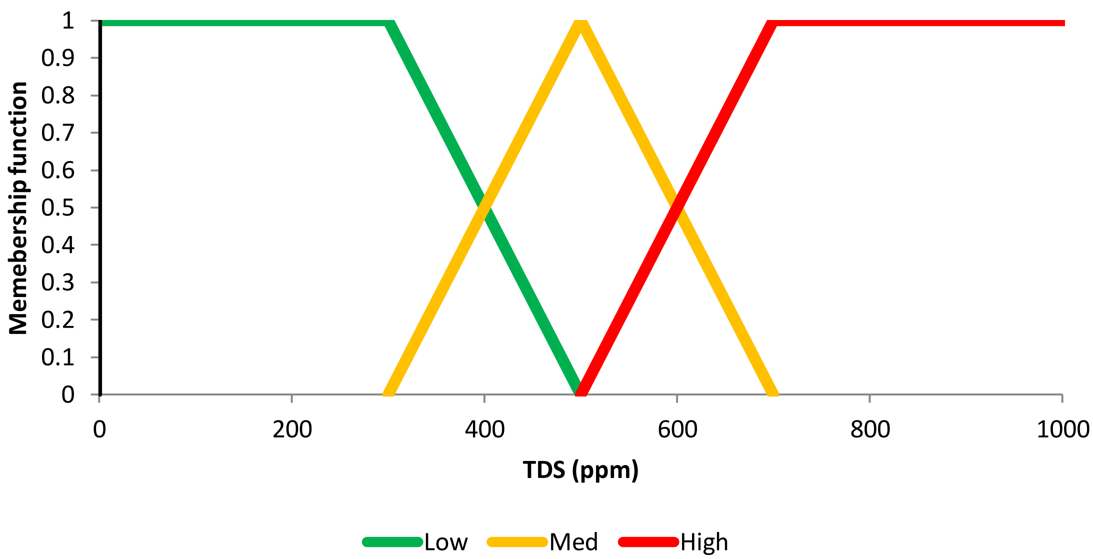


Figure 4.1 Fuzzy set for TDS

Table 4.1 Fuzzy sets thresholds and types

Parameter	Nature of fuzzy set	Thresholds						Type
		A	**B**	**C**	**D**	**E**	**F**	
TDS	Data (ppm)	0	300	500	700	∞		Triangular 1
	Representative Diversions (%)	0	25	50	100			Triangular 2
	Optimal Diversions (%)	0	25	50	100			Triangular 2
Temperature	Data (C°)	0	20	25	30	100		Triangular 1
	Representative Diversions (%)	0	25	50	100			Triangular 2
	Optimal Diversions (%)	0	25	50	100			Triangular 2
pH	Data	0	5.5	6.5	8.5	9.5	14	Trapezoidal
	Representative Diversions (%)	0	25	50	100			Triangular 2
	Optimal Diversions (%)	0	25	50	100			Triangular 2
Free Chlorine	Data (ppm)	0	0.2	0.3	1.2	1.3	∞	Trapezoidal
	Representative Diversions (%)	0	25	50	100			Triangular 2
	Optimal Diversions (%)	0	25	50	100			Triangular 2
Turbidity	Data (NTU)	0	0.5	0.8	1	∞		Triangular 1
	Representative Diversions (%)	0	25	50	100			Triangular 2
	Optimal Diversions (%)	0	25	50	100			Triangular 2
Pipes 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 (Option 2)	Average age	0	20	30	40	60		Triangular 2
Pipe Break (Option 3)	Breakage ratio	0	0.25	0.5	0.75	1		Triangular 3

Table 4.1 Continued

Parameter	Nature of fuzzy set	Thresholds						Type
		A	**B**	**C**	**D**	**E**	**F**	
Schools	No. of Elementary students	0	709	1418	2835	∞		Triangular 1
	No. of Intermediate students	0	317	633	1266	∞		Triangular 1
	No. of Secondary students	0	273	546	1092	∞		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	9420	18840	300000			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

be thought of as penalties which will increase the risk indices if there is a high divergence between the "representative value" and attribute's field data. Similarly, additional penalties will be added to risk indices if there is high divergence between "optimal standards" and attribute's field data.

Most of the attributes' boundaries for fuzzy sets were determined based on the standards of each attribute published in literature and operational standards – for Al-Khobar WDN – (WHO, 1996; AWWA, 2002; WHO, 2003; Sarbatly and Krishnaiah, 2007; Gupta, 2008; WHO, 2008; USEPA, 2009; Francisque et al., 2009), as shown in Table 4.1. However, since some of the attributes did not have predefined standards or they may change from one place to another or from one sub-region to another, therefore some standards were developed to determine the boundaries for these attributes. Examples of such attributes include number of students in elementary, intermediate and secondary schools, population density, pipe breaks and pipe age.

For the number of school students in a sub-region, fuzzy med class for number of students boundary was determined using Equation (4.1) as follows:

$$\frac{\sum_i^n S_i}{n} \tag{4.1}$$

where:

n = number of sub-regions

i = school type (elementary, intermediate and secondary)

S = number of students at sub-region i

Low and high fuzzy classes are half and twice med class boundary, respectively. Fuzzy med class for population density was determined using the average population density for the city as shown in Equation (4.2). Low and high fuzzy classes for population density are zero and twice the average, respectively.

$$\sum_i^n \left(\frac{P_i}{A_i}\right) \tag{4.2}$$

where:

P_i = Population at sub-region *i*.

A_i = Area at sub-region *i*.

To evaluate the pipe breaks in any sub-region, a weighted breakage ratio index was developed to enhance risk prioritization. The weighted breakage ratio (*WBR*) ranges between zero and 1, where zero indicates low fuzzy class and 1 indicates high fuzzy class. WBR is defined as follows:

$$WBR_i = \frac{RB_i}{PM_i} \tag{4.3}$$

where:

WBR_i = Weighted breakage ratio for i^{th}pipe material.

i = Pipe material (AC, PVC, Steel…etc.).

RB = Historical breakage ratio for i^{th}pipe material.

PM = Percentage of pipe material *i* in the sub-region.

Based on the data collected from Al-Khobar municipality, PMs for AC, PVC and steel pipes are 65%, 10% and 25%, respectively. Accordingly, sub-regions where AC pipes are dominant will be characterized with high risk of pipe breakage and sub-regions where PVC pipes are dominant will be characterized with low risk of pipe breakage.

For evaluating the pipes age in the sub-regions, a weighted age average index was developed. In every sub-region, there are different pipe sets. Each set represents pipes that have been installed in the same period. In this tool, the weighted age average (*WAA*) ratio is defined as follows:

$$WAA_i = \frac{PA_i}{PP_i} \tag{4.4}$$

$$RA = \sum_i WAA_i \tag{4.5}$$

where:

i : Pipes set i.

PA_i : Pipe ages for pipe set i at the sub-region.

PP_i : Percentage by area of pipe set i in the sub-region.

RA : Average age of pipes in the sub-region.

Pipes with zero, 30 and 60 years of age represent the low, med and high fuzzy class, respectively. Pipe breakage risks vary for different types of pipe materials, however, AC pipes are the worst in terms of breakage ratio and health concerns. Accordingly, percentage of AC pipes in each sub-region was used as the risk index for pipe breakage as presented in Table 4.1.

Percentage of areas in which water table fluctuates above and below WDN was used to evaluate the water level effect on pipes. This variation in water level can cause intrusion and breakage due to variation of external pressure acting on pipes. The percentage of pipes that were experiencing fluctuation of groundwater level were used to classify this attribute as shown in Table 4.1.

Potential industrial intrusion was approximated by the industrial areas within the sub-regions. Similarly, area of corrosive soils – that might harm the pipelines – in each sub-region was used to approximate the aggressiveness of the surrounding soil on pipes.

For standard of living and activity index, setting boundaries for these attributes was approximated based on real estate values at each sub-region and the existing activities. In general, standard of living is characterized to have three classes, namely low, med and high income rates, while activity is classified to include the following three classes: residential, commercial and industrial. These classes were numerated by using the percentage of area of each class within the specified sub-region. Subsequently, each class was assigned a different weight during the aggregation process based on the severity of each class. For example, people in areas with low income rate, will tend more to drink water from the WDN compared to people with high income rates who will tend to buy bottled drinking water. Therefore, the risk on the low income rate class due to deterioration of water quality is expected to be high compared to areas or sub-regions occupied by high income rate class. Tables 4.2 to 4.11 show weights used for

Table 4.2 Weights for Hydraulics attribute

	Pressure	Velocity	Water age
Pressure	1	3	4
Velocity	0.33	1	1.33
Water age	0.25	0.75	1

Table 4.3 Weights for Physical and chemical attribute

	TDS	Temp	pH
TDS	1	3	0.33
Temp	0.33	1	0.1
pH	3	0.9	1

Table 4.4 Weights for microbial attribute

	Chlorine R.	Turbidity
Chlorine R.	1	4
Turbidity	0.25	1

Table 4.5 Weights for Water Quality attribute

	P-C	Microbial
P-C	1	0.5
Microbial	2	1

Table 4.6 Weights for Intrusion attribute

	Industrial	Sewer
Industrial	1	0.33
Sewer	3	1

Table 4.7 Weights for Structure Integrity attribute

	Type	Age	Break	P. Int.	Water table
Pipe type	1	2	1	3	9
Pipe age	0.5	1	0.5	1.5	4.5
Pipe break	1	2	1	3	9
Potential intrusion	0.33	0.67	0.33	1	3
Water table	0.11	0.22	0.11	0.33	1

Table 4.8 Weights for Schools attribute

	Elementary	Intermediate	Secondary
Elementary	1	3	5
Intermediate	0.33	1	1.67
Secondary	0.2	0.6	1

Table 4.9 Weights for Sensitivity attribute

	Population	Schools	Hospital	Activity	Standard of living
Population	1	3	2	4	5
Schools	0.33	1	0.67	1.33	1.67
Hospital	0.5	1.5	1	2	2.5
Activity	0.25	0.75	0.5	1	1.25
Standard of living	0.2	0.6	0.4	0.8	1

Table 4.10 Weights for Vulnerability attribute

	Water Quality	Structure I.	Hydraulics
Water Quality	1	1	1
Structure I.	1	1	1
Hydraulics	1	1	1

Table 4.11 Weights for Risk attribute

	Vulnerability	Sensitivity
Vulnerability	1	1
Sensitivity	1	1

aggregation process. These weights were developed based on inputs collected from experts in addition to weights published in literature (Francisque et al., 2009). These weights were used to evaluate the importance of each attribute compared to other attributes as explained in Chapter 3. A copy of the survey can be found in Appendix A.

The attribute indices were developed after performing the following: fuzzification, aggregation and defuzzification as discussed in Chapter 3. The development of the indices can be illustrated by the following example for physico-chemical attribute as shown below.

The physico-chemical attribute was developed by aggregating the fuzzified three child attributes including TDS, pH and temperature as shown in Figure 3.1. Each child attribute has three membership functions, $[\mu_{low}, \mu_{med}, \mu_{high}]$, which indicate low, med and high fuzzy class for each child attribute. Suppose the membership functions for representative values and diversions penalties for TDS, pH and temperature child attribute are presented in matrices form as shown in Tables 4.12 and 4.13, respectively. Using FRB as discussed in Chapter 3, the overall membership functions for child attributes can be developed as shown in Table 4.14.

Based on the relative weights matrix for physico-chemical attribute shown in Table 4.3, the developed weights for TDS, pH and temperature are:

$$W_{Physico-chemical} = \begin{bmatrix} W_{TDS} \\ W_{pH} \\ W_{Temp} \end{bmatrix} = \begin{bmatrix} 0.70 \\ 0.07 \\ 0.23 \end{bmatrix}$$

Table 4.12 Assumed membership functions for TDS, pH and temperature

	μ_L	μ_M	μ_H
TDS	1	0	0
Temp	0	0.48	0.52
pH	1	0	0

Table 4.13 Assumed diversion membership functions for TDS, pH and temperature

	μ_L	μ_M	μ_H
TDS	0.49	0.26	0.25
Temp	0	0	1
pH	1	0	0

Table 4.14 Overall membership functions for TDS, pH and temperature

	μ_L	μ_M	μ_H
TDS	0.49	0.51	0
Temp	0	0	1
pH	1	0	0

Accordingly, aggregating child attributes to determine parent attribute (physico-chemical) membership functions, gives:

$$\begin{bmatrix}\mu_{low}^{PC} & \mu_{med}^{PC} & \mu_{high}^{PC}\end{bmatrix} = [0.70 \quad 0.07 \quad 0.23] \times \begin{bmatrix}0.49 & 0.51 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0\end{bmatrix}$$

$$\begin{bmatrix}\mu_{low}^{PC} & \mu_{med}^{PC} & \mu_{high}^{PC}\end{bmatrix} = [0.80 \quad 0.12 \quad 0.08]$$

Finally, crisp value for parent attribute (usually used for risk, vulnerability and sensitivity indices) can be determined by using weights (Table 4.15) which were developed using weighted average method (Lu et al., 1999; Silvert, 2000; Sadiq and Rodriguez, 2004; Francisque et al., 2009) as follows:

Physico-chemical Index (Crisp value) = (0 x 0.80) + (0.5 x 0.12) + (1 x 0.008)

Physico-chemical Index (Crisp value) = 0.14

Similar procedure was applied for every child and parent attributes. It should be noted that diversions penalties matrix was developed by applying FRB between representative diversions and optimal diversions.

4.2 Decision Support System (DSS) Tool

The DSS tool was developed using Excel platform and macros. It is capable of estimating the risk indices for a wide variety of factors affecting WDN including water quality, infrastructure, population distribution as well as human and industrial activities. The DSS was applied on each sub-region in the WDN to prioritize regional indices such as vulnerability, sensitivity and risk. Input data used for the DSS are either changing on short time basis such as water quality parameters including TDS, chlorine residuals, pH, TDS…etc., or variables that do not change in short period such as types of pipes, pipes

Table 4.15 Weights for different indices based on weighted average method

Index	μ_{low}	μ_{med}	μ_{high}
Physical and Chemical	0	0.5	1
Microbial	0	0.5	1
Water Quality	0	0.5	1
Structural Integrity	0	0.5	1
Schools	0	0.5	1
Hospitals	0	0.5	1
Activity	0.2	0.3	1
Standard of living	0.2	0.5	1
Pressure	0	0.5	1
Velocity	0	0.5	1
Water Age	0	0.5	1
Hydraulics	0	0.5	1
Population	0.2	0.5	1
Sensitivity	0	0.5	1
Vulnerability	0	0.5	1
Risk	0	0.5	1

materials, number of hospital beds, human and industrial activities, income rate…etc. In general, the developed DSS tool can be applied for any WDN.

The DSS was developed so that it updates all indices such as vulnerability, sensitivity and risk, directly as soon as the input data are entered into the Excel sheet prepared for data input. The DSS tool is capable of showing daily, monthly and annual indices for hydraulics, water quality, structure integrity, vulnerability, sensitivity and risk.

The developed DSS tool consists of 32 sheets in which all the operations related to FSE and FRB are performed, which include fuzzification, aggregation, weighting, defuzzification and crisp values development, in addition to presenting output indices for every attribute shown in Figure 3.1. Sample snapshots of the developed DSS tool are presented in Figures 4.2 to 4.6.

In order to make sure that FSE and FRB operations are operating correctly as well as the inputs were entered and output are presented correctly, 195 checks were used in the developed DSS tool. Soft copy of the DSS tool is in appendix D.

Sources of input data vary depending on the attribute, which are mainly collected from the field, either for daily varying attributes such as water quality parameters or long-term varying attributes such as infrastructure characteristics. However, hydraulic parameters were simulated using WaterGEM software package based on the developed and calibrated WDN model for Al-Khobar city (Al-Zahrani and Al-Ghamdi, 2008).

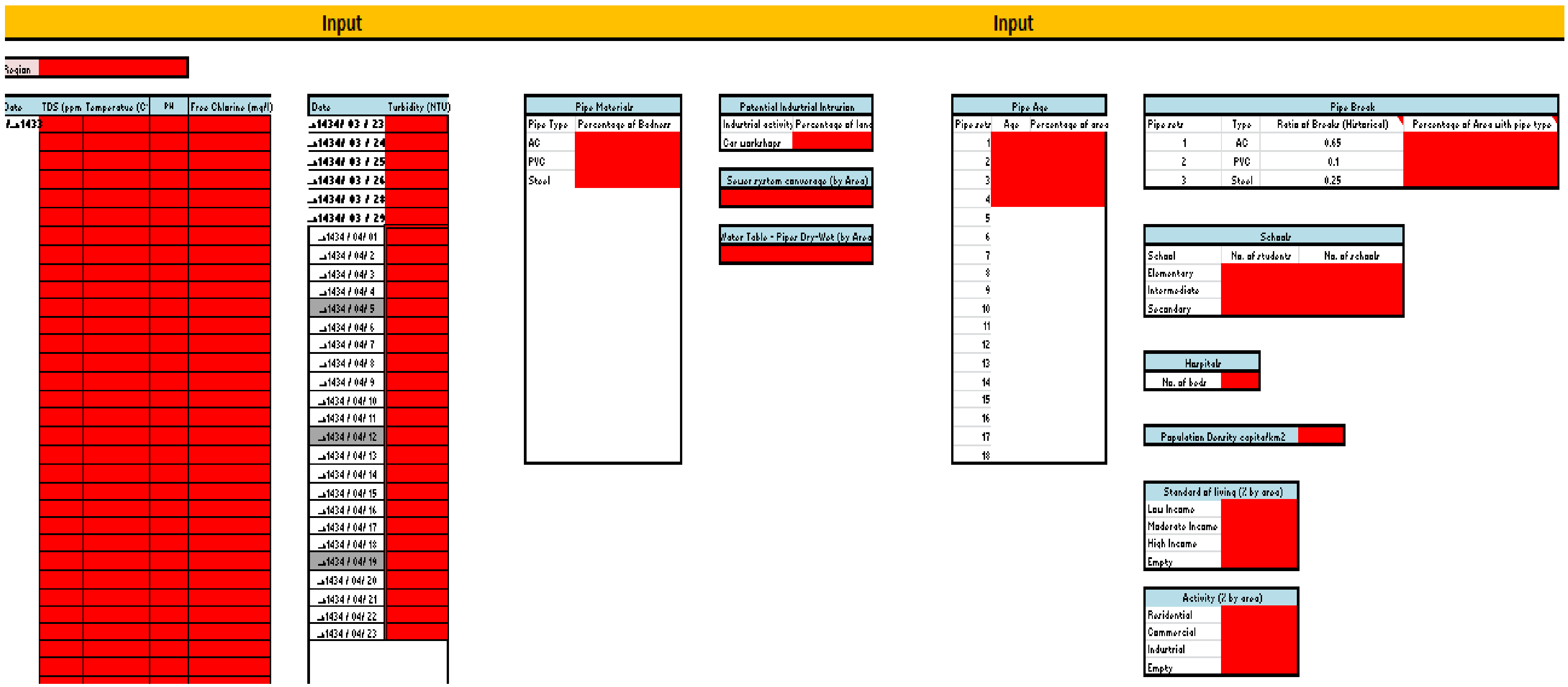


Figure 4.2 Sample input sheet for DSS tool

Thresholds for Fuzzy sets for all parameters

ging these values will automatically changes the thresholds at the entire spreadsheat !!

Parameter	Nature of data	Thresholds A	B	C	D	E	F	Type
TDS	Data (ppm)	0	300	500	700	10000		Triangular 1
	Representative Diversions %	0	25	50	100			Triangular 2
	Optimal Diversions %	0	25	50	100			Triangular 2
Temperature	Data (C°)	0	20	25	30	100		Triangular 1
	Diversions %	0	25	50	100			Triangular 2
	Optimal Diversions %	0	25	50	100			Triangular 2
PH	Data	0	5.5	6.5	8.5	9.5	14	Trapezoidal
	Diversions %	0	25	50	100			Triangular 2
	Optimal Diversions %	0	25	50	100			Triangular 2
Free Chlorine	Data (ppm)	0	0.2	0.3	1.2	1.3	100	Trapezoidal
	Diversions %	0	25	50	100			Triangular 2
	Optimal Diversions %	0	25	50	100			Triangular 2
Turbidity	Data (NTU)	0	0.5	0.8	1	20000		Triangular 1
	Diversions %	0	25	50	100			Triangular 2
	Optimal Diversions %	0	25	50	100			Triangular 2
Pipes Type	Data % of badness	0	25	50	75	100		Triangular 3
Potential Industrial intrusion	Data % possible lands	0	25	50	75	100		Triangular 3
Pipe Age (option 2)	Average age	0	20	30	40	60		Triangular 2
Pipe Break (option 3)	Ratio of breakage	0	0.25	0.5	0.75	1		Triangular 3
Schools	No. of Elementary students	0	709	1418	2835	20000		Triangular 1
	No. of Intermediate students	0	317	633	1266	20000		Triangular 1
	No. of Secondary students	0	273	546	1092	20000		Triangular 1
Hospitals	No. of beds	0	40	80	120	160	10000	Triangular 2
Pressure	Data % of nodes with low pressure	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
Low Pressure	Data % of nodes with low pressure	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
High Pressure	Data % of nodes with high pressure	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
Velocity	Data % of pipes with low velocity	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
Low Velocity	Data % of pipes with low velocity	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
High Velocity	Data % of pipes with high velocity	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
Water Age	Data % of nodes with high water ag	0	25	50	100			Triangular 2
	Diversions %	0	25	50	100			Triangular 2
Population	Population density	0	9420	18840	300000			Triangular 2
Sewer system converage	Data % of coverage	0	25	50	75	100		Triangular 3
Water Table	Data % of Dry-Wet pipes	0	25	50	100			Triangular 2

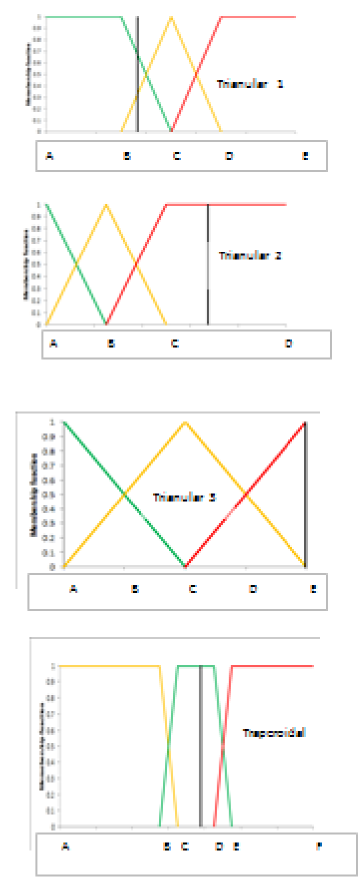
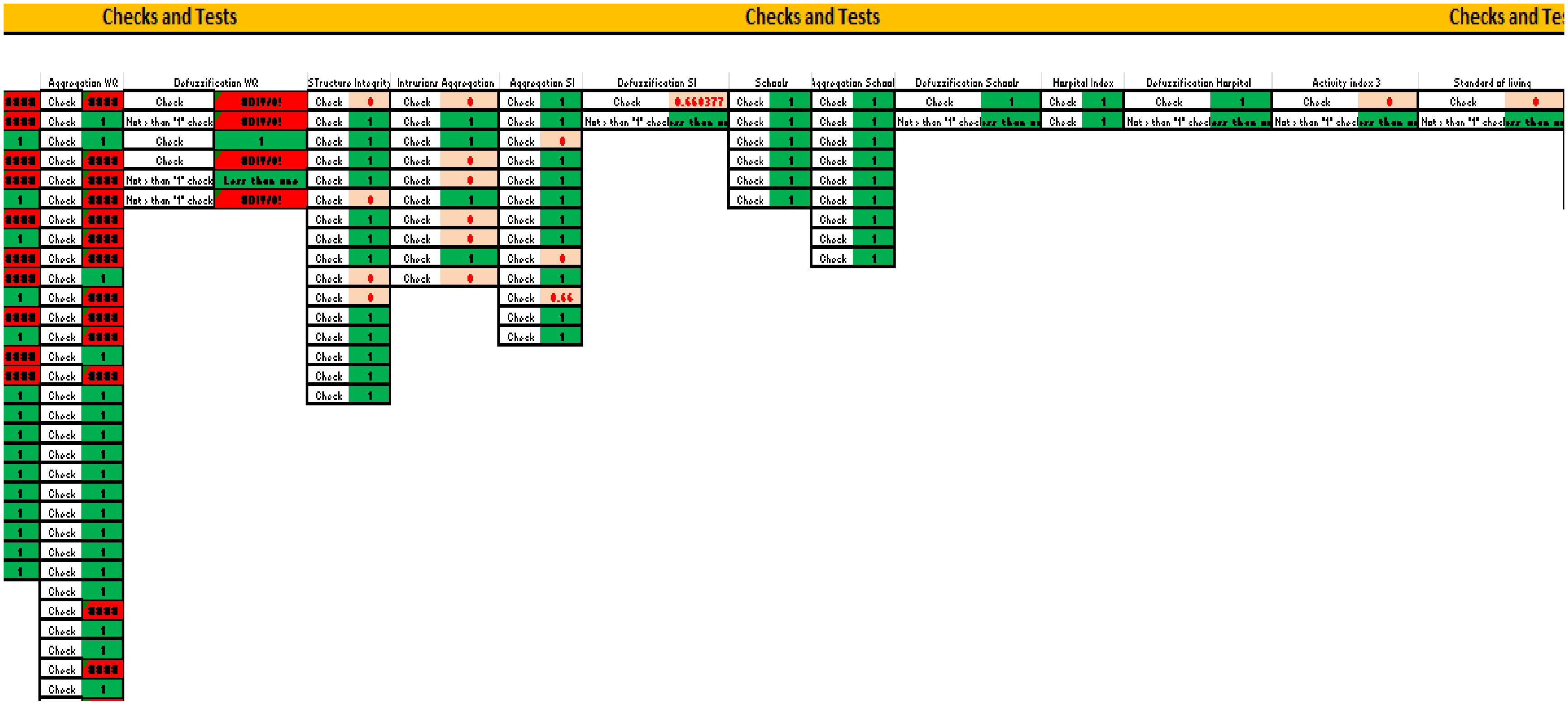


Figure 4.3 Thresholds sheet used for the DSS tool



	Aggregation WQ		Defuzzification WQ	
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1	Check	1	Check	1
####	Check	####	Check	#DIV/0!
####	Check	####	Not > than "1" check	Less than one
1	Check	####	Not > than "1" check	#DIV/0!
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Defuzzification SI		Schools		Aggregation School		Defuzzification Schools		Hospital Index		Defuzzification Hospital		Activity index 3		Standard of living	
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Figure 4.4 Internal check sheet of the DSS tool

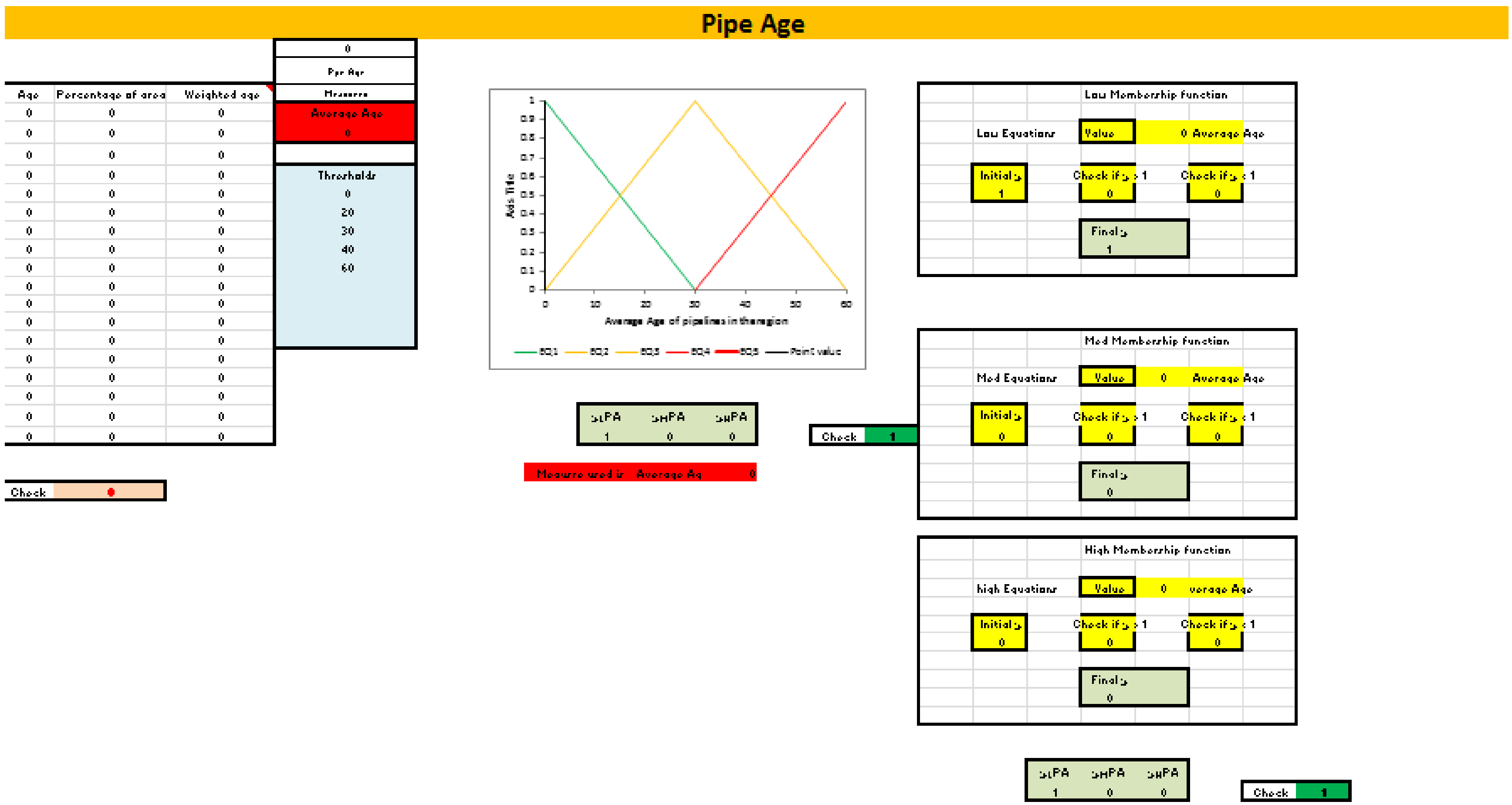


Figure 4.5 Sample analysis of one of the FSE processes for one attribute

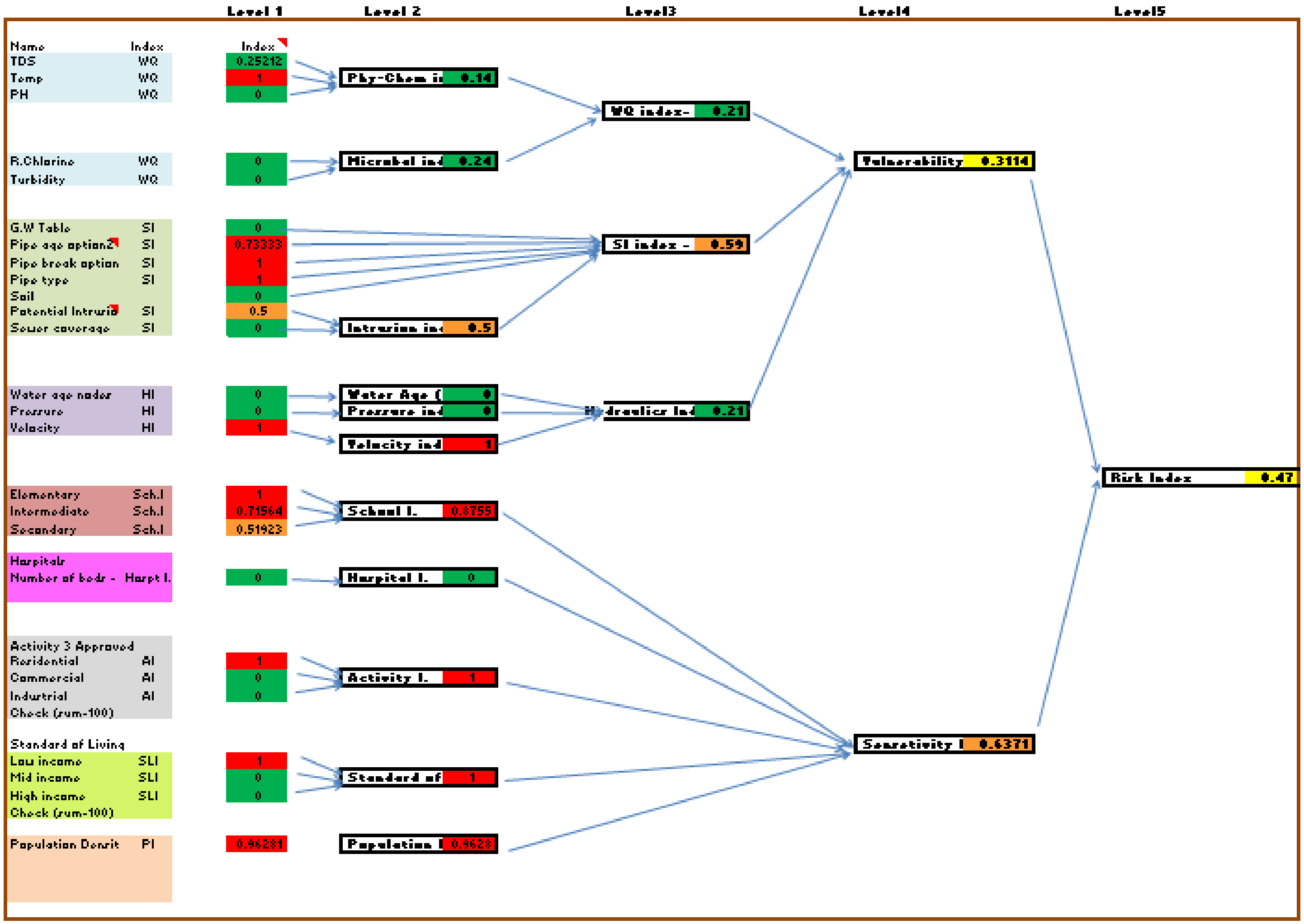


Figure 4.6 Sample output sheet of the DSS tool

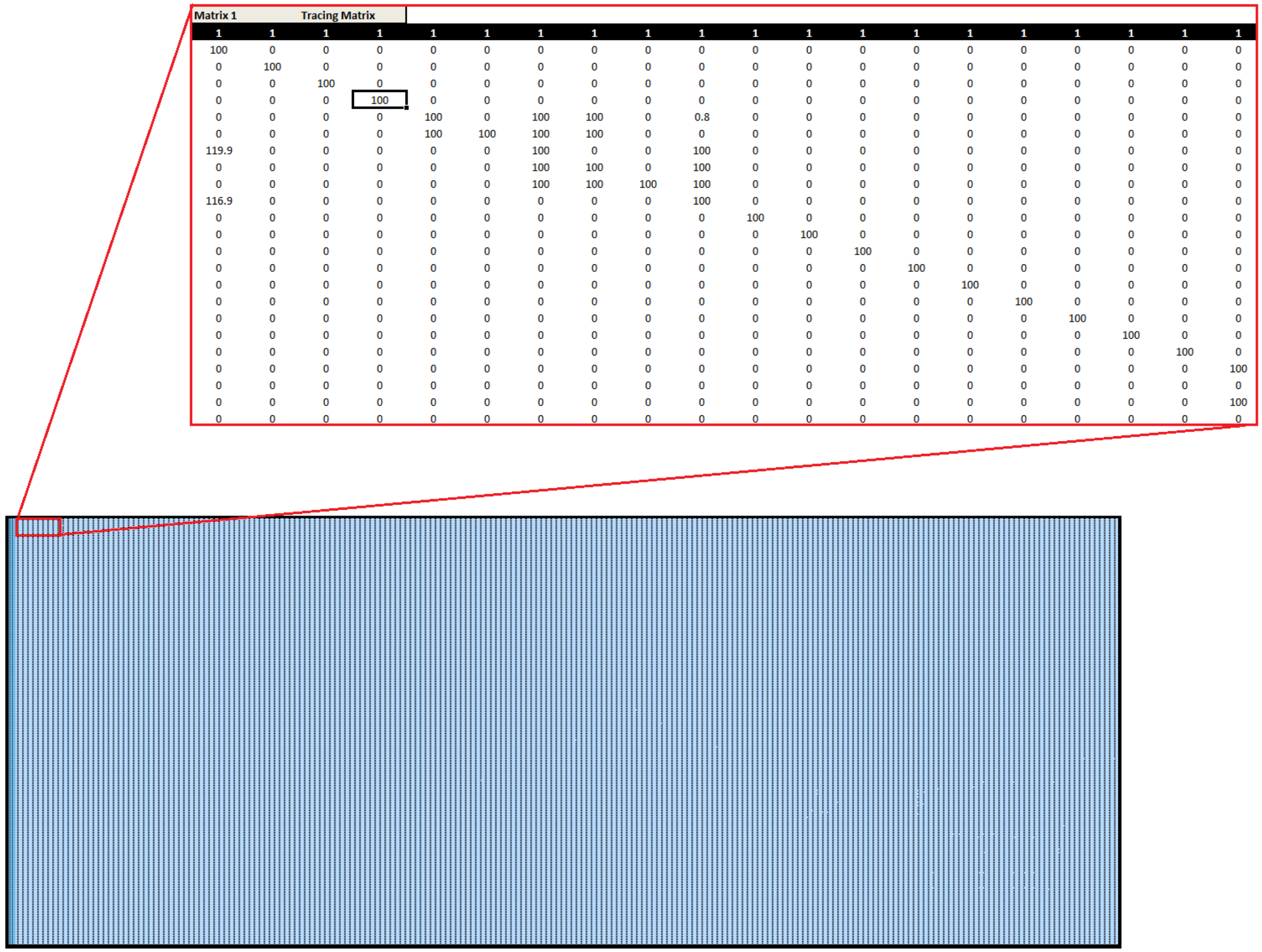
4.3 Optimization Model

Another objective of this research was to optimize water quality monitoring stations in WDN. The main component in locating MS using DCM is developing the demand matrix, which shows the percentage of flow from each PMS node. To develop the demand matrix, each node was considered as a potential contamination node and accordingly, flow from each node has to be traced all over the network. In this study, WaterGEM package was used for tracing the flow. Each simulation traces water flow from a single node all over the network and, consequently, tracing matrix shows the percentage of water flowing from the specified single node towards the other nodes in the network during a simulation period of 24 hours. These tracing matrices were used to construct flow fraction and demand coverage matrices. Figure 4.7 shows a snapshot of tracing matrix at hour 1 of the day.

Converting the tracing matrix into demand matrix is a very complex process, especially for real network. For each tracing matrix, 12 supporting matrices were used to:

- eliminate traced flow less than the flow threshold (*CT*),
- construct initial demand matrix,
- select maximum demand for each node in case a single node covers several flow paths, and
- ensure that each demand at each node will be covered once only.

In other words, to determine the demand matrix for one hour from the 24 hours in the day, 12 supporting matrices were required to develop the final demand matrix which will



Matrix 1 Tracing Matrix

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	100	0	100	100	0	0.8	0	0	0	0	0	0	0	0	0	0
0	0	0	0	100	100	100	100	0	0	0	0	0	0	0	0	0	0	0	0
119.9	0	0	0	0	0	100	0	0	100	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	100	100	0	100	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	100	100	100	100	0	0	0	0	0	0	0	0	0	0
116.9	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 4.7 Tracing matrix

be used for developing coverage matrices for optimization. At this stage, it was necessary to use nine macro-algorithms to control this huge size of database.

Finally, coverage matrices were developed from the demand matrices. Coverage matrices show the demand monitored by PMS. For each CT value and demand pattern, one coverage matrix was developed.

Four optimization models were developed for to determine the optimal locations for monitoring stations based on different four objective functions. These models are:

- Demand coverage optimization: In this model water demand was the only key parameter used in the optimization. The objective was to locate optimal monitoring stations that will maximize demand coverage.
- Risk optimization: In this model, water demand as well as risk indices produced by the DSS were used for determining the optimal locations for monitoring stations. The monitoring stations with the highest demand and risk index were selected to be the optimal monitoring stations.
- Vulnerability optimization: In this model, water demand and vulnerability indices produced by the DSS were used for determining the optimal locations for monitoring stations. The monitoring stations with the highest demand and vulnerability index were considered as optimal monitoring stations.
- Sensitivity optimization: Similar to risk and vulnerability optimizations, sensitivity index and water demand were used for locating the optimal monitoring stations.

Mathematical formulation for these models is presented in sections 4.3.1 and 4.3.2.

4.3.1 Demand coverage optimization

The main objective of identifying optimal locations of monitoring stations in WDN is to increase the representativeness of the monitoring system and, consequently, maximize the monitored (covered) demand. If $\boldsymbol{D_i}$ is the total demand covered by node $\boldsymbol{N_i}$ as shown in Equation (4.6), then the objective function for maximizing demand coverage can be expressed as follows:

$$Max \sum_{i=1}^{n} D_i x_i \tag{4.6}$$

$$D_i = \sum_{j=1}^{m} d_{i,j} \tag{4.7}$$

subjected to:

$$\sum_{i=1}^{n} x_i \leq MS \tag{4.8}$$

$$\frac{\sum_{i=1}^{w}\left(\boldsymbol{d_{i,j}} * \boldsymbol{x_i}\right)}{\boldsymbol{d_i}} \leq \mathbf{1} \tag{4.9}$$

where:

$\boldsymbol{m}$ = number of total nodes covered by node *i*.

$\boldsymbol{x_i}$ = An integer value that determines if there is a monitoring station at the node or none, where "1" represents the existence of the monitoring station at node *i*. Similarly, "0" implies that there is no monitoring station at node *i*.

$\boldsymbol{n}$ = number of total nodes in the network.

$\boldsymbol{MS}$ = maximum allowable number of monitoring stations to be used for the network. This number is a predefined value based on the economical and practical factors.

w = number of PMS covering node i.

To avoid the duplication of coverage for each demand, constraint 4.9 was added so that each node must be covered only once so that the total covered demand will not exceed 100% if "hypothetically" each node was a monitoring station in the network. This constraint will force the optimization algorithm to cover each node once to avoid coverage duplication.

For the previous example, this constraint 4.9 can be rewritten as:

$(15x_3 + 15x_4 + 15x_5)/15 \leq 1$ for N_3

$(30x_4 + 30x_5)/30 \leq 1$ for N_4

$25x_5/25 \leq 1$ for N_5

$20x_6/20 \leq 1$ for N_6

$(10x_6 + 10x_7)/10 \leq 1$ for N_7

Furthermore, regional constraint was added to ensure that every sub-region in the network will have at least one monitoring station as shown in Equation (4.10). In this research, the analysis was performed for two cases (i) considering regional constraint, and (ii) without considering regional constraint. This was done to understand and examine the effect of regional constraint on the total coverage of the monitoring system.

$$\sum_{i=1}^{z} x_{A,i} \geq 1 \tag{4.10}$$

where:

z = Total number of monitoring stations in sub-region A.

$\boldsymbol{x_{A,i}}$ = An integer variable $\boldsymbol{x_i}$ for nodes in sub-region A.

4.3.2 Risk optimization

Rather than considering only demand as the key parameter for locating monitoring stations, other parameters were considered which include risk, vulnerability and sensitivity indices developed from the DSS. This intends to enhance the optimization analysis such that sub-regions with higher risk, vulnerability and/or sensitivity should have first priority when locating monitoring stations. The objective function developed for this case can be explained as follows:

$$D_i = \sum_{j=1}^{m} d_{i,j}\, I \tag{4.11}$$

$$Max \sum_{i=1}^{n} D_i x_i \tag{4.12}$$

where $\boldsymbol{I}$ is the risk, vulnerability or sensitivity index for node *j*.

Similar to absolute demand optimization, risk optimization was subjected to the same constraints presented in Equations (4.6) to (4.10).

Using LINGO optimization platform, optimization code was developed to fulfill and maximize the coverage of the monitoring system at Al-Khobar WDN using the coverage matrices. Appendix C shows the optimization code used.

CHAPTER 5

Application and Analysis of Results

5.1 Study Area

Al-Khobar city is located in the Eastern Coast of Saudi Arabia and it extends from the sea coast in the east to the west as shown in Figure 5.1. It has an area of approximately 64 km^2 with a population of about 300,000, which is expected to rise to approximately 590,000 by 2015. The general topography and elevation of the area is sea level near the corniche area then gradually rising in the northwest direction up to 30 meters. This high variation in elevations throughout the city domain causes the pressure to increase in water mains near the corniche area (e.g., typical pressure close to sea level 120 is 29 m), and for low pressure in the northwest of the city (e.g., typical pressure in high lands is 13 m). Contour map for Al-Khobar city is shown in Figure 5.2.

The rapid growth in population as well as the comprehensive development resulted in a sharp increase in water consumption. Water demands in Al-Khobar city have increased from 23.61 million cubic meters (MCM) in 1983 to 58.52 MCM in 2004 and are expected to reach 111.95 MCM by the year 2020 (Al-Zahrani, 2002).

Al-Khobar WDN mainly serves urban areas. The total length of the network is approximately 472,652 m as shown in Table 5.1. Historically, growth and expansion of the city happened during different periods, therefore, the network consists of pipes with different materials and ages. Figure 5.3 shows the skeleton of Al-Khobar WDN.

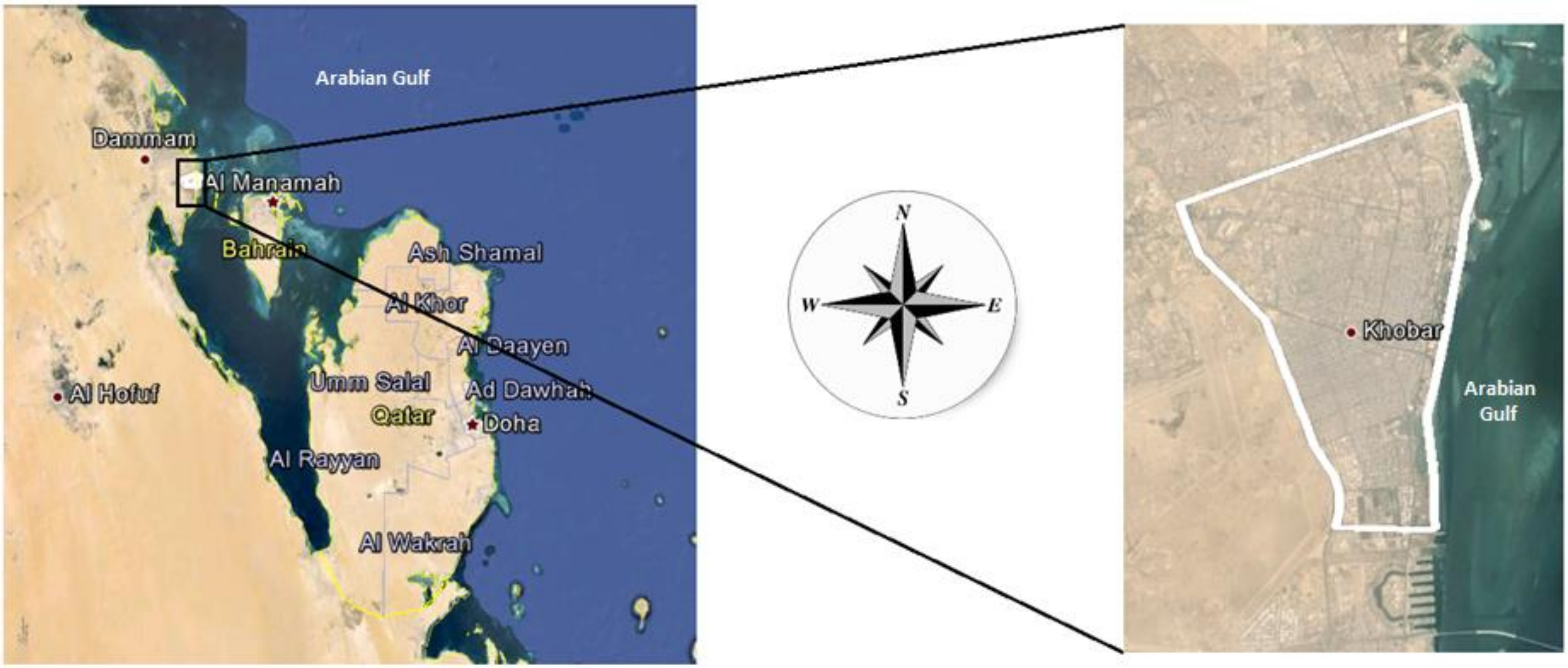


Figure 5.1 Location of Al-Khobar city

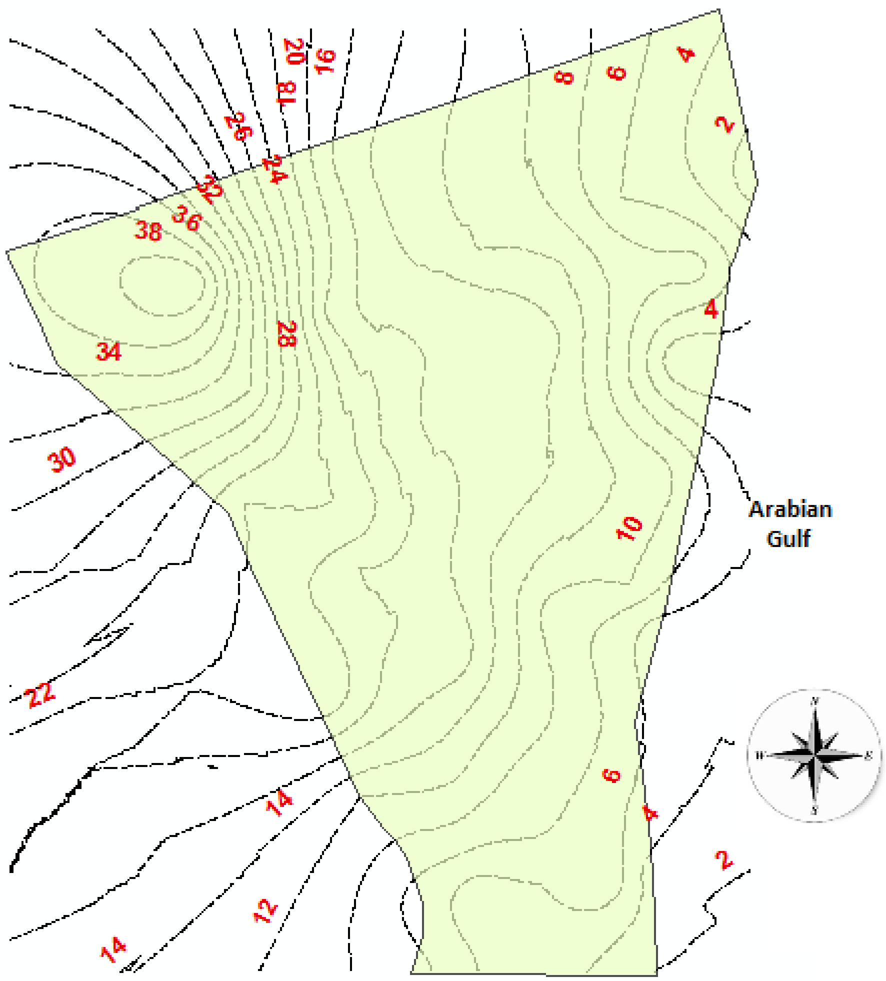


Figure 5.2 Elevation contour map for Al-Khobar city

Table 5.1 Lengths, materials and sizes of pipes used in Al-Khobar water distribution system (Al-Zahrani and Al-Ghamdi, 2008)

Diameter		**Length according to the type**				**Total**
mm	**inch**	**Plastic**	**Ductile Iron**	**Asbestos**	**Fiber Glass**	**m**
50	2	627				627
60	2.5					0
75	3	8422				8422
80	3.2	15209		47500		62709
100	4	9275		21310		30585
110	4.4	54168				54168
150	6	30464	11376	48403		90243
160	6.4	84035		429		84464
200	8	15120	3519	9528		28167
225	9	19354		3700		23054
250	10	306		543		849
280	11	7687				7687
300	12	26746		10082		36828
315	12.6	6822				6822
350	14		42			42
380	15.2					0
400	16	9435	160	11520	123	21238
500	20			4960		4960
600	24		130	7520		7650
700	28					0
800	32		494			494
1000	40		3643			3643
Total						472,652

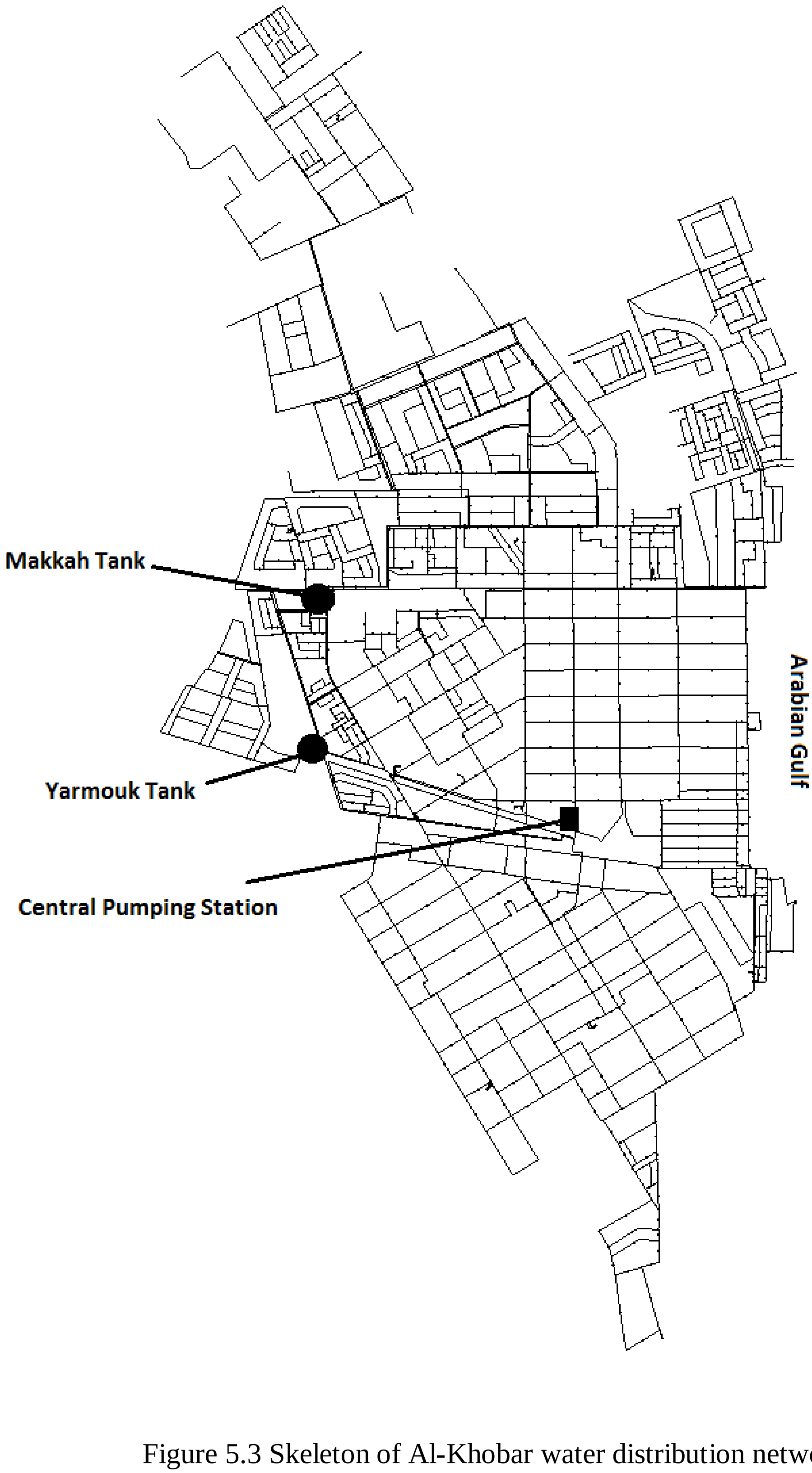


Figure 5.3 Skeleton of Al-Khobar water distribution network

Desalinated water from Al-Aziziah plant and groundwater wells are the two main sources of water supply for Al-Khobar WDN. Detailed information about Al-Khobar WDN and its hydraulics has been reported by Al-Zahrani and Al-Ghamdi (2008).

5.2 Hydraulics of Al-Khobar WDN

Al-Khobar WDN is modeled hydraulically and calibrated using WaterGEM package. The hydraulic model is capable of performing hydraulic and water quality simulations. To develop the overall risk using the DSS, simulations were performed to estimate three hydraulic variables, namely pressure, velocity and water age.

5.2.1 Pressure head characteristics

In Al-Khobar WDN, there is only one central pumping station and several elevated tanks distributed all over the city to maintain operational pressure head in the WDN, which is ranging between 5 and 35 m. Figure 5.4a shows simulated average pressure head for all demand scenarios and patterns from the calibrated hydraulic model of the sub-regions of Al-Khobar WDN. The average maximum pressure for all demand scenarios of all sub-regions varies between 13 and 41 m while the average minimum pressure for the same demands varies between 7 and 31 m as shown in Figures 5.4b and 5.4c, respectively. The highest pressure in the city usually occurred at the city center, especially at sub-region 94 and its surroundings, since the main pumping station is located in this sub-region. It is observed that pressure decreases for sub-regions away from the center but it does not violate the minimum acceptable pressure set by the water authorities (5 m) as indicated in

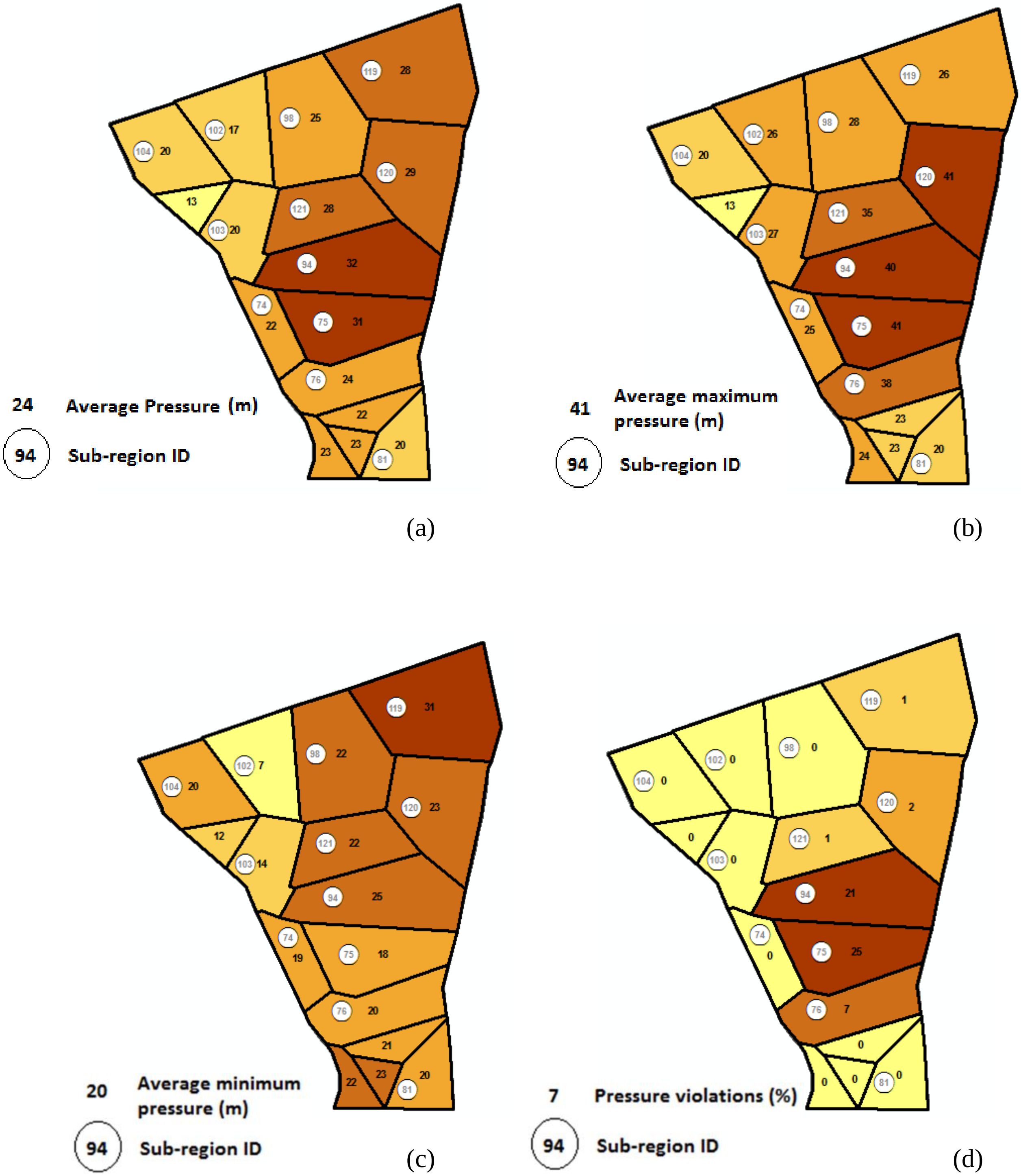


Figure 5.4 Pressure head characteristics:

a) average pressure , b) average maximum pressure, c) average minimum pressure and d) percentage of nodes having pressure violating upper and lower limits

Figures 5.4a and 5.4c. Analysis of pressure head of approximately 1000 nodes shows that the percentage of nodes in each sub-region where recorded pressure violates the upper or lower pressure limits – based on all conducted scenarios – were less than 25%. Figure 5.4d shows regional percentages of nodes exceeding 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 due to high pressure existing at the central pumping station. Away from sub-region 94, pressure violations decrease till it becomes almost zero in most of the sub-regions.

5.2.2 Velocity characteristics

To avoid erosion and sedimentation, Gupta (2008) recommends that velocity should range between 0.4 and 1.5 m/s. Figure 5.5a shows that average regional velocity in the WDN ranges between 0.06 and 0.77 m/s. Only four out of the 16 sub-regions have average velocity within the recommended range. The average maximum velocity for all demand scenarios is ranging between 0.27 and 4.58 m/s while the average minimum velocity for all demand scenarios is ranging between 0 and 0.1 m/s as shown in Figures 5.5b and 5.5c. The results indicate that the velocity in the WDN is not within the recommended range which may cause erosion in sub-regions where velocities are high such as sub-regions 75 and 94, or may cause sedimentation in sub-regions where low velocity exists such as sub-regions 105 and 119. Detailed investigation of velocities within sub-regions 75 and 94 indicates that pipes having velocities higher than 2 m/s are very few and mainly at pipes connected directly to pumps or tanks. Accordingly, velocities at these pipes did not have any effect on the regional average velocities for

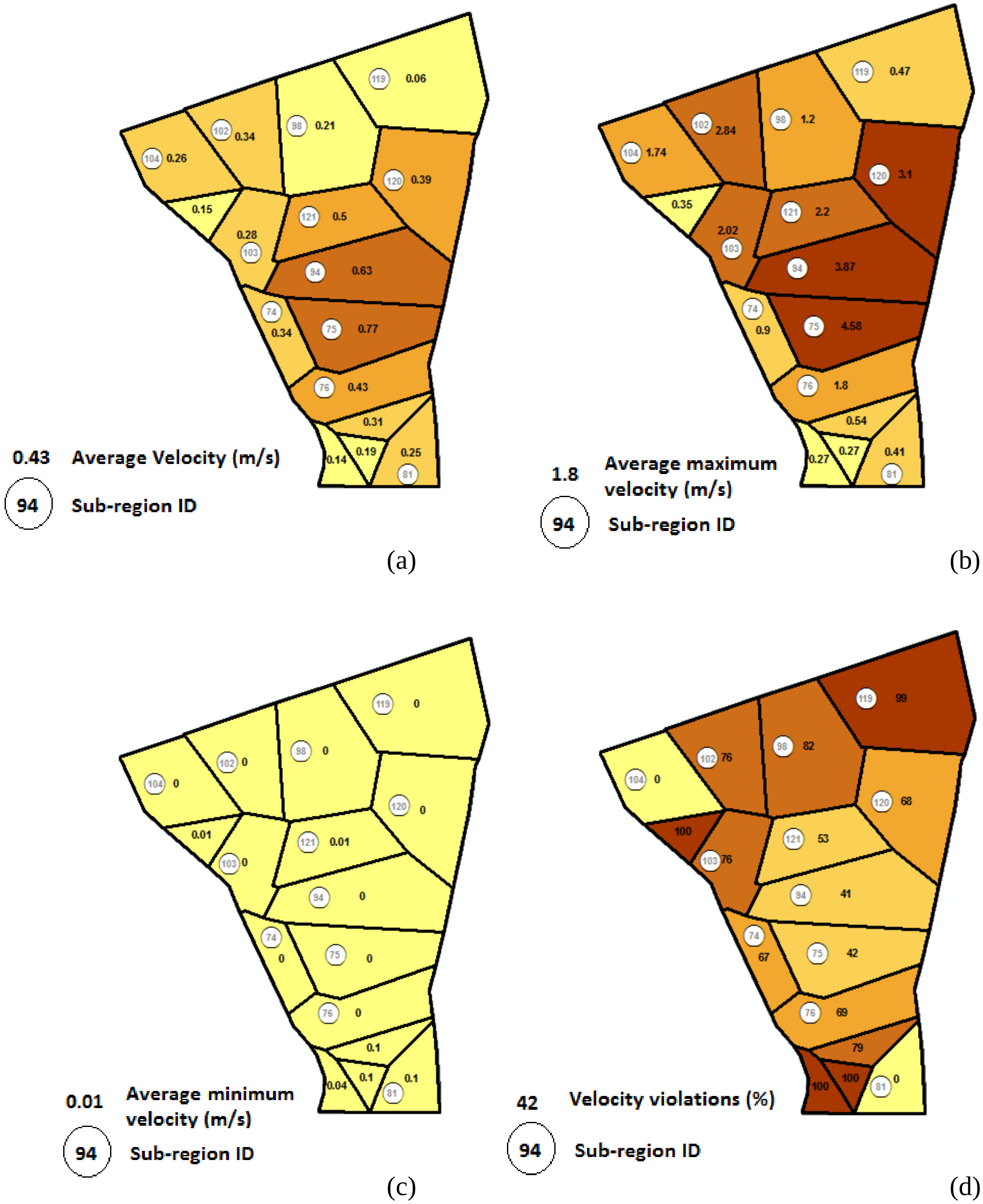


Figure 5.5 Velocity characteristics:

a) average velocity, b) average maximum velocity, c) average minimum velocity and d) percentage of pipes having velocity violating the upper and lower limits these sub-regions. On the other hand, it can be said that significant number of pipes in the city have velocities less than 0.4 m/s. Figure 5.5d shows the percentages of pipes having velocity either above or below the recommended range. Most of the pipes violating the recommended velocity range are those having low velocity. Obviously, the results indicate that there is a high possibility for sediments to accumulate in the pipes due to low velocity.

5.2.3 Water age characteristics

To avoid stagnant zones in WDN, which could be a suitable environment for bacterial growth and deterioration of water quality, the water within the network should not stay more than 3 days (72 hours). In literature, some conservative studies emphasize that water age must be less than 1.3 days (31.2 hours) (AWWA, 2002). Figure 5.6a shows the average water age in Al-Khobar city which varies between 1.6 and 9.64 hours. Remote sub-regions away from the city center and pumping station have higher water age, such as sub-regions 77 and 119, which are 6.14 and 9.64 hours, respectively.

The average maximum water age for all demand scenarios shows similar trend as revealed from Figure 5.6b, which ranges between 1.65 and 15.11 hours. Similarly, the average minimum water age for all demand scenarios shows higher water age in the northern and southern borders of the city as can be seen in Figure 5.6c, which ranges between 1.65 and 15.11 hours. For all demand scenarios, water age was always less than the recommended standards. Figure 5.6d indicates that for all sub-regions of Al-Khobar WDN, the percentage of junctions having water age higher than the standards is zero.

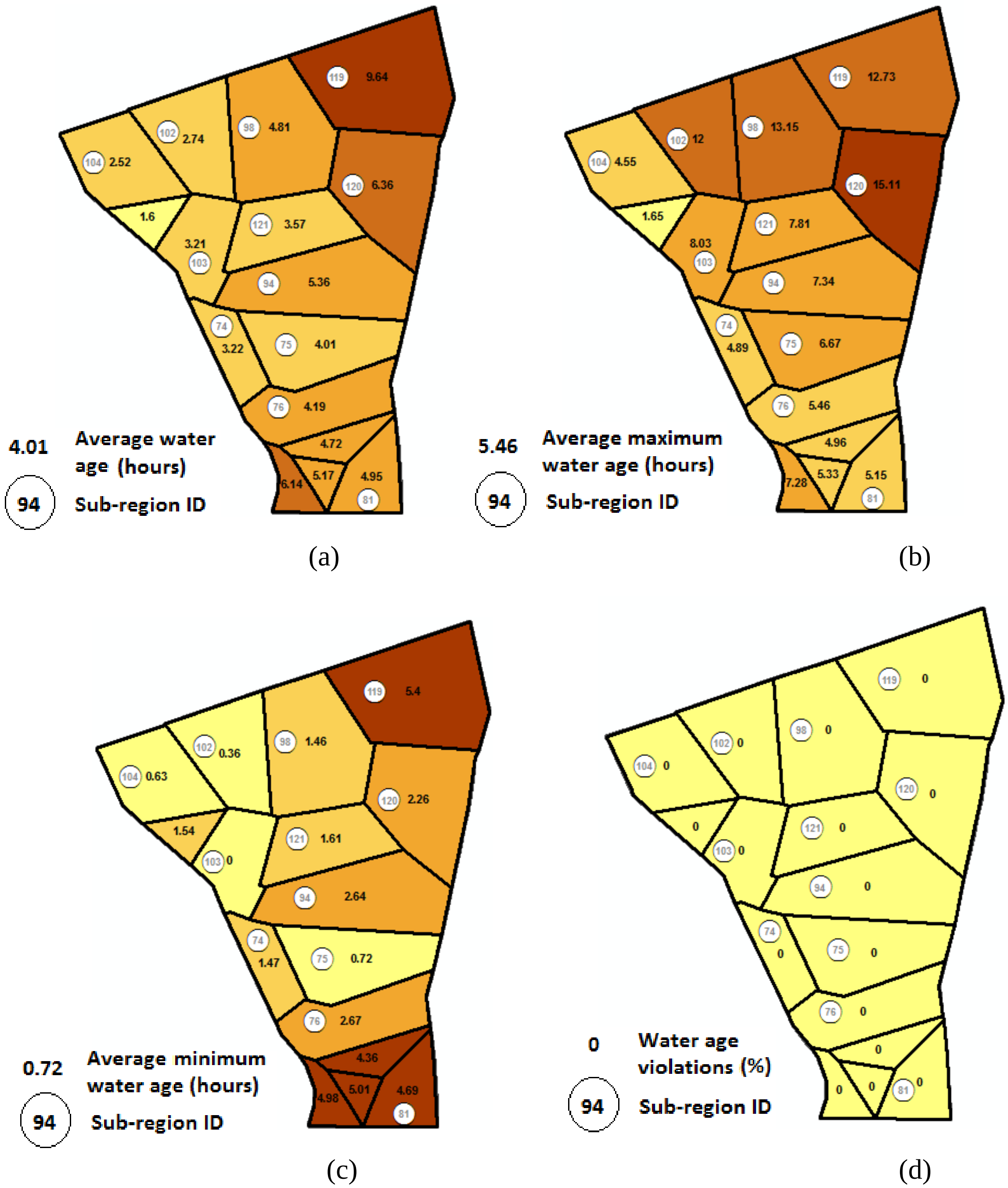


Figure 5.6 Water age characteristics:

a) average water age , b) average maximum water age, c) average minimum water age and d) percentage of junctions having water age higher than recommended limits

5.2.4 Hydraulic index

Pressure, velocity and water age represent the hydraulic characteristics of the WDN. According to Figures 5.4d, 5.5d and 5.6d, it is clear that in most of the sub-regions, hydraulic properties are within the acceptable limits. There are two sub-regions (75 and 94) in which more than 20% of the nodes showed pressure either higher or lower than the recommended limits, while for the other sub-regions the percentage is less than 7% and mostly 0% as shown in Figure 5.4d. For velocity, the percentage of pipes having higher or lower velocity (mainly lower velocities) than the acceptable limits exceeds 41% and approaches 100% in some sub-regions such as sub-regions 77 and 105 as shown in Figure 5.5d. Unlike pressure and velocity, water age was within the recommended range in all sub-regions for all demand scenarios, which implies that water age will have no effect in the prioritization of risk between sub-regions since it shows 0% violations for all sub-regions as shown in Figure 5.6d. Thus, based on WDN characteristics of Al-Khobar, pressure and velocity will control risk level caused by hydraulic properties and the effect of pressure will be higher than velocity since it was given higher weight during the aggregation process according to the opinion of the experts. Figure 5.7 shows the risk index for hydraulic properties for all the sub-regions. Sub-regions 75 and 94 show high hydraulic risk index of 0.80 and 0.75, respectively, while other sub-regions have 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. This causes the pressure to violate the recommended limits at these sub-regions and, subsequently, increases the hydraulic risks at these sub-regions.

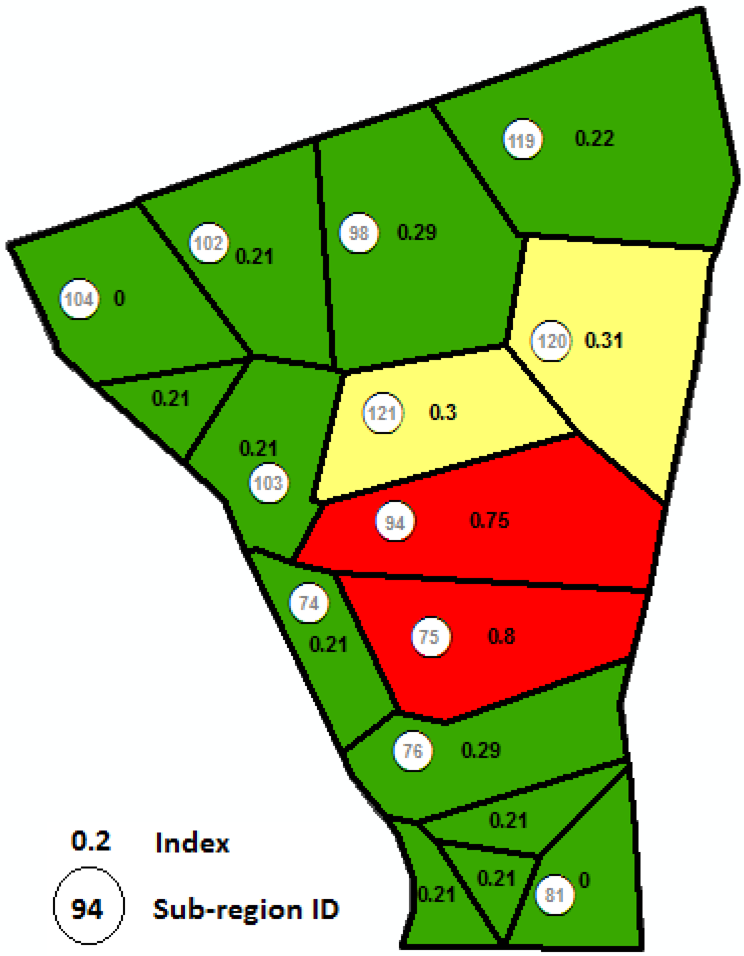


Figure 5.7 Risk index for hydraulic properties

5.3 Structure Integrity

5.3.1 Potential intrusion

Infrastructure and structure integrity of the WDN are judged based on pipe breaks, age and material, in addition to potential intrusions of wastewater or industrial waste in case of the occurrence of pipe breaks. Historical records of Al-Khobar municipality indicate that 65%, 25% and 10% of pipe breaks occurred in the red, yellow and green areas, respectively, as shown in Figure 5.8. Based on the pipe break ratio, pipe breakage risk index was developed for each sub-region. Figure 5.9 shows pipe breakage risk index for each sub-region of Al-Khobar WDN. Southern sub-regions have high breakage ratio indicating high risk index. Sub-regions located in the low breakage ratio zone have a risk of zero, such as sub-regions 102 and 119. Sub-regions falling between different breakage ratio zones, such as sub-region 98, 103, 120 and 121, have risk index based on the aggregation of different breakage ratios in those sub-regions. It should be noted that the age of pipes in the northern part of the city is approximately 31 years and mostly made of PVC, while pipes age in the center and south of the city is 44 years and mostly made of asbestos as shown in Figures 5.10 and 5.11.

Intrusions of contaminants to the system could occur due to the following: (1) dumping of wastewater in areas with no sanitary system or (2) industrial activities such as automobile workshops and wastewater treatment plant. Possible intrusion of contaminants or wastes from the surface to the surroundings of the pipes may cause hazardous risk if there are cracks or leaks in the WDN. In places where household wastewater is dumped in private manholes, the possibility that water in the distribution

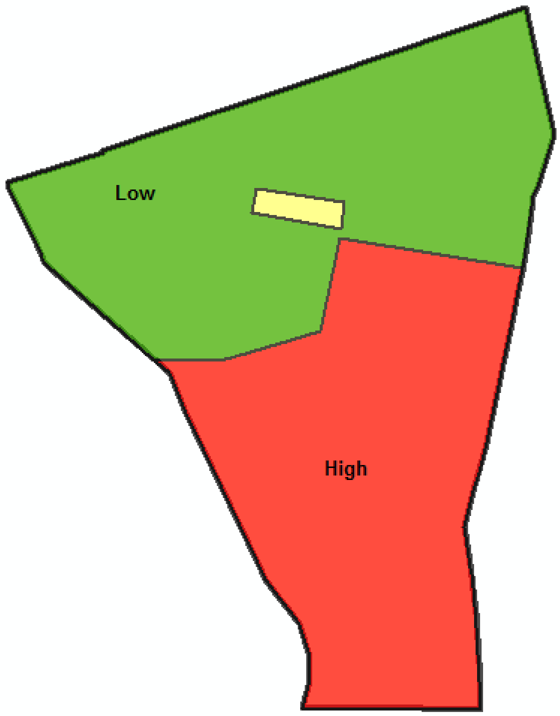


Figure 5.8 Areas with high, med and low breakage ratios

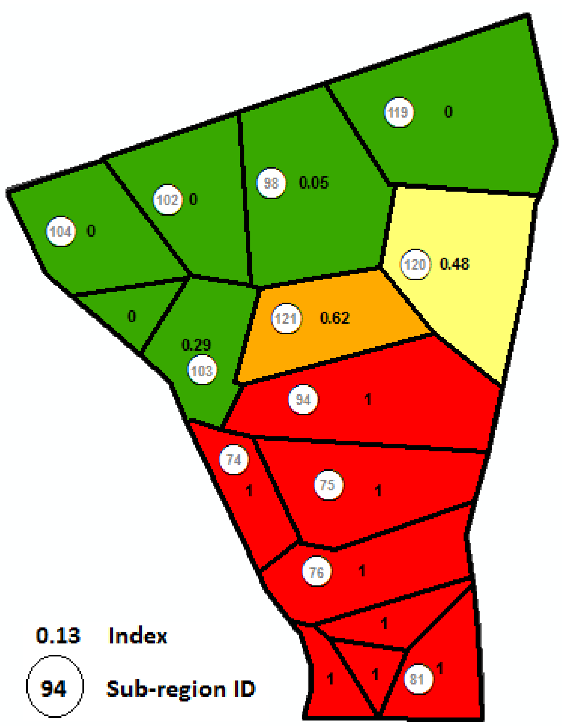


Figure 5.9 Pipes breakage risk index for each sub-region

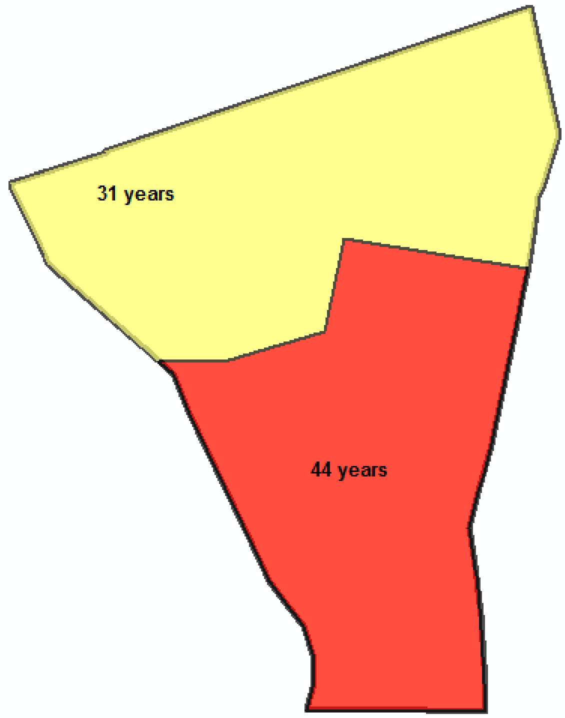


Figure 5.10 Pipes' age in the city

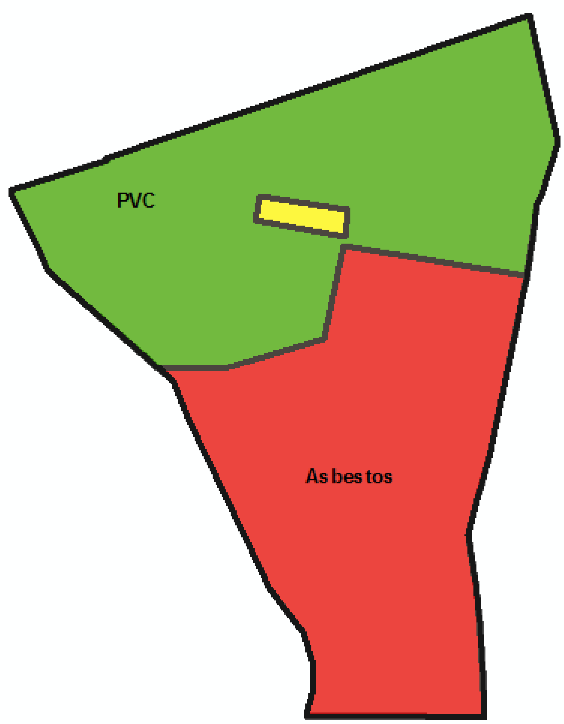


Figure 5.11 Pipes material in Al-Khobar city

network might get contaminated is high. However, if the area is served by a sanitary sewer system, the possibility for contamination risk is low. In this study area, all sub-regions are served by a sanitary sewer system, which indicates that the risk due to dumped wastewater is almost zero as shown in Figure 5.12, assuming no leakage in the sanitary system. To the extreme south of the city, wastewater treatment plant and automobile workshops are located, where both have the potential for causing hazardous contamination to the water transported by the distribution system in case of pipe break or leakage. Figure 5.13 shows the locations of the activities within Al-Khobar city. Figure 5.14 shows that industrial intrusion risk index for the city is low except for sub-regions 76, 77, 81 and 82. Sub-region 82 has the maximum risk index (0.87) since the wastewater treatment plant is located in this sub-region, while sub-regions 76, 77 and 81 have automobile workshops.

Based on the analysis of pipes breaks and potential intrusions caused by wastewater or industrial contaminations, potential intrusion risk index was developed as shown in Figure 5.15. The major factors that have significant influence on the risk index are pipe break ratios and industrial intrusions. The contribution of sanitary system to the risk index is negligible since the whole city of Al-Khobar is served with a sanitary sewer system. The northern part of the city has low potential intrusion risk (such as sub-regions 98 and 102). Also, pipe breakage ratios at these sub-regions are low since there is no industrial activity in this part of the city. Moving to the south, risk increases due to the increase of pipe breakage ratios and it reaches maximum risk in the extreme south where wastewater treatment plant and automobile workshops are located.

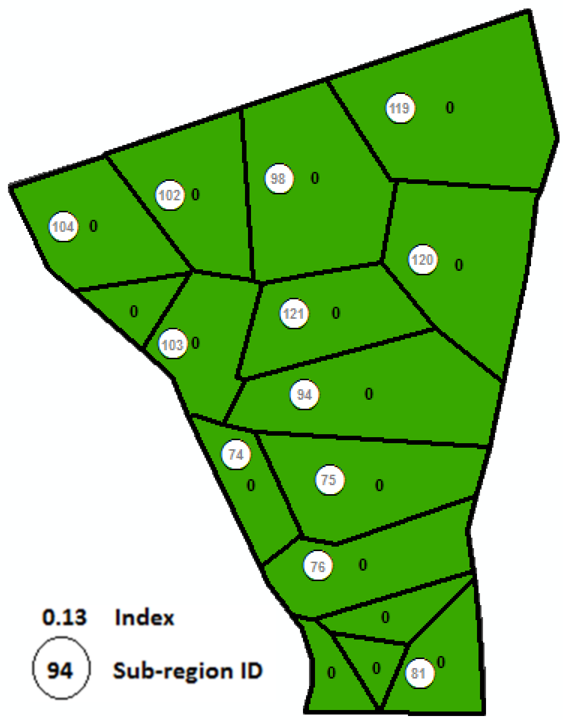


Figure 5.12 Sanitary system coverage risk index for each sub-region

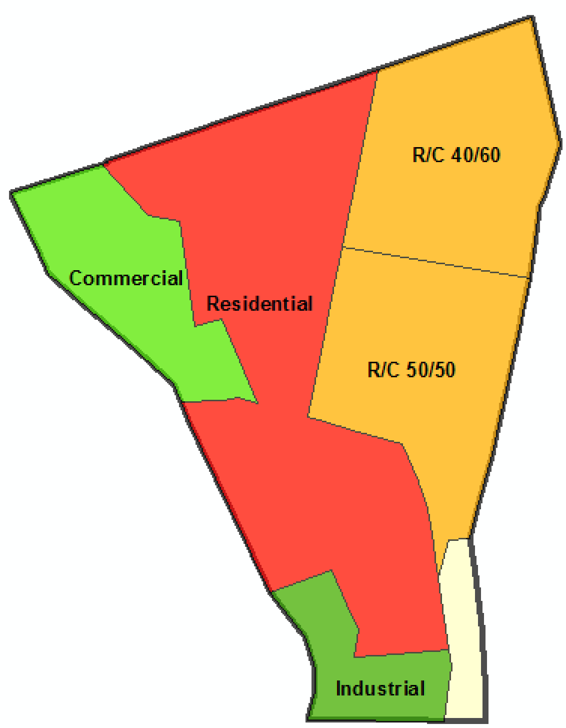


Figure 5.13 Activities in Al-Khobar city

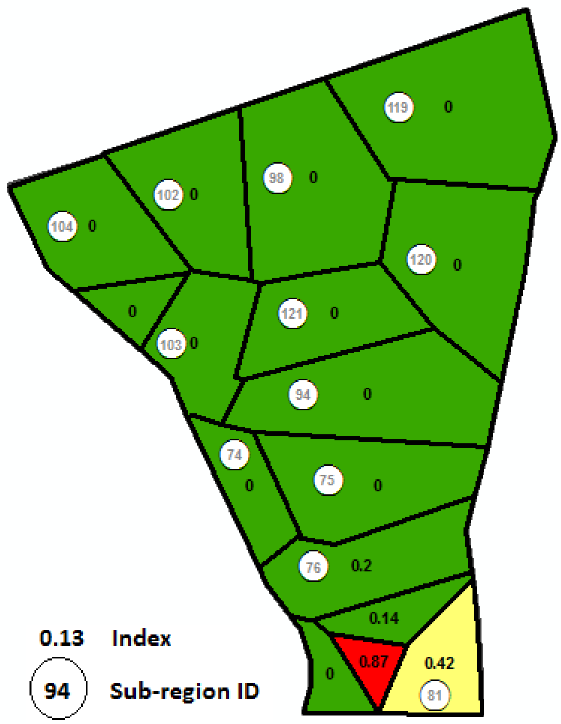


Figure 5.14 Industrial intrusion risk index for each sub-region

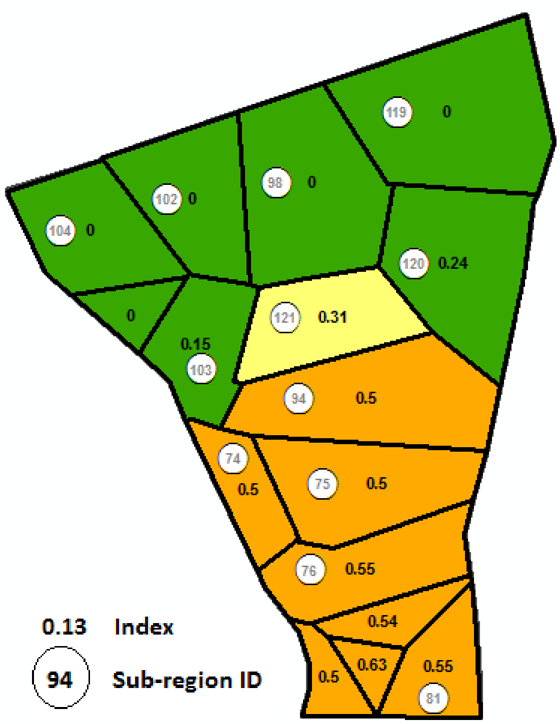


Figure 5.15 Potential intrusion risk index for each sub-region

5.3.2 Pipe material

In general, the WDN of Al-Khobar city is either asbestos or PVC, as shown in Figure 5.11, except for a small part 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 as a carcinogen material, although its risk relevant to drinking water is not substantial (Morris, 1995). However, some studies show that there was a correlation between high levels of asbestos in drinking water and risk of cancers in areas where asbestos is naturally found in water sources (Millette et al., 1983). On the other hand, PVC has been used as a replacement for asbestos pipes since there is no proven carcinogen risk associated with using PVC to transport water. In addition, PVC pipes are cheaper in the long run (Subramanian and Madhavan, 2005). Figure 5.16 shows risk index based on pipe material for each sub-region within Al-Khobar WDN. Since asbestos is classified as risky to transport water, then maximum risk in sub-regions where asbestos pipes exist is expected and risk will decrease as the percentage of asbestos pipes reduces in the sub-regions such as sub-regions 102, 103 and 121.

5.3.3 Pipe age

In general, the pipes in the northern part of the city are 31 years old, while in the center and south of the city the pipes are 44 years old as shown in Figure 5.10. Based on the fact

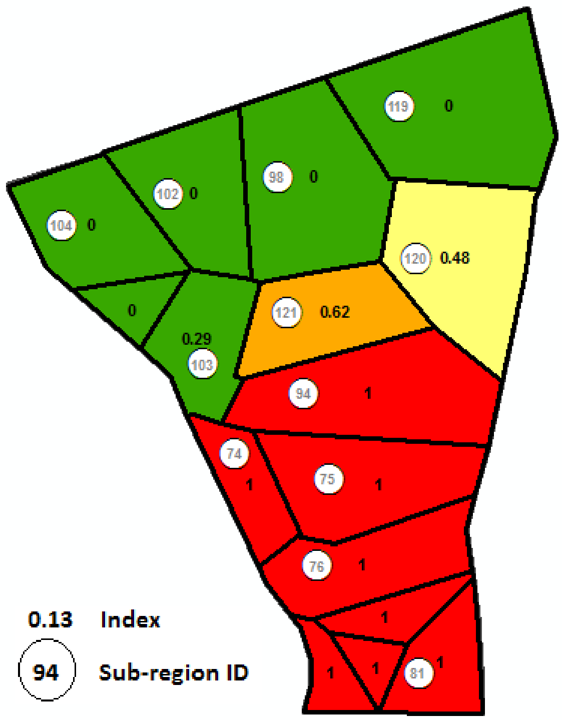


Figure 5.16 Pipe material risk index for each sub-region

that pipes in the southern sub-regions are asbestos and are old compared to sub-regions in the north where pipes are PVC and relatively new, pipe age risk index was developed as shown in Figure 5.17. In general, new pipes tend to have less problems such as cracks or leakage compared to the old pipes. However, in Al-Khobar WDN the situation is more critical since the old pipes are asbestos, which accordingly will increase the risk in sub-regions having older pipe connections.

5.3.4 Water table and soil

In addition to pipe material, age and breakage, there are other factors which might affect pipes condition such as water table levels and soil aggressiveness surrounding the pipes. It is assumed that there will be no significant effect on pipes if water table is totally above or below the pipe network. However, if the level of water table is fluctuating, then any change in external pressure acting on the pipes might cause cracks and pipes failure (Najjaran et al., 2006). Records from Al-Khobar municipality show that WDN is located within the first 3 m below ground surface, while maximum elevation of water table is 3 m below ground surface, which implies that the WDN is totally above the water table even in the coastal areas. For soil, if it is aggressive, pipes might corrode and weaken especially steel pipes. Fortunately, in Al-Khobar city most of the pipes are asbestos and PVC which excludes the corrosion risk for pipes. Therefore, in this study no risks are expected to be generated from water table and soil surrounding the pipes. Pipes material, age, breaks, sanitary coverage, industrial and wastewater intrusions, water table levels and soil surrounding pipes give a clear view about the infrastructural condition of the WDN. It is obvious that the southern sub-regions of the city have multi issues that may

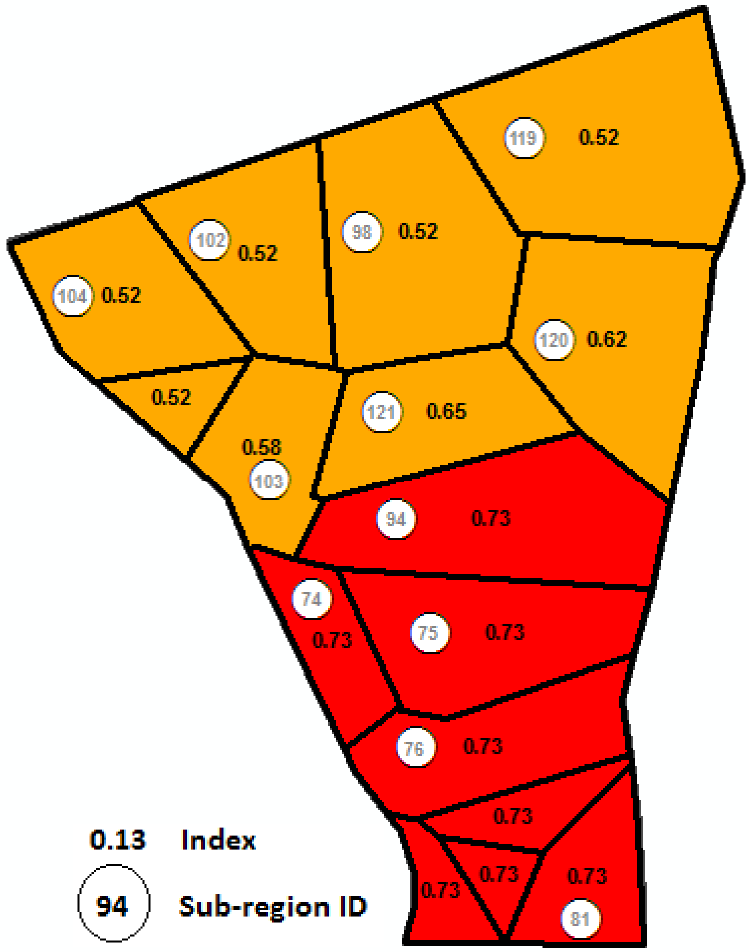


Figure 5.17 Pipe age risk index for each sub-region

increase risk index, such as high pipe breakage ratio and presence of industrial activities as well as aged pipes with low quality material. Considering and aggregating these factors together will map the risks threatening the infrastructure and structure integrity of the WDN. Figure 5.18 shows the structure integrity risk index which ranges between 0.18 and 0.63. As expected, sub-regions in the southern part of the city have 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 relative low risk in these sub-regions. Sub-regions in the south such as 79 and 82 have asbestos pipes, older pipes, high pipe breakage ratio and industrial potential intrusions, which explains the higher risk index compared to the northern sub-regions. Sub-regions in the city center such as 103 and 121 have interrelated characteristics from northern and southern sub-regions, which explains why risk index in these sub-regions is in the midway between low risk northern sub-regions and high risk southern sub-regions.

5.4 Water Quality

In this study, the characteristics of the quality of water transported in the network were investigated, which are physico-chemical and microbial properties. Daily water quality data records for about a year between 2012 and 2013 were used to develop water quality risk indices.

5.4.1 Physico-chemical index

In Al-Khobar WDN, TDS level can be considered as an indicator of the amount of groundwater pumped into the network. High TDS in a region usually indicates that the

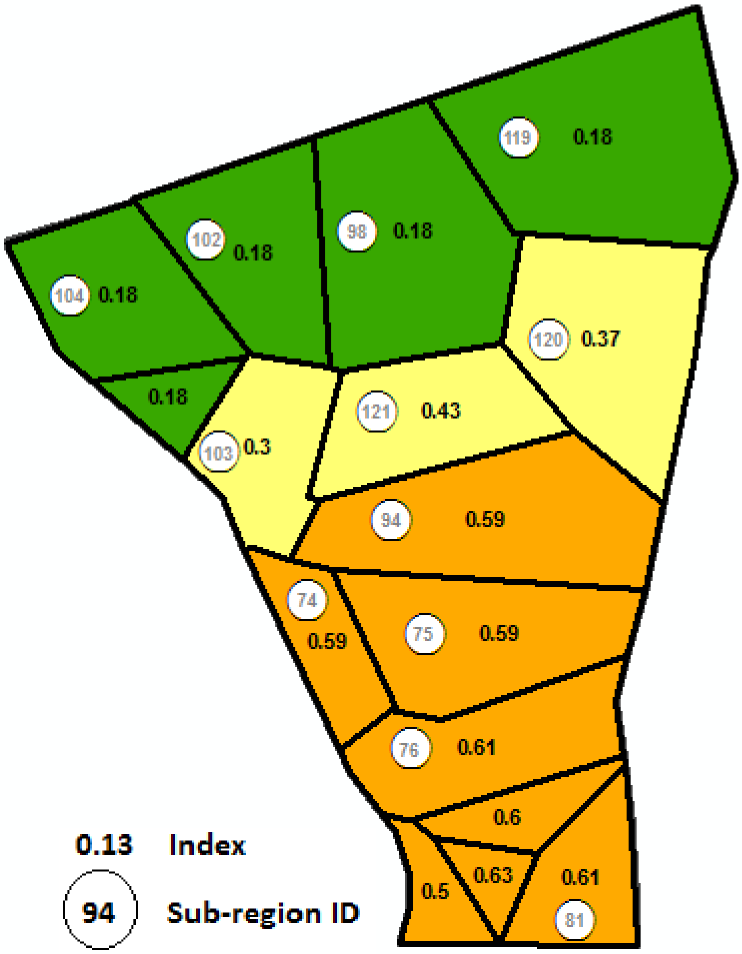


Figure 5.18 Structural integrity risk index for each sub-region

major source of water feeding that region is groundwater. Similarly, low TDS indicates that the main feeding source is desalinated water. However, if TDS is high in regions where desalinated water is supposed to be the main source, this might indicate a groundwater intrusion into the water network. In addition, TDS higher than 500 ppm results in excessive scaling in water pipes (WHO, 1996).

Studying TDS levels all over the WDN of Al-Khobar shows higher levels to the northern part of Al-Khobar city and sub-region 81 located south of the city. Average daily TDS over a period of about 10 months ranges between 500 and 1600 ppm in most of the areas in the north as shown in Table 5.2. Generally, the levels are low (less than 500 ppm) in the south except for sub-region 81 where average TDS level is 2129 ppm, which is the highest all over 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. The city in the last decades was expanding to the north and south directions more than the west direction. The newly developed areas are fed partially or totally by groundwater wells to cover the increasing demand, which explains the significant high TDS levels in the north and south areas. The central part of the city is mainly fed by desalinated water and, consequently, TDS levels are low. In addition to supporting demand coverage, groundwater wells are also used to increase pressure in case any zones in the WDN are suffering from low pressure. Figure 5.19 shows TDS distribution in the city, which was developed based on data collected during 2012 and 2013. TDS levels were higher in the city before 2012, but Al-Khobar municipality is recently becoming more dependent on desalinated water to reduce groundwater usage since it is considered as a strategic reserve as stated in the 9th Strategic Plan for the country. Sub-regions 81,

Table 5.2 Statistical summary for TDS (ppm)

Sub-Region	Average	Max	Min
74	248	1330	58
75	301	852	58
76	461	1094	82
77	442	2020	89
78	144	2110	49
81	2128	2540	0
82	360	2200	55
94	366	835	129
98	507	2340	70
102	461	2350	70
103	147	2190	52
104	1603	3770	105
105	1612	2740	100
119	531	832	97
120	528	841	96
121	402	1711	83

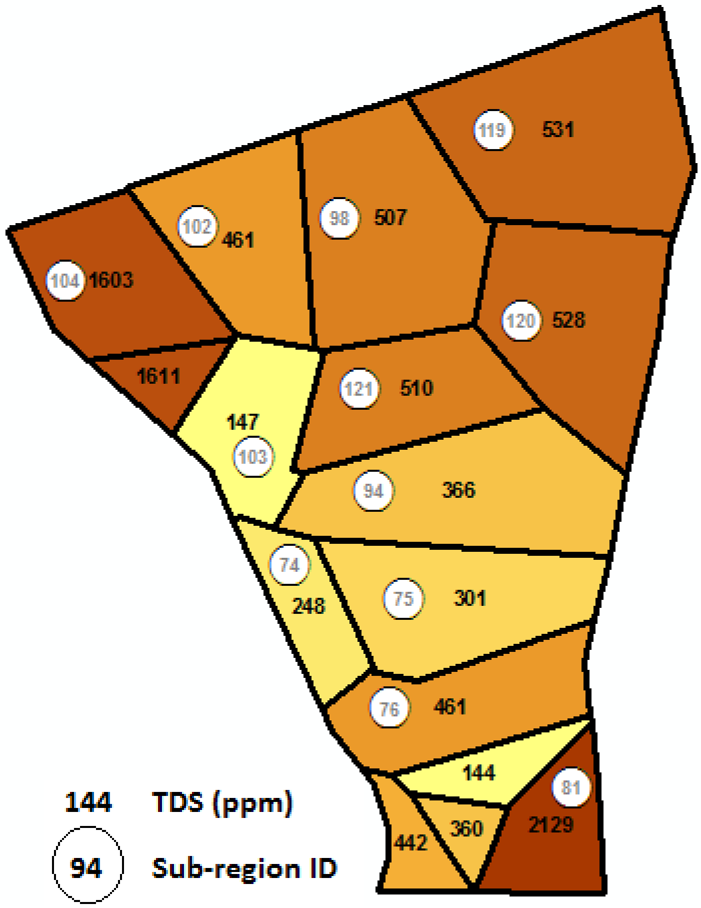


Figure 5.19 TDS distribution (ppm)

104 and 105 have average TDS of 2129, 1603 and 1611 ppm, respectively, which are the highest in the city. While water source in sub-region 81 is mainly from groundwater, sub-regions 104 and 105 have a significant share of groundwater which is reflected clearly in the TDS level. As can be revealed from Figure 5.19, TDS levels can be used as an indicator for water source in each sub-region, such that sub-regions with relatively high TDS represent relatively higher share of groundwater compared to desalinated water as in the case of sub-regions 104, 105 and 119. Similarly, low TDS represents low share of groundwater feeding the sub-region compared to desalinated water share as in the case of sub-regions 74, 76 and 94. Water in the city center and in the south is mainly desalinated water such as in sub-regions 74, 75, 76, 77 and 82. Water in sub-regions 79 and 103 is totally desalinated water, with a very low TDS (less than 150 ppm). In sub-region 79, the elevated tank is fed with desalinated water only, and in sub-region 103, the main reservoir (Al-Yarmook) is fed directly from the desalinated plant. This reservoir feeds the surrounding sub-regions to the north and city center.

Exposure to high or low pH might cause different health consequences such as eye irritations and skin disorders (WHO, 1996). Unlike TDS, pH levels, as shown in Table 5.3 and Figure 5.20, seem to be consistent all over the WDN ranging between 7 and 8 which is the optimal pH level.

WHO (2011) recommends that water temperature in pipes should be less than 25 C°. Temperatures higher than 25 C° were found to be suitable for the growth of some microorganisms. In Al-Khobar WDN, the average temperature in the southern part of the city is about 25 C° and increases gradually till it reaches 28 C° to the north as shown in Figure 5.21 and Table 5.4.

Table 5.3 Statistical summary for Temperature (C°)

Sub-region	Average	Max	Min
74	27.81	39.60	15.40
75	26.43	37.20	2.04
76	25.58	36.50	15.50
77	25.97	36.60	16.10
78	26.12	36.70	3.40
81	25.13	37.20	0.00
82	25.47	38.70	15.10
94	26.91	37.10	16.10
98	27.80	36.90	14.90
102	27.65	37.10	16.20
103	27.66	37.60	16.90
104	27.59	37.10	17.10
105	27.53	37.40	15.60
119	27.94	39.00	16.20
120	28.00	39.10	16.40
121	27.60	37.56	16.10

Table 5.4 Statistical summary for pH

Sub-region	Average	Max	Min
74	7.87	8.22	7.00
75	7.84	8.15	7.50
76	7.73	8.10	7.17
77	7.77	8.10	7.15
78	7.98	8.30	7.15
81	7.33	8.18	7.02
82	7.91	8.22	7.07
94	7.78	8.10	7.18
98	7.76	8.20	7.26
102	7.76	8.15	7.15
103	7.96	8.50	7.07
104	7.41	8.17	7.00
105	7.42	8.43	7.02
119	7.71	8.00	7.18
120	7.70	8.12	7.20
121	7.79	8.21	7.17

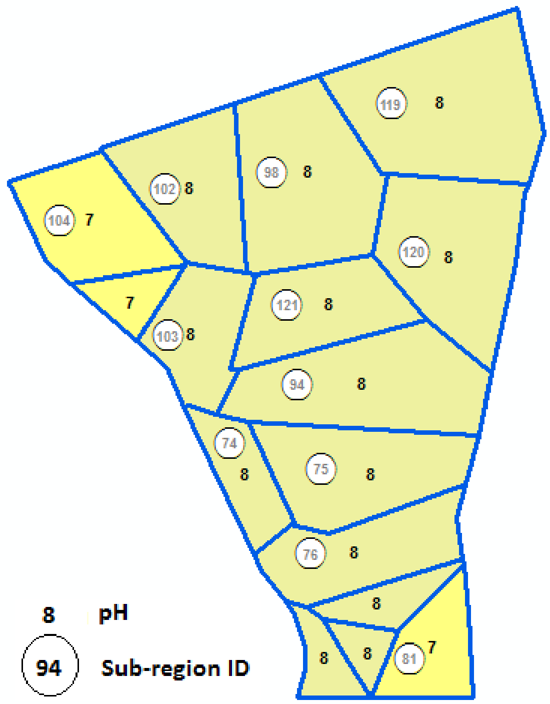


Figure 5.20 pH distribution of water in Al-Khobar network

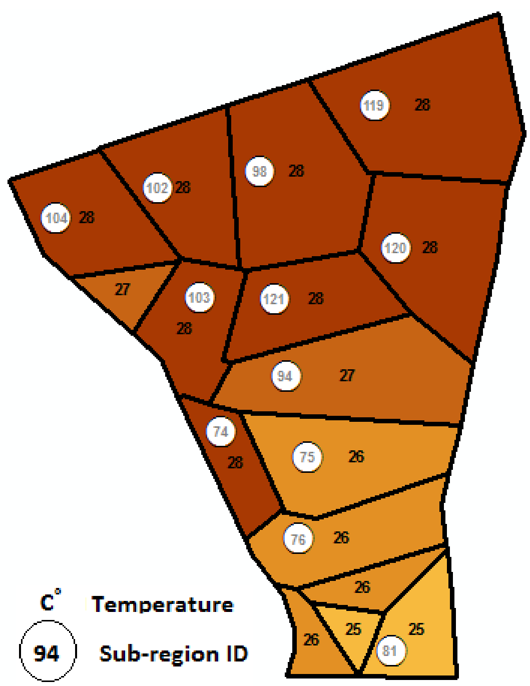


Figure 5.21 Temperature distribution (C°) of water transported in Al-Khobar network

Based on the fuzzy analysis for TDS, pH and temperature, distribution of risk index for physico-chemical properties is shown in Figure 5.22. In general, risk index associated with physico-chemical parameters is ranging between 0.11 and 0.31, which is a relatively low risk, since most of the sub-regions have risk index less than 0.28. This index reflects that the condition of the WDN in terms of physico-chemical properties is acceptable compared to the recommended limits of TDS, pH and temperature listed in literature. Sub-regions 81, 104, 105, 119 and 120 show relatively higher risk compared to the other sub-regions, which can be explained by comparing Figures 5.19 to 5.21 with Figure 5.22. Figures 5.20 and 5.21 indicate consistent levels of pH and temperature in the city, which makes TDS the key parameter in risk prioritization between sub-regions. Figures 5.19 and 5.22 show that sub-regions with relatively high TDS levels (Figure 5.19) are the same sub-regions with relatively high risk in terms of physico-chemical properties (Figure 5.22). On the other hand, Figures 5.23 to 5.25 show the percentage of diversions of TDS, pH and temperature from optimal values and standards. Again, while pH and temperature show relative consistency between different sub-regions in the city, TDS shows significant difference between the sub-regions in terms of diversion of TDS levels from optimal standards. Figure 5.23 shows that maximum diversions from optimal standards are recorded in the same sub-regions showing higher TDS levels, which explains why these sub-regions have relatively higher risks compared to other sub-regions in the city in terms of physico-chemical properties.

5.4.2 Microbial index

Free chlorine serves as a security factor for protecting water in the WDN from any possible bacterial or microbial risks. Optimal level of free chlorine at any location and

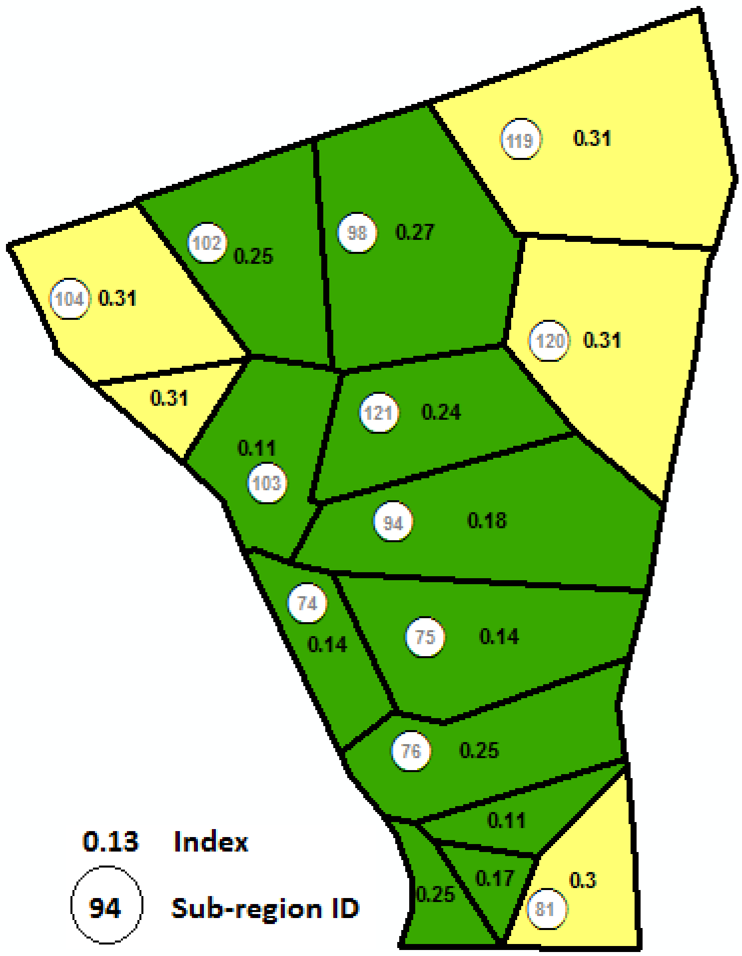


Figure 5.22 Risk index for physico-chemical properties

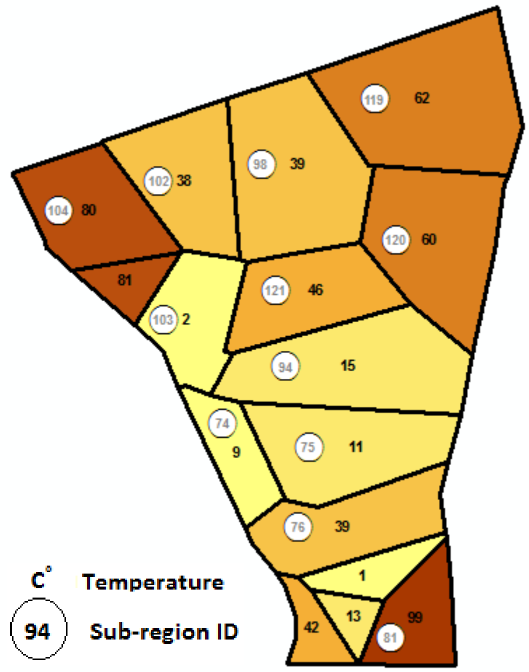


Figure 5.23 TDS percentage of diversion from optimal standards

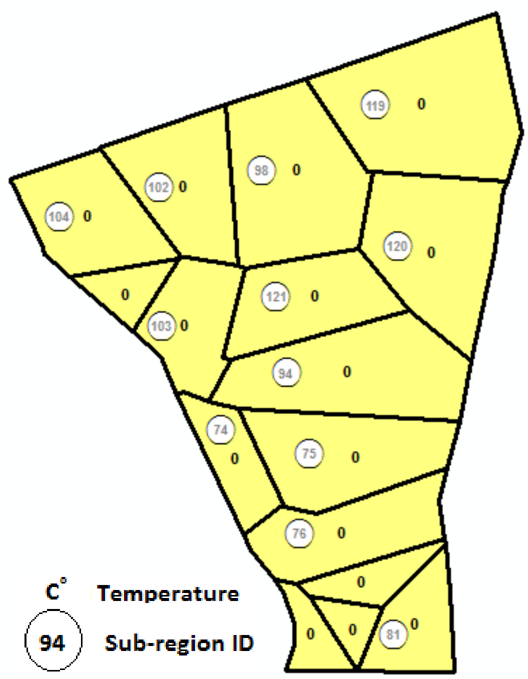


Figure 5.24 pH percentage of diversion from optimal standards

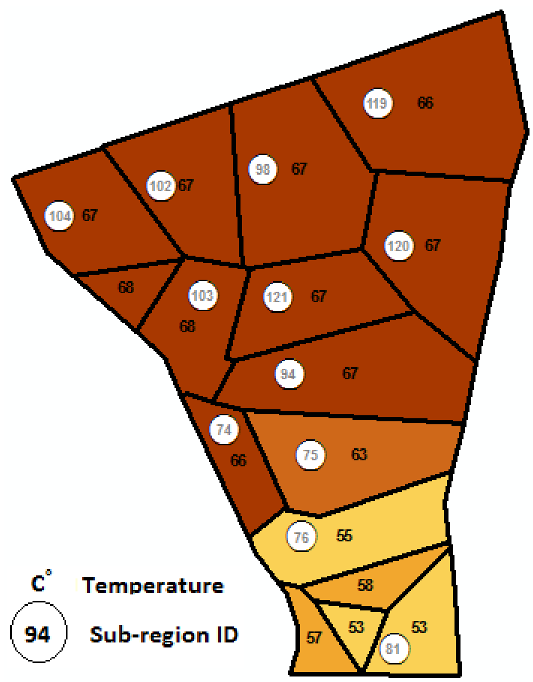


Figure 5.25 Temperature percentage of diversion from optimal standards

any time should range between 0.3 and 1.2 mg/l, but should not exceed 2 mg/l or be less than 0.2 mg/l. Table 5.5 shows average free chlorine levels in different sub-regions which range between 0.35 and 1.07 mg/l. Average free chlorine levels are acceptable and within the optimal range as shown in Figure 5.26. In sub-region 94, average free chlorine level was the highest because it is the sub-region where the central pumping station and chlorine boosters are located. Excluding sub-region 94 which represents the maximum level, average free chlorine in the other sub-regions ranges between 0.37 and 0.69 mg/l. In general, the southern part of the city has relatively higher levels of free chlorine compared to the northern part which can be related to the water supply in each sub-region and disinfection practices for desalinated water (which makes most of the water in the southern part of the city) and groundwater (which makes a significant share of water in the northern part of the city). On the other hand, free chlorine diversions from acceptable limits show that the majority of the sub-regions do not have any significant violations. Percentage of diversions ranges between 1 and 36% as shown in Figure 5.27.

Turbidity is another indicator of water quality. WHO (2008) recommends that turbidity of water in WDN should be ranging between 0.1 and 5 NTU while USEPA (2009) was more conservative and emphasized that it should not be more than 1 NTU. In Al-Khobar city, regional turbidity did not exceed 0.29 NTU as shown in Figure 5.28. Although turbidity levels are within the acceptable limit, with zero percentages of diversion, as shown in Figure 5.29, it seems to be relatively higher in the southern part of the city, most probably due to the higher possibility of breaks, age and material of the pipes.

Based on the analysis and aggregation of free chlorine and turbidity, microbial risk distribution was developed. Figure 5.30 shows microbial risk index for each sub-region.

Table 5.5 Statistical summary for residual chlorine (ppm)

Sub-region	Average	Max	Min
74	0.50	0.70	0.10
75	0.61	1.00	0.30
76	0.59	0.80	0.00
77	0.59	0.80	0.00
78	0.37	0.80	0.00
81	0.60	0.80	0.00
82	0.48	0.80	0.00
94	1.07	2.00	0.10
98	0.52	0.80	0.10
102	0.35	0.80	0.10
103	0.69	0.90	0.00
104	0.56	0.80	0.10
105	0.54	0.80	0.10
119	0.43	0.70	0.10
120	0.43	0.70	0.00
121	0.61	1.04	0.06

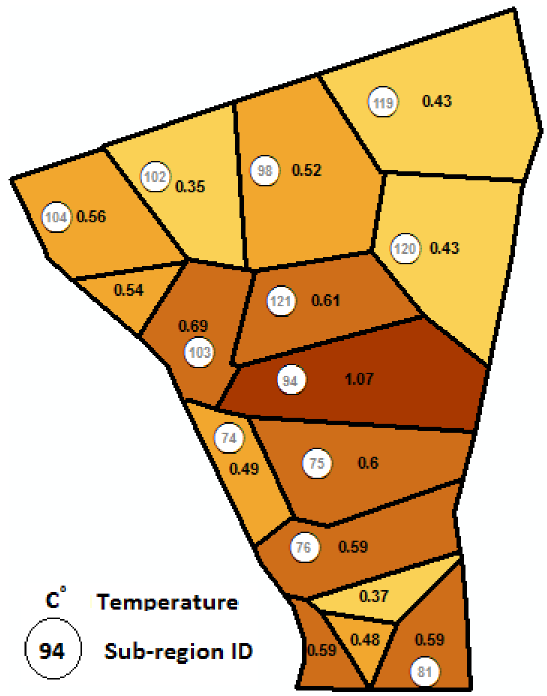


Figure 5.26 Free chlorine levels in the city (mg/l)

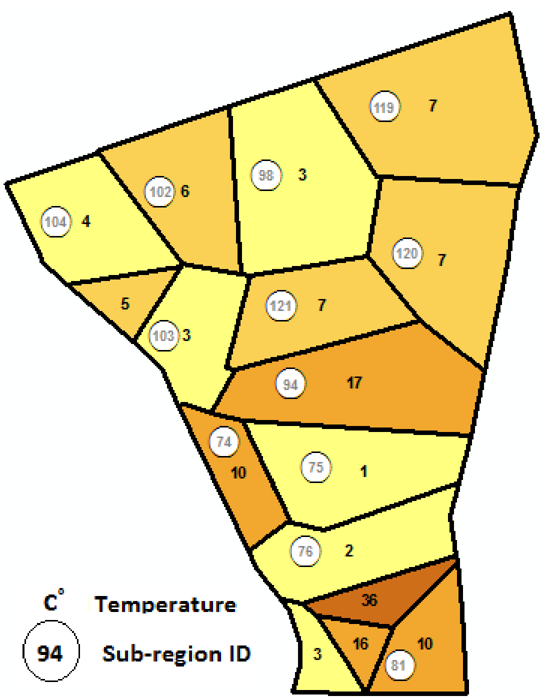


Figure 5.27 Free chlorine percentage of diversion from optimal standards

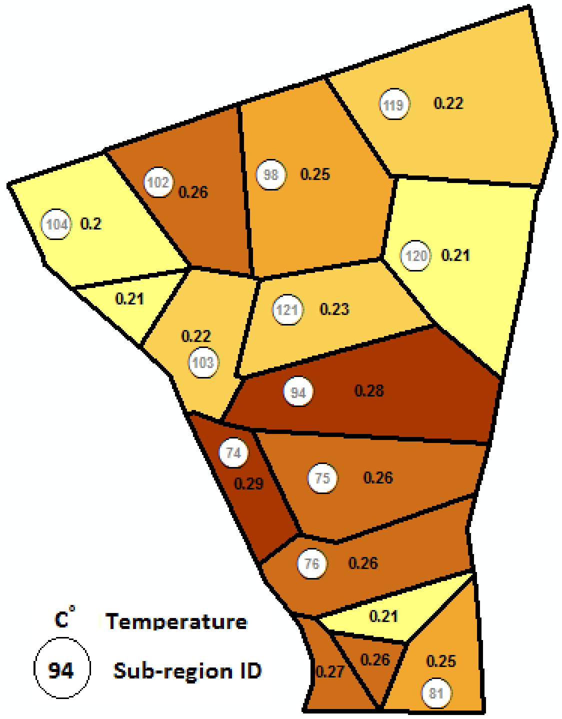


Figure 5.28 Turbidity levels in the city (NTU)

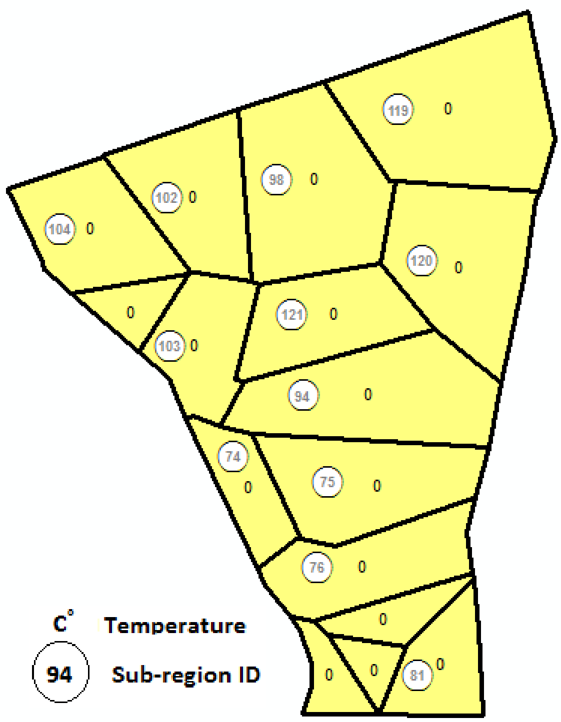


Figure 5.29 Turbidity percentage of diversion from optimal standards

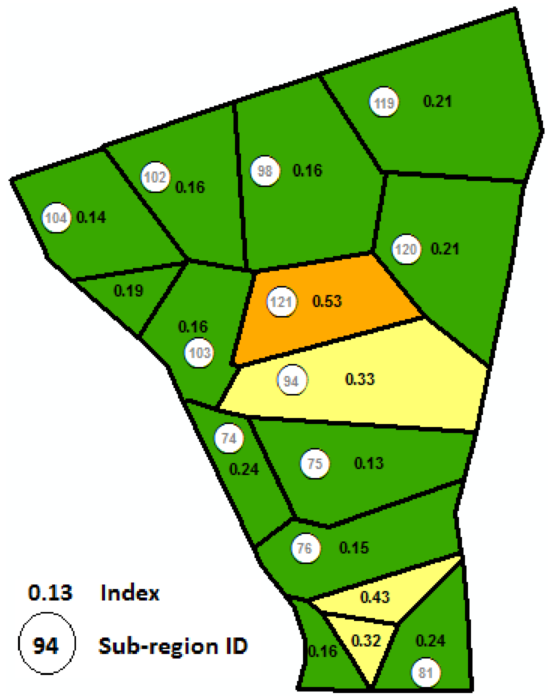


Figure 5.30 Risk index for microbial properties

Since turbidity is consistent all over the city in terms of values and percentage diversions from optimal standards (as shown in Figures 5.28 and 5.29), free chlorine plays a vital role in controlling prioritization of risks between sub-regions. It can be seen from Figure 5.30 that there is low microbial risk index with relatively higher risk in sub-regions.

Accordingly, water quality risk index for each sub-region was developed using physico-chemical and microbial indices (Figures 5.22 and 5.30) as shown in Figure 5.31. It is obvious that water quality risk is low in the WDN since water quality parameters (TDS, pH, temperature, free chlorine and turbidity) are generally within the recommended standards. Water quality regional risk indices range between 0.14 and 0.43, which indicates relatively low risk.

5.5 Vulnerability

Vulnerability of the WDN is identified by aggregating hydraulic properties, water quality and structural integrity. Risk indices for hydraulic properties, structural integrity and water quality are presented in Figures 5.7, 5.18 and 5.31, respectively. Figure 5.7 shows that in terms of hydraulic properties such as pressure and water age, sub-regions in the center have high risk indices such as sub-regions 75 and 94. Structure integrity for the WDN has low risk index in the northern sub-regions of the city compared to both southern and central sub-regions as shown in Figure 5.18. Structure integrity risk index increases towards the south till it reaches maximum risk index of 0.63 in sub-region 82. In terms of water quality, there is no significant risk as shown in Figure 5.31. Aggregation of these factors will develop vulnerability index for the WDN as shown in

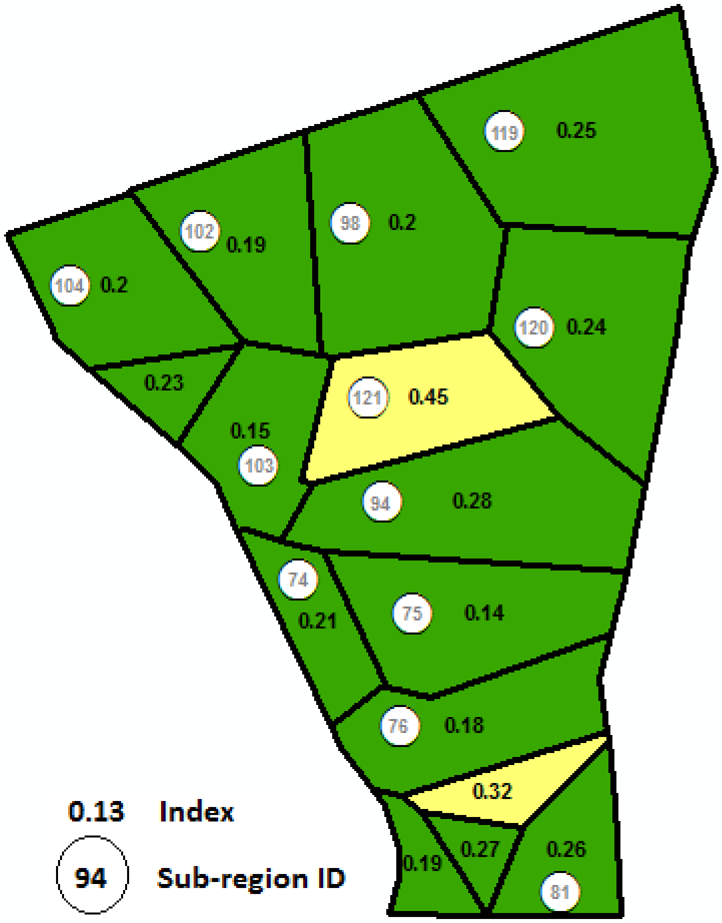


Figure 5.31 Risk index for water quality

Figure 5.32. Vulnerability index ranges between 0.12 and 0.54. Most of the sub-regions have moderate to low vulnerability except for sub-regions 75 and 94 which have relatively high vulnerability.

Major factors affecting vulnerability are hydraulics properties and structure integrity since water quality risk index is low all over 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 indices in that zone are higher than the northern sub-regions but at the same time less than sub-regions in the city center.

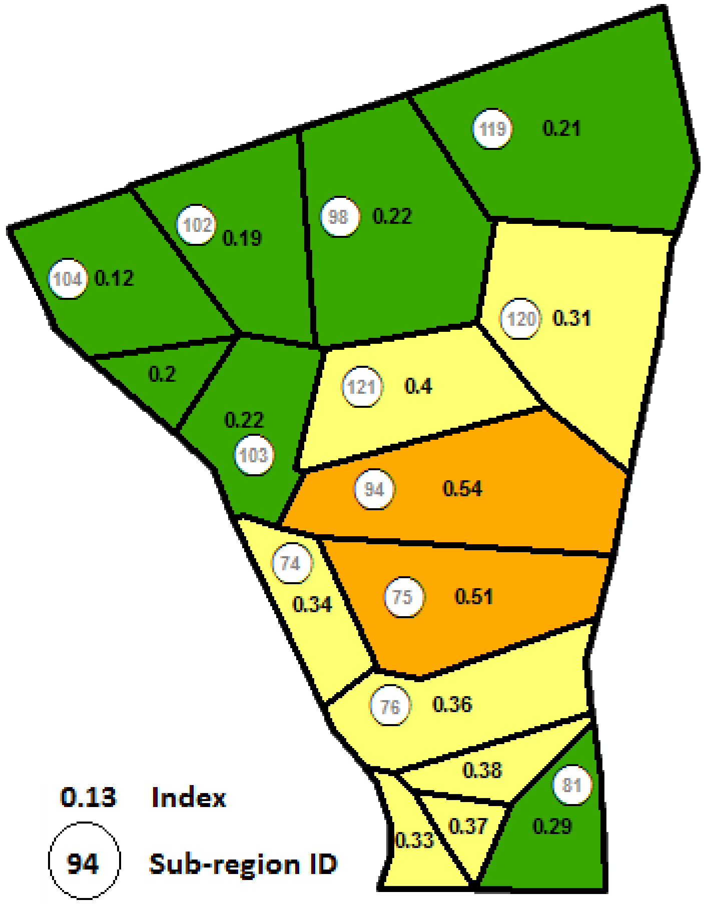


Figure 5.32 Vulnerability risk index for water quality

5.6 Sensitivity

Sensitivity of the sub-region gives a sense of possible consequences and casualties in case anything went wrong in the WDN. Standard of living, population density, activity, number of beds in hospitals and number of students are measures for regional sensitivity in case any possible deterioration of water quality, hydraulics or structure integrity occurred within the WDN. Standard of living of individuals is highly dependent on income rate. Usually, individuals with high income rate tend to improve their life quality in terms of residence, vehicles, food and drinks such as water. Individuals with high income rate tend to buy bottled water for drinking and cooking rather than using pumped water through the WDN. On the other side, individuals with low income rates tend to use pumped water for drinking and/or cooking, which makes them more sensitive to any consequences that may happen in the WDN. Figures 5.33 shows an estimation for high, moderate and low standard of living zones in Al-Khobar city. Standards of living were estimated based on real estate prices in these sub-regions. Each sub-region has different mixture of individuals with different income rates and standard of living as shown in Figure 5.34. From Figure 5.33, the southwestern part of the city is the most sensitive in which most of the low income individuals live, especially sub-regions 74, 76, 77 and 94, as shown in Figure 5.34. Population density is high at the city center and decreases towards the northern and southern borders of the city. Sub-regions 74, 75, 94 and 121 have the highest population density as shown in Figure 5.35. In residential areas, people tend more to use water either for drinking, cooking, washing or bathing compared to areas with different activities such as commercial and industrial. Accordingly, residential areas are more sensitive to any change in water quality than other zones. Figure 5.36

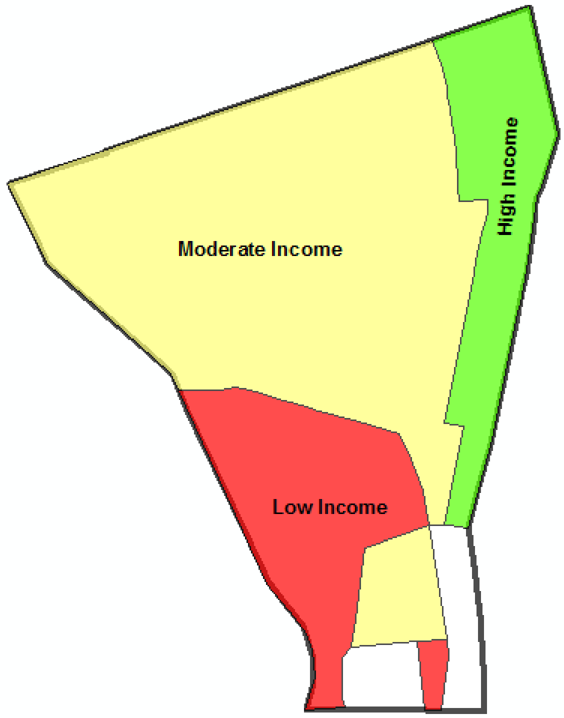


Figure 5.33 High, moderate and low standard of living zones in the city

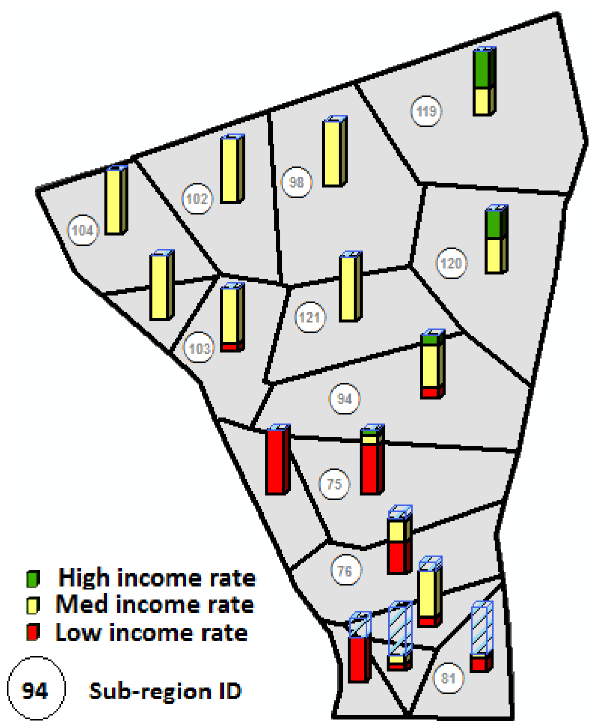


Figure 5.34 Ratio of income rate for individual in each sub-region

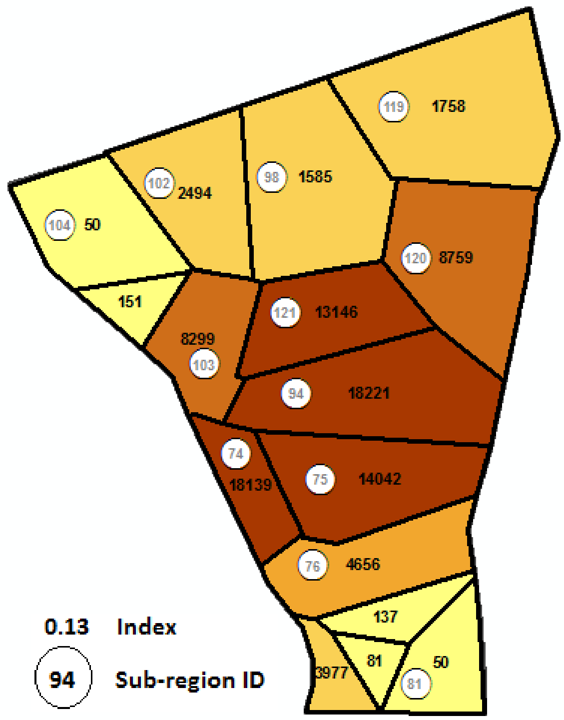


Figure 5.35 Population density across the city

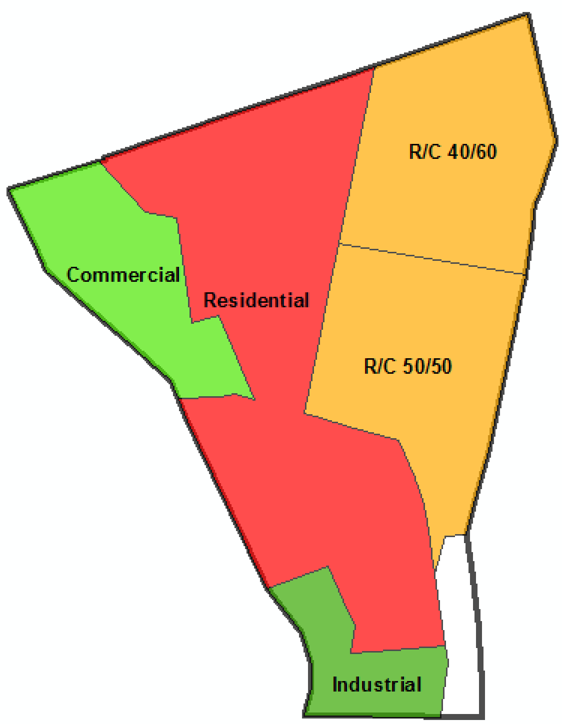


Figure 5.36 Zones for different activities in the city

shows zones of different activities in the city and Figure 5.37 shows the ratio of activities in each sub-region. Figure 5.37 shows that sub-regions 74, 76, 94, 98, 102 and 121 have higher residential areas than commercial and industrial areas.

In addition to the above, there are groups in the community who are more sensitive to any deterioration of water quality than others. Patients and school students are more sensitive to waterborne illnesses and their immune system is either weak or not fully developed (Francisque et al., 2009). In Al-Khobar city, there are 8 main hospitals with varying capacities ranging from 30 to 600 beds. Figure 5.38 shows the locations of these hospitals. Figures 5.39, 5.40 and 5.41 show the locations of elementary, intermediate and secondary schools in the city, respectively. Students in elementary schools are more sensitive to waterborne illnesses than other students since their age is less than 12 years and their immune system is not fully developed (Francisque et al., 2009). Figure 5.42 shows regional comparison in terms of total number of elementary, intermediate and secondary students in the city. Sub-regions such as 74, 75 and 121 have the maximum number of students, especially elementary students, which makes these sub-regions more sensitive compared to other sub-regions.

Aggregation of all these factors determines the sensitivity of each sub-region. It is obvious that sub-regions 74, 75, 94, 120 and 121 are more sensitive than others. Fuzzy methods were used to aggregate these factors to determine the sensitivity prioritization for different sub-regions in the city as shown in Figure 5.43. Sensitivity index ranges between 0.03 and 0.86. Sub-regions in the center, such as 74, 75, 94 and 121, are more sensitive to any deterioration of water quality in the WDN compared to others. On the

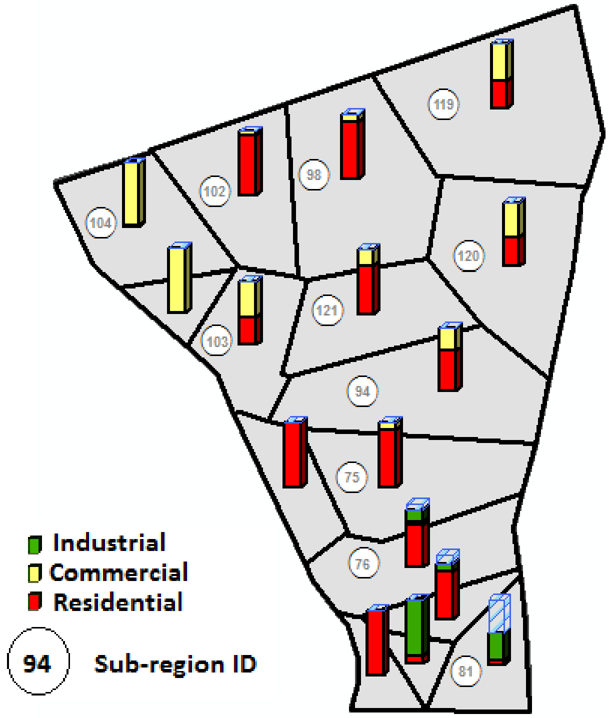


Figure 5.37 Ratio of activities in each sub-region

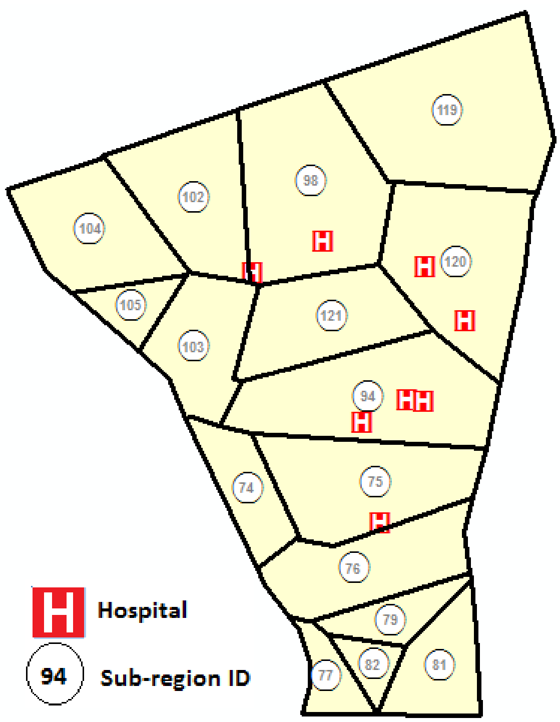


Figure 5.38 Locations of hospitals

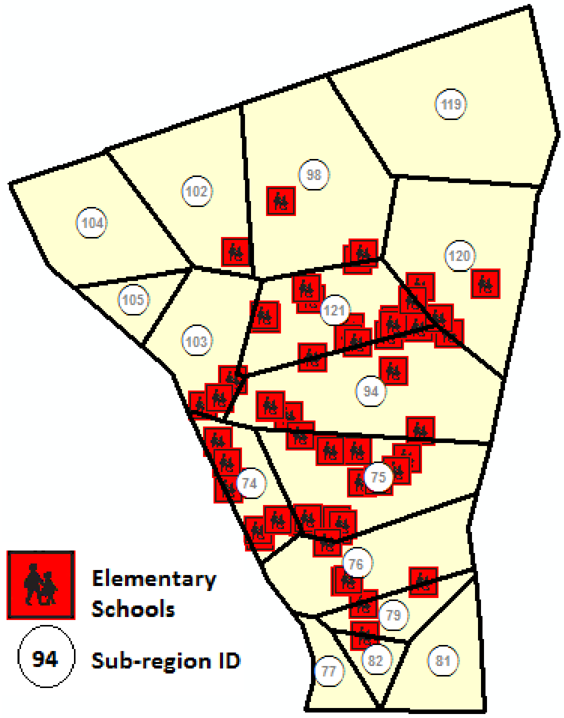


Figure 5.39 Locations of elementary schools

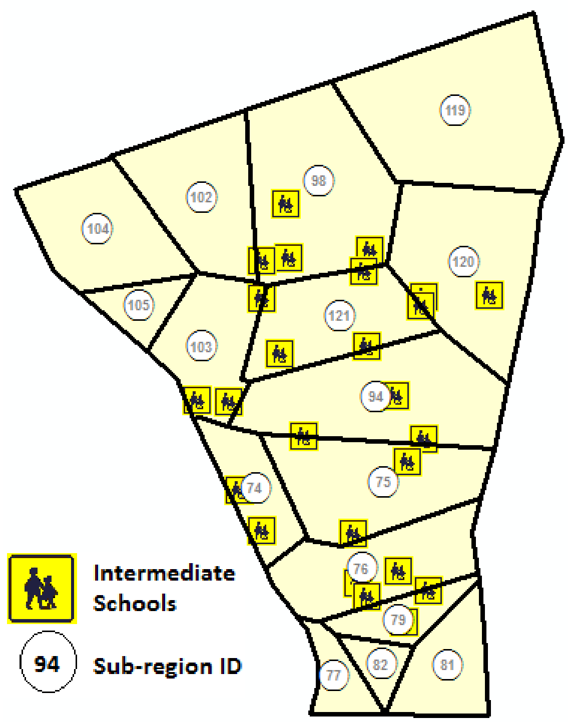


Figure 5.40 Locations of intermediate schools

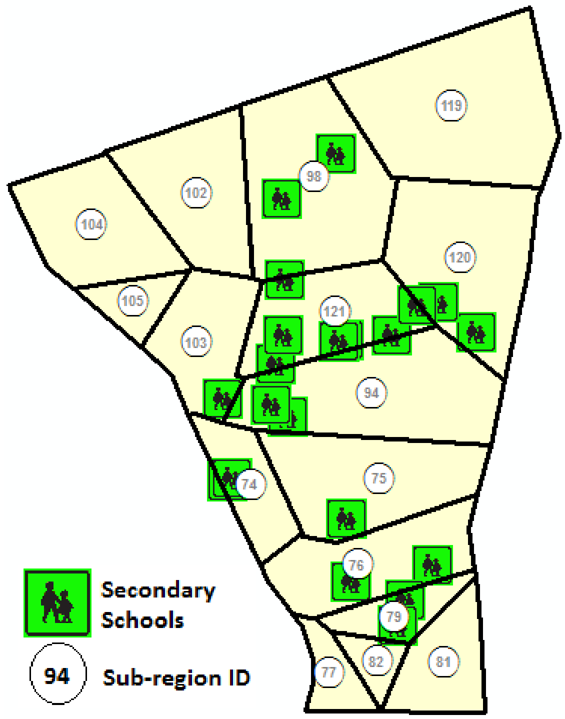


Figure 5.41 Locations of secondary schools

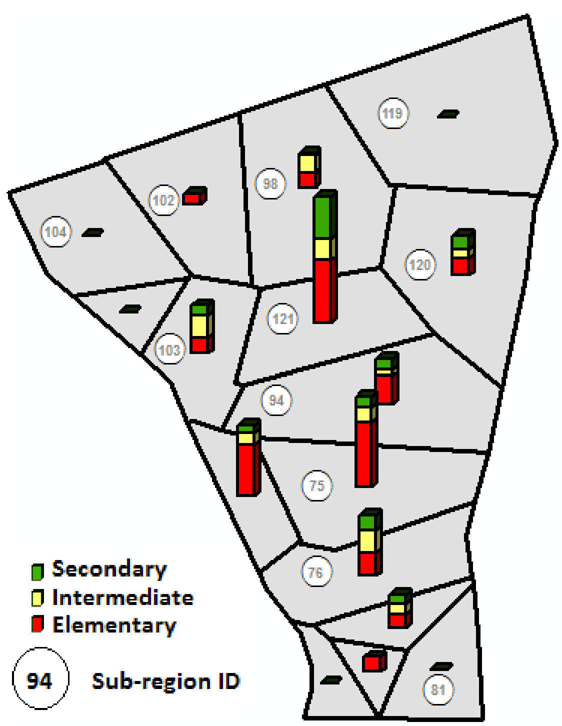


Figure 5.42 Regional comparison of number of students in the city

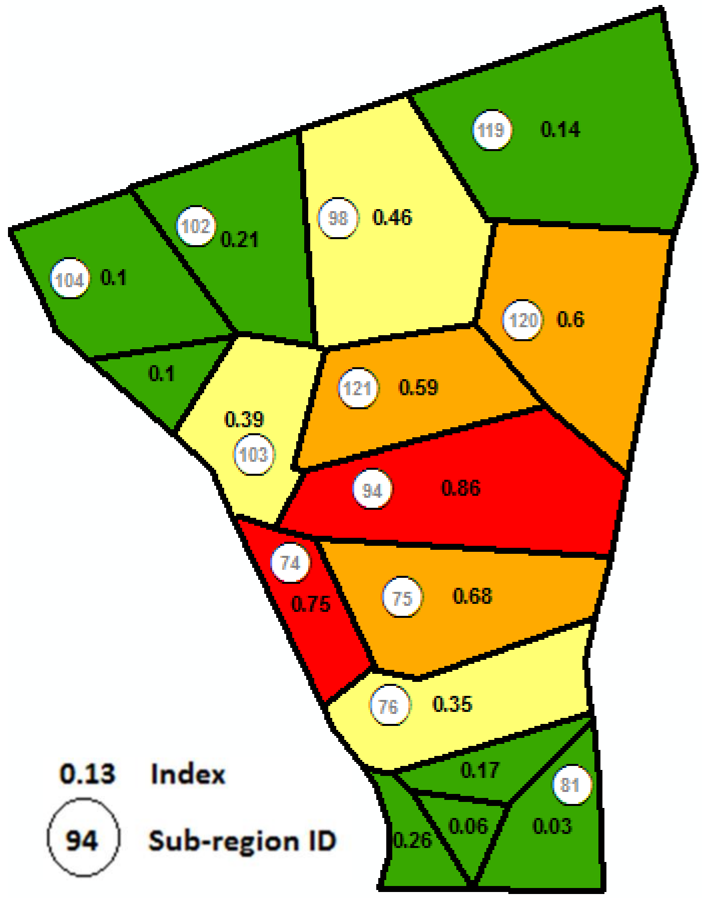


Figure 5.43 Sensitivity of sub-regions

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 less residential areas.

5.7 Risk Assessment

Total regional risk is based on the vulnerability and sensitivity of each sub-region. Most vulnerable and sensitive sub-regions are the sub-regions with the highest risk index. Sub-regions with the highest vulnerability, as shown in Figure 5.32, are sub-regions 75 and 94 with vulnerability index of 0.51 and 0.54, respectively. On the other hand, sub-regions 74, 75, 94, 120 and 121, as shown in Figure 5.44, are the most sensitive sub-regions with sensitivity index of 0.75, 0.68, 0.86, 0.60 and 0.59, respectively. Sub-regions 75 and 94 are from the most vulnerable and sensitive sub-regions, which indicates that they have high risks compared to other sub-regions, accordingly, it is expected that they will have the highest risk indices. Total risk indices range between 0.11 and 0.70. 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, as shown in Figure 5.43, and also the most vulnerable, especially sub-regions 75 and 94, as shown in Figure 5.32. This explains the relatively high risk in the city center compared to other sub-regions in the city. Table 5.6 shows risk indices for all sub-regions. It is clear that 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.

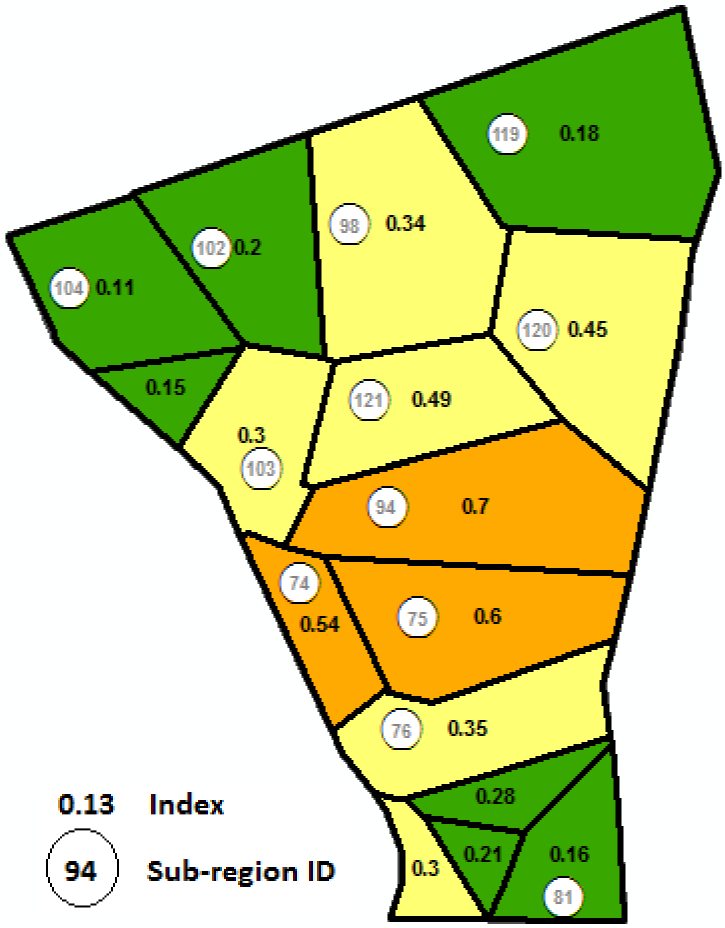


Figure 5.44 Total risk index for each sub-region

Table 5.6 Indices for sub-regions with highest and lowest total risk

Index	Sub-Regions															
	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

5.8 Locating Monitoring Stations (MSs)

Distributing water through the piping networks is the final process before the treated water reaches the end points of use. Beyond this process, there is no defense line that would provide protection to consumers if water quality deteriorates, regardless of the causes, during distribution. In WDN, efficient monitoring system can track water quality during distribution and reflects its condition in addition to raising alerts in case of water quality deterioration. Developing monitoring system requires defining some parameters such as the coverage threshold (*CT*) and sampling strategies in situ. Although there is no predefined value for *CT*, it can range from 25% to 75% (Lee, 1990). As *CT* increases, the monitoring system becomes more conservative and, consequently, less number of flow paths will be monitored. For example, if *CT* is assumed to be 80%, it means that the flow path which makes up 80% (or more) of the water passing through a node will be considered in the analysis. However, flow paths making less than 80% of water passing through the node will not be covered. On the other side, using low value for *CT* will cover more flow pathways, but it will be questionable in terms of its representativeness of water quality. If *CT* was 10%, this implies that the water quality of a flow path will be considered as "*covered*" at a specific node even if it makes only 10% of the total water passing through that node. Therefore, wise choices based on preliminary analysis should be taken to avoid drawbacks for using high or low *CT*, especially considering that the relation between *CT* and final optimized monitoring system is highly dependent on the layout and operation of the WDN. It should be noted that words such as covered or monitored are used interchangeably in this discussion. Both words mean that the downstream MS (Monitoring Station) is capable of representing water quality of the nodes upstream. Therefore, these upstream nodes are considered “covered” or “monitored” by the downstream MS.

5.8.1 Preliminary analysis

Preliminary analysis of investigating the effect of *CT* on the optimal selection of MSs locations and the total monitored demand (TMD) was conducted to understand the relation between *CT* and the proposed monitoring system for the specific network under consideration, i.e. Al-Khobar WDN. Four different scenarios were examined with the *CT* values of: 40%, 50%, 60% and 70%. This range of *CT* values was selected since it covers the most practical values that maximize TMD and also it minimizes the possible drawbacks for using high or low *CT* as much as possible. In most of the studies, *CT* values did not exceed 70% (Kumar et al., 1997; Al-Zahrani and Moied, 2003; Liu et al., 2012).

Interesting fact about WDN is that flow patterns and demands are not constant or steady during 24 hours of operation. The demand variation during the day means that the optimal locations of the MSs will also vary. For Al-Khobar WDN, demand pattern changes every hour, which means that there are 24 different demand patterns. Selecting the optimal locations (nodes) for MSs based on these 24 pattern demands will result in 24 sets of optimal locations for MSs, one set for each pattern. Furthermore, seven grouped demand patterns were developed in this study. Instead of using 24 hourly demand patterns, another alternative was to consider four 6 hours, two 12 hours or a single 24 hours demand patterns as will be discussed later.

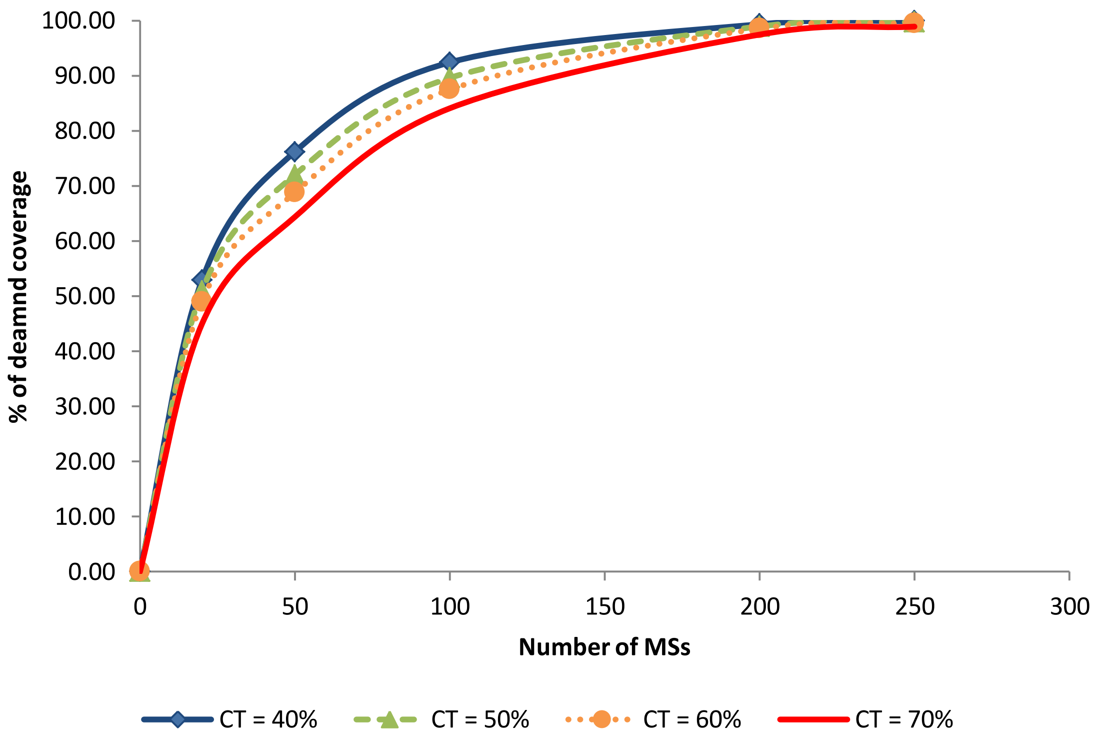
Since there were four *CT* values that were investigated and 31 different single and grouped demand patterns, the preliminary study examined 124 different optimization scenarios as shown in Table 5.7. In addition, the analysis investigated the effect of using different number of MSs, including 15, 20, 30, 50, 100, 200 and 250. Accordingly, the total number of scenarios for the preliminary study is 868 scenarios.

The general trend of TMD for the different *CT* values was as expected; as *CT* values increase, less flow paths were considered. Figures 5.45 and 5.46 show the effect of *CT* in TMD percentages for different number of MSs in the WDN. TMD is the highest when *CT* is 40%, while it is the lowest when *CT* is 70%. For *CT* values of 40%, 50% and 60%, the differences between coverages are relatively insignificant compared to the estimated TMD when *CT* is 70% as shown in Figures 5.45 and 5.46. Usually, a single value for *CT* is used, but using two values representing the upper and lower limits for *CT* will show the effect of this parameter on the final optimization process for selecting MSs optimal locations.

Accordingly, in this study *CT* values of 40% and 60% were considered, since there is no significant difference in terms of TMD between 40%, 50% and 60% and most of the previous studies assumed *CT* values to be within this range. Another reason for analyzing the network for *CT* values of 40% and 60% is because higher values of *CT* such as 70% may ignore valuable flow paths if they count less than 70% of the water passing through the proposed monitoring nodes.

Table 5.7 Demand pattern scenarios for each CT

Pattern	Coverage Threshold (CT)			
	40%	50%	60%	70%
Single hour	Hour 1	Hour 1	Hour 1	Hour 1
	Hour 2	Hour 2	Hour 2	Hour 2
	Hour 3	Hour 3	Hour 3	Hour 3
	Hour 4	Hour 4	Hour 4	Hour 4
	Hour 5	Hour 5	Hour 5	Hour 5
	Hour 6	Hour 6	Hour 6	Hour 6
	Hour 7	Hour 7	Hour 7	Hour 7
	Hour 8	Hour 8	Hour 8	Hour 8
	Hour 9	Hour 9	Hour 9	Hour 9
	Hour 10	Hour 10	Hour 10	Hour 10
	Hour 11	Hour 11	Hour 11	Hour 11
	Hour 12	Hour 12	Hour 12	Hour 12
	Hour 13	Hour 13	Hour 13	Hour 13
	Hour 14	Hour 14	Hour 14	Hour 14
	Hour 15	Hour 15	Hour 15	Hour 15
	Hour 16	Hour 16	Hour 16	Hour 16
	Hour 17	Hour 17	Hour 17	Hour 17
	Hour 18	Hour 18	Hour 18	Hour 18
	Hour 19	Hour 19	Hour 19	Hour 19
	Hour 20	Hour 20	Hour 20	Hour 20
	Hour 21	Hour 21	Hour 21	Hour 21
	Hour 22	Hour 22	Hour 22	Hour 22
	Hour 23	Hour 23	Hour 23	Hour 23
	Hour 24	Hour 24	Hour 24	Hour 24
Six hours	1st 6 hours	1st 6 hours	1st 6 hours	1st 6 hours
	2nd 6 hours	2nd 6 hours	2nd 6 hours	2nd 6 hours
	3rd 6 hours	3rd 6 hours	3rd 6 hours	3rd 6 hours
	4th 6 hours	4th 6 hours	4th 6 hours	4th 6 hours
Twelve hours	1st 12 hours	1st 12 hours	1st 12 hours	1st 12 hours
	2nd 12 hours	2nd 12 hours	2nd 12 hours	2nd 12 hours
Twenty-four hours	24 hours	24 hours	24 hours	24 hours



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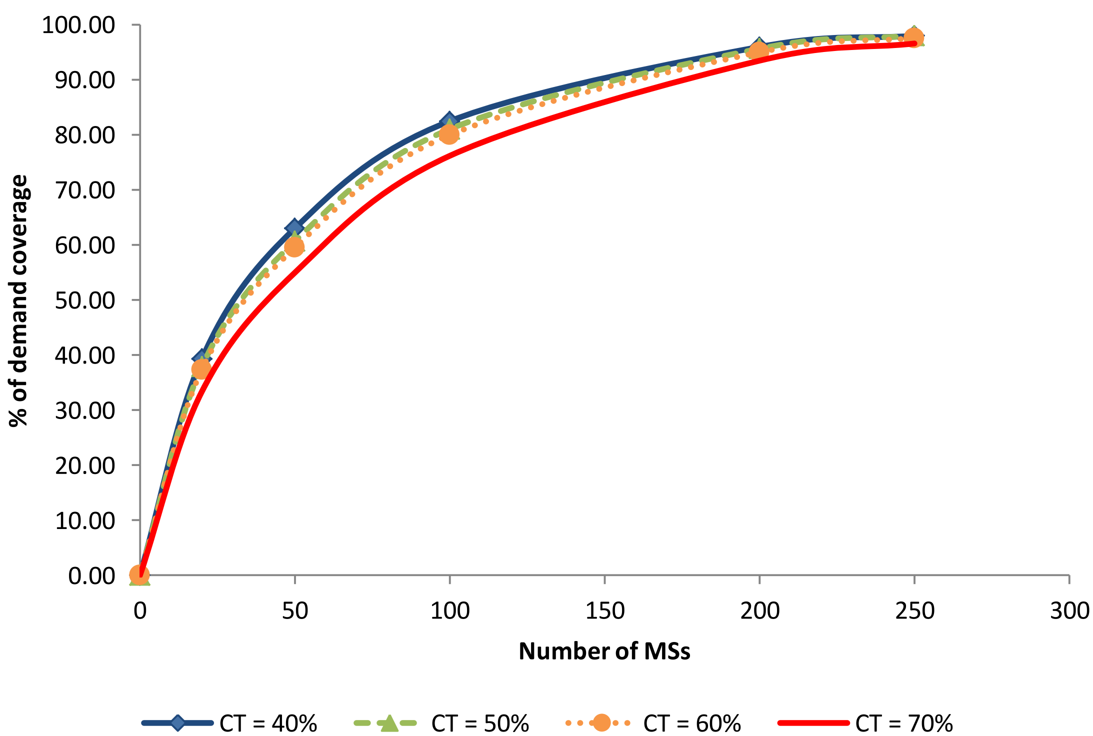
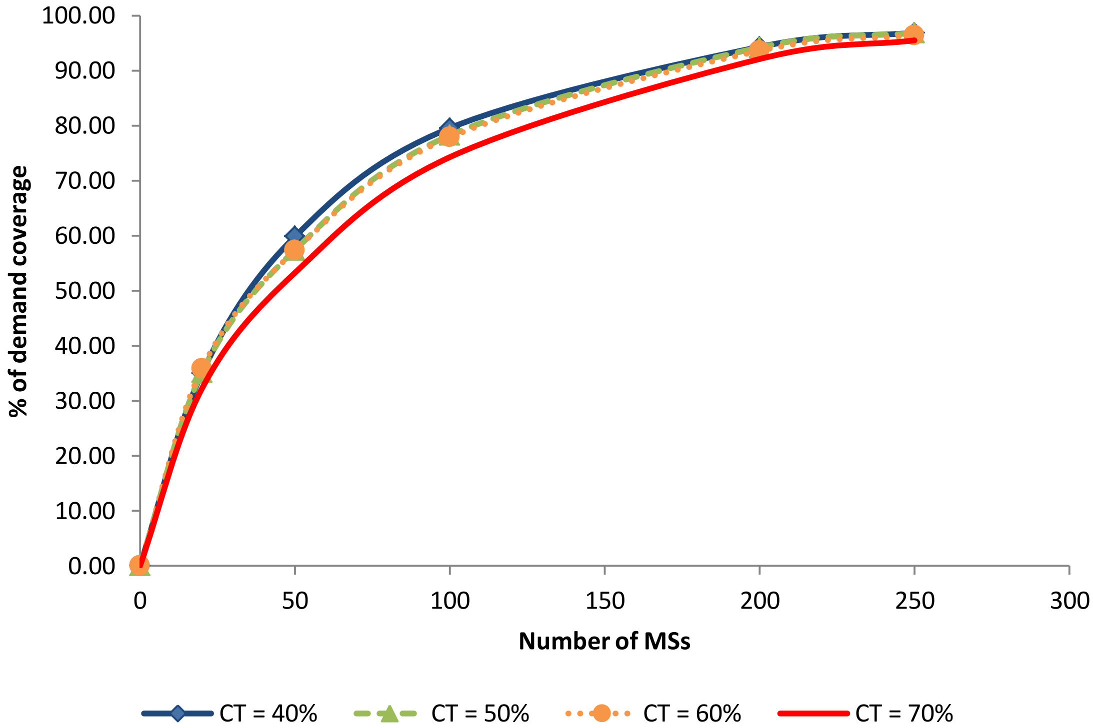


(b)

Figure 5.45 Average TMD percentages for:
(a) Hourly demand patterns and (b) 6 hours demand patterns



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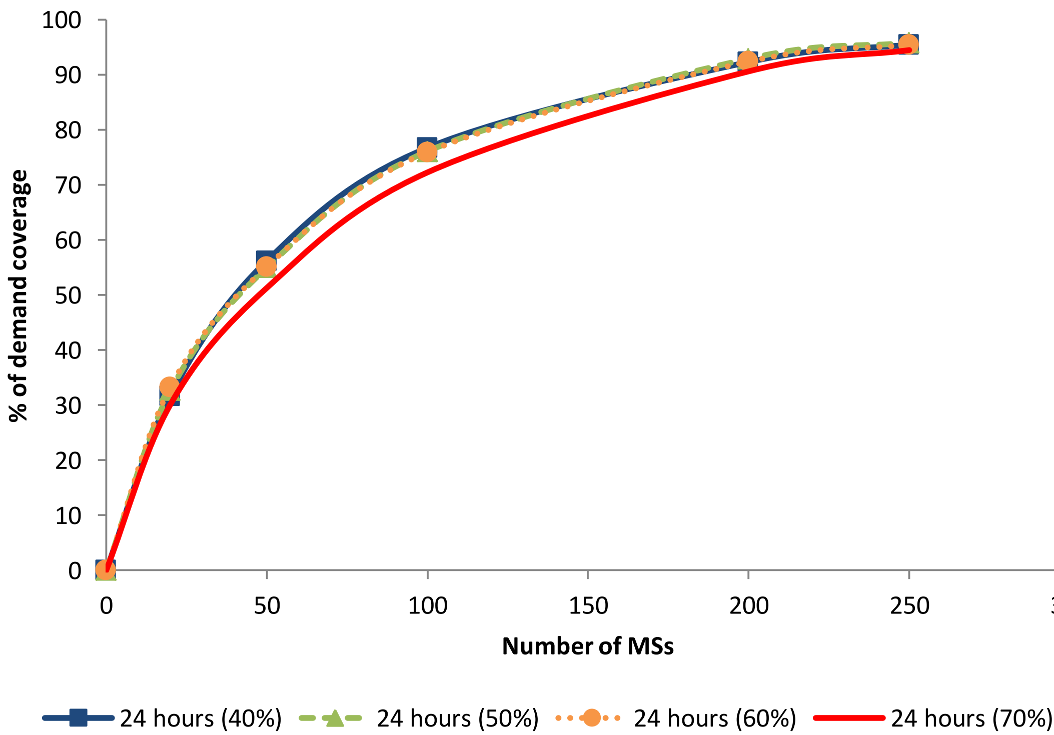


(b)

Figure 5.46 Average TMD percentages for:
(a) 12 hours demand patterns and (b) 24 hours demand patterns

5.8.2 Demand coverage optimization

In order for the water quality monitoring system to secure and protect consumers from any possible deterioration of water quality, MSs should be located optimally in order to maximize covered and monitored water. Once the water is pumped to the network, there is no defense line that can protect consumers other than monitoring. Failure of the monitoring system or its low efficiency could cause delivery of water in unacceptable quality and, consequently, casualties due to water quality deterioration may occur. Therefore, it is very important to make sure that MSs are placed in the right optimal or proper location(s).

Currently, there are 16 MSs in Al-Khobar city WDN. According to Al-Khobar authority, one of the MSs is out of service, which leaves the network with 15 MSs. The MSs are distributed over the WDN as shown in Figure 5.47. In general, most of the MSs are located close to major pumping locations such as Makkah tank, central pumping stations and pumping wells.

The main reason behind locating MSs in these locations is to monitor water quality directly after pumping to make sure that chlorine levels and TDS (after blending groundwater and desalinated water) are within the acceptable limits. Although it is beneficial to locate few of the MSs immediately after blending, chlorine injection, and pumping points, but exclusively locating MSs at these places ignores the fact that water quality can be disrupted and deteriorated during delivery through WDN at locations far away from these points due to intrusion of contaminants through crack or due to intentional criminal and/or terrorist acts.

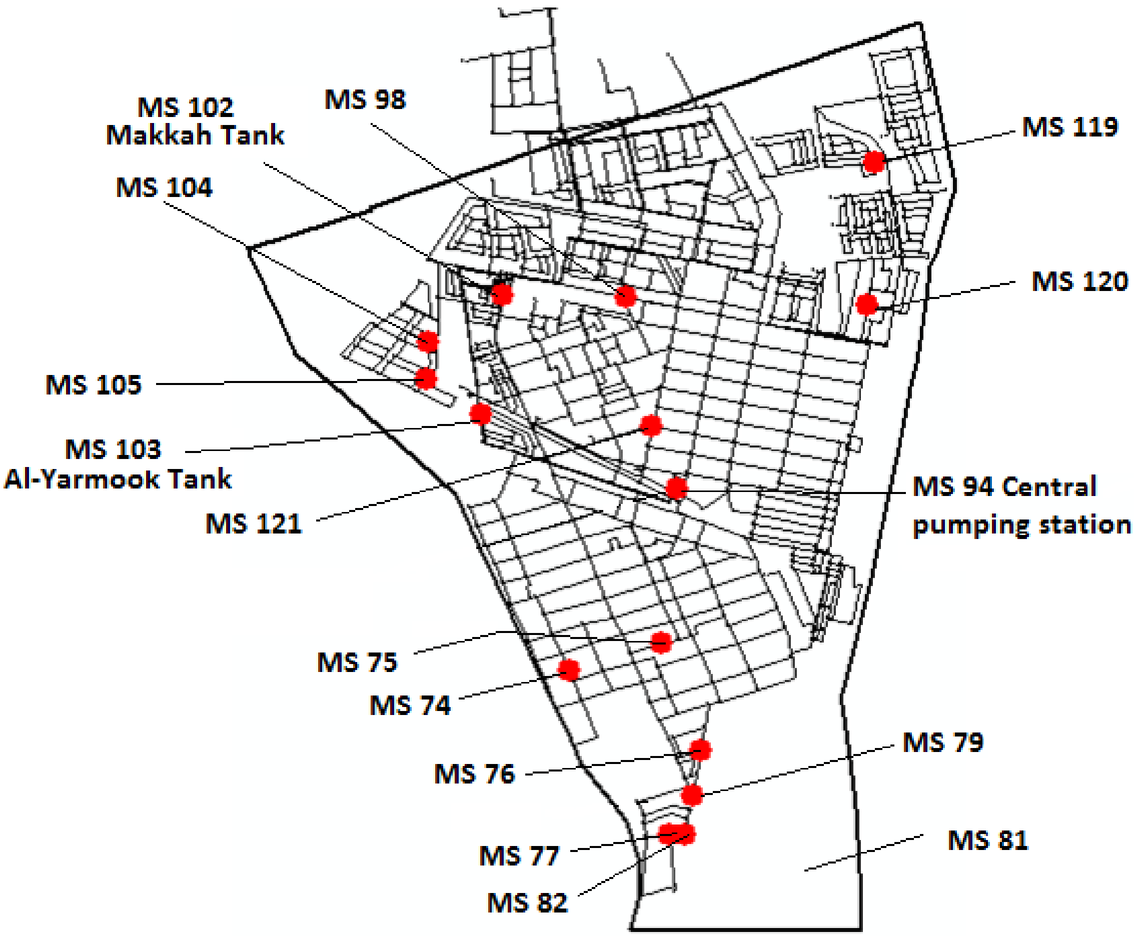


Figure 5.47 Existing locations of MS at Al-Khobar WDN

MSs located at nodes which have significant high water demand can protect more consumers and can minimize possible casualties caused by any possible accidental or intentional contamination events.

In Al-Khobar WDN, there are 871 non-zero nodes, where each node has water demand ranging from 1 to 20 m^3/hr. All of these nodes are considered potential monitoring stations (PMSs) and have equal chance for being chosen during the optimization process based on the objective functions and constraints explained in Chapter 3.

Water demand for the network under study at Al-Khobar city is approximately 135,310 m^3/day. Demand varies from one hour to another and between day and night. Locating MSs was conducted by considering hourly, 6 hours, 12 hours and 24 hours demand patterns (total of 31 demand patterns) and setting every non-zero demand node as PMS.

TMD for each pattern is shown in Figures 5.48 and 5.49. The figures indicate that the ratio between the number of MSs used and TMD is not linear, so for example, when 50 MSs were able to cover 56.91% (for 24 hours demand pattern) of the total demand during 24 hours, 250 MSs were able to increase demand coverage by only 38.55%, resulting in a total demand coverage of 95.46%.

The results indicate that the ratio between the TMD and the number of MSs decreased beyond 30 MSs. In other words, the demand coverage efficiency per single MS was reduced and higher number of MSs is required to increase TMD significantly. However, according to the water authorities in Al-Khobar city, it is not possible to establish a monitoring system that contains more than 50 MSs due to economic and practical

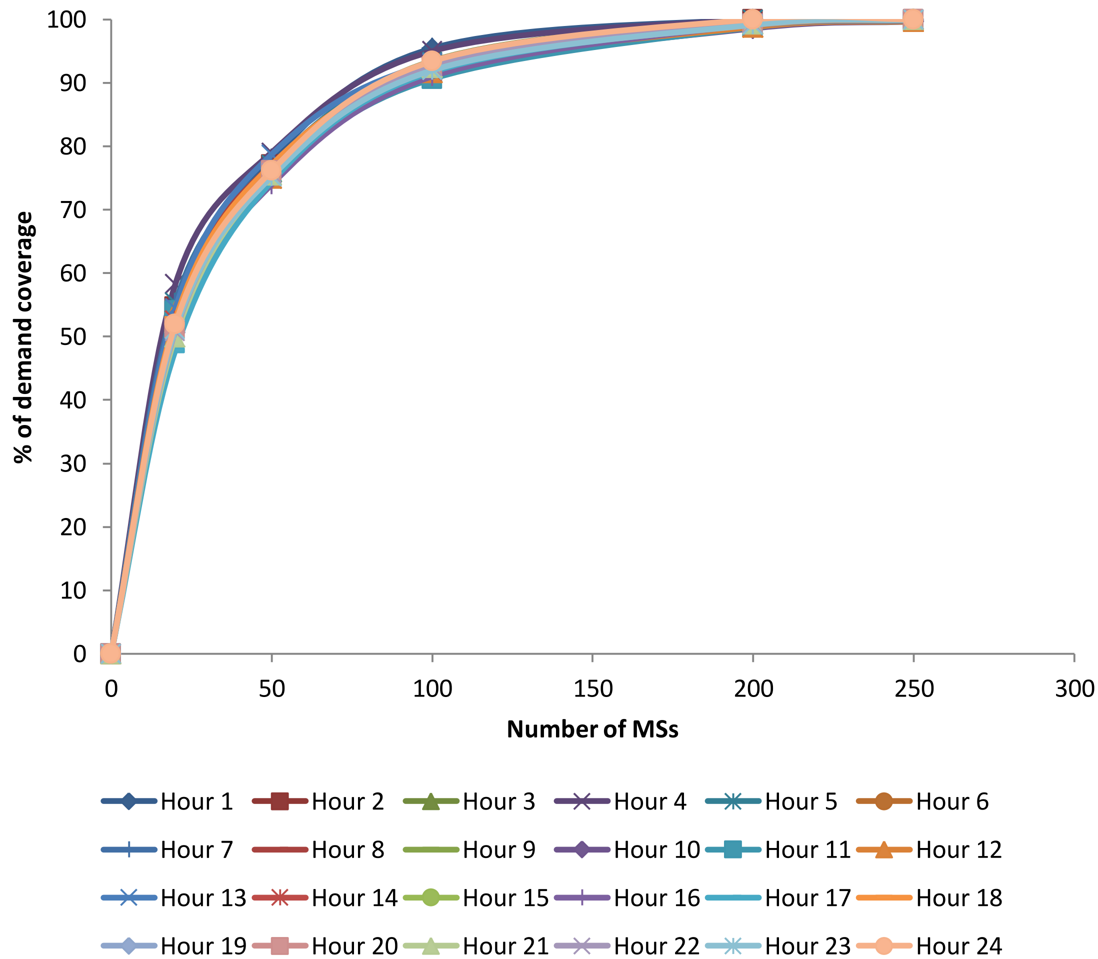


Figure 5.48 Demand coverage when CT equals 40%

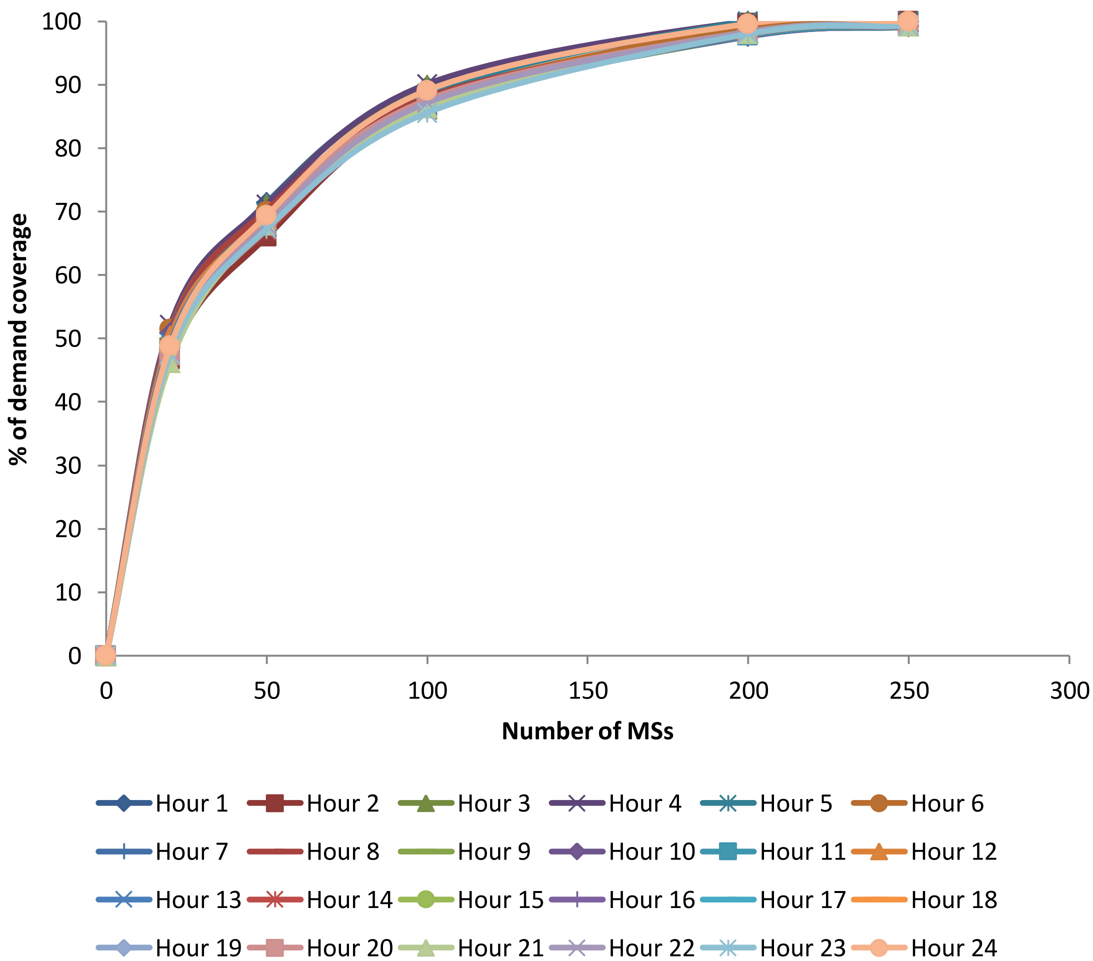


Figure 5.49 Demand coverage when CT equals 60%

constraints. Based on this, the maximum possible number of MSs that can be used is 50 MSs. Therefore, in this study, two *CT* values were considered with 31 demand patterns, and four possible choices as candidate number of MSs can be used for Al-Khobar WDN (15, 20, 30 and 50). Accordingly, the total scenarios investigated in this research summed up to 248 scenarios. However, the possibility of locating 100, 200 and 250 MSs was also investigated.

There are 24 hourly demand patterns in Al-Khobar WDN. For each single hourly demand pattern, a complete optimization analysis was conducted to select the optimal locations for the MSs. Besides the 24 hourly demands, the analysis for each pattern was done twice using *CT* values of 40% and 60%. Accordingly, 48 optimization analyses were conducted for hourly demands using objective function for absolute demand optimization and constraints 3.25 and 3.26 as discussed in section 3.4.2 of Chapter 3. Tables 5.8 and 5.9 show TMD based on the optimization analyses for hourly demands using 50 MSs or less. As expected, the estimated TMD is higher when *CT* equals 40% compared to TMD when *CT* was 60%. Increasing the *CT* value limits the number of PMSs that can be selected and excludes valuable water flow paths if their contribution to water at nodes (PMSs) is less than the *CT*. However, for Al-Khobar WDN, the difference in TMD when *CT* equals 40% and 60% was insignificant. For example, the demand coverage at hour 7 considering 20 MSs is 55.19% and 49.07% for *CT* values of 40% and 60%, respectively.

Table 5.8 TMD percentages for different hourly demand patterns for different numbers of MSs (CT = 40%)

Demand Patterns	**Number of MSs proposed**				
	0	15	20	30	50
Hour 1	0	47.62	53.93	64.28	77.99
Hour 2	0	48.70	54.71	64.18	77.02
Hour 3	0	48.25	54.49	63.97	76.01
Hour 4	0	51.88	58.27	67.23	79.03
Hour 5	0	49.41	55.40	64.36	77.11
Hour 6	0	47.94	53.75	62.94	74.97
Hour 7	0	49.23	55.19	64.80	76.98
Hour 8	0	47.50	53.75	64.13	77.13
Hour 9	0	47.70	53.39	63.27	75.61
Hour 10	0	46.42	53.12	63.28	75.95
Hour 11	0	48.31	54.09	63.00	75.05
Hour 12	0	46.92	53.83	63.46	74.96
Hour 13	0	48.45	54.46	64.52	78.72
Hour 14	0	46.13	52.59	62.69	76.21
Hour 15	0	44.43	50.86	60.94	75.98
Hour 16	0	44.03	50.54	60.22	73.98
Hour 17	0	41.87	47.82	58.41	74.43
Hour 18	0	46.91	52.71	62.38	77.08
Hour 19	0	43.63	50.68	61.40	75.76
Hour 20	0	44.26	51.21	61.21	76.16
Hour 21	0	43.67	49.96	60.44	75.50
Hour 22	0	45.04	50.85	60.60	75.79
Hour 23	0	45.37	51.16	61.16	75.23
Hour 24	0	45.17	51.97	62.83	76.13

Table 5.9 TMD percentages for different hourly demand patterns for different numbers of MSs (CT = 60%)

Demand Patterns	**Number of MSs proposed**				
	0	15	20	30	50
Hour 1	0	44.51	49.94	59.08	71.40
Hour 2	0	41.50	46.69	55.22	66.04
Hour 3	0	45.17	50.76	59.50	71.13
Hour 4	0	46.77	52.15	60.63	71.12
Hour 5	0	45.72	50.56	59.10	69.69
Hour 6	0	46.58	51.44	59.40	70.04
Hour 7	0	44.39	49.07	57.16	68.45
Hour 8	0	45.95	51.19	59.38	70.27
Hour 9	0	44.51	49.72	58.00	68.30
Hour 10	0	45.44	50.88	58.55	68.21
Hour 11	0	43.13	47.90	56.23	67.99
Hour 12	0	45.13	50.30	58.40	68.70
Hour 13	0	43.67	49.34	57.57	68.60
Hour 14	0	43.10	48.37	56.58	67.01
Hour 15	0	43.28	48.49	56.80	68.43
Hour 16	0	42.65	48.64	57.06	68.70
Hour 17	0	40.85	47.19	56.19	68.00
Hour 18	0	41.42	47.33	56.40	68.60
Hour 19	0	42.56	48.54	57.28	69.07
Hour 20	0	41.62	47.27	55.95	68.72
Hour 21	0	39.87	46.21	55.30	67.87
Hour 22	0	41.54	47.59	56.49	67.89
Hour 23	0	42.13	47.53	55.74	67.25
Hour 24	0	42.66	48.85	57.70	69.41

Similar conclusion can be drawn for each of the 24 hourly demand patterns as shown in Tables 5.8 and 5.9.

From the 7-hr demand pattern (Figure 5.50), it is clear that TMD is higher when *CT* equals 40% compared to TMD when *CT* was 60%, regardless of the number of MSs used in the optimization analysis. Similarly, summary of results shown in Tables 5.8 and 5.9 supports the same conclusion for each of all the 24 hourly demand patterns.

When considering 15 MSs (which is the same number of existing MSs), not less than 41.87% and 39.78% of demand is covered in the WDN for *CT* values of 40 and 60%, respectively. TMD percentage can be increased to be more than 73% and 66% if 50 MSs were selected for hourly demand patterns for *CT* values of 40% and 60%, respectively. In other words, using 50 out of 871 nodes (ratio of 0.057), at least 66% of the demand can be monitored. For this small ratio of MSs used, the percentage of covered demand is interesting, especially if compared to previous studies. Lee and Deininger (1992) were able to cover 50% of the demand using 14 out of 211 nodes (ratio of 0.066), while Liu et al. (2012) were able to cover 96% of the demand using 7 out of 34 nodes (ratio of 0.206). If similar ratios were used in this study, such as 0.066 and 0.206, then about 58 and 180 MSs should be selected. However, when selecting 58 and 180 MSs for Al-Khobar WDN, TMD becomes 82 and 97%, respectively, which is higher than the covered demand achieved by Lee and Deininger (1992) and Liu et al. (2012). In addition, this study is one of few studies where the analysis was conducted for a real network rather than a hypothetical one.

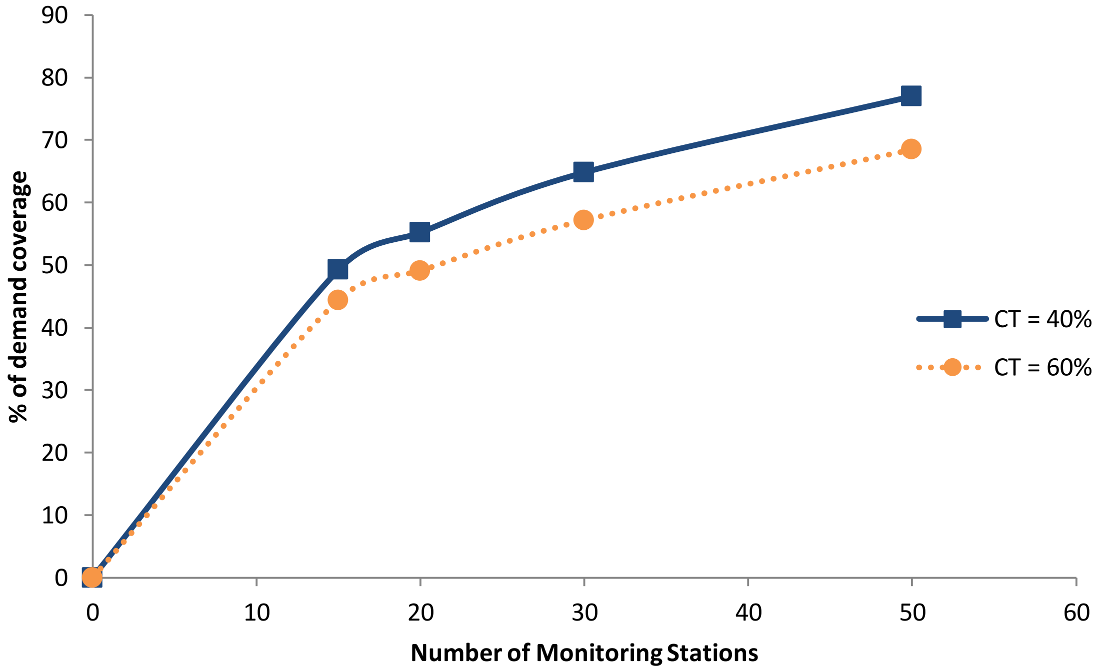


Figure 5.50 TMD comparison at hour 7 demand pattern for CT values of 40 and 60%

What is the best number of MSs that should be used? What is the minimum TMD that should be considered? These are open questions with no specific answer! Each network is a unique system, and answers to these questions are highly dependent on the WDN's economical and logistic constraints. From a theoretical point of view, the higher TMD the better, at least 50% of the demand should be covered. The idea here is that the monitoring system should reflect the actual water quality condition at the WDN as well as notify operators as soon as possible if there is any contamination risk. Both of these objectives require that the monitoring system should cover the demand in the network as much as possible.

For the hourly demand patterns, if only 15 MSs were considered for each demand pattern, then the total number of MSs required will sum up to 106 and 84 possible optimal MSs, for *CT* values of 40% and 60%, respectively. The summary for hourly demand patterns scenarios (192 scenarios) is shown in Table 5.10. In fact, the sampling process at Al-Khobar WDN does not take place on hourly basis. Actually, it would be economically and practically infeasible to operate 84 or 106 MSs, especially that the maximum number of MSs that can be used in the network is 50. Therefore, using less number of demand patterns by regrouping the 24 hourly demand patterns (number of patterns, not amount of flow) was considered as an alternative to overcome this economic and logistic obstacle. Instead of considering 24 hourly demand patterns, seven patterns were used: 1st 6 hours, 2nd 6 hours, 3rd 6 hours, 4th 6 hours, 1st 12 hours, 2nd 12 hours, and 24 hours patterns. Each pattern represents the summation of demand for the time duration it stands for. For example, 2nd 6 hours simply represents the summation of demands for the second 6 hours

Table 5.10 Total number of MSs proposed for all hourly demand patterns

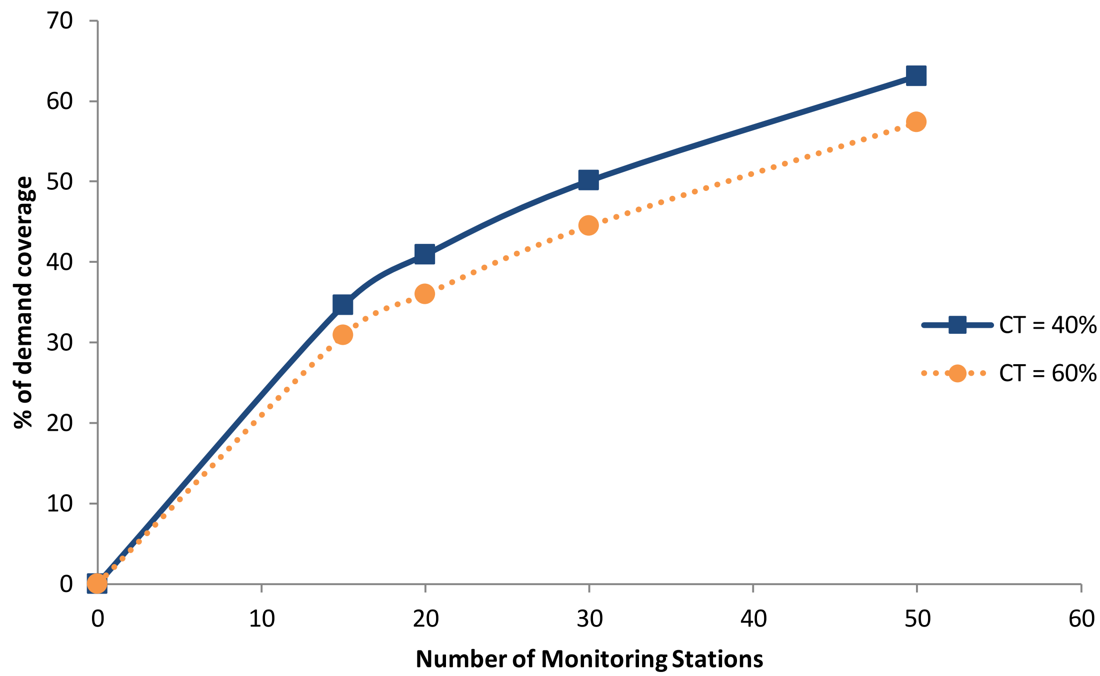
Possible number of MSs at each demand pattern per day	Proposed number of MS	
	(CT = 40%)	(CT = 60%)
0	0	0
15	106	84
20	130	107
30	162	133
50	210	172
100	299	257
200	562	496
250	646	619

Table 5.11 Time duration for each grouped demand pattern

Grouped Demand Pattern	Duration
1st 6 hours	00:00 – 06:00
2nd 6 hours	06:00 – 12:00
3rd 6 hours	12:00 – 18:00
4th 6 hours	18:00 – 24:00
1st 12 hours	00:00 – 12:00
2nd 12 hours	12:00 – 24:00
24 hours	00:00 – 24:00

of the day (from 6 am to 12 pm) and 1st 12 hours is the summation of demands for the first 12 hours of the day (from 12 am to 12 pm). Table 5.11 shows time duration for each grouped demand pattern.

For the case of 6 hours demand patterns, daily demand was divided into four patterns, such that each one extends for 6 hours. Total demand at each 6 hours pattern equals to the sum of hourly demands during the same period. Figures 5.51 and 5.52 show demand coverage for the four 6 hours demand patterns (32 scenarios). In general, the same behavior was noted compared to hourly demand patterns; demand coverage is higher for lower *CT* values. The major difference between hourly demand patterns and 6 hours patterns is the reduction of TMD for 6 hours demand patterns compared to hourly demand patterns. Suppose 50 MSs were selected, while TMD for hourly patterns was more than 70% and 60% (for *CT* equals 40% and 60%, respectively), TMD for 6 hours patterns was reduced to less than 65% and 62% (for *CT* equals 40% and 60%, respectively) as shown in Tables 5.12 and 5.13. This reduction in coverage was due to the attempts for the optimization model to select the optimal locations of MSs for 6 hours interval in which the demand patterns change 6 times, which requires some sort of tradeoff. However, for hourly demand pattern, the model will select optimal locations of MSs for a single hour interval. This reduction of coverage can be thought of as a tradeoff between total number of MSs selected and TMD. For example, if only 15 MSs were selected at each demand pattern, then in the case of hourly demand patterns, the total number of MSs required during the entire day to reach TMD shown in Table 5.10 are 106 and 84, respectively; while for 6 hours demand patterns, only a total of 38 and 31 MSs is required to achieve the TMD for 40% and 60% coverage criteria, respectively, as shown



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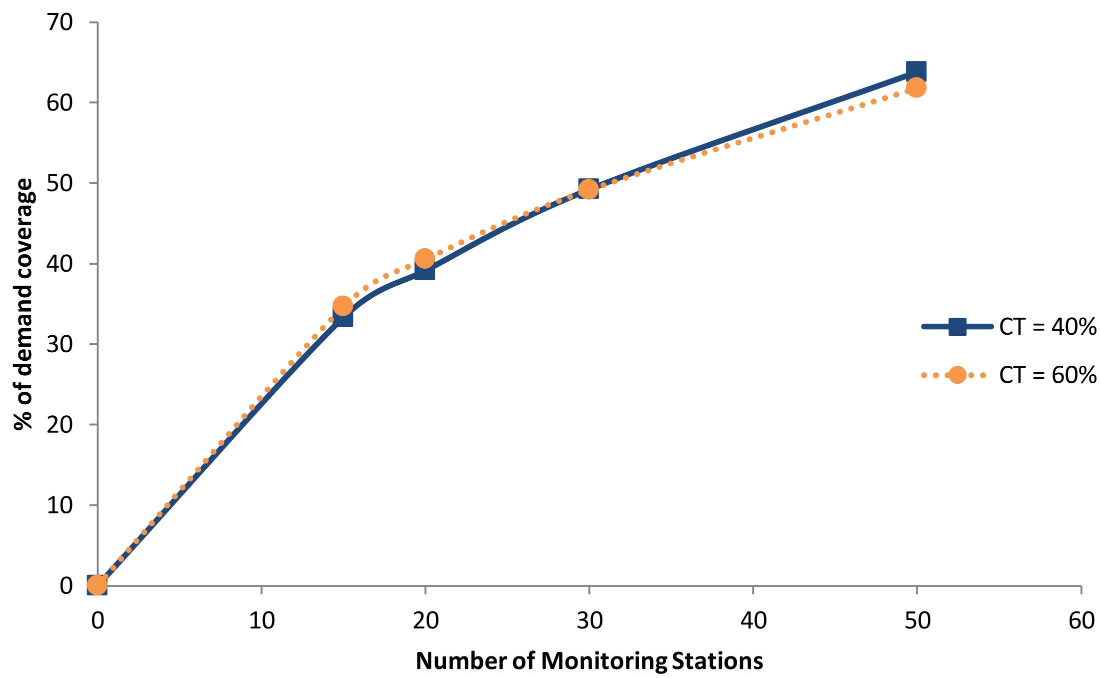
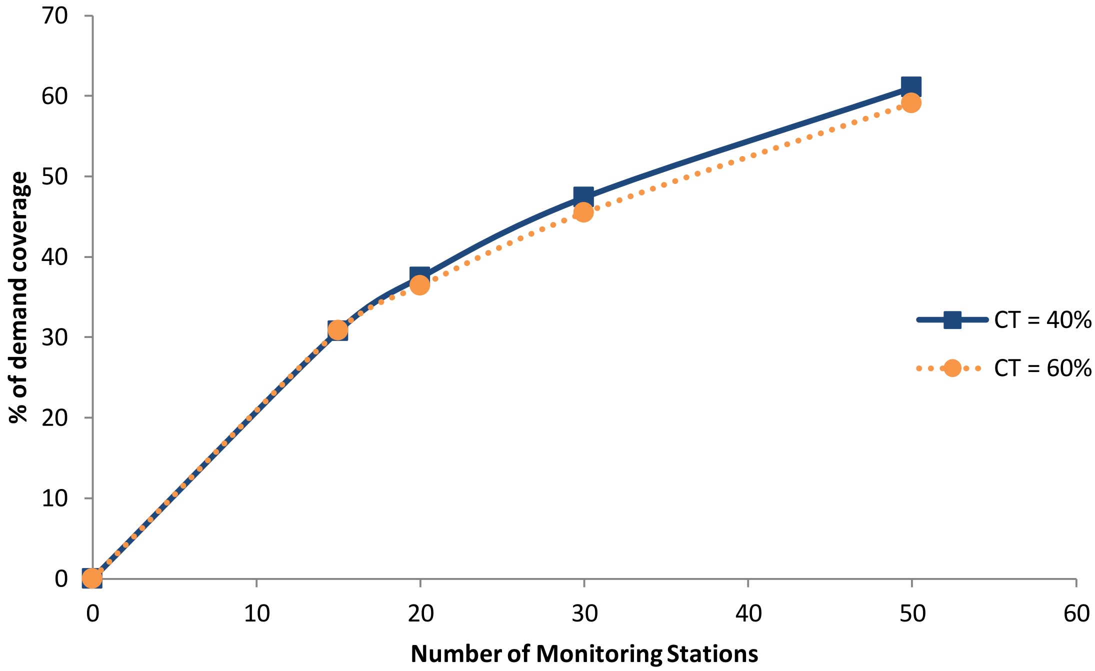


(b)

Figure 5.51 TMD for demand patterns: (a) 1st 6 hours and (b) 2nd 6 hours



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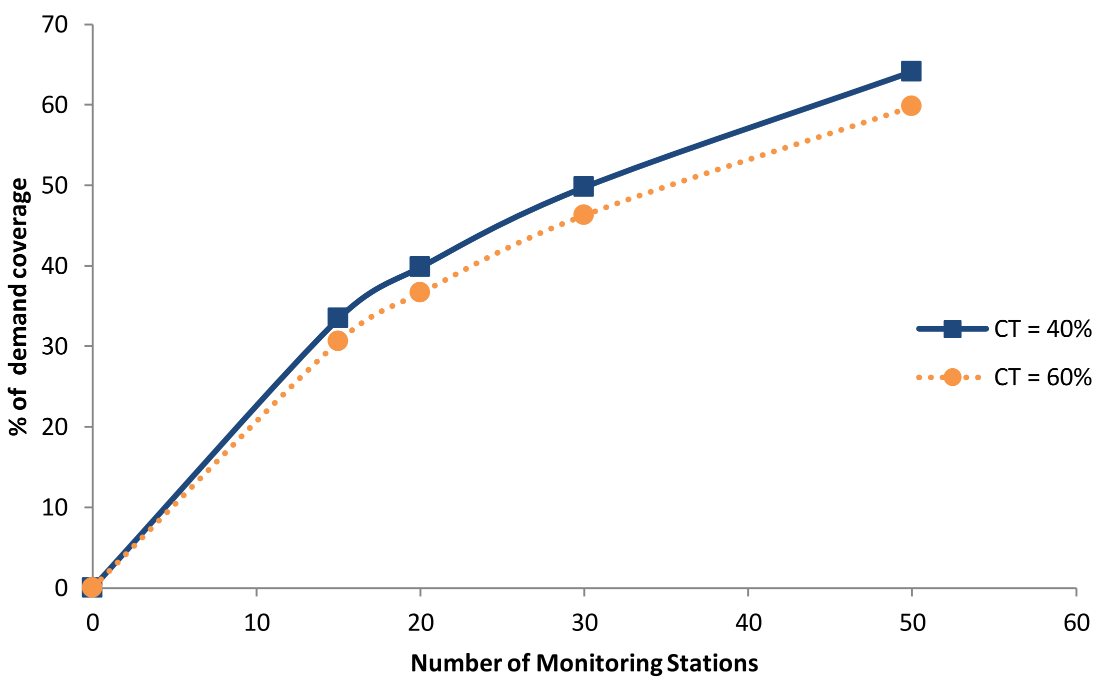


(b)

Figure 5.52 TMD for demand patterns: (a) 3rd 6 hours and (b) 4th 6 hours

Table 5.12 TMD percentages for different 6 hours demand patterns (CT = 40%)

Demand Patterns	**Number of MSs proposed**				
	0	15	20	30	50
1st 6 hours	0	34.61	40.90	50.08	63.09
2nd 6 hours	0	33.33	39.14	49.22	63.80
3rd 6 hours	0	30.79	37.45	47.38	61.03
4th 6 hours	0	33.43	39.82	49.76	64.12
1st 12 hours	0	28.32	34.27	44.36	59.54
2nd 12 hours	0	29.98	35.78	45.85	60.12
24 hours	0	25.37	31.70	41.87	56.19

Table 5.13 TMD percentages for different 6 hours demand patterns (CT = 60%)

Demand Patterns	**Number of MSs proposed**				
	0	15	20	30	50
1st 6 hours	0	30.89	35.98	44.47	57.31
2nd 6 hours	0	34.64	40.51	49.15	61.79
3rd 6 hours	0	30.84	36.38	45.48	59.10
4th 6 hours	0	30.59	36.61	46.28	59.76
1st 12 hours	0	31.47	36.48	44.47	56.59
2nd 12 hours	0	29.72	35.24	44.55	57.97
Total 24 hours	0	28.24	33.31	41.89	55.13

in Table 5.14. However, using more MSs will increase the TMD. For the 1st 6 hours demand pattern, TMD reached 63.09 and 57.31% when using 50 MSs for *CT* values of 40% and 60%, respectively. Other 6 hours demand patterns (2nd 6 hours, 3rd 6 hours and 4th 6 hours) show exactly the same behavior as presented in Tables 5.12 and 5.13. Table 5.14 shows the proposed number of MSs for all 6 hours demand patterns.

In addition to the 6 hours grouped demand patterns, two 12 hours demand patterns were used to determine the optimal locations for MSs as shown in Table 5.11. In this scenario, the day was divided into two demand patterns, where each 12 hours demand pattern represents the summation of hourly demand patterns of the relevant duration. Tables 5.12 and 5.13 show that when considering 12 hours demand patterns, further reduction in demand coverage was observed due to the same reasons that caused coverage reduction for 6 hours demand patterns. If 15 MSs were selected at each 12 hours demand pattern, then the total number of MSs required to achieve the TMD shown in Tables 5.12 and 5.13 is 27 and 23, respectively, as shown in Table 5.15. TMD for 12 hours demand patterns (16 scenarios) is the least compared to the total number of MSs proposed for hourly demand patterns (Tables 5.8 and 5.9) and 6 hours demand patterns, as shown in Tables 5.12 and 5.13, since less number of MSs was used. Similarly, selecting more MSs will increase the TMD.

The results indicate that 24 hours demand pattern requires less number of MSs compared to other demand patterns as shown in Table 5.16. However, the TMD for this demand pattern is the least compared to hourly, 6 hours and 12 hours demand patterns as presented in Tables 5.12 and 5.13.

Table 5.14 Total number of MSs proposed for all 6 hours demand patterns

Possible number of MSs at each demand pattern per day	**Proposed number of MSs**	
	(CT = 40%)	(CT = 60%)
0	0	0
15	38	31
20	48	41
30	60	57
50	91	87

Table 5.15 Total number of MSs proposed for all 12 hours demand patterns

Possible number of MSs at each demand pattern	**Proposed number of MSs**	
	(CT = 40%)	(CT = 60%)
0	0	0
15	27	23
20	32	31
30	43	44
50	70	68

Table 5.16 Total number of MSs proposed for 24 hours demand patterns

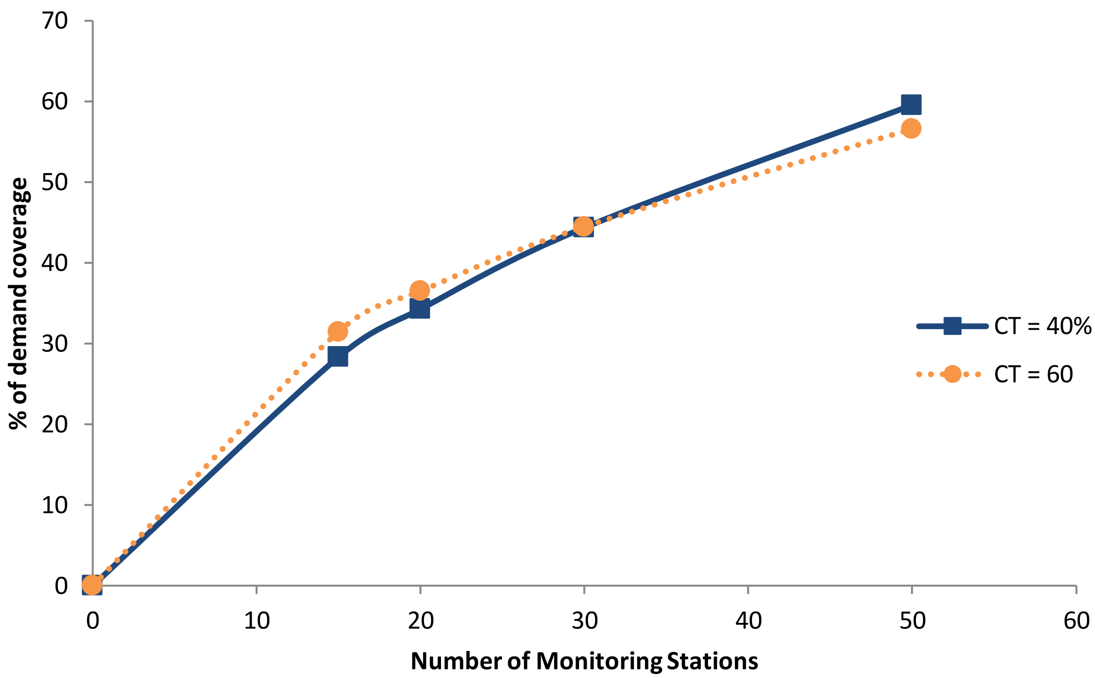
Possible number of MSs at each demand pattern	**Proposed number of MSs**	
	(CT = 40%)	(CT = 60%)
0	0	0
15	15	15
20	20	20
30	30	30
50	50	50

The least TMD recorded was for a 24 hours demand pattern (8 scenarios). Tables 5.12 and 5.13 show TMD for 24 hours demand pattern for different number of MSs. However, 24 hours demand pattern requires the least number of MSs to reach TMD level in Tables 5.12 and 5.13, as shown in Table 5.16.

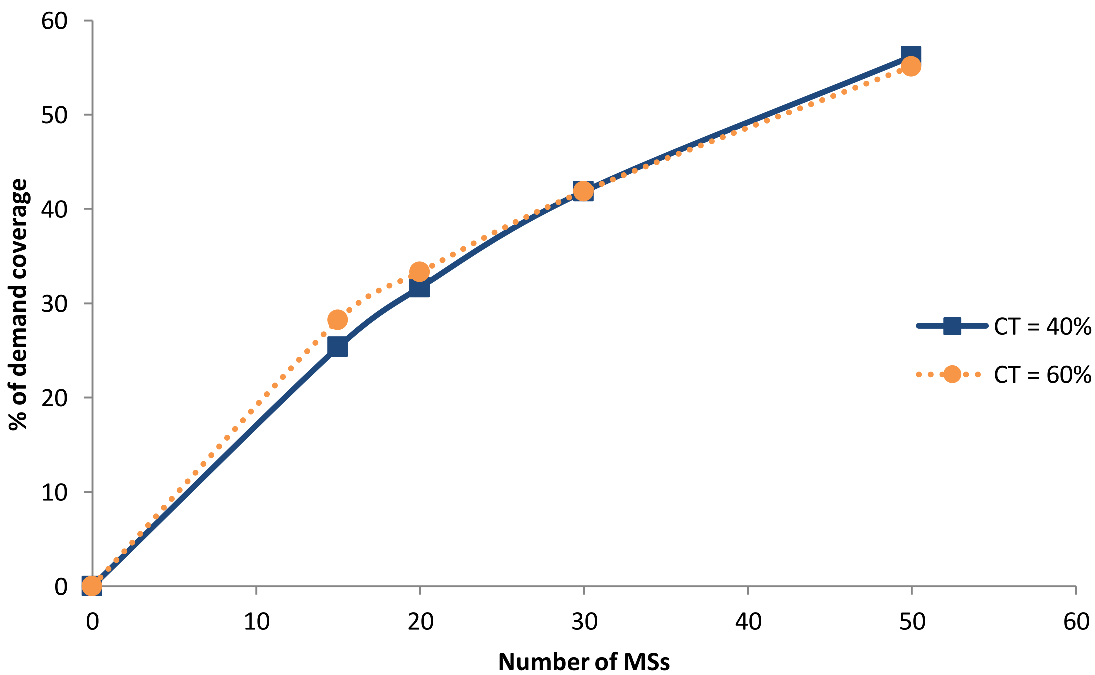
Due to the generalization of grouped demand patterns (compared to hourly patterns) and tradeoff between TMD and number of MSs selected, TMD was higher when *CT* was 60% compared to TMD when *CT* was 40%, such as 1st 12 hours and 24 hours demand patterns. However, this behavior during the selection of optimal locations of MSs using these demand patterns is limited by the selection of less number of MSs, particularly less than 30, as shown in Figure 5.53. When using more than 30 MSs, TMD is higher when *CT* is equal to 40%.

It is also noticed that when *CT* is 40% and 60%, the TMD is not significant for Al-Khobar distribution network, since there is a single central pumping station in which the flow paths do not change significantly. Accordingly, most of the flow paths fulfilling the 40% coverage criteria will also be fulfilling the 60% coverage criteria.

Four different classes of demand patterns were investigated, which are: hourly, 6 hours, 12 hours and 24 hours. It was observed that as the time duration for each demand pattern increases, TMD decreases due to the tradeoff between maximizing TMD and the number of MSs used for grouped demand patterns (6, 12 and 24 hours). Accordingly, TMD maximization tendency for grouped demand patterns is lower compared to maximum



(a)



(b)

Figure 5.53 TMD for demand patterns: (a) 1st 12 hours and (b) 24 hours

TMD for hourly demand pattern due to the competition between optimal nodes at each hour (in the grouped demand pattern) in order to choose representative optimal locations for MSs for the entire demand pattern (6, 12 and 24 hours). Tables 5.17 and 5.18 show the average TMD for the four classes of demand patterns investigated in this study. Obviously, hourly patterns show higher coverage compared to the other patterns. Unfortunately, the selected MSs at each hourly pattern are not always the same. Therefore, to achieve the demand coverage for hourly patterns as shown in Tables 5.8 and 5.9, or simply the average coverage as shown in Tables 5.17 and 5.18, high number of MSs are required as shown in Table 5.19. Similar conclusion can be drawn for 6 hours and 12 hours demand patterns. For example, if the maximum number of MSs allowed at each demand pattern is 15, therefore, to reach maximum demand coverages (TMD) and monitor the demand in the entire day, the total number of MSs required is 106, 38, 27 and 15 for hourly, 6 hours, 12 hours and 24 hours demand patterns, respectively. Since the 24 hours demand pattern is a single pattern, the number of MSs was 15. For other patterns, i.e. 6 hours demand patterns which consist of 1st 6 hours, 2nd 6 hours, 3rd 6 hours and 4th 6 hours, the demand and water flow change frequently which might cause change in MS locations from one pattern to another. If 50 MSs were allowed to be selected at each demand pattern, the total number of MSs required to reach maximum demand coverages would increase to 210 for the case of hourly patterns as shown in Table 5.19. Instead, if a location is selected in one demand pattern, then it will not be counted again in the proceeding demand pattern. For example, if 15 MSs were selected for demand pattern and considering hourly demand patterns only, then the total number of MSs used to cover water demand for the entire day is 106 and not 360 (15*24 = 360) because there are

Table 5.17 Average TMD percentages for different number of MSs (CT = 40%)

Demand Patterns	**Proposed number of MSs**				
	0	15	20	30	50
Hourly Average	0.00	46.62	52.86	62.74	76.20
6 Hours Average	0.00	33.04	39.33	49.11	63.01
12 Hours	0.00	29.15	35.02	45.10	59.83
24 Hours	0.00	25.37	31.70	41.87	56.19

Table 5.18 Average TMD percentages for different number of MSs (CT = 60%)

Demand Patterns	**Proposed number of MSs**				
	0	15	20	30	50
Hourly Average	0.00	43.51	49.00	57.49	68.79
6 Hours Average	0.00	31.74	37.37	46.34	59.49
12 Hours	0.00	30.59	35.86	44.51	57.28
24 Hours	0.00	28.24	33.31	41.89	55.13

Table 5.19 Total number of MSs required to reach maximum TMD level for different demand patterns

(a) CT = 40%

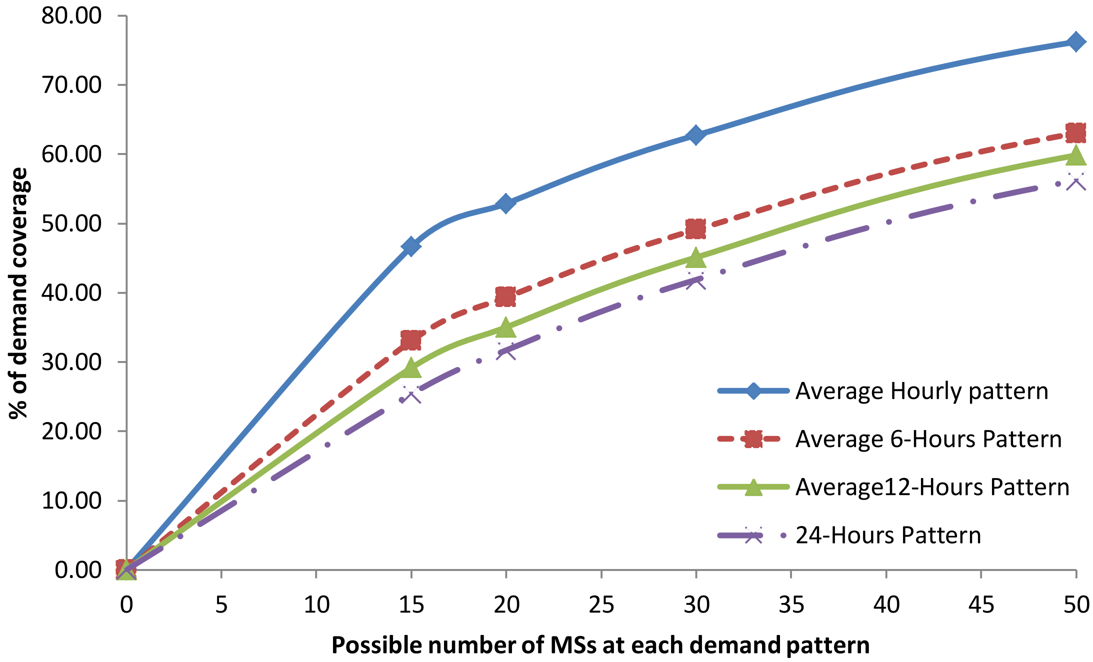
Number of MSs allowed per pattern	Demand Pattern			
	Hourly	6 Hours	12 Hours	24 Hours
0	0	0	0	0
15	106	38	27	15
20	130	48	32	20
30	162	60	43	30
50	210	91	70	50
100	299	163	125	100
200	562	311	250	200
250	646	382	314	250

(b) CT = 60%

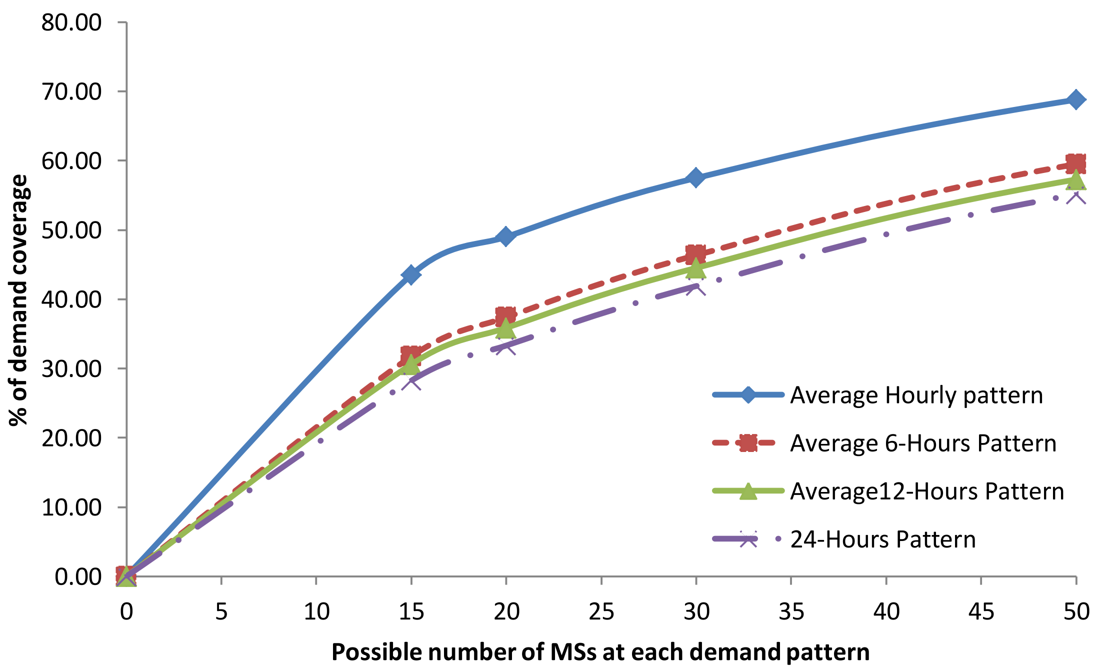
Number of MSs allowed per pattern	Demand Pattern			
	Hourly	6 Hours	12 Hours	24 Hours
0	0	0	0	0
15	84	31	23	15
20	107	41	31	20
30	133	57	44	30
50	172	87	68	50
100	257	146	120	100
200	496	287	233	200
250	619	361	300	250

several optimal locations which were selected more than once during the analysis of different demand patterns.

Practically and economically, it is impossible to consider the number of MSs selected based on the hourly demand patterns since the water samples are taken manually from the WDN. There should be a tradeoff between the number of MSs to be selected and TMD. Figure 5.54 shows the demand coverages for average demand patterns. Hourly demand patterns show the highest demand coverage, but at the same time the number of MSs required to achieve this coverage is infeasible. It would be difficult to collect samples on hourly basis from too many stations. On the other hand, although the 24 hours demand pattern requires fewer number of MSs, the low demand coverage accompanying this pattern makes it less attractive alternative. For 6 hours patterns, although it has a coverage less than that of the hourly patterns, it is higher than the coverages for 12 hours and 24 hours patterns as shown in Figure 5.54. In addition, 6 hours demand patterns require less number of MSs compared to hourly demand patterns as shown in Table 5.19. Furthermore, competition of optimal locations during the optimization process is less for 6 hours demand patterns compared to 12 hours and 24 hours demand patterns since they (6 hours patterns) cover less duration. In other words, the competition between 6 sets of optimal locations is less compared to 12 and 24 sets of optimal locations, which is reflected in the higher levels of TMD for 6 hours patterns as shown in Tables 5.12, 5.13, 5.17, and 5.18 compared to TMD levels for 12 hours and 24 hours demand patterns. From this perspective, 6 hours demand patterns are preferred over other demand patterns for selecting optimal locations for MSs in Al-Khobar WDN.



(a)



(b)

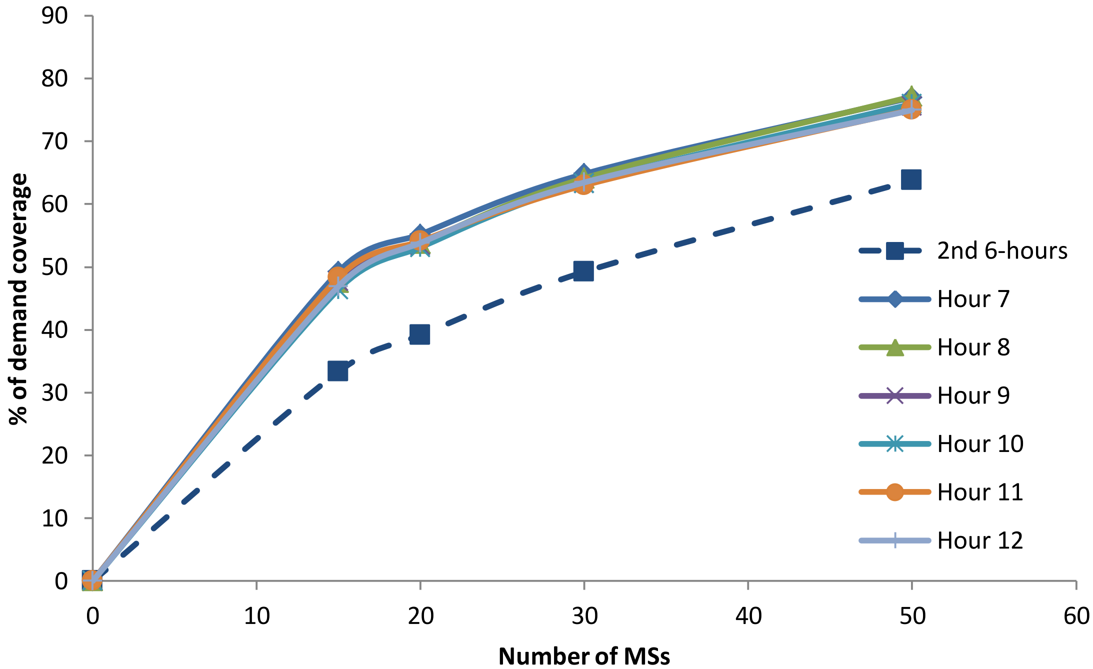
Figure 5.54 Daily average TMD for: (a) 40% CT and (b) 60% CT

In Al-Khobar WDN, water samples are collected between 6:00 am and 10:00 am. Accordingly, for the samples to be representative for the water quality during this timing in addition to increasing detection chances for any possible contamination, MSs should be identified during this specific duration. This will guarantee that the selected MSs will cover the demand at that specific timing. If 12 hours or 24 hours demand patterns were considered for locating MSs, then these stations will represent the optimal locations for the 12 hours and 24 hours duration, respectively. Based on Al-Khobar hydraulic simulation, the average water age for all the sub-regions in the WDN ranges between 1.6 and 9.64 hours (Figure 5.6a), which implies that water quality is changing completely in the WDN within or in about 9.64 hours. This emphasizes that the MSs optimization should match with this input to ensure that the optimal locations of the stations represent the actual condition of water quality flowing during the sampling process. Based on the range of water age, it is obvious that 12 hours and 24 hours demand patterns may provide a general representation about water quality, however, careful attention should be paid since it covers time range higher than the water age in the WDN. For the sampling time between 6:00 am and 10:00 am, hourly and 6 hours patterns are more appropriate to be considered, but again for the hourly pattern, high number of MSs is an obstacle. Therefore, 6 hours demand pattern is more appropriate for Al-Khobar WDN. Identifying water quality MSs based on the 6 hours demand pattern will also provide more flexibility for field engineers to collect water samples within this period but not beyond it. In addition, sampling process in the WDN takes about 4 hours, which means that using 6 hours pattern is more reasonable and practical compared to other demand patterns. Based on Table 5.11, the sampling period lies in the 2nd 6 hours demand pattern.

Figure 5.55 shows TMD comparison between 2nd 6 hours and hourly patterns for the sampling duration, between 6:00 am and 12:00 pm. Although TMD is less for 2nd 6 hours demand pattern, it should be considered, however, that 2nd 6 hours demand pattern requires less number of MSs compared to hourly patterns as shown in Figure 5.56. Table 5.20 show the total number of monitoring stations required when adopting hourly and 2nd 6 hours demand patterns for maximizing TMD during the sampling period. Note that the number of MSs considered at hour 8 demand pattern is less than the possible numbers because some MSs have already been selected (common between the demand patterns) during the previous demand pattern (hour 7). Similar observation is also valid for other hourly demand patterns.

Figures 5.57 and 5.58 show the optimal MSs locations for 2nd 6 hours pattern. Although the proposed locations of the MSs maximize water demand coverage, but as can be revealed from the figures, there are some sub-regions, especially those far away from the city center, that do not have any recommended MSs. Even though hourly demand patterns have higher number of MSs as shown in Table 5.19, but similar to the 2nd 6 hours demand pattern, some sub-regions do not have MSs as shown in Figures 5.59 and 5.60. As can be observed from the figures, most of the MSs are located at the center of the city where most of the demands exist, but this leaves about half of the sub-regions unprotected as shown in Figure 5.61.

By comparing Figures 5.57 and 5.58, it can be seen that MSs locations are scattered more through the network when *CT* is 40% compared to MSs locations when *CT* is 60%. This is more obvious for the case when proposing 15 MSs as shown in Figures 5.57a and 5.58a. The majority of MSs, as shown in Figure 5.58a, are located in one sub-region



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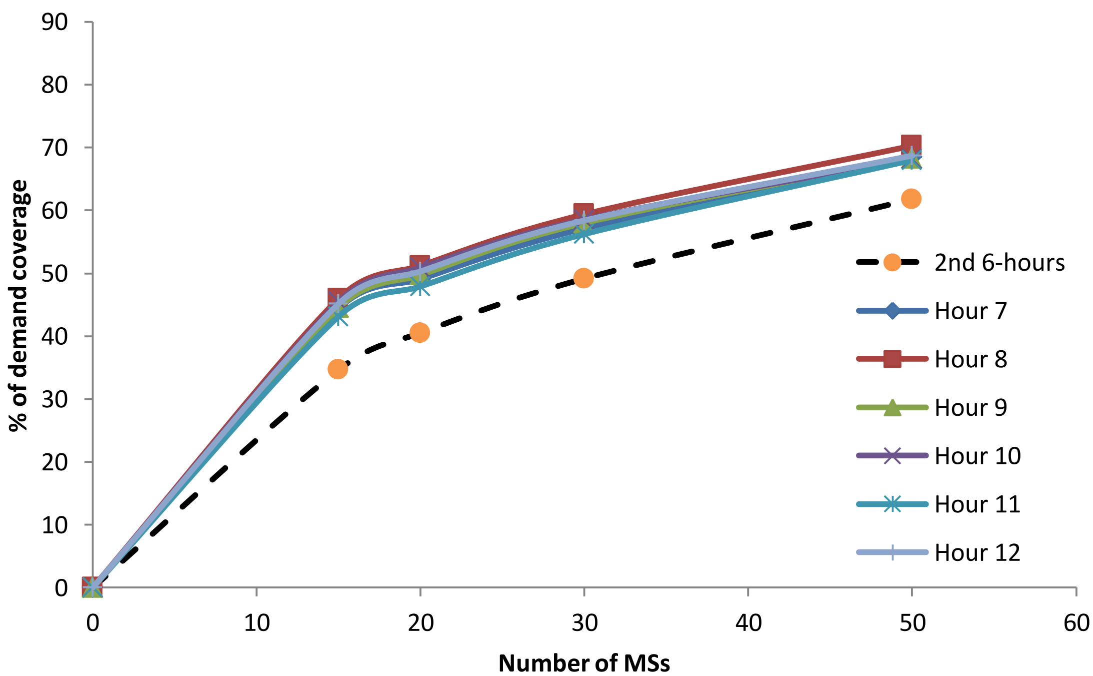
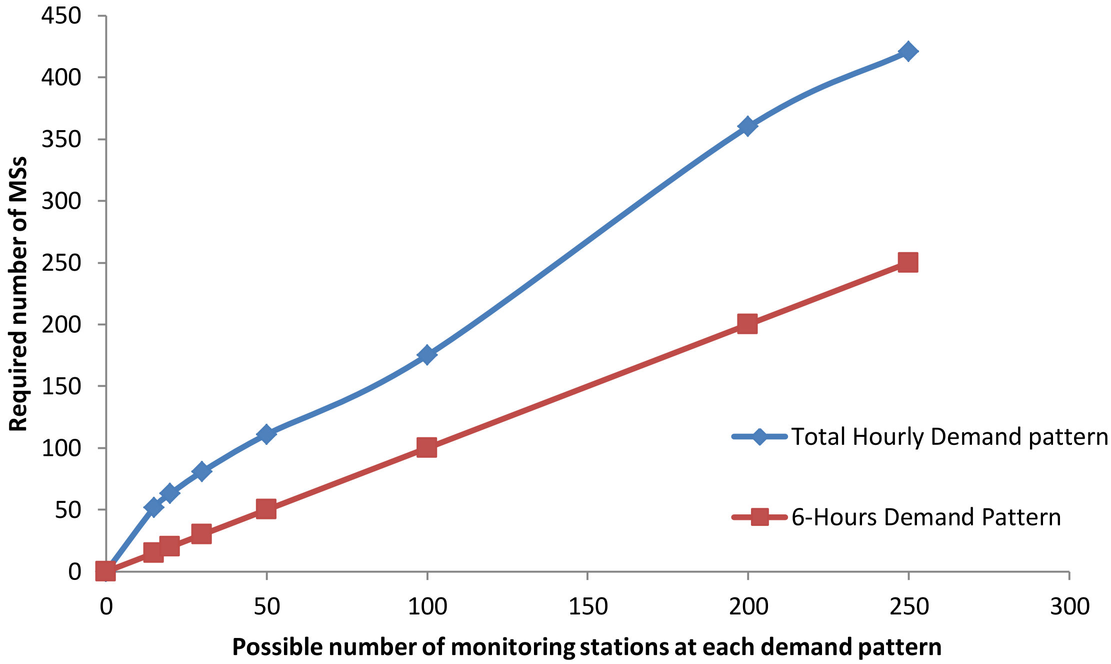
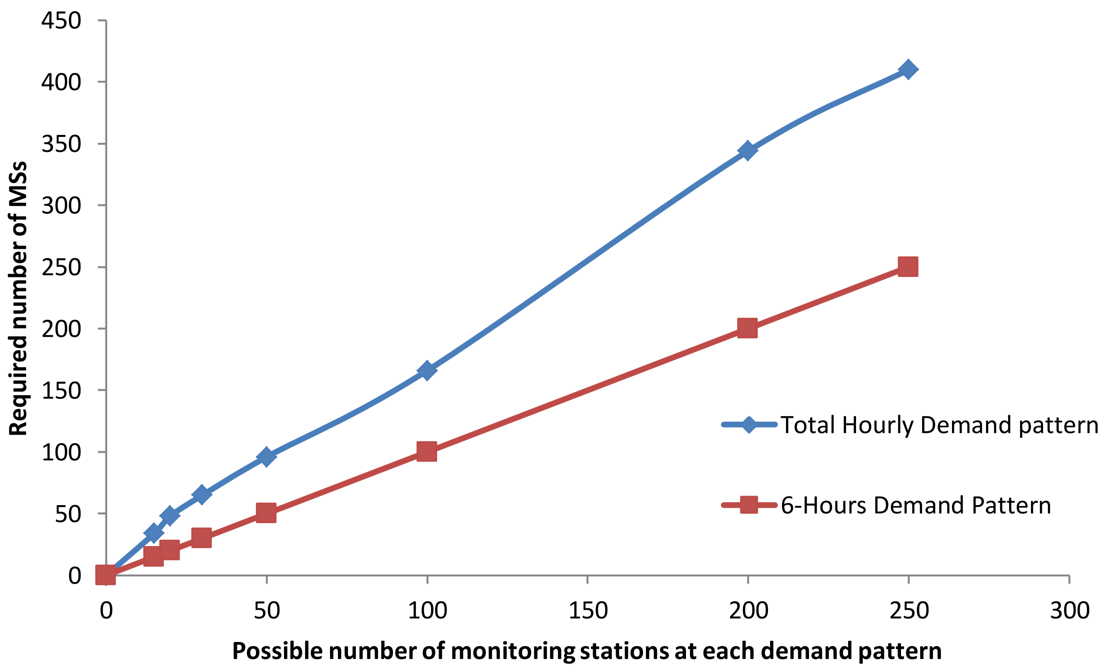


(b)

Figure 5.55 Demand coverage comparison between hourly and 2nd 6 hours demand patterns for: (a) 40% CT and (b) 60% CT



(a)



(b)

Figure 5.56 TMD comparison between required number of MSs for total hourly pattern from 6 am to 12 pm and 2nd 6 hours for: (a) CT = 40% and (b) CT = 60%

Table 5.20 Possible number of MSs demand pattern for sampling duration (6 hours)

(a) CT = 40%

Possible number of MSs	Demand Pattern for sampling duration (6 hours)							
	Hour 7	Hour 8	Hour 9	Hour 10	Hour 11	Hour 12	Total hourly	2nd 6 hours
0	0	0	0	0	0	0	0	0
15	15	8	10	7	6	6	52	15
20	20	10	12	11	5	7	65	20
30	30	14	17	10	7	8	86	30
50	50	18	17	12	9	10	116	50
100	100	32	20	12	17	9	190	100
200	200	66	41	30	31	21	389	200
250	250	72	46	30	36	18	452	250

(b) CT = 60%

Possible number of MSs	Demand Pattern for sampling duration (6 hours)							
	Hour 7	Hour 8	Hour 9	Hour 10	Hour 11	Hour 12	Total hourly	2nd 6 hours
0	0	0	0	0	0	0	0	0
15	15	6	3	4	5	1	34	15
20	20	8	5	5	8	2	48	20
30	30	12	6	8	8	1	65	30
50	50	17	8	9	9	3	96	50
100	100	28	11	13	10	4	166	100
200	200	57	31	28	19	9	344	200
250	250	73	34	26	18	9	410	250

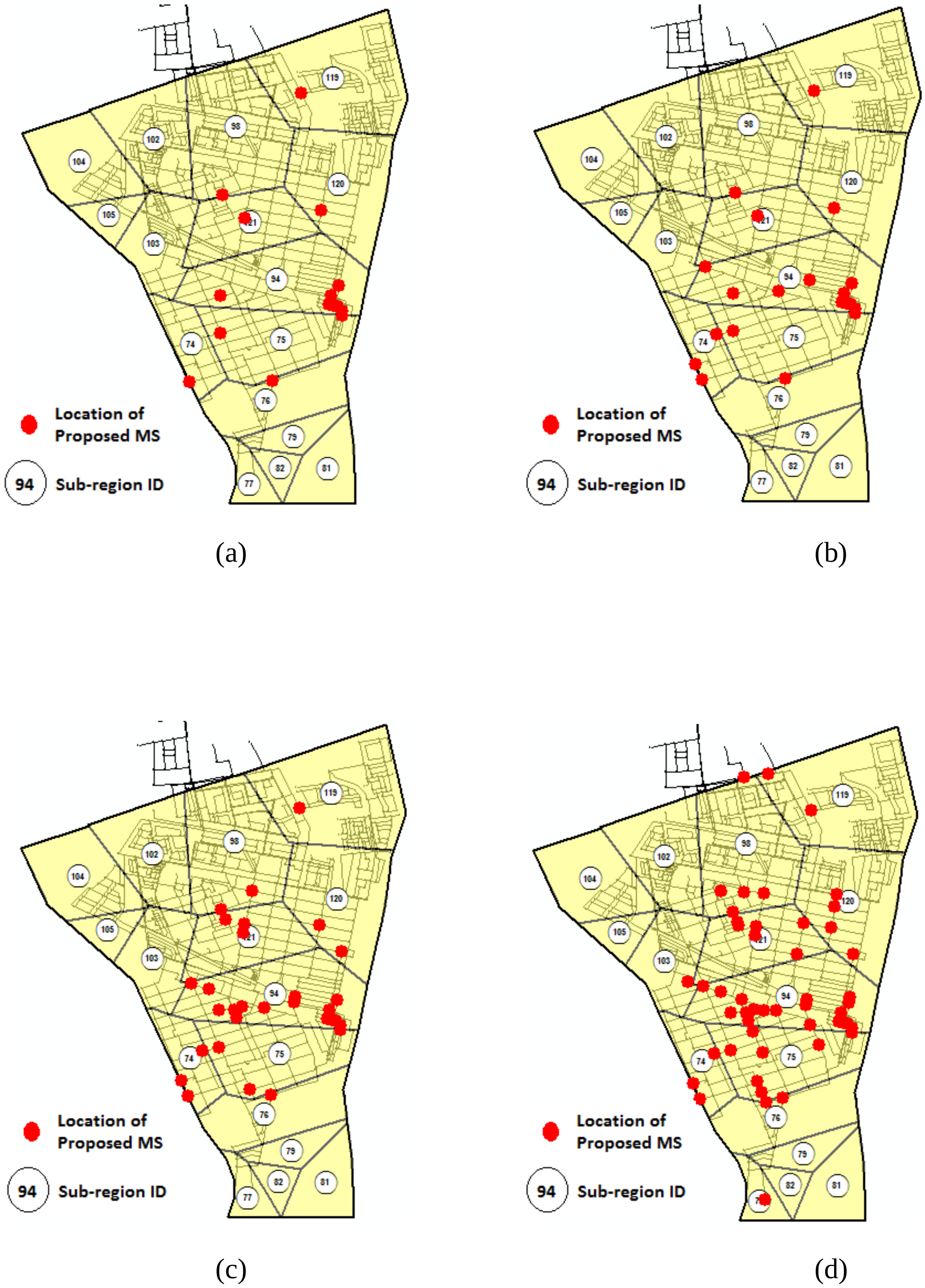


Figure 5.57 Proposed locations of MSs based on 2nd 6 hours pattern considering 40% CT for: (a) 15 (b) 20 (c) 30 and (d) 50 MSs

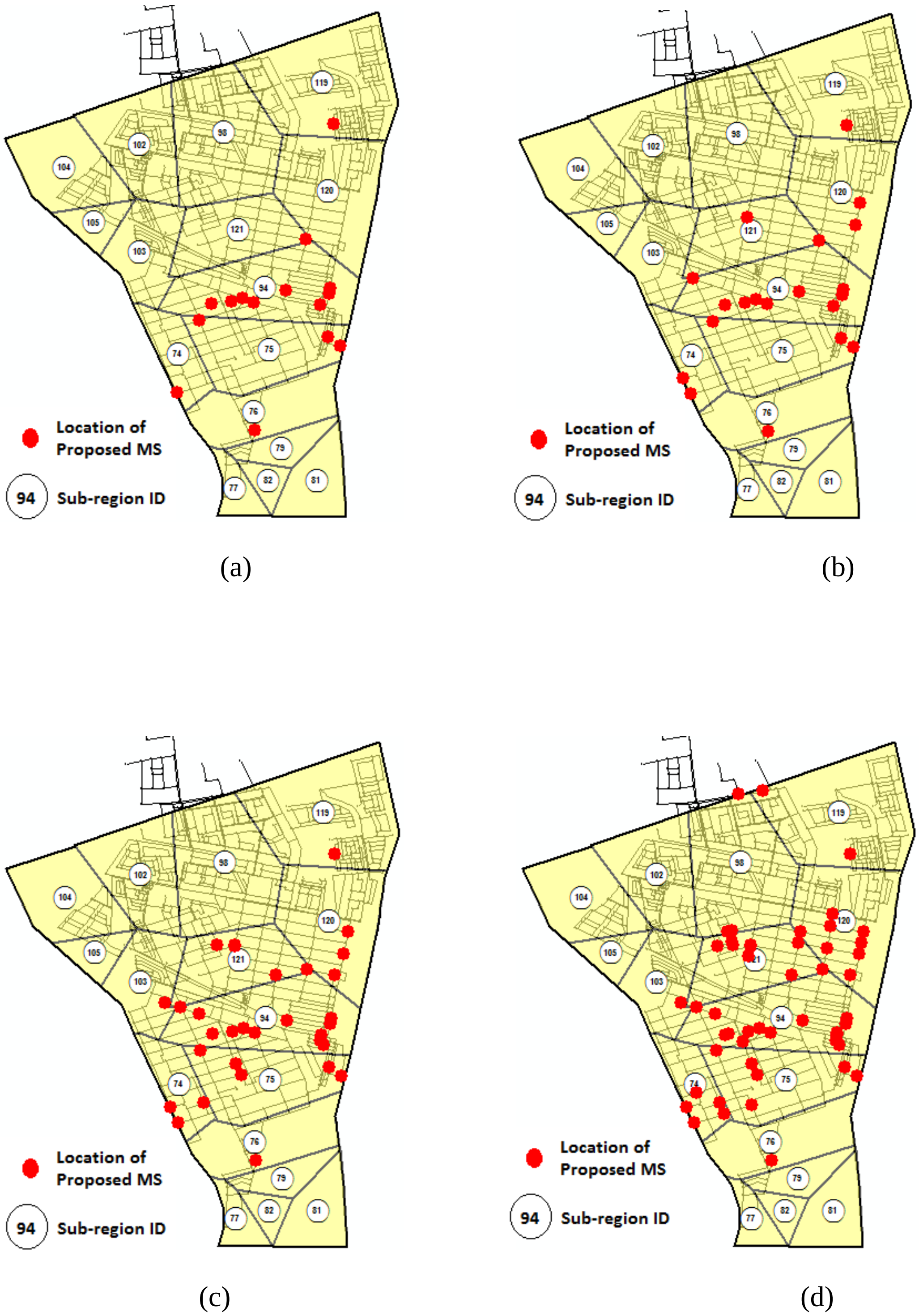
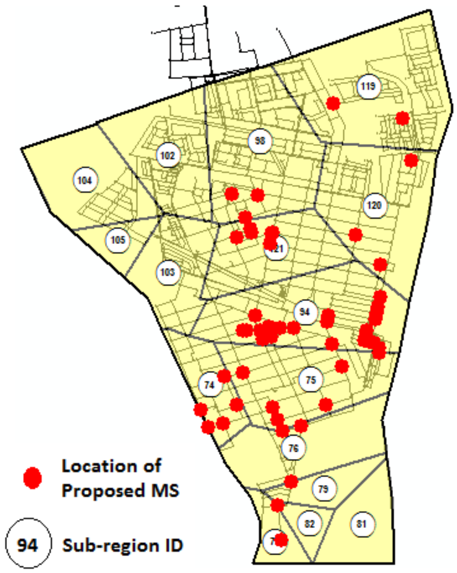
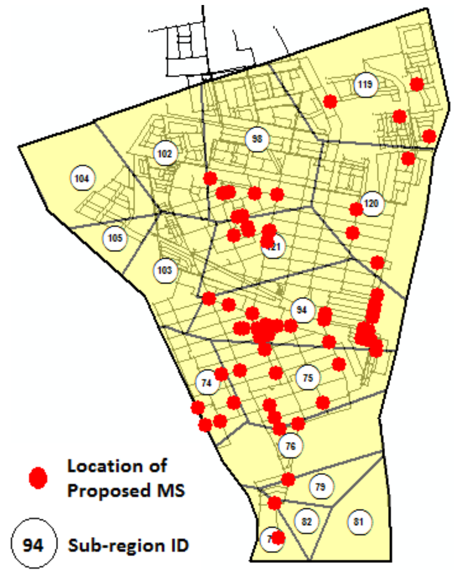


Figure 5.58 Proposed locations of MSs based on 2nd 6 hours pattern considering 60% CT for: (a) 15 (b) 20 (c) 30 and (d) 50 MSs



(a)



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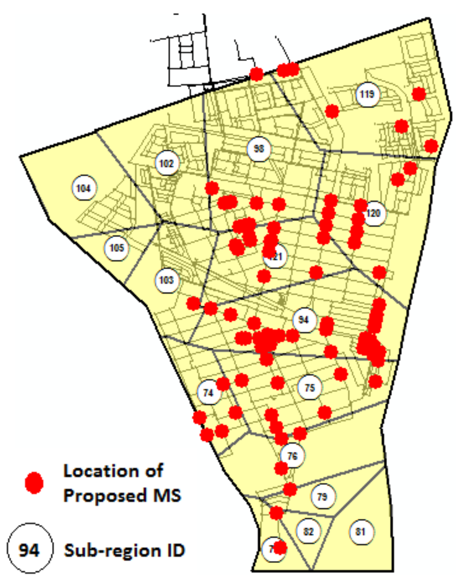

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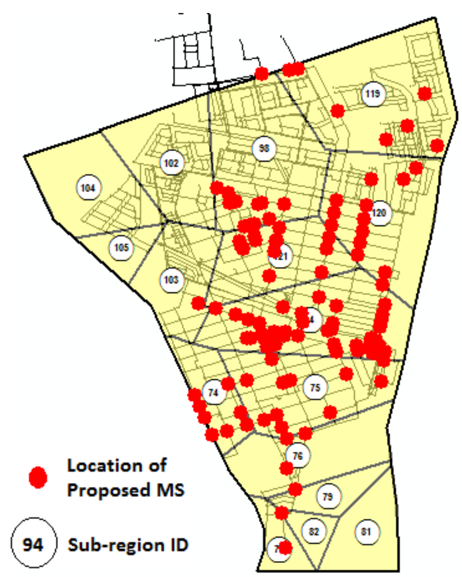
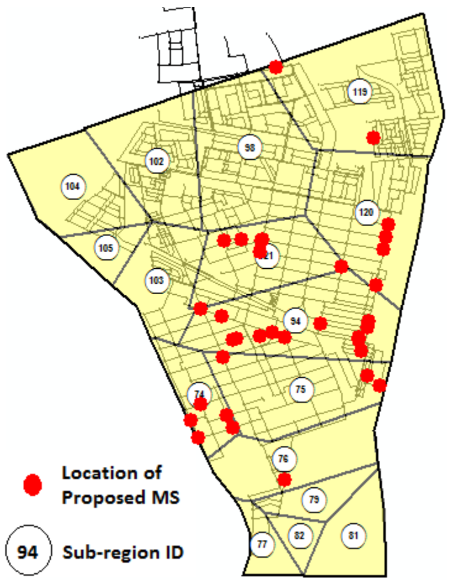
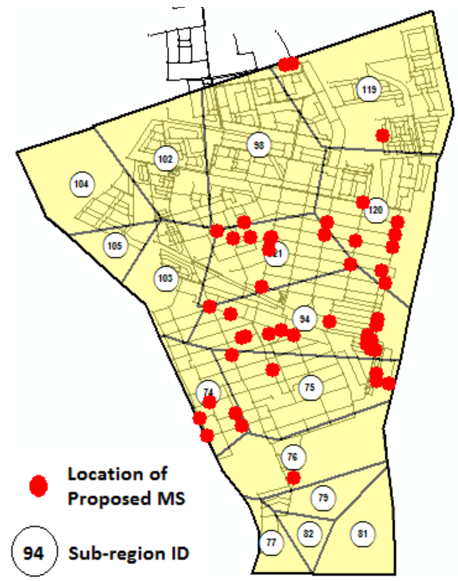


(d)

Figure 5.59 Proposed locations of MSs for all 6 hourly patterns considering 40% CT for: (a) 15 (b) 20 (c) 30 and (d) 50 MSs



(a)



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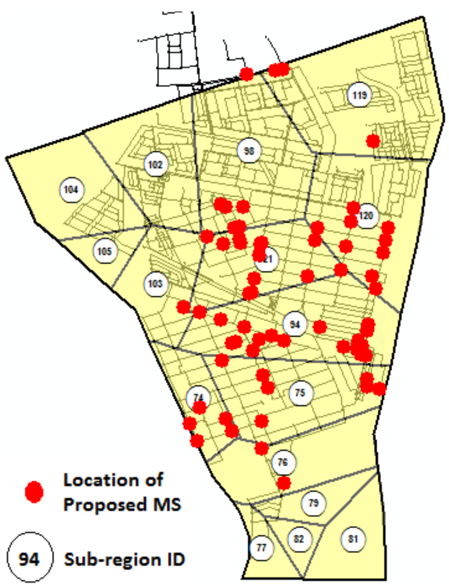

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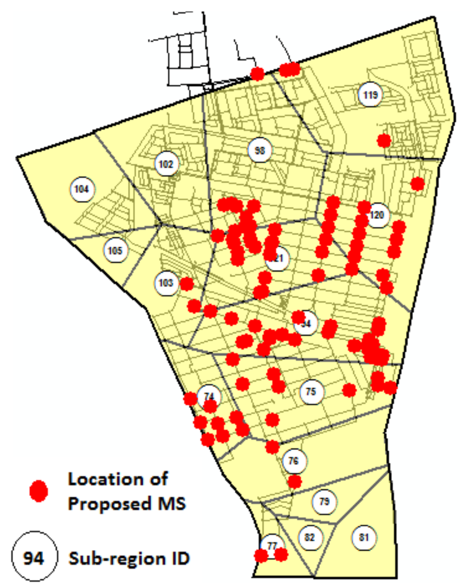


(d)

Figure 5.60 Proposed locations of MSs for all 6 hourly patterns considering 60% CT for:
(a) 15 (b) 20 (c) 30 and (d) 50 MSs

Figure 5.61 Comparison of MSs numbers at each sub-region considering 40% and 60% CT for: (a) 15 (b) 20 (c) 30 and (d) 50 MSs

because the model was constrained by selecting nodes that maximize TMD (*CT* = 60%), which happened to occur in the central part of Al-Khobar WDN where most of the MSs were proposed. Although the difference in demand coverage using 2nd 6 hours pattern for *CT* values of 40% and 60% ranges between 1.31 and 2.01% only (in favor of the system where *CT* equals 40%) as shown in Tables 5.12 and 5.13, the fact that most of the MSs are grouped and clustered when *CT* is 60% may indicate a drawback for using high *CT* values. When using 50 MSs as shown in Figures 5.57d and 5.58d, the difference in monitoring distribution is insignificant regardless of the *CT* value used. In general, it can be concluded that the distribution of the MSs is directly affected by the number of MSs and *CT* values, i.e. decreasing the number of MSs and *CT* values will cause the MSs to be scattered all over the distribution network.

While maintaining that maximum demand coverage was the main objective, the analysis showed that some sub-regions did not have MSs. In order to improve the distribution of MSs in the WDN, at least one MS should be located in every sub-region to assure minimum level of demand coverage for each sub-region. Accordingly, additional constraint was added to the optimization model to ensure that at least one MS **must** be located within each sub-region.

5.8.3 Regional MSs

Developing monitoring systems for WDN is not only about protecting the majority of the population by maximizing TMD but it is also related to monitoring water quality in all sub-regions of the city. Distributing monitoring stations all over the WDN will ensure protection around the network and reflect the existing condition of water quality in the entire network. Sub-regions downstream as well as upstream sub-regions should be monitored, even if demand at downstream sub-regions is low compared to that at upstream sub-regions. When water quality deteriorates due to operational deficiencies such as injecting too much chlorine or pumping contaminated water from tanks, MSs at upstream sub-regions will have the chance to detect this type of risk earlier before downstream sub-regions. However, if water quality deteriorates due to criminal/terroristic act, then all sub-regions should have minimum protection since there is usually no clue about where the strike is going to happen.

Table 5.21 shows TMD for different number of MSs when *CT* is 40% and 60% after incorporating the regional constraint to the optimization model. Comparing demand coverages for *CT* values of 40% and 60% shows generally higher coverage when *CT* is 40%. This is similar to what was observed from the previous analysis before adding the regional constraint (absolute optimal analysis). However, TMD was reduced after adding the regional constraint compared to coverages without the regional constraint, as shown in Tables 5.8, 5.9, 5.12, 5.13 and 5.21, regardless of the demand pattern used, due to forcing the optimization algorithm to locate at least one MS within each sub-region. Although new MSs locations do not guarantee maximum demand coverage compared to locations selected without considering the regional constraint, they are optimal in the sense of maximizing demand coverage as well as maintaining minimum monitoring and coverage for each sub-region. Similar to non-regional optimization, demand coverage for hourly demand patterns is higher than grouped patterns including 6 hours, 12 hours and 24 hours demand patterns as shown in Table 5.21. Average TMD for different demand patterns classes for regional optimization is shown in Table 5.22. Coverage increased

Table 5.21 TMD percentages for regional optimization scenarios

(a) CT = 40%

Demand Pattern	Proposed number of MSs			
	15	20	30	50
Hour 1	32.50	45.17	59.26	75.75
Hour 2	36.51	47.75	59.77	75.05
Hour 3	35.58	46.36	59.60	74.38
Hour 4	35.55	50.11	63.71	77.28
Hour 5	37.25	47.77	60.27	75.58
Hour 6	32.57	45.85	58.46	73.30
Hour 7	33.70	48.21	60.74	75.16
Hour 8	34.42	46.68	59.31	75.07
Hour 9	34.57	46.69	58.26	73.62
Hour 10	34.02	44.93	58.13	73.93
Hour 11	31.74	47.36	58.98	73.08
Hour 12	32.82	44.83	58.83	72.92
Hour 13	30.98	47.28	59.76	76.53
Hour 14	33.00	44.46	58.16	73.95
Hour 15	31.26	42.86	56.50	73.12
Hour 16	27.05	42.02	55.77	71.62
Hour 17	27.81	39.45	53.23	71.43
Hour 18	32.38	45.45	57.97	74.45
Hour 19	28.73	41.52	56.80	73.69
Hour 20	29.80	42.78	56.72	73.56
Hour 21	29.29	42.14	55.99	73.35
Hour 22	31.16	45.55	57.14	73.45
Hour 23	26.99	45.09	57.81	73.12
Hour 24	29.20	43.67	57.74	73.97
1st 6 hours	18.55	30.24	45.62	61.12
2nd 6 hours	20.85	32.14	44.16	61.28
3rd 6 hours	17.53	28.04	42.06	58.28
4th 6 hours	20.01	31.18	45.24	61.66
1st 12 hours	16.79	26.53	39.26	56.87
2nd 12 hours	17.33	28.43	40.56	57.55
Total 24 hours	14.36	23.29	36.32	53.56

Table 5.21 Continue

(b) CT = 60%

Demand Pattern	Proposed number of MSs			
	15	20	30	50
Hour 1	28.60	43.48	55.14	69.71
Hour 2	24.46	39.48	51.19	64.11
Hour 3	30.86	44.51	56.16	69.57
Hour 4	28.02	45.11	56.68	69.30
Hour 5	35.72	45.17	55.37	67.51
Hour 6	28.09	45.68	55.78	68.08
Hour 7	25.95	43.11	54.07	67.03
Hour 8	28.74	45.08	56.37	68.83
Hour 9	28.45	44.09	54.82	66.80
Hour 10	31.97	44.18	55.78	66.76
Hour 11	26.09	42.74	52.87	66.47
Hour 12	31.25	44.29	55.44	67.21
Hour 13	28.62	41.91	54.48	67.12
Hour 14	24.82	40.96	52.84	65.13
Hour 15	24.62	41.02	53.06	66.50
Hour 16	25.02	40.13	53.14	66.77
Hour 17	27.07	38.36	51.94	66.10
Hour 18	25.66	40.13	52.93	67.11
Hour 19	23.78	39.23	53.13	67.16
Hour 20	23.67	38.68	51.82	66.79
Hour 21	22.92	36.69	50.96	66.04
Hour 22	23.91	38.78	52.87	66.46
Hour 23	24.91	41.18	52.49	65.79
Hour 24	29.64	41.50	54.30	67.87
1st 6 hours	18.94	29.16	40.99	55.26
2nd 6 hours	19.56	32.07	45.61	59.94
3rd 6 hours	18.90	29.14	42.01	57.15
4th 6 hours	17.11	28.10	42.13	57.90
1st 12 hours	18.51	29.91	41.27	54.77
2nd 12 hours	17.46	27.41	40.75	56.12
Total 24 hours	16.37	26.53	38.35	53.27

Table 5.22 Average TMD percentages for regional optimization

(a) CT = 40%

Demand Pattern	Proposed number of MSs			
	15	20	30	50
Hourly Average	32.04	45.17	58.29	74.06
6-Hours Average	19.24	30.40	44.27	60.58
12 Hours	17.06	27.48	39.91	57.21
24 Hours	14.36	23.29	36.32	53.56

(b) CT = 60%

Demand Pattern	Proposed number of MSs			
	15	20	30	50
Hourly Average	27.20	41.90	53.90	67.09
6 Hours Average	18.63	29.62	42.69	57.56
12 Hours	17.99	28.66	41.01	55.44
24 Hours	16.37	26.53	38.35	53.27

when more MSs were proposed. In addition, as more MSs are proposed, the demand coverage difference between regional and non-regional optimization decreases for all demand patterns and *CT* values. Table 5.23 shows average TMD differences between regional and non-regional optimization.

Table 5.24 shows the total number of MSs proposed considering regional optimization. There is no significant difference between the total number of MSs used for regional and non-regional optimization as shown in Figure 5.62. TMD for all hourly and 6 hours demand patterns is shown in Figure 5.63.

Hourly demand patterns have the highest TMD for regional optimization as shown in Table 5.22. In addition, similar to non-regional optimization, to reach maximum coverage levels shown in Table 5.21, higher number of MSs should be used as shown in Table 5.24. This will not be practically and economically possible as discussed earlier.

Recall that sampling period at Al-Khobar WDN is between 6:00 am and 12:00 pm, in addition to limiting the total number of MSs to 50. Grouped demand patterns including 12 hourly and 24 hours demand patterns have the least demand coverages as can be seen in Tables 5.22 and 5.23, which show average TMD for different demand patterns classes. Therefore, two demand patterns can be investigated in which one of them can be selected, either hourly demand pattern for the sampling period or 2nd 6 hours pattern. Figure 5.64 shows that average demand coverage for hourly patterns is higher compared to 2nd 6 hours pattern. However, to reach the hourly pattern level of coverage, more MSs are required. Figure 5.65 shows the number of MSs required for hourly and 2nd 6 hours patterns to reach coverage levels shown in Figure 5.64. Coverage difference between the

Table 5.23 Average TMD difference between regional and non-regional optimization

(a) CT = 40%

Demand Pattern	**Proposed number of MSs**			
	15	20	30	50
Hourly Average	14.58	7.70	4.45	2.14
6 Hours Average	13.80	8.93	4.84	2.43
12 Hours	12.09	7.55	5.19	2.62
24 Hours	11.01	8.41	5.56	2.63

(a) CT = 60%

Demand Pattern	**Proposed number of MSs**			
	15	20	30	50
Hourly Average	16.30	7.10	3.59	1.69
6 Hours Average	13.11	7.75	3.66	1.93
12 Hours	12.61	7.20	3.51	1.84
24 Hours	11.87	6.78	3.54	1.85

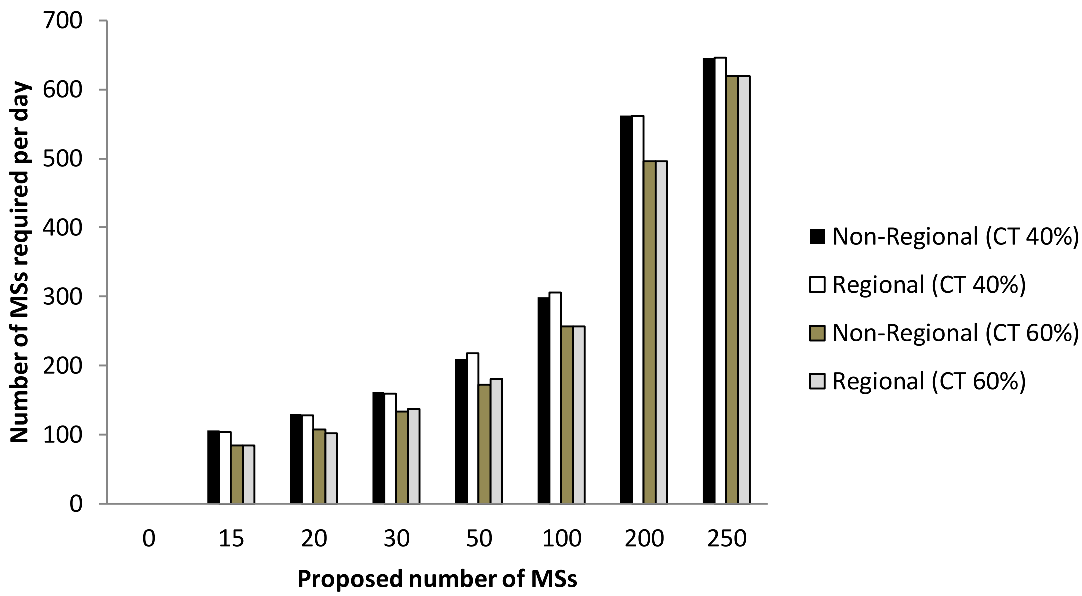
Table 5.24 Proposed number of MSs to achieve maximum TMD levels for regional optimization

(a) CT = 40%

Number of MSs allowed per pattern	Demand Pattern			
	Hourly	6 Hours	12 Hours	24 Hours
0	0	0	0	0
15	104	35	22	15
20	128	44	31	20
30	159	66	43	30
50	218	93	68	50
100	306	163	125	100
200	562	311	250	200
250	646	382	314	250

(b) CT = 60%

Number of MSs allowed per pattern	Demand Pattern			
	Hourly	6 Hours	12 Hours	24 Hours
0	0	0	0	0
15	84	28	22	15
20	102	38	29	20
30	137	55	45	30
50	181	85	66	50
100	257	146	120	100
200	496	287	233	200
250	619	361	300	250



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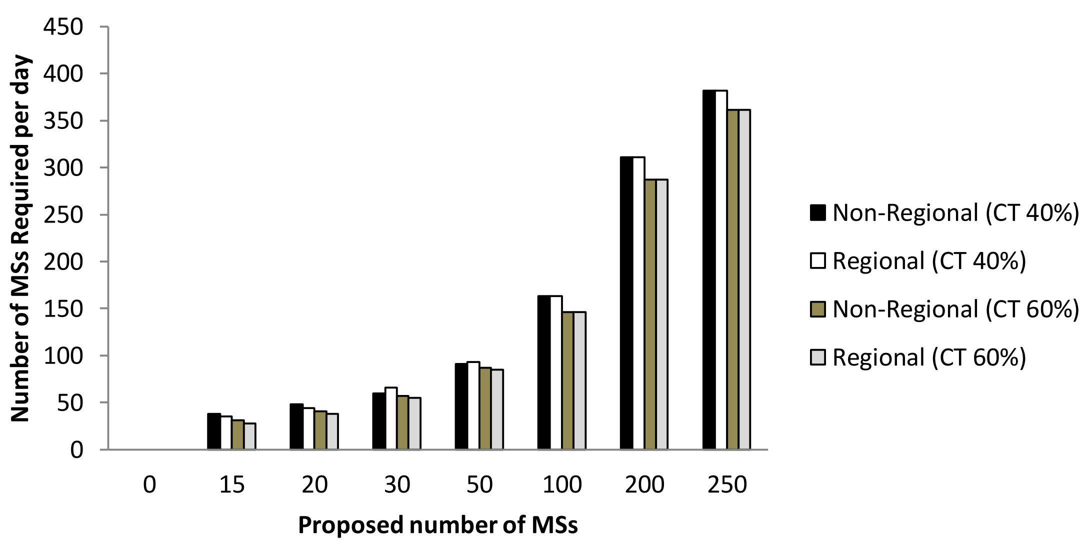

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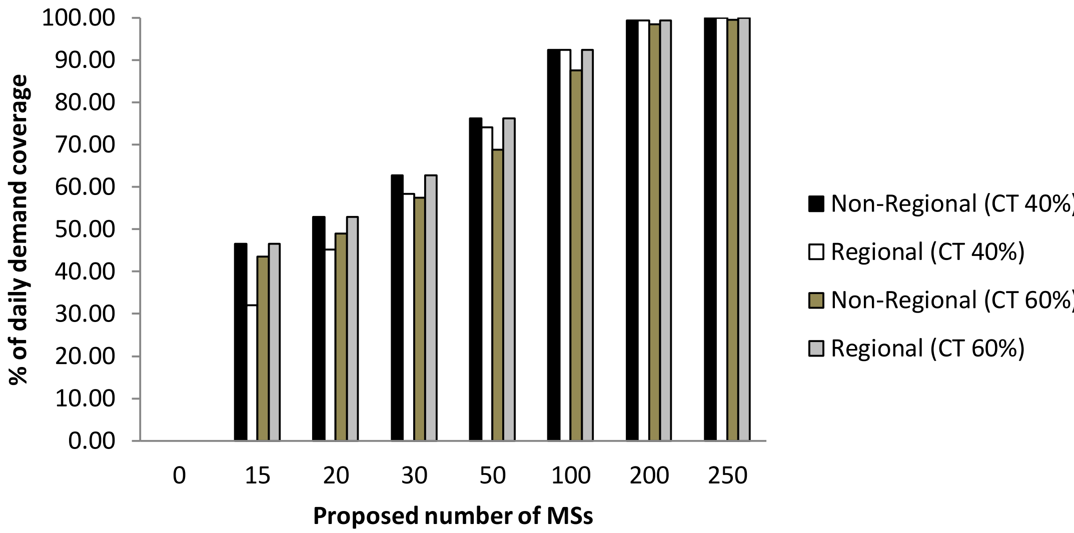
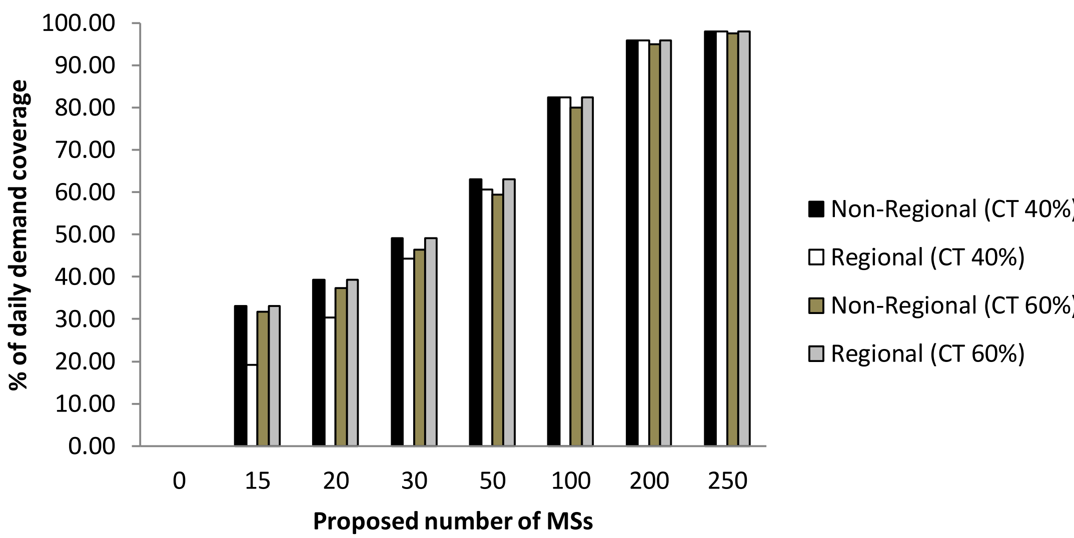
Figure 5.62 Total number of MSs required for regional and non-regional optimization: (a) Hourly demand pattern, (b) 6 hours demand patterns



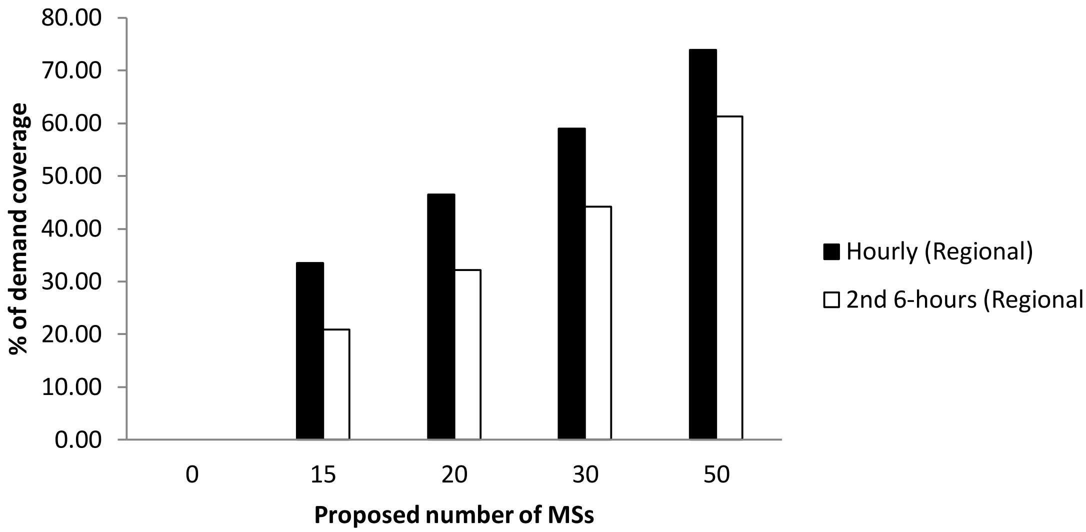
(a)



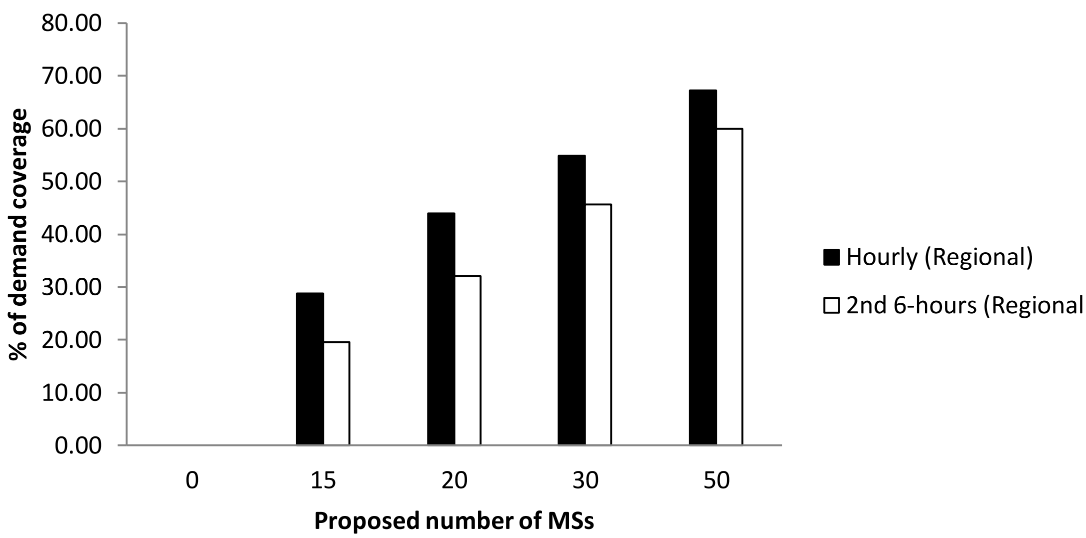
(b)

Figure 5.63 Average TMD for regional and non-regional optimization:

(a) Hourly demand pattern, (b) 6 hours demand patterns



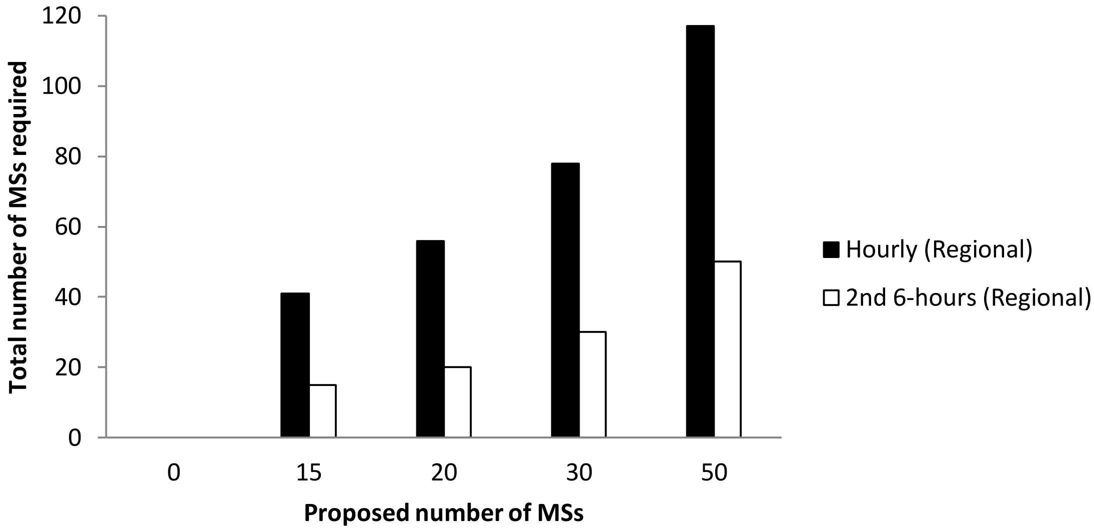
(a)



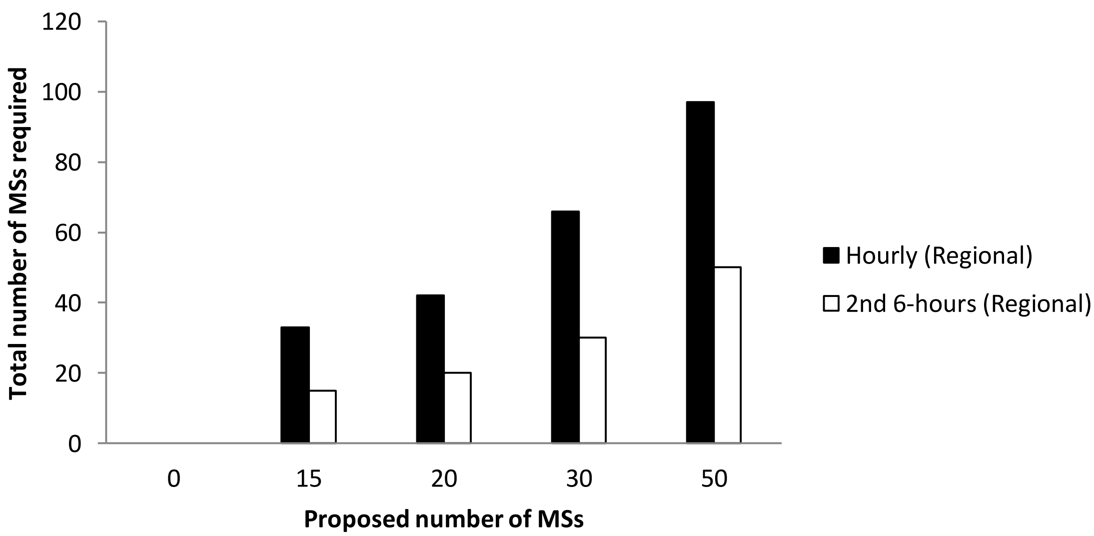
(b)

Figure 5.64 Demand coverage for hourly and 2nd 6 hours patterns:

(a) CT = 40%, (b) CT = 60%



(a)



(b)

Figure 5.65 Number of required MSs for hourly and 2nd 6 hours patterns

(a) CT = 40%, (b) CT = 60%

two patterns ranges between 7.24 and 14.88% in favor of hourly patterns as shown in Table 5.25, which indicates that as the allowable number of MSs increases, the coverage difference between hourly demand patterns and 2nd 6 hours demand patterns decreases. On the other hand, while 2nd 6 hours patterns require a range of MSs between 15 and 250 to reach coverage levels in Figure 5.64, hourly patterns require between 33 and 452 MSs as shown in Table 5.26. In addition, higher coverage for hourly patterns requires the use of more than 50 MSs (Table 5.26), which is not a feasible option for Al-Khobar WDN due to practical and economical obstacles. However, the maximum number of MSs used for 2nd 6 hours demand pattern is 50. Therefore, 2nd 6 hours pattern is preferred over hourly demand patterns to be used for locating MSs even after adding the regional constraint.

For both cases, when considering or relaxing the regional constraint, the 2nd 6 hours demand pattern was preferred over other demand patterns as discussed earlier. Figure 5.66 shows that the total number of MSs used before and after adding the regional constraint for the 2nd 6 hours demand pattern did not change. Although adding the regional constraint has reduced the TMD, especially when the allowable number of MSs is less than 50 as shown in Figure 5.67, it should be clearly noted that the lack of distribution of MSs and the absence of minimum regional protection in the non-regional optimization were the reasons in the first place which led to adding the regional constraint. However, increasing the allowable number of MSs used will decrease the difference between demand coverage for regional and non-regional optimization significantly as shown in Table 5.27. Accordingly, it is recommended to identify the

Table 5.25 Coverage difference between hourly and the 2nd 6 hours demand patterns

CT	Proposed number of MSs at each pattern							
	0	15	20	30	50	100	200	250
40%	0.00	12.69	14.30	14.88	12.68	8.81	3.82	2.82
60%	0.00	9.18	11.84	9.28	7.24	5.87	3.49	2.41

Table 5.26 Number of MSs required for hourly and the 2nd 6 hours patterns

(a) CT = 40%

Number of MSs allowed per pattern	Demand Pattern	
	Hourly	**2nd 6 Hours**
0	0	0
15	41	15
20	56	20
30	78	30
50	117	50

(b) CT = 60%

Number of MSs allowed per pattern	Demand Pattern	
	Hourly	**2nd 6 Hours**
0	0	0
15	33	15
20	42	20
30	66	30
50	97	50

Table 5.27 Coverage difference between regional and non-regional optimization for 2nd 6 hours demand pattern

CT	Proposed number of MSs				
	0	15	20	30	50
40%	0.00	12.48	6.99	5.05	2.52
60%	0.00	15.08	8.44	3.54	1.85

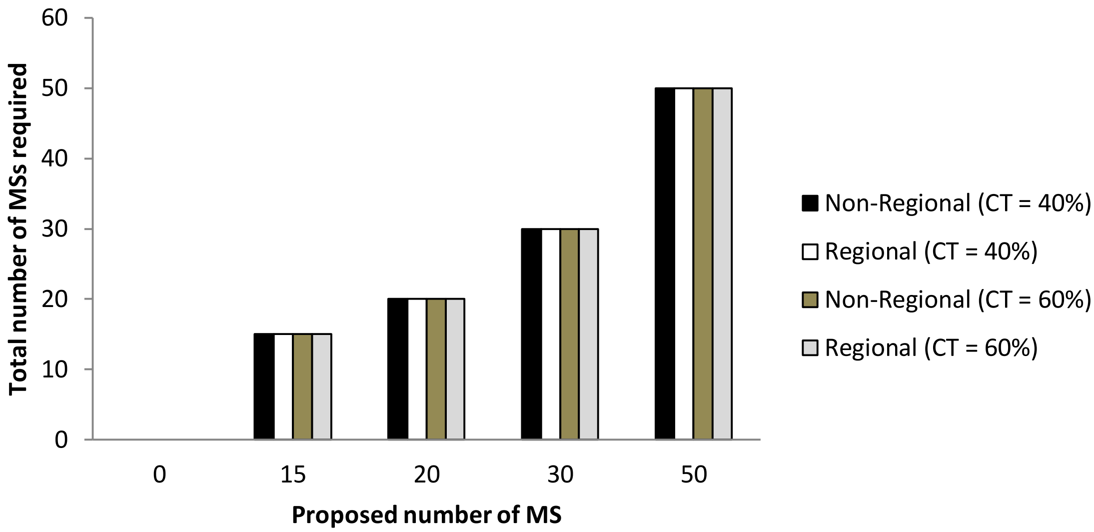


Figure 5.66 Proposed number of MSs for 2nd 6 hours water demand pattern

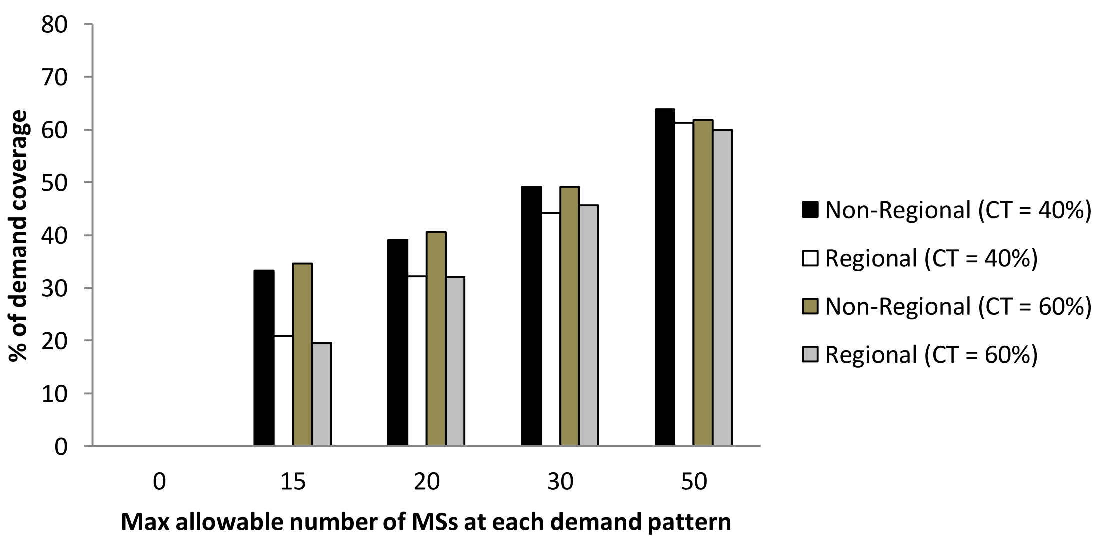


Figure 5.67 Demand coverage for 2nd 6 hours water demand pattern

locations of the water quality monitoring stations based on the regional constraint with a minimum number of 15 MSs. Such an action will help increase the demand coverage and reduce the difference between regional and non-regional optimization, and will guarantee minimum protection level for all sub-regions in the city. For non-regional optimization, increasing the number of MSs did not guarantee that every sub-region is expected to be monitored by at least one station as shown in Figure 5.62, but for regional optimization, almost the same level of coverage can be achieved and at the same time it ensures that every sub-region is monitored as shown in Figures 5.68 and 5.69. There is at least one MS within each sub-region, while for non-regional optimization there are several sub-regions without any MS even when the allowable number of MSs was 50. Figures 5.70 and 5.71 show the proposed optimal locations for MSs based on regional optimization.

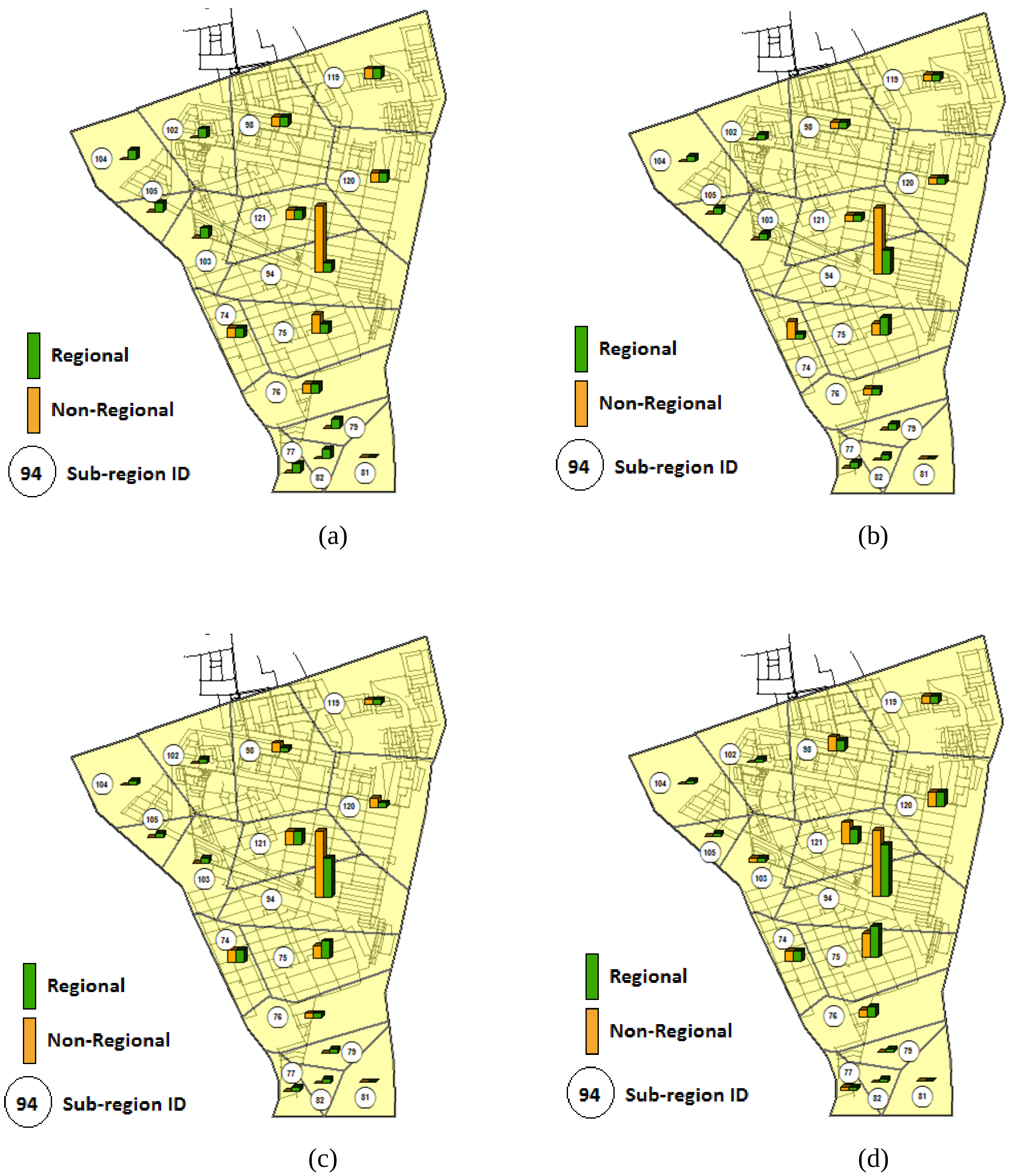


Figure 5.68 Comparison of number of MSs for regional and non-regional optimization based on 2nd 6 hours demand pattern and 40% CT for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs

Figure 5.69 Comparison of number of MSs for regional and non-regional optimization based on 2nd 6 hours demand pattern and 60% CT for:

(a) 15 (b) 20 (c) 30 and (d) 50 monitoring sets

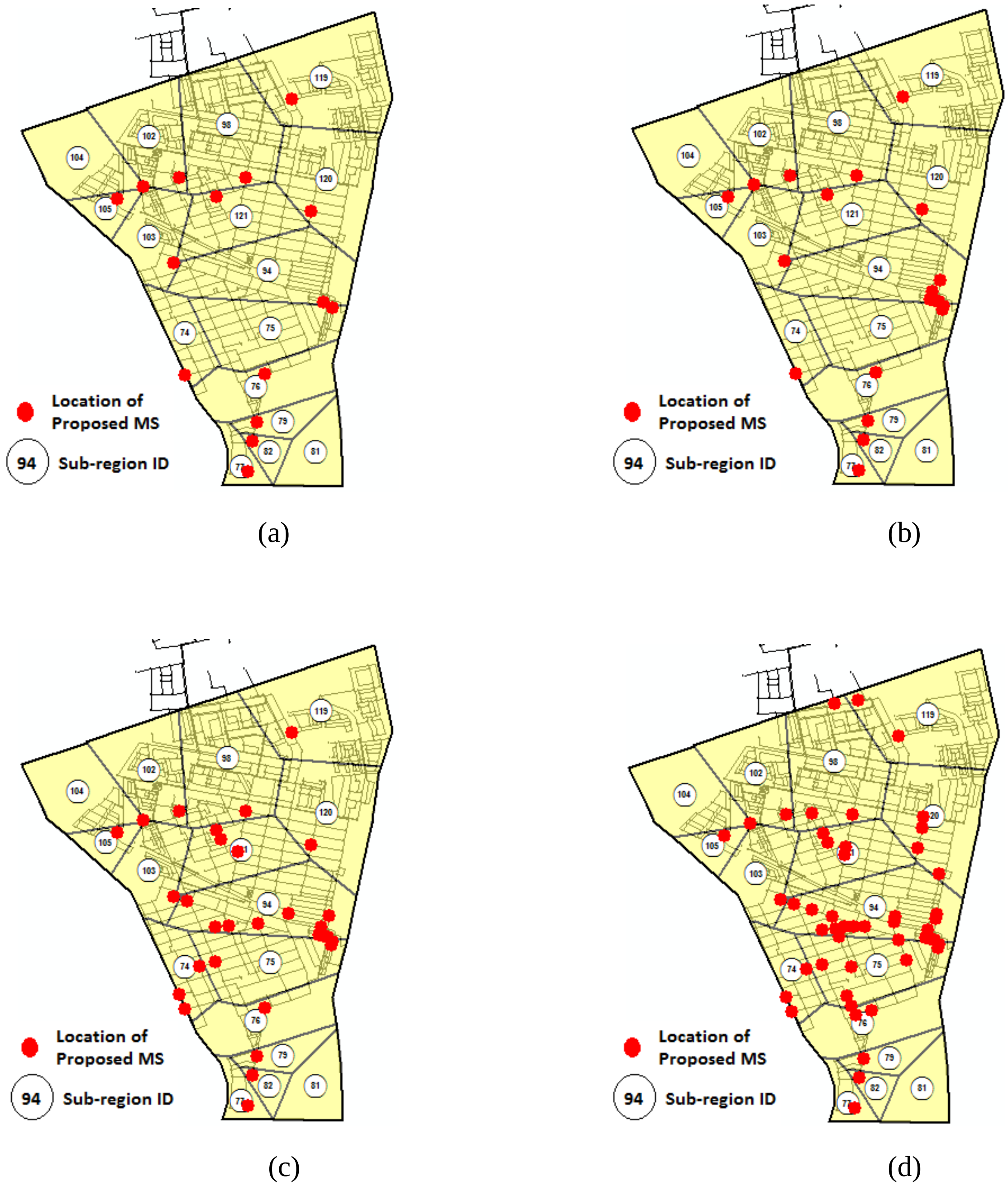


Figure 5.70 Locations of monitoring stations for 2nd 6 hours demand pattern and 40% CT for: (a) 15 (b) 20 (c) 30 and (d) 50 MSs

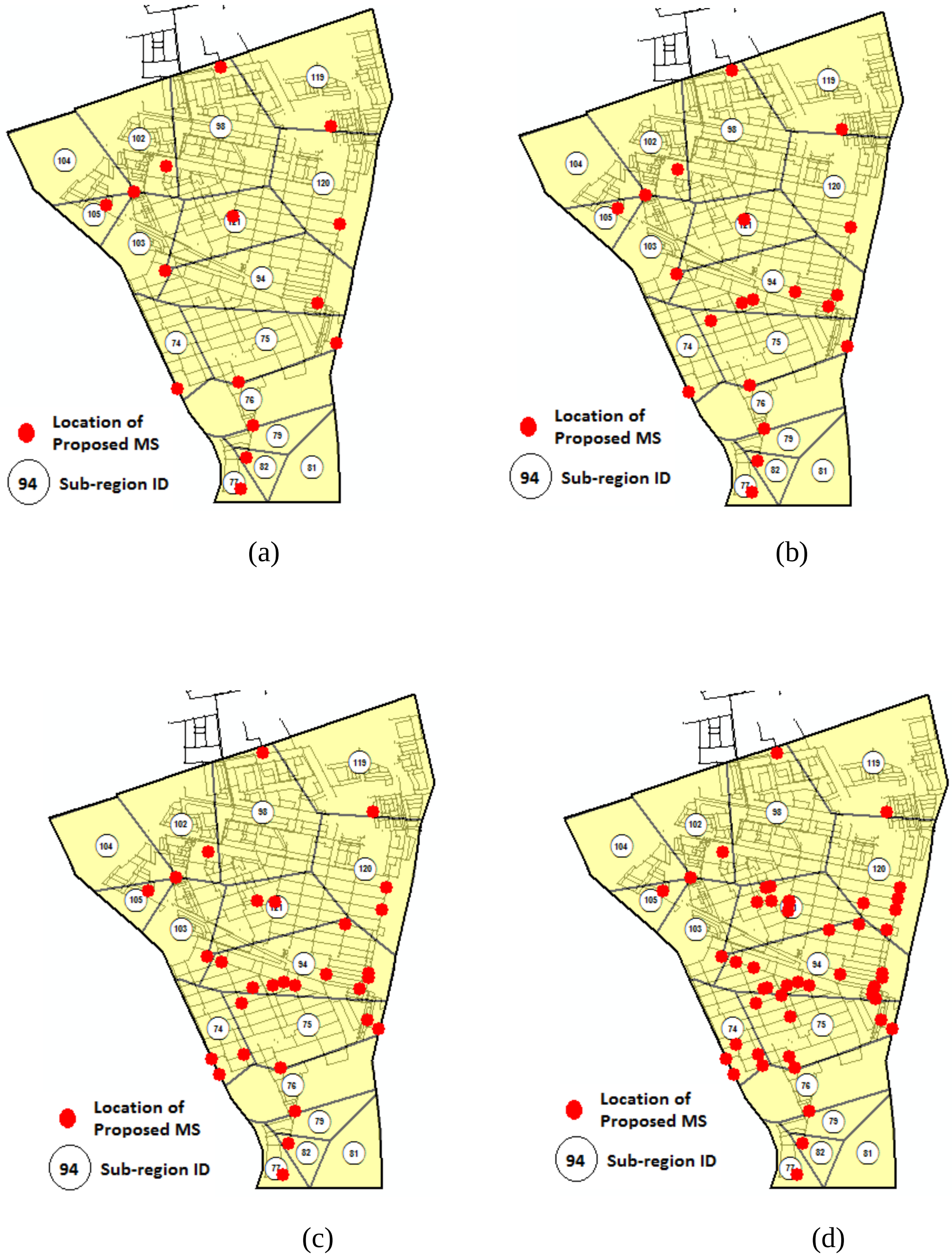


Figure 5.71 Locations of monitoring stations for 2nd 6 hours demand pattern and 60% CT for: (a) 15 (b) 20 (c) 30 and (d) 50 MSs

5.8.4 Risk, vulnerable and sensitive optimization

Most of the studies that dealt with identifying optimal locations of MSs in water distribution systems have used water demand as the key parameter for locating the MSs (Lee and Deininger, 1992; Kumar et al., 1997; Kessler et al., 1998; Harmant et al., 1999; Liu et al., 2011 and 2012). It is also considered as a reflection of the distribution and density of population in urban areas. Using demand for developing monitoring systems is logically accepted since the target is to monitor as much demand as possible to, consequently, protect consumers. However, it should be noted that possible consequences of potential accidental and/or intentional contaminations vary for different consumers in different sub-regions. Some sub-regions and population categories would be more vulnerable and/or sensitive to water quality deterioration in the WDN, such as densely populated sub-regions and children less than 10 years, respectively. The developed DSS using fuzzy synthetic evaluations showed that each sub-region has different characteristics than other sub-regions, which makes the expected consequences in case of water quality deterioration to vary for different sub-regions. Higher consequences are expected for some sub-regions more than the others since these sub-regions are having higher risk, vulnerability and sensitivity to water quality deterioration compared to other sub-regions as shown in Figures 5.32, 5.43 and 5.44. Therefore, in addition to demand, regional risk, vulnerability and sensitivity were also investigated in the study. This improvement of incorporating risk, vulnerability and sensitivity will enhance the monitoring system not only by maximizing TMD in all sub-regions, but also it will provide extra protection for sub-regions that are expected to have higher consequence or casualties for any water quality deterioration. Furthermore, additional constraints were considered such as limiting the allowable number of MSs to 50 or less, and regional constraint was set to minimum level of protection for every sub-region as explained in Chapter 3. For this analysis, the 2^{nd} 6 hours demand pattern was used, since it is the suitable demand pattern for Al-Khobar WDN.

Table 5.28 shows the TMD for optimal locations of MSs based on the 2^{nd} 6 hours demand pattern. There is insignificant coverage difference between MSs located based on demand (only), risk, vulnerability or sensitivity. When the allowable numbers of MSs are 15 and 20, TMD for demand (regional), risk, vulnerability and sensitivity objective functions is the same, especially when *CT* is 40%. This indicates that the selected MSs based on the four objective functions are the same. The reason for a small coverage difference when using more than 20 MSs is because MSs locations using risk, vulnerability and sensitivity are a little bit different compared to the locations of MSs identified based on demand objective function only. Compared to MSs locations selected exclusively based on demand objective function, the change in MSs locations did not exceed 5, 6 and 15 MSs for risk, vulnerability and sensitivity objective functions, respectively. These relocated MSs were moved from sub-regions with relatively low risk, vulnerability or sensitivity to sub-regions having higher risk, vulnerability or sensitivity.

The insignificant TMD difference and similarity of locations distributions of MSs between demand, risk, vulnerability and sensitivity optimizations can be explained using Figure 5.72 which shows regional populations density and regional risk, vulnerability and sensitivity indices. The central sub-regions in Al-Khobar city have the highest demand

Table 5.28 TMD for optimal locations of MSs based on the 2nd 6 hours demand pattern

(a) CT = 40%

Objective function	**Proposed number of MSs**			
	15	20	30	50
Demand (only)	20.85	32.14	44.16	61.28
Risk	20.85	32.14	43.81	60.63
Vulnerability	20.85	32.14	43.64	60.69
Sensitivity	20.85	32.14	43.81	60.63

(b) CT = 60%

Objective function	**Proposed number of MSs**			
	15	20	30	50
Demand (only)	19.56	32.07	45.61	59.94
Risk	19.56	31.94	44.97	59.18
Vulnerability	19.56	32.07	44.75	58.93
Sensitivity	19.56	31.94	45.24	59.18

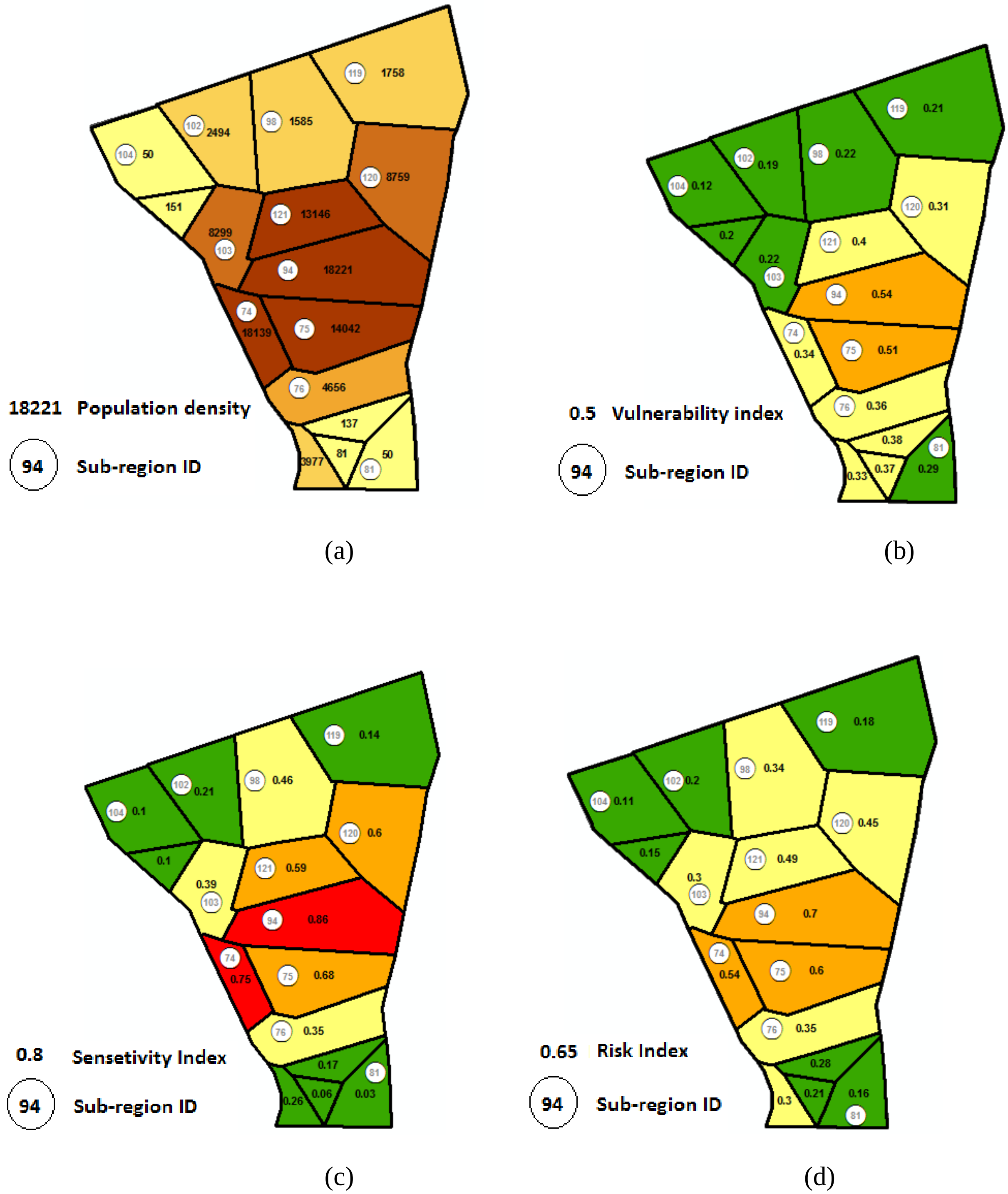


Figure 5.72 Population density and risk indices:

(a) Population density (b) Vulnerability indices (c) Sensitivity indices (d) Risk indices (and population density) as well as having the highest risk, vulnerability and sensitivity compared to sub-regions to the north and south of the city. On the other hand, for risk, vulnerability and sensitivity analysis, demand was also used as a component in the objective function because the target was to locate MSs that are capable to cover maximum demand taking into consideration risk, vulnerability and sensitivity variability between sub-regions. Quantifying risk, vulnerability and sensitivity based on regional indices is another reason for the insignificant differences in TMD and MSs distribution for the four objective functions. In regional analysis, regional risk, vulnerability and sensitivity indices for each node are equal to the overall indices for the sub-region they belong to. Developing nodal risk, vulnerability and sensitivity indices rather than regional indices would be recommended to show significant variability between the four scenarios (demand, risk, vulnerability and sensitivity). However, using nodal indices requires macro level of data collection which will significantly increase the costs for developing such monitoring systems. Also, this option may be difficult to implement for Al-Khobar WDN because it requires comprehensive data collection (nodal level) for water quality and sensitivity components (population, activity, standard of living, …etc.). This is beyond the ability of Al-Khobar municipality which is currently limited to only 15 MSs for water quality for the entire network. Therefore, it is reasonable that optimization results show similarities between the four objective functions. Figures 5.73 to 5.78 show the distribution of MSs based on risk, vulnerability and sensitivity objective functions.

Table 5.29 shows comparison of the percentage of TMD for different objective functions. Maximum demand coverage was achieved when using demand as the only key parameter

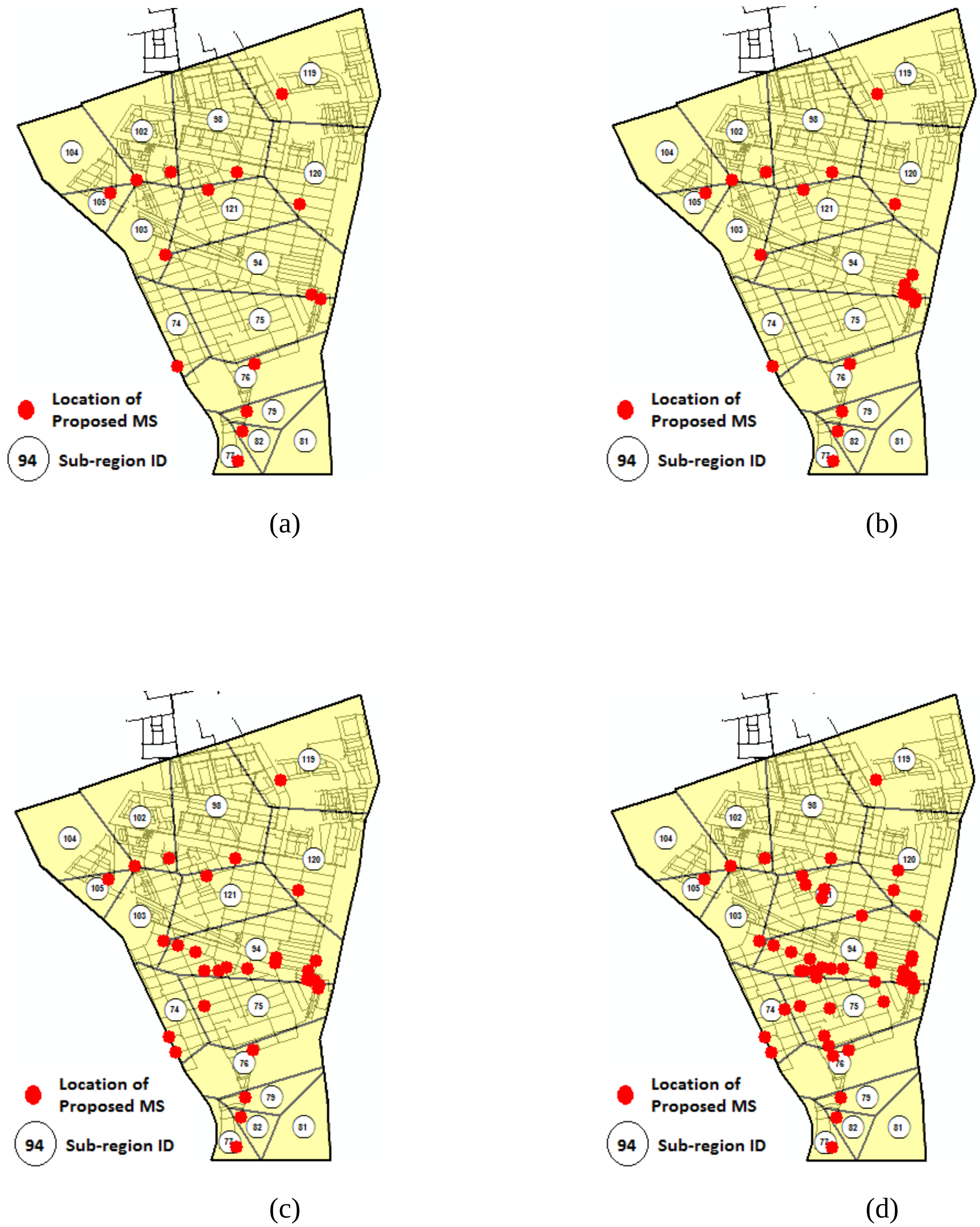


Figure 5.73 Optimal monitoring locations for 2nd 6 hours demand pattern and 40% CT based on risk objective function for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs

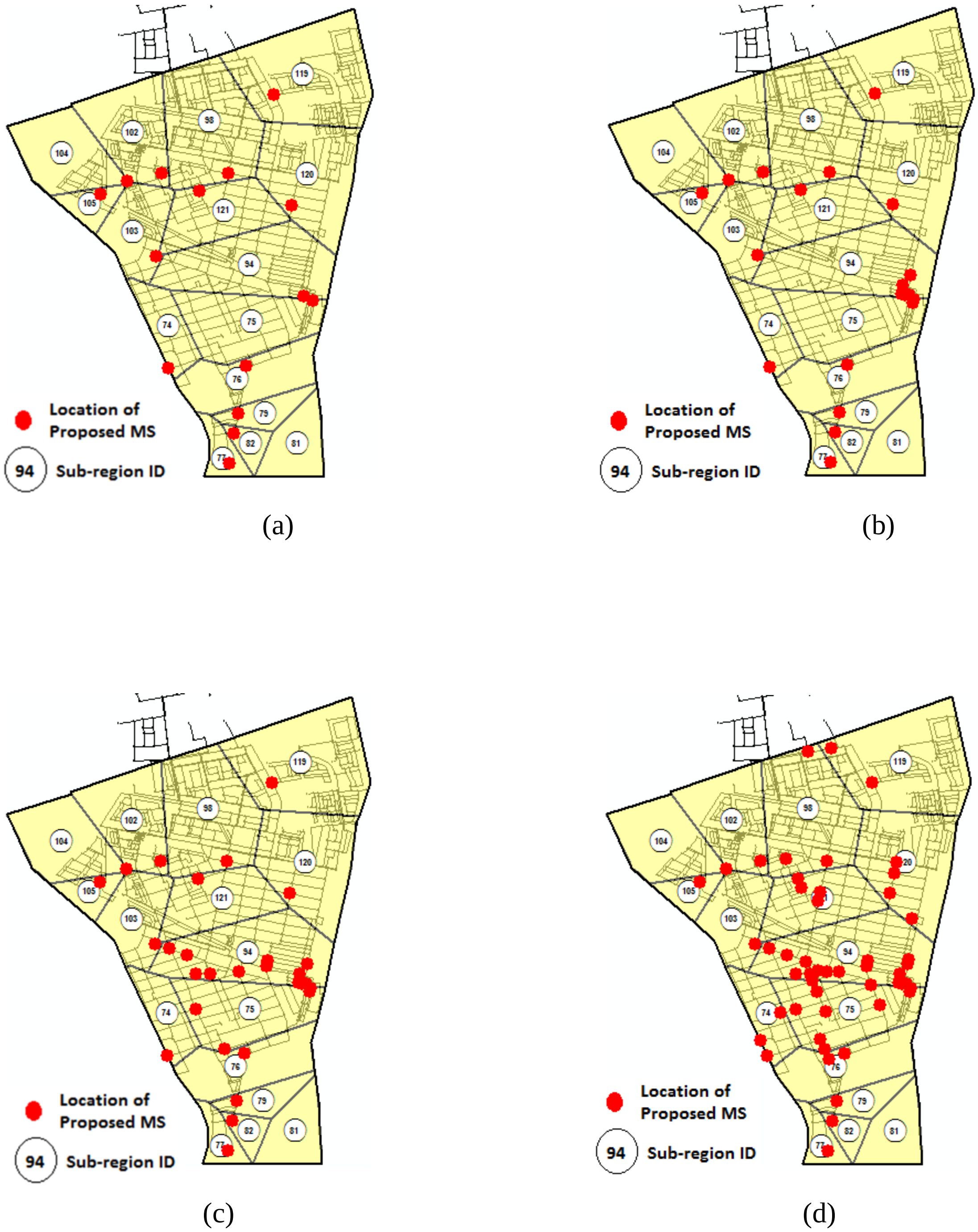


Figure 5.74 Optimal monitoring locations for 2nd 6 hours demand pattern and 40% CT based on vulnerability objective function for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs

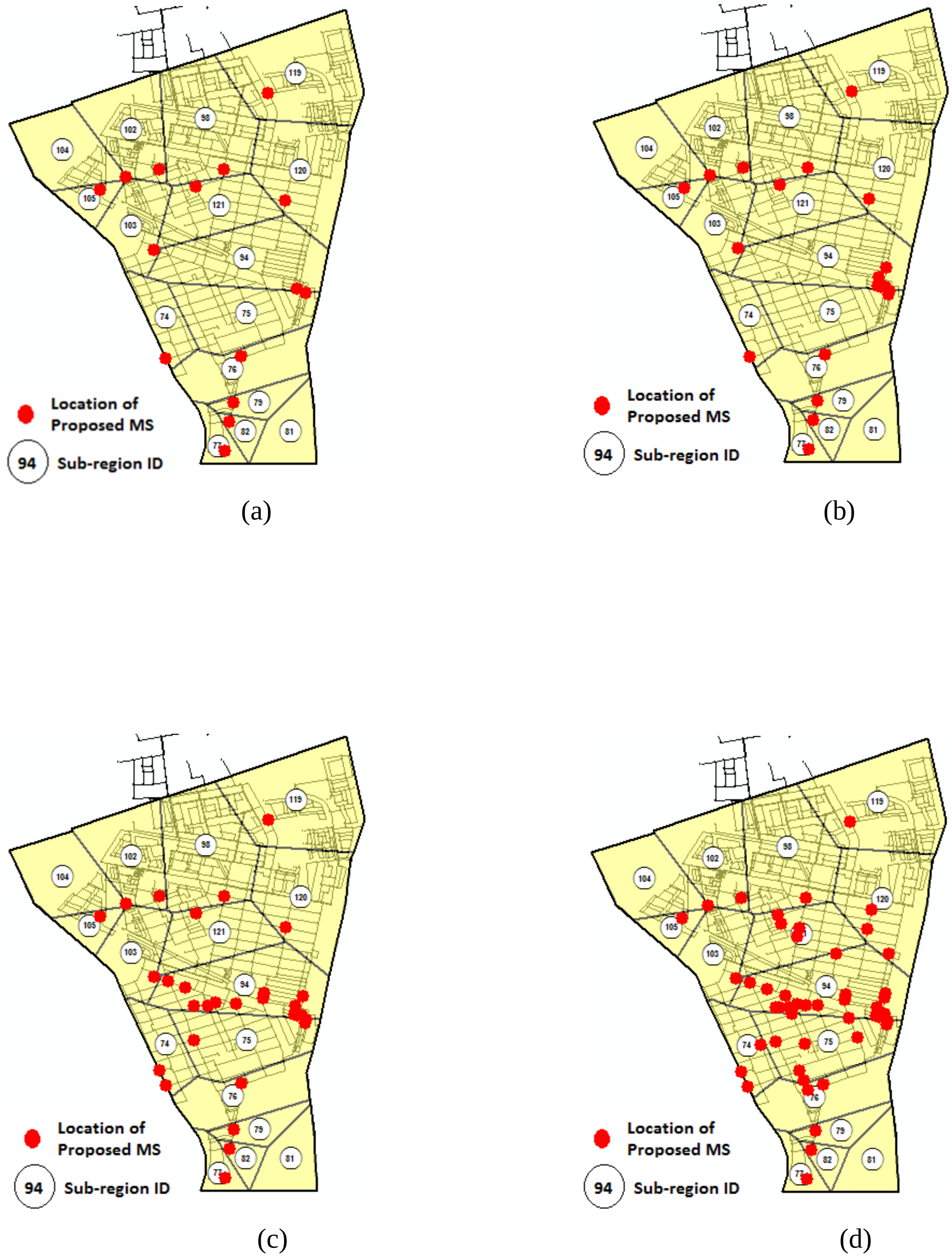


Figure 5.75 Optimal monitoring locations for 2nd 6 hours demand pattern and 40% CT based on sensitivity objective function for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs

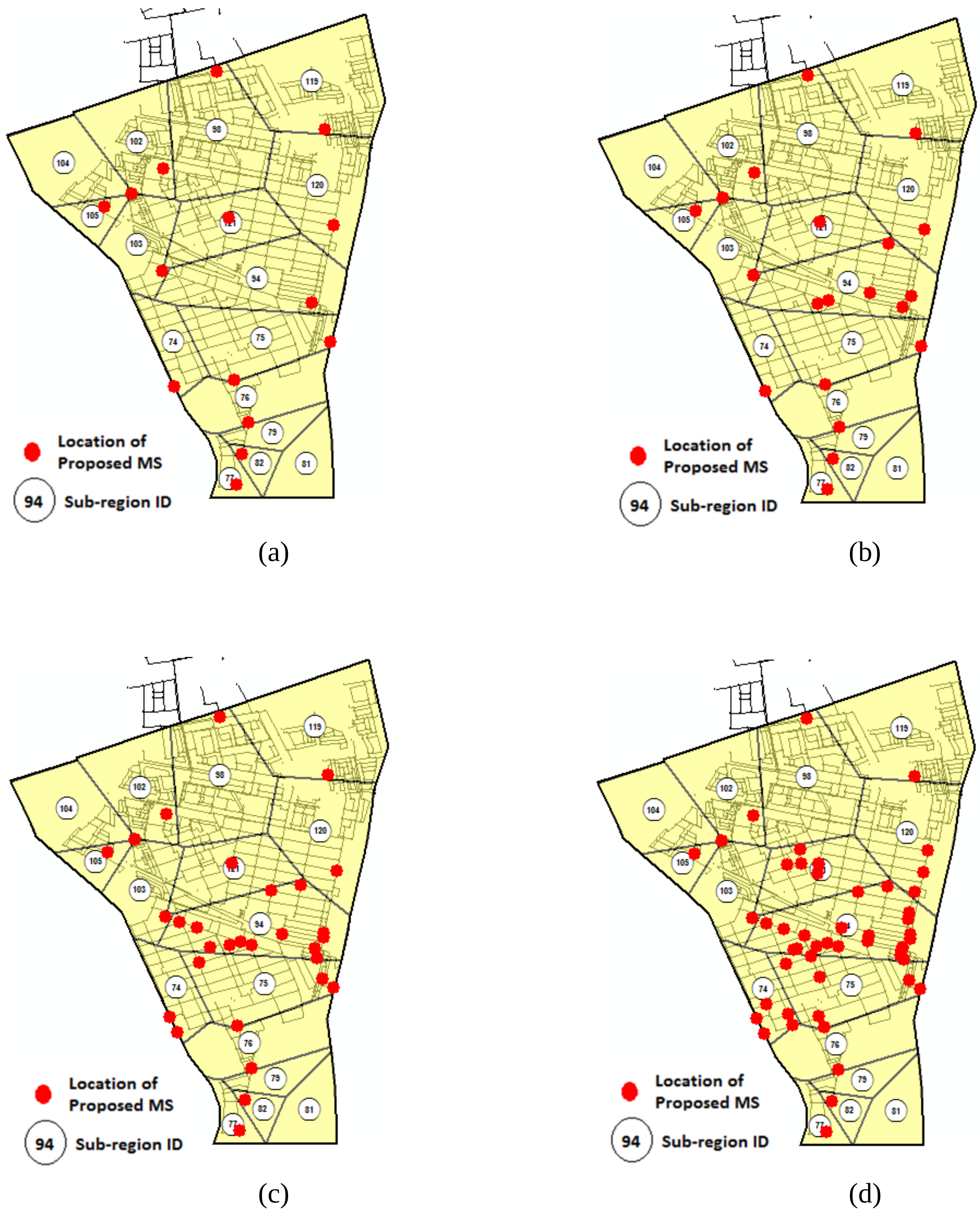


Figure 5.76 Optimal monitoring locations for 2nd 6 hours demand pattern and 60% CT based on risk objective function for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs

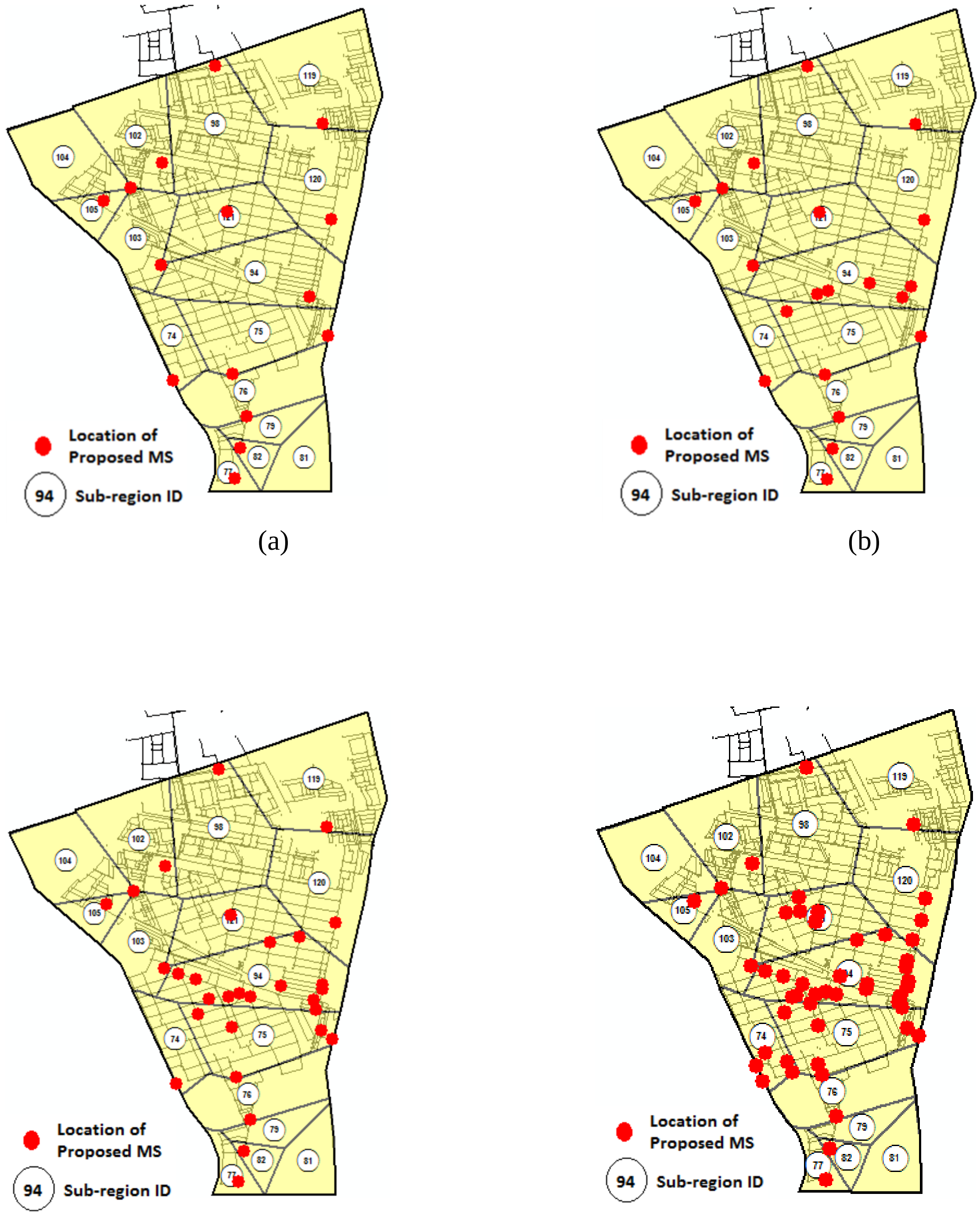
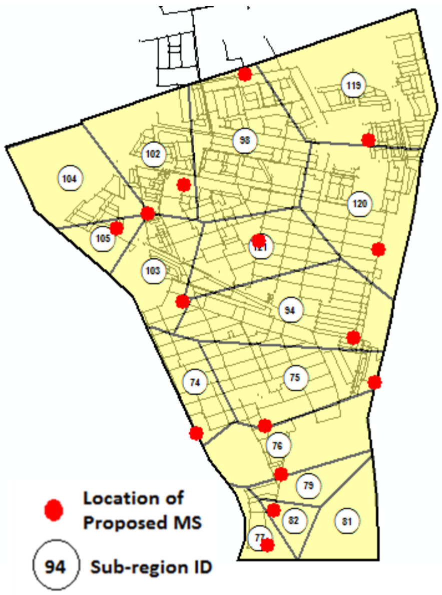
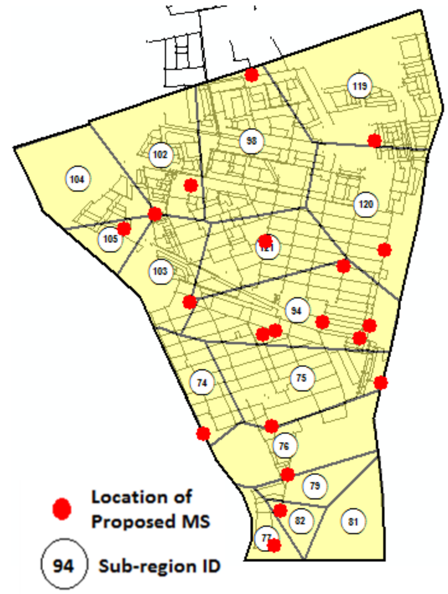


Figure 5.77 Optimal monitoring locations for 2nd 6 hours demand pattern and 60% CT based on vulnerability objective function for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs



(a)



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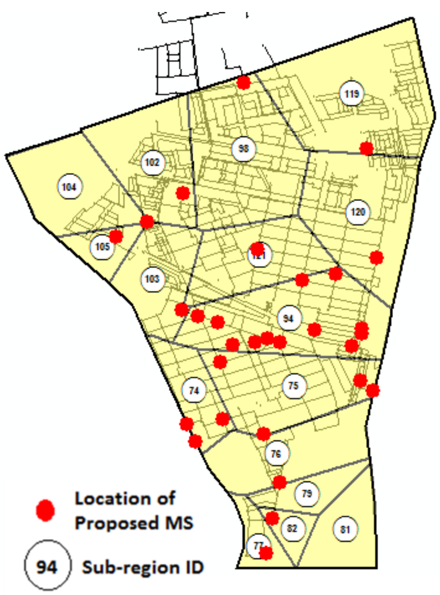

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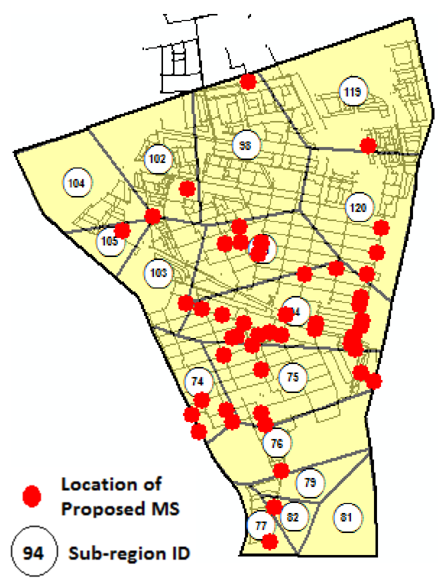


(d)

Figure 5.78 Optimal monitoring locations for 2nd 6 hours demand pattern and 60% CT based on sensitivity objective function for:

(a) 15 (b) 20 (c) 30 and (d) 50 MSs

Table 5.29 TMD for different objective functions

(a) CT = 40%

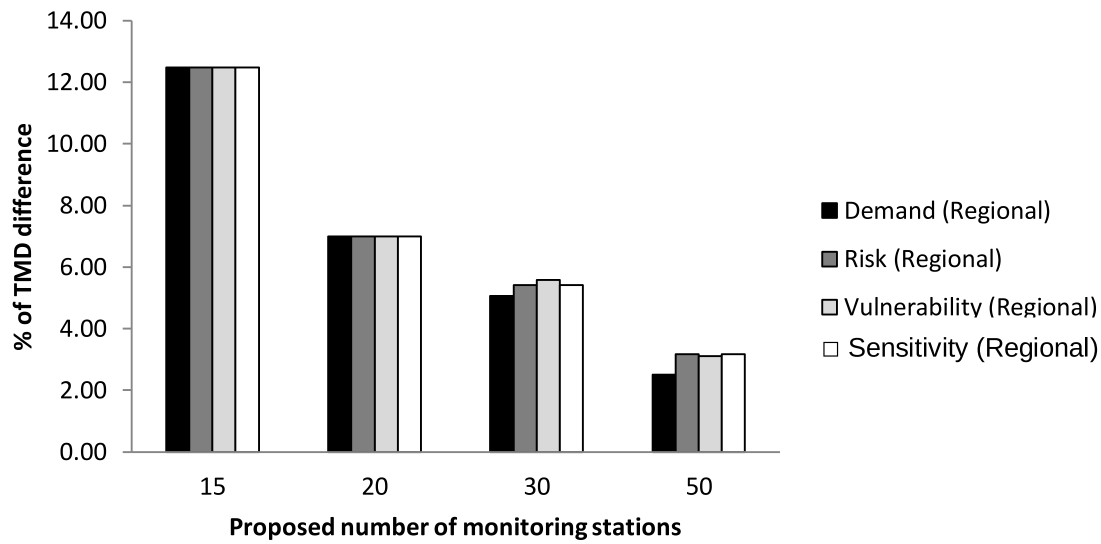
Objective function	Proposed number of MSs			
	15	20	30	50
Demand (Non-Regional)	33.33	39.14	49.22	63.80
Demand (Regional)	20.85	32.14	44.16	61.28
Risk (Regional)	20.85	32.14	43.81	60.63
Vulnerability (Regional)	20.85	32.14	43.64	60.69
Sensitivity (Regional)	20.85	32.14	43.81	60.63

(b) CT = 60%

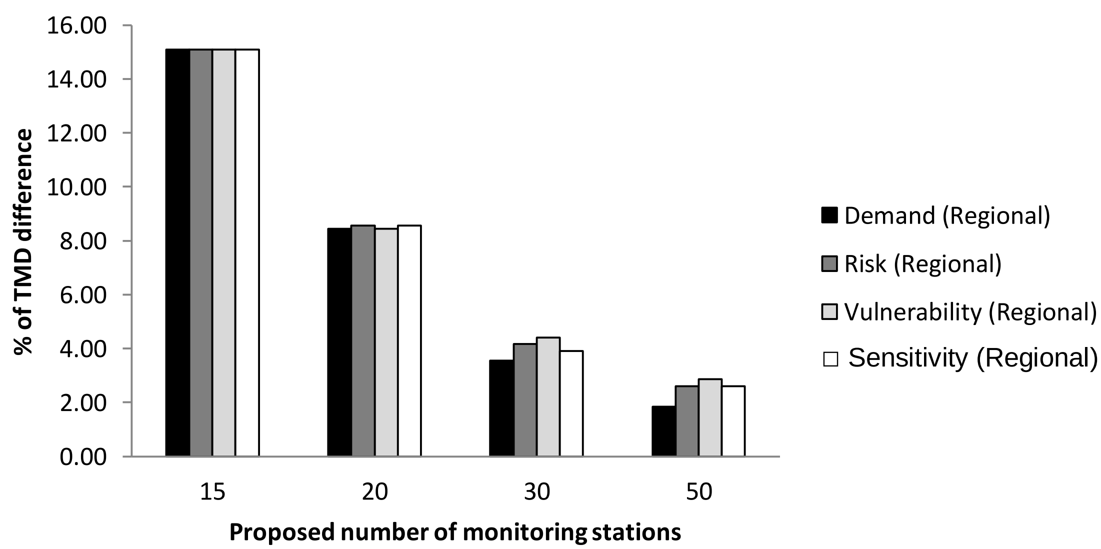
Objective function	Proposed number of MSs			
	15	20	30	50
Demand (Non-Regional)	34.64	40.51	49.15	61.79
Demand (Regional)	19.56	32.07	45.61	59.94
Risk (Regional)	19.56	31.94	44.97	59.18
Vulnerability (Regional)	19.56	32.07	44.75	58.93
Sensitivity (Regional)	19.56	31.94	45.24	59.18

without considering the regional constraint. The drawback for this alternative is that some sub-regions are totally unprotected due to their low demand rates compared to highly populated sub-regions. Therefore, non-regional approach cannot be used due to the lack of minimum protection level for all sub-regions. On the other side, maximum TMD reduces (compared to non-regional approach) when adding regional constraints to guarantee minimum regional protection level as shown in Table 5.29, either for demand or risk, vulnerability and sensitivity objective functions.

However, the difference between non-regional and regional demand coverage decreases as the number of MSs increases. For example, when selecting 50 MSs, the difference is only about 3% as shown in Figure 5.79. Accordingly, when considering regional alternative and selecting more than 15 MSs, the gap in demand coverage can be reduced between regional and non-regional alternatives while at the same time assuring that every sub-region is protected and monitored as well as the risk, vulnerability and sensitivity of each sub-region are considered.



(a)



(b)

Figure 5.79 Coverage difference between regional and non-regional scenarios for:

(a) 40% CT and (b) 60% CT

CHAPTER 6

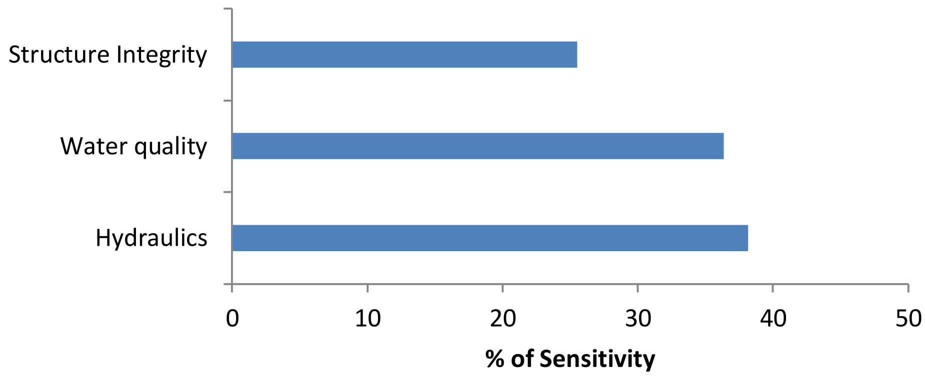
RISK MANAGEMENT

The overall risk of failure of delivering water to consumers in an acceptable quality depends on some factors which include physico-chemical properties of water, possibility of microbial growth, infrastructure condition, water hydraulics, population distribution, economic status, and services. To control and/or reduce regional risks indices, risks associated with either one or more of these factors should be reduced or eliminated. The reduction in the overall risk indices varies based on the contribution of each factor. On the other hand, logistic and economic expenses to reduce total risk vary significantly based on the strategy adopted for reducing total risk. For example, minimizing total risk by reducing TDS levels in sub-regions having high level of TDS is a relatively cheap solution compared to using PVC pipes instead of AC pipes. At the end, it is a matter of tradeoff, how much reduction of total risk is required and what are the possible and bearable solutions? The factors that can be considered to manage, control and/or reduce total risk are physico-chemical and microbial properties, structure integrity of the WDN, hydraulic properties of water and sensitivity of each sub-region in terms of population density, distribution, activities and presence of schools and hospitals. However, the sensitivity of each of these factors on the vulnerability and sensitivity risk indices varies based on the assigned weight (importance) in the fuzzy model. To determine this sensitivity, Montecarlo simulation was used. Montecarlo simulation is one of the most common approaches for determining the sensitivity of competing factors and for probability-based uncertainty analysis (Abrahamsson, 2002). In Montecarlo simulation the uncertainity in the inputs can be modeled by developing probability density functions for input parameters. However, this is not always possible and therefore inputs are assumed to follow specific distributions based on the previous knowledge of each input parameter (Ferdous et al., 2009). Inputs in this study (TDS, temperature, pH levels, residual chlorine, turbidity, pipes age, pipes type, water age, pressure, velocity, standard of living, activity in regions, number of students, number of hospital beds and population density) were simulated using Montecarlo simulation by assuming uniform distribution for all the parameters and running the simulation for 1000 times.

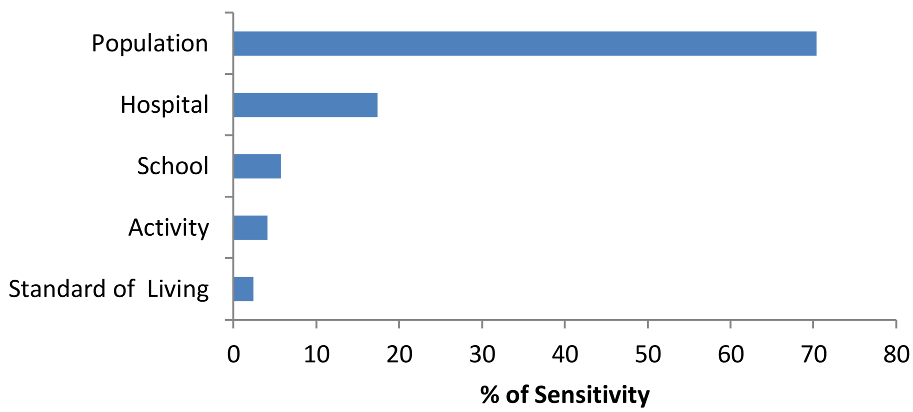
Outputs of the simulations show that vulnerability is more sensitive to changes in hydraulics and water quality as can be seen in figure 6.1 a. On the other hand, sensitivity risk index is more affected by the change in population density as shown in figure 6.1 b. In addition to the sensitivity of vulnerability and sensitivity risk indices, figure 6.1c shows that overall risk index is more sensitive to the changes in the sensitivity risk index compared to vulnerability risk index.

Figures 6.1 shows that the sensitivity of the input factors is proportional to the weights assigned to each parameter in the DSS, which indicates the importance and the effect of these weight in the over all risks

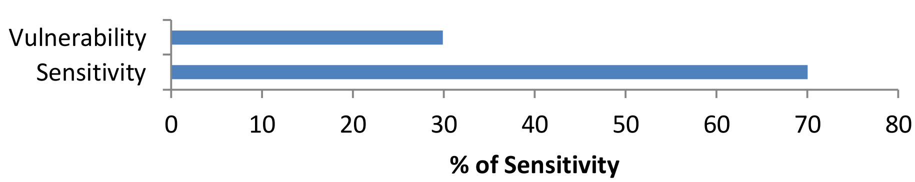
The reduced total risk is determined by eliminating risks expected from each of the previous factors at a time. By applying MCDM, the contribution of each factor on the total risk can be identified by assigning equal weight for all the factors. For the Goal Programming optimization and MCDM, the objective was to reduce the risk from every



(a)



(b)



(c)

Figure 6.1 Sensitivity percentage for each factor
for: (a) Vulnerability risk index, (b) sensitivity risk index and (c) overall risk index

factor. Table 6.1 shows total risk indices for each sub-region when eliminating risks caused by each factor. For example, when controlling physico-chemical levels so that it lies within optimal standards, the total risk in sub-region 76 reduces from 0.354 to 0.340. However, if the structure integrity including pipes materials, breaks, ages, water table levels, soil conditions and potential intrusions was improved, the total risk will reduce from its original index of 0.354 to 0.253.

It can be seen that most of the contribution on the total risk comes from structure integrity and sensitivity factors. Table 6.2 shows that the average contribution to the total risk from structure integrity and sensitivity are the highest. However, there is no way to reduce risks caused by sensitivity since it represents population density, standard of living, activities in the city, and distribution of schools and hospitals, which are factors that cannot be modified or changed. Therefore, risk contribution from sensitivity on the total risk can be considered as the minimum level of risk, since there is no possibility to have zero risk. Accordingly, structure integrity is considered as the factor with the highest contribution on the overall risk in the WDN, caused by several factors including pipes breakage ratio, material, age and potential intrusions.

Hydraulic contribution on the total risk is relatively significant, with an average contribution of 13.1%, and physico-chemical and microbial contribution is the least with an average of 5.4 and 9.5% of the total risk as shown in Table 6.2.

Total risk can be controlled and/or reduced by managing physico-chemical, microbial and hydraulic properties in addition to improving the structure integrity of the system. However, improving structure integrity should be considered as the first priority since

Table 6.1 Summary of the total risk after eliminating each factor at a time

Sub-regions	Current	Factor controlled and/or eliminated				
		Phy-Chem	Microbial	Structure	Hydraulics	Sensitivity
74	0.541	0.534	0.514	0.443	0.506	0.168
75	0.595	0.587	0.580	0.497	0.461	0.255
76	0.354	0.340	0.337	0.253	0.305	0.180
77	0.296	0.282	0.279	0.198	0.261	0.165
78	0.275	0.269	0.228	0.175	0.240	0.188
81	0.160	0.143	0.133	0.059	0.160	0.145
82	0.213	0.203	0.177	0.108	0.178	0.185
94	0.701	0.691	0.664	0.603	0.576	0.269
98	0.339	0.324	0.321	0.309	0.290	0.110
102	0.201	0.187	0.184	0.172	0.166	0.096
103	0.305	0.299	0.287	0.255	0.270	0.109
104	0.113	0.096	0.098	0.084	0.113	0.062
105	0.154	0.137	0.133	0.125	0.119	0.102
119	0.175	0.158	0.152	0.146	0.139	0.106
120	0.453	0.436	0.430	0.391	0.401	0.155
121	0.493	0.477	0.435	0.421	0.443	0.198

Table 6.2 Percentages of contribution of each factor to the total risk

Sub-regions	Factors				
	Phy-Chem	Microbial	Structure	Hydraulics	Sensitivity
74	1.4	5.0	18.1	6.5	69.0
75	1.4	2.5	16.5	22.5	57.2
76	4.0	4.7	28.5	13.8	49.0
77	4.8	5.9	33.1	11.8	44.4
78	2.2	17.2	36.4	12.8	31.5
81	10.6	16.8	63.1	0.0	9.5
82	4.5	16.7	49.4	16.5	13.0
94	1.4	5.2	14.0	17.8	61.6
98	4.4	5.3	8.6	14.3	67.4
102	7.0	8.7	14.5	17.4	52.4
103	2.1	5.9	16.2	11.5	64.3
104	15.1	13.9	25.8	0.0	45.2
105	11.1	13.7	19.0	22.8	33.4
119	9.7	13.6	16.7	20.6	39.4
120	3.8	5.1	13.8	11.6	65.8
121	3.3	11.8	14.6	10.3	60.0
Average	5.4	9.5	24.3	13.1	47.7

most of the pipes in the WDN are made up of AC, which have the highest percentage of pipe breakage in the network and are the oldest, in addition to health concerns relevant to the use of AC pipes which are classified as a carcinogenic material and were banned in several places in the world. Table 6.3 shows the minimum expected total risk when all the factors were controlled.

Accordingly, managing risks in the WDN can be achieved based on a plan of two phases. The first and urgent phase is to improve the infrastructure of the WDN, mainly replacing asbestos by PVC pipes in the southern parts of the city. This will reduce the overall risks caused by pipe breaks, materials and ages as well as potential intrusion by 24.3%. The second phase is to improve the hydraulics and water quality within the system. These phases can be done simultaneously since the second phase will require less efforts and financial support relative to the first phase, where the overall risk reduction will be 52.3% as shown in Table 6.3. Soft copy of the MCDM model is in appendix D.

Table 6.3 Comparison between current and minimum total risks

Sub-region	Total Risk		Reduction percentage
	Current	Minimum	
74	0.541	0.374	31
75	0.595	0.340	43
76	0.354	0.173	51
77	0.296	0.131	56
78	0.275	0.087	68
81	0.16	0.015	90
82	0.213	0.028	87
94	0.701	0.431	38
98	0.339	0.228	33
102	0.201	0.106	48
103	0.305	0.196	36
104	0.113	0.051	55
105	0.154	0.051	67
119	0.175	0.069	61
120	0.453	0.298	34
121	0.493	0.296	40
Average reduction			52.3

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

In this research, a decision support system (DSS) was developed to prioritize regional risk for water distribution system (WDN) to ensure delivery of water to consumers with acceptable water quality level. The DSS considered 22 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 sub-region and the presence of public service such as schools and hospitals. The developed DSS tool was able to prioritize risk, vulnerability and sensitivity in the WDN by aggregating 32 attributes using Fuzzy Synthetic Evaluation (FSE), Analytical Hierarchical Process (AHP) and Fuzzy Rule-Based (FRB).

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

The results of this study found that the highest and lowest regional risk indices were 0.65 and 0.13, respectively. Risk indices can be reduced by eliminating one or more of the factors contributing on the total risk, such as water quality properties, structure integrity and hydraulics.

Total risk cannot practically be reduced to zero. However, it can be reduced to acceptable minimum levels. In general, the risk contribution of factors including physico-chemical and microbial properties, structure integrity, hydraulics and sensitivity to the total risk was found to be 5.4, 9.5, 24.3, 13.1 and 47.7%, respectively. Reducing total risk by improving the structure integrity of the system might be challenging from an economic point of view, however, major improvements in infrastructure should be considered as the first priority in risk management plans. In addition, improving water quality parameters and hydraulics of water as well as improving the infrastructure of the WDN can reduce the total risk by an average of 47.7%.

It is recommended to manage risks in the WDN based on a plan of two phases. The urgent phase is to improve the infrastructure of the WDN, mainly replacing asbestos by PVC pipes in the southern parts of the city. This will reduce the overall risks caused by pipe breaks, materials and ages as well as potential intrusion. The second phase is to improve the hydraulics and water quality within the system. These phases can be done simultaneously since the second phase will require less efforts and financial support relative to the first phase. Overall risk reduction if both phases were completed is 52.3%.

Monitoring system has also been developed for Al-Khobar WDN based on Demand Coverage Method (DCM). In this research, several scenarios based on 24 hourly and 7 grouped demand patterns (6 hours, 12 hours and 24 hours), four *CT* values (40, 50, 60 and 70%) and monitoring stations ranging from 15 to 250 were studied. A total of **2046** scenarios were investigated to develop a monitoring system for Al-Khobar city. The existing monitoring system was used for monitoring TDS and chlorine levels in the water and, consequently, the MSs were located directly after the blending stations, close to tanks and pumping stations. The objective was to develop a monitoring system that is capable of reflecting water quality in the entire network and protect consumers from any possible action that might cause water quality deterioration. DCM was applied to develop the monitoring system by maximizing the monitored demand. In general, using higher values for coverage threshold (*CT*) eliminates more flow pathways and, consequently, decreases the total monitored demand (TMD), while using low values for *CT* will not reflect the actual water quality in the WDN. It was shown that *CT* value has an effect on the selection of optimal MSs since potential monitoring stations (PMSs) change for different *CT* values.

For non-regional optimization, where demand was the only parameter controlling the process and there was no regional constraint for locating MSs, TMD was higher for hourly demand patterns compared to grouped demand patterns. The maximum average TMD was found to be 76.20, 63.01, 59.83 and 56.19% for hourly, 6 hours, 12 hours and

24 hours demand patterns, respectively, when 50 MSs were used. However, it was noticed that no MS was proposed for areas with low water demand. Thus, a regional constraint was incorporated in the optimization model (regional optimization) to ensure minimum level of protection, such that at least one MS should exist in each sub-region.

The results indicate that the TMD for regional optimization was lower than the non-regional optimization. When 50 MSs were proposed, the maximum average TMD was found to be 74.06, 60.58, 57.21 and 56.56% for hourly, 6 hours, 12 hours and 24 hours demand patterns, respectively. However, this difference in TMD between regional and non-regional optimization increases as the number of MSs decreases. The average difference in TMD between regional and non-regional optimization was 14.58, 7.70, 4.45 and 2.14% when using 15, 20, 30, and 50 MSs, respectively, for hourly demand patterns. Grouped demand patterns show similar behavior.

In general, although hourly demand patterns showed higher TMD compared to grouped patterns all over this study, they required higher number of MSs as well, which is a drawback considering that increasing the number of MSs may not be practically and economically feasible. It was also noted that increasing the number of MSs per demand pattern has reduced the TMD difference between hourly and grouped demand patterns.

For Al-Khobar WDN, the sampling period runs between 6:00 am and 12:00 pm. Accordingly, two demand patterns alternatives were investigated: hourly demand patterns and 2nd 6 hours demand pattern. Although hourly demand patterns have higher TMD compared to 2nd 6 hours demand pattern, the number of MSs required was twice the number of monitoring stations for 2nd 6 hours demand pattern. In addition, the difference between the two alternatives reduces as the number of MSs used increases. However, the main drawback for hourly demand patterns is that they require more than 50 MSs, which is a constraint for Al-Khobar WDN. Therefore, 2^{nd} 6 hours demand pattern is more applicable for this network.

In addition to water demand, other parameters were considered to develop the monitoring system including risk, vulnerability and sensitivity indices which resulted from the DDS using fuzzy synthetic evaluation. Some of the locations of the MSs have been relocated based on the risk, vulnerability and sensitivity for each sub-region. In general, however, the TMD difference in regional optimization (demand only) compared to risk, vulnerability and sensitivity optimization was insignificant.

Two *CT* values were investigated thoroughly in this study, including 40% and 60%. In general, TMD was relatively higher when *CT* was 40%, although in most cases the difference in TMD for both *CT* values was insignificant. However, if there is no regional constraint considered in the analysis, *CT* values alter the optimal locations of the MSs. While MSs were more scattered for non-regional optimization when *CT* was 40%, locations were more clustered when *CT* was 60%, especially when less number of MSs was considered. The total number of MSs used was relatively higher when *CT* was 40% compared to 60%.

The proposed monitoring system considers demand and distribution in the city, risk, vulnerability and sensitivity of different sub-regions, in addition to ensuring that each sub-region has a minimum coverage level. Final locations of MSs show that the central area of the city requires more MSs compared to the northern and southern side of the city due to the higher intensity of population and demands in addition to higher risk, vulnerability and sensitivity levels in the central area.

However, in order to increase the monitoring duration for Al-Khobar WDN from the sampling period to the entire day, an automated monitoring system should be used. For this new monitoring system, hourly demand patterns can be used and, consequently, higher demand coverages can be achieved.

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APPENDICES

List of Appendices

APPENDIX A

Sample Questioner

The survey used for estimating fuzzy weights

Dear Sir,

Thanks for participating in this survey.

You are requested to rate the relative importance of different parameters relevant to water delivery through Water Distribution Networks. The aim of ranking is to determine (from your own expertise and opinion) what are the factors which have more effect and could cause higher risk to consumers.

Rating scale should be between 1 – 9. Table 1 provides a scale to assign relative importance to different factors, while 1 indicates equal importance between the two factors compared, 9 indicates a supreme and extreme importance of one factor over the other.

Table 1 – Importance scale

Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak importance	-
3	Moderate importance	Experience and judgment slightly favor one activity over other
4	Moderate plus	-
5	Strong importance	Experience and judgment strongly favor one activity over other
6	Strong plus	-
7	Very strong or demonstrated importance	An activity is favored very strongly over another, its dominance demonstrated in practice
8	Very, very strong	-
9	Extreme importance	The evidence favoring one activity over another is of highest possible order of affirmation

Illustrative example

Suppose you are required to rank comparative importance of temperature, PH and TDS as shown in Table 2.

Table 2

	Temperature	pH	TDS
Temperature	1		
pH		1	
TDS			1

Ranking procedure:

1- You are required to fill yellow cells only
2- Based on the scaling range (Table 1), suppose you think pH has a higher importance over temperature by factor of 2, than you will rank as follows:

	Temperature	pH	TDS
Temperature	1	2	
pH		1	
TDS			1

3- Suppose you think TDS has a higher importance over temperature by a factor of 5, than you will rank as follows:

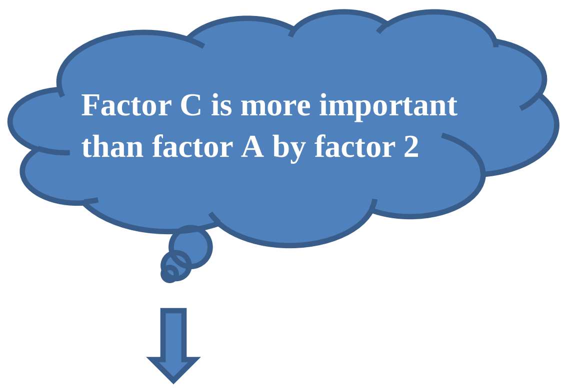
	Temperature	pH	TDS
Temperature	1	2	5
pH		1	
TDS			1

4- Suppose you think TDS has an equal importance as pH, than you will rank as follows:

	Temperature	pH	TDS
Temperature	1	2	5
pH		1	1
TDS			1

5- Suppose you think Temperature has a higher importance over pH by a factor of 7, than you will rank as follows:

	Temperature	pH	TDS
Temperature	1	1/7	
pH		1	
TDS			1



	A	B	C
A	1		2
B		1	
C			1

Survey

Part 1: Water Quality

a- In your opinion, which factor of these has more effect than others on water quality delivered to consumers through water distribution networks?

	Temperature	pH	TDS
Temperature	1		
pH		1	
TDS			1

b- In your opinion, which factor of these has more effect than others on water quality delivered to consumers through water distribution networks?

	Residual Chlorine	Turbidity
Residual Chlorine	1	
Turbidity		1

Part 2: Potential intrusion

In your opinion, if there was an intrusion of contaminants to the water distribution system, how do you rank the dangerous effect of sewer intrusion and industrial (car workshops) intrusion compared to each other?

	Industrial	Sewer
Industrial	1	
Sewer		1

Part 3: Structure Integrity

In your opinion, regarding water distribution networks infrastructure, what factors have more effect on water quality? How would you rank them?

Note:

Soil Type : The effect of soil surrounding pipes

Water table : The effect of level of water table on the pipes.

	P. Type	P. Age	Soil Type	P. Intrusion	Water Table
Pipe type	1				
Pipe age		1			
Soil Type			1		
Potential intrusion				1	
Water Table					1

Part 4: School index

In your opinion, what schools category will be more affected if students drink contaminated water delivered by the water distribution system?

Note:

Elementary schools : Students from 5 to 12 years old.

Intermediate schools: Students from 12 to 15 years old.

Secondary schools : Students from 15 to 18 years old.

	Elementary	Intermediate	Secondary
Elementary	1		
Intermediate		1	
Secondary			1

<u>Part 5: Sensitivity index</u>

In your opinion, If contaminated water was pumped through the water distribution network, How would you rank the following factors? Higher ranking indicates that the expected risks from one factor are higher than the other.

Note:

Population : Population density.

Schools : All schools, elementary, intermediate or secondary.

Hospitals : Possible patients affected.

Activity : The activity of the area under study, residential, industrial, commercial.

Standard of living : The average income rates for the area under study, high, med and low. Example: zones with low income have a higher possibility to drink water directly from tabs, while high income zones usually buy water.

	Population	Schools	Hospital	Activity	Standard of living
Population	1				
Schools		1			
Hospital			1		
Activity				1	
Standard of living					1

Thanks for participating in this survey.

APPENDIX B

Shapes of membership functions used

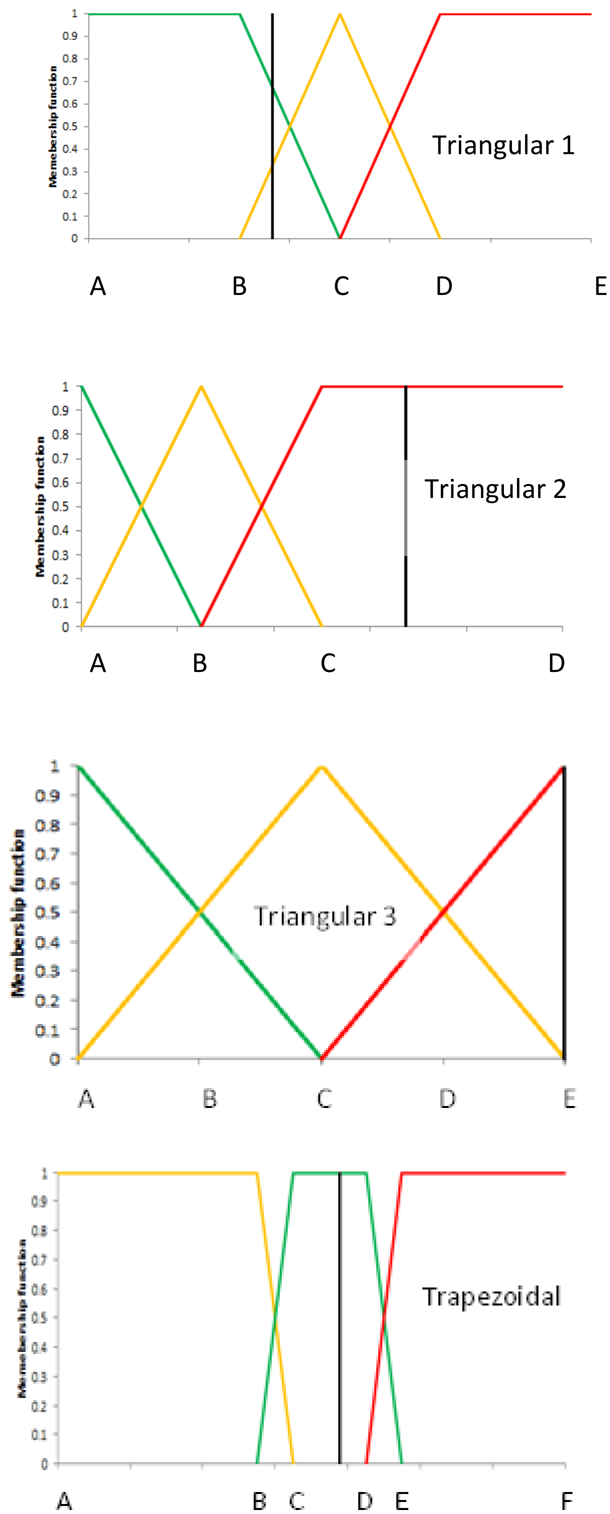


Figure A.1 Shapes of fuzzy sets used in the study

APPENDIX C

Optimization Models

Non-Regional optimization

```
MODEL:
! Optimization sample problem using coverage method 50%;

SETS:
   Nodes: Coverage_sum ,Include, Hydraulic_Index;

!Nodes, Coverage_sum,Include,Risk_index, Sensetivity_Index,
          Vulnerability_Index, Hydraulic_Index, SI_Index, WQ_Index,
          Sum_Indicies, Coverage_hour1, Coverage_6_1, Coverage_12_1;
ENDSETS

!========================================================================
========;

! Here is the data;
DATA:
   !Importing attribute values and set members from Excel;
   Nodes, Coverage_sum , Hydraulic_Index=

   @OLE('C:\LINGO12\Dissertation\Network\Excel for lingo 40%.xlsx');


   !Exporting Results to Excel;
   @OLE('C:\LINGO12\Dissertation\Network\Excel for lingo
40%.xlsx')=Include;



ENDDATA

!========================================================================
========;
! Total Monitoring Nodes constraint nodes,
  in which I am forcing the complier to use the sum to "include"
  parameter as a tool for determining number of monitoring
  stations ;

! Setting constraint so that at least one monitoring station is choosen
  from each region;

Region_74 = @Sum(Nodes(J) | J #LE# 25: Include(J));

Region_75_A = @Sum(Nodes(J) | J #GE# 26: Include(J));
Region_75_B = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_75 = Region_75_A - Region_75_B;

Region_76_A = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_76_B = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_76 = Region_76_A - Region_76_B;
```

```
Region_77_A = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_77_B = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_77 = Region_77_A - Region_77_B;

Region_78_A = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_78_B = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_78 = Region_78_A - Region_78_B;

Region_82_A = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_82_B = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_82 = Region_82_A - Region_82_B;

Region_94_A = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_94_B = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_94 = Region_94_A - Region_94_B;

Region_98_A = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_98_B = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_98 = Region_98_A - Region_98_B;

Region_102_A = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_102_B = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_102 = Region_102_A - Region_102_B;

Region_103_A = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_103_B = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_103 = Region_103_A - Region_103_B;

Region_104_A = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_104_B = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_104 = Region_104_A - Region_104_B;

Region_105_A = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_105_B = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_105 = Region_105_A - Region_105_B;

Region_119_A = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_119_B = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_119 = Region_119_A - Region_119_B;

Region_120_A = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_120_B = @Sum(Nodes(J) | J #GE# 830: Include(J));
Region_120 = Region_120_A - Region_120_B;

Region_121 = @Sum(Nodes(J) | J #GE# 830: Include(J));


 !In this case I will force the compiler to use at least 1 node in each
region;



=======================================================================!
;===

 !Optimization Process;
```

```
 !Number of monitoring stations allowed from the total nodes (871;(
@  For)Nodes@ :Sum)Nodes:Include)=50;(


 !The Binary constraints ;
@  For)Nodes@:BIN)Include;((

 !The objective;
 !Maximizing demand coverage;

MAX@) = SUM )Nodes: Coverage_sum * Hydraulic_Index * Include;((

END
```

Regional optimization

```
MODEL:
! Optimization sample problem using coverage method 50%;

SETS:
   Nodes: Coverage_6_2 , Include;

!Nodes, Coverage_sum,Include,Risk_index, Sensetivity_Index,
          Vulnerability_Index, Hydraulic_Index, SI_Index, WQ_Index,
          Sum_Indicies, Coverage_hour1, Coverage_6_1, Coverage_12_1;
ENDSETS

!=======================================================================
========;

! Here is the data;
DATA:
   !Importing attribute values and set members from Excel;
   Nodes, Coverage_6_2 =

   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx');


   !Exporting Results to Excel;
   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx')=Include;



ENDDATA

!=======================================================================
========;
```

```
! Total Monitoring Nodes constraint nodes,
  in which I am forcing the complier to use the sum to "include"
  parameter as a tool for determining number of monitoring
  stations ;

! Setting constraint so that at least one monitoring station is choosen
  from each region;

Region_74 = @Sum(Nodes(J) | J #LE# 25: Include(J));

Region_75_A = @Sum(Nodes(J) | J #GE# 26: Include(J));
Region_75_B = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_75 = Region_75_A - Region_75_B;

Region_76_A = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_76_B = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_76 = Region_76_A - Region_76_B;

Region_77_A = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_77_B = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_77 = Region_77_A - Region_77_B;

Region_78_A = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_78_B = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_78 = Region_78_A - Region_78_B;

Region_82_A = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_82_B = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_82 = Region_82_A - Region_82_B;

Region_94_A = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_94_B = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_94 = Region_94_A - Region_94_B;

Region_98_A = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_98_B = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_98 = Region_98_A - Region_98_B;

Region_102_A = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_102_B = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_102 = Region_102_A - Region_102_B;

Region_103_A = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_103_B = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_103 = Region_103_A - Region_103_B;

Region_104_A = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_104_B = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_104 = Region_104_A - Region_104_B;

Region_105_A = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_105_B = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_105 = Region_105_A - Region_105_B;

Region_119_A = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_119_B = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_119 = Region_119_A - Region_119_B;
```

```
Region_120_A = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_120_B = @Sum(Nodes(J) | J #GE# 830: Include(J));
Region_120 = Region_120_A - Region_120_B;

Region_121 = @Sum(Nodes(J) | J #GE# 830: Include(J));


 !In this case I will force the compiler to use at least 1 node in each
region;

@For)Nodes: Region_74>=1;(
@For)Nodes: Region_75>=1;(
@For)Nodes: Region_76>=1;(
@For)Nodes: Region_77>=1;(
@For)Nodes: Region_78>=1;(
@For)Nodes: Region_82>=1;(
@For)Nodes: Region_94>=1;(
@For)Nodes: Region_98>=1;(
@For)Nodes: Region_102>=1;(
@For)Nodes: Region_103>=1;(
@For)Nodes: Region_104>=1;(
@For)Nodes: Region_105>=1;(
@For)Nodes: Region_119>=1;(
@For)Nodes: Region_120>=1;(
@For)Nodes: Region_121>=1;(

======================================================================!
;===

 !Optimization Process;



 !Number of monitoring stations allowed from the total nodes (871;(
@  For)Nodes@ :Sum)Nodes:Include)=50;(


 !The Binary constraints ;
@  For)Nodes@:BIN)Include;((

 !The objective;
 !Maximizing demand coverage;

MAX@) = SUM )Nodes: Coverage_6_2 * Include;((

END
```

```
MODEL:
! Optimization sample problem using coverage method 50%;

SETS:
   Nodes: Coverage_6_2 , Include;

!Nodes, Coverage_sum,Include,Risk_index, Sensetivity_Index,
          Vulnerability_Index, Hydraulic_Index, SI_Index, WQ_Index,
          Sum_Indicies, Coverage_hour1, Coverage_6_1, Coverage_12_1;
ENDSETS

!======================================================================
========;

! Here is the data;
DATA:
   !Importing attribute values and set members from Excel;
   Nodes, Coverage_6_2 =

   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx');


   !Exporting Results to Excel;
   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx')=Include;



ENDDATA

!======================================================================
========;
! Total Monitoring Nodes constraint nodes,
  in which I am forcing the complier to use the sum to "include"
  parameter as a tool for determining number of monitoring
  stations ;

! Setting constraint so that at least one monitoring station is choosen
  from each region;

Region_74 = @Sum(Nodes(J) | J #LE# 25: Include(J));

Region_75_A = @Sum(Nodes(J) | J #GE# 26: Include(J));
Region_75_B = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_75 = Region_75_A - Region_75_B;
```

```
Region_76_A = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_76_B = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_76 = Region_76_A - Region_76_B;

Region_77_A = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_77_B = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_77 = Region_77_A - Region_77_B;

Region_78_A = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_78_B = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_78 = Region_78_A - Region_78_B;

Region_82_A = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_82_B = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_82 = Region_82_A - Region_82_B;

Region_94_A = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_94_B = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_94 = Region_94_A - Region_94_B;

Region_98_A = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_98_B = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_98 = Region_98_A - Region_98_B;

Region_102_A = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_102_B = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_102 = Region_102_A - Region_102_B;

Region_103_A = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_103_B = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_103 = Region_103_A - Region_103_B;

Region_104_A = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_104_B = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_104 = Region_104_A - Region_104_B;

Region_105_A = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_105_B = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_105 = Region_105_A - Region_105_B;

Region_119_A = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_119_B = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_119 = Region_119_A - Region_119_B;

Region_120_A = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_120_B = @Sum(Nodes(J) | J #GE# 830: Include(J));
Region_120 = Region_120_A - Region_120_B;

Region_121 = @Sum(Nodes(J) | J #GE# 830: Include(J));


 !In this case I will force the compiler to use at least 1 node in each
region;

@For)Nodes: Region_74>=1;(
@For)Nodes: Region_75>=1;(
@For)Nodes: Region_76>=1;(
```

```
@For)Nodes: Region_77>=1;(
@For)Nodes: Region_78>=1;(
@For)Nodes: Region_82>=1;(
@For)Nodes: Region_94>=1;(
@For)Nodes: Region_98>=1;(
@For)Nodes: Region_102>=1;(
@For)Nodes: Region_103>=1;(
@For)Nodes: Region_104>=1;(
@For)Nodes: Region_105>=1;(
@For)Nodes: Region_119>=1;(
@For)Nodes: Region_120>=1;(
@For)Nodes: Region_121>=1;(

========================================================================!
;===

 !Optimization Process;



 !Number of monitoring stations allowed from the total nodes (871;(
@  For)Nodes@ :Sum)Nodes:Include)=50;(


 !The Binary constraints ;
@  For)Nodes@:BIN)Include;((

 !The objective;
 !Maximizing demand coverage;

MAX@) = SUM )Nodes: Coverage_6_2 * Risk_Include;((

END
MODEL:
! Optimization sample problem using coverage method 50%;

SETS:
   Nodes: Coverage_6_2 , Include;

!Nodes, Coverage_sum,Include,Risk_index, Sensetivity_Index,
          Vulnerability_Index, Hydraulic_Index, SI_Index, WQ_Index,
          Sum_Indicies, Coverage_hour1, Coverage_6_1, Coverage_12_1;
ENDSETS

!========================================================================
========;

! Here is the data;
DATA:
   !Importing attribute values and set members from Excel;
   Nodes, Coverage_6_2 =

   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx');
```

```
   !Exporting Results to Excel;
   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx')=Include;



ENDDATA

!=======================================================================
========;
! Total Monitoring Nodes constraint nodes,
  in which I am forcing the complier to use the sum to "include"
  parameter as a tool for determining number of monitoring
  stations ;

! Setting constraint so that at least one monitoring station is choosen
  from each region;

Region_74 = @Sum(Nodes(J) | J #LE# 25: Include(J));

Region_75_A = @Sum(Nodes(J) | J #GE# 26: Include(J));
Region_75_B = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_75 = Region_75_A - Region_75_B;

Region_76_A = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_76_B = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_76 = Region_76_A - Region_76_B;

Region_77_A = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_77_B = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_77 = Region_77_A - Region_77_B;

Region_78_A = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_78_B = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_78 = Region_78_A - Region_78_B;

Region_82_A = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_82_B = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_82 = Region_82_A - Region_82_B;

Region_94_A = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_94_B = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_94 = Region_94_A - Region_94_B;

Region_98_A = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_98_B = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_98 = Region_98_A - Region_98_B;

Region_102_A = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_102_B = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_102 = Region_102_A - Region_102_B;

Region_103_A = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_103_B = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_103 = Region_103_A - Region_103_B;
```

```
Region_104_A = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_104_B = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_104 = Region_104_A - Region_104_B;

Region_105_A = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_105_B = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_105 = Region_105_A - Region_105_B;

Region_119_A = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_119_B = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_119 = Region_119_A - Region_119_B;

Region_120_A = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_120_B = @Sum(Nodes(J) | J #GE# 830: Include(J));
Region_120 = Region_120_A - Region_120_B;

Region_121 = @Sum(Nodes(J) | J #GE# 830: Include(J));


 !In this case I will force the compiler to use at least 1 node in each
region;

@For)Nodes: Region_74>=1;(
@For)Nodes: Region_75>=1;(
@For)Nodes: Region_76>=1;(
@For)Nodes: Region_77>=1;(
@For)Nodes: Region_78>=1;(
@For)Nodes: Region_82>=1;(
@For)Nodes: Region_94>=1;(
@For)Nodes: Region_98>=1;(
@For)Nodes: Region_102>=1;(
@For)Nodes: Region_103>=1;(
@For)Nodes: Region_104>=1;(
@For)Nodes: Region_105>=1;(
@For)Nodes: Region_119>=1;(
@For)Nodes: Region_120>=1;(
@For)Nodes: Region_121>=1;(

======================================================================!
;===

 !Optimization Process;



 !Number of monitoring stations allowed from the total nodes (871;(
@  For)Nodes@ :Sum)Nodes:Include)=50;(


 !The Binary constraints ;
@  For)Nodes@:BIN)Include;((

 !The objective;
 !Maximizing demand coverage;

MAX@) = SUM )Nodes: Coverage_6_2 * Vulnerability_Include;((
```

```
END



MODEL:
! Optimization sample problem using coverage method 50%;

SETS:
   Nodes: Coverage_6_2 , Include;

!Nodes, Coverage_sum,Include,Risk_index, Sensetivity_Index,
          Vulnerability_Index, Hydraulic_Index, SI_Index, WQ_Index,
          Sum_Indicies, Coverage_hour1, Coverage_6_1, Coverage_12_1;
ENDSETS

!======================================================================
========;

! Here is the data;
DATA:
   !Importing attribute values and set members from Excel;
   Nodes, Coverage_6_2 =

   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx');


   !Exporting Results to Excel;
   @OLE('C:\LINGO12\Dissertation\Network\With Regional
Constraints\Excel for lingo (Regional Constraints) 60%
corrected.xlsx')=Include;



ENDDATA

!======================================================================
========;
! Total Monitoring Nodes constraint nodes,
  in which I am forcing the complier to use the sum to "include"
  parameter as a tool for determining number of monitoring
  stations ;

! Setting constraint so that at least one monitoring station is choosen
  from each region;

Region_74 = @Sum(Nodes(J) | J #LE# 25: Include(J));

Region_75_A = @Sum(Nodes(J) | J #GE# 26: Include(J));
Region_75_B = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_75 = Region_75_A - Region_75_B;

Region_76_A = @Sum(Nodes(J) | J #GE# 84: Include(J));
Region_76_B = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_76 = Region_76_A - Region_76_B;
```

```
Region_77_A = @Sum(Nodes(J) | J #GE# 104: Include(J));
Region_77_B = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_77 = Region_77_A - Region_77_B;

Region_78_A = @Sum(Nodes(J) | J #GE# 112: Include(J));
Region_78_B = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_78 = Region_78_A - Region_78_B;

Region_82_A = @Sum(Nodes(J) | J #GE# 118: Include(J));
Region_82_B = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_82 = Region_82_A - Region_82_B;

Region_94_A = @Sum(Nodes(J) | J #GE# 120: Include(J));
Region_94_B = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_94 = Region_94_A - Region_94_B;

Region_98_A = @Sum(Nodes(J) | J #GE# 223: Include(J));
Region_98_B = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_98 = Region_98_A - Region_98_B;

Region_102_A = @Sum(Nodes(J) | J #GE# 374: Include(J));
Region_102_B = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_102 = Region_102_A - Region_102_B;

Region_103_A = @Sum(Nodes(J) | J #GE# 485: Include(J));
Region_103_B = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_103 = Region_103_A - Region_103_B;

Region_104_A = @Sum(Nodes(J) | J #GE# 553: Include(J));
Region_104_B = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_104 = Region_104_A - Region_104_B;

Region_105_A = @Sum(Nodes(J) | J #GE# 583: Include(J));
Region_105_B = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_105 = Region_105_A - Region_105_B;

Region_119_A = @Sum(Nodes(J) | J #GE# 594: Include(J));
Region_119_B = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_119 = Region_119_A - Region_119_B;

Region_120_A = @Sum(Nodes(J) | J #GE# 741: Include(J));
Region_120_B = @Sum(Nodes(J) | J #GE# 830: Include(J));
Region_120 = Region_120_A - Region_120_B;

Region_121 = @Sum(Nodes(J) | J #GE# 830: Include(J));


 !In this case I will force the compiler to use at least 1 node in each
region;

@For)Nodes: Region_74>=1;(
@For)Nodes: Region_75>=1;(
@For)Nodes: Region_76>=1;(
@For)Nodes: Region_77>=1;(
@For)Nodes: Region_78>=1;(
@For)Nodes: Region_82>=1;(
```

```
@For)Nodes: Region_94>=1;(
@For)Nodes: Region_98>=1;(
@For)Nodes: Region_102>=1;(
@For)Nodes: Region_103>=1;(
@For)Nodes: Region_104>=1;(
@For)Nodes: Region_105>=1;(
@For)Nodes: Region_119>=1;(
@For)Nodes: Region_120>=1;(
@For)Nodes: Region_121>=1;(

=======================================================================!
;===

 !Optimization Process;



 !Number of monitoring stations allowed from the total nodes (871;(
@  For)Nodes@ :Sum)Nodes:Include)=50;(


 !The Binary constraints ;
@  For)Nodes@:BIN)Include;((

 !The objective;
 !Maximizing demand coverage;

MAX@) = SUM )Nodes: Coverage_6_2 * Sensetivity_Include;((

END
```

APPENDIX D

(CD)

Multi-Criteria Decision Making Model
&
DSS Model

Vitae

Name :Amin Ali Abo-Monasar

Nationality :Yemeni

Date of Birth :3/4/1981

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Address :Dhahran – Saudi Arabia

Academic Background :- PhD – Water Resources and Environmental Engineering, KFUPM , Master of science – Water Resources and Environmental Engineering, KFUPM and Bachelor – Civil Engineering from Umm Al-Qura University. Lecturer and research assistant at KFUPM since 2007, member of the Water Research Group (WRG) since 2009 and member of the Water Environment Federation (WEF) since 2010. Interested in developing optimal water distribution systems and developing monitoring systems for distribution networks. Interested also in developing decision support systems for distribution networks and modeling floods in arid regions.