A Decision-making Framework for Water Distribution Systems using Fuzzy Inference and Centrality Analysis

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ABSTRACT: Water Distribution Systems (WDSs) are among the most important infrastructures that are critical for the smooth functioning of communities. However, age-old existing WDSs are progressively at risk in the United States. Since failure in a WDS may affect other interdependent infrastructure and result in high economic consequences, water utilities are more interested in preventing rather than reacting to failure. The current study proposes a decision support framework that employs fuzzy hierarchical inference and network graph analysis to rank the most vulnerable water pipelines considering a set of risk factors and their negative consequences. Fourteen (14) risk factors are identified considering water and road network interdependence. These factors are classified into four main vulnerability indices (strength, hydraulic, environmental, road) and one consequence class in order to evaluate the integrated risk of water mains. Fuzzy analytical hierarchy process is used to quantify the uncertainty in the risk factors to aid the decision-making process. Network centrality analysis is used to identify the most critical components of the WDS. The final decision is made by combining the outputs from the fuzzy inference and the network centrality analysis. The WDS of Modena, Italy is used to demonstrate the proposed approach.

1. INTRODUCTION

The performance of a WDS is often closely linked with other infrastructures (e.g. road network) due to physical proximity, functional dependency, shared resources, etc. (Rinaldi et al. 2001). Most water pipelines are laid underground and often follow road networks. Past failures in water mains often led to failures of other inter-dependent infrastructures and resulted in huge economic losses (Zimmerman 2004). Hence, water utilities have become more interested in preventing rather than reacting to water pipeline failures.

Existing water networks in the United States are at risk as a majority of water pipelines are old, with many of them past their expected lifespan. Each year, about 240,000 water main breaks occur throughout the United States (ASCE 2017). In the current context, many municipalities need to prioritize maintenance decisions under financial constraints and identify the riskiest pipelines under interdependency consideration.

Performance evaluation and condition assessment have been extensively studied in the past for water pipelines (e.g. Shamir and Howard 1979; Rajani and Makar 2000). However, studies on the integrated performance assessment that leads to decision making considering interdependency effect are rare. Most of the studies on WDS performance evaluation are performed separately from other infrastructure systems. Recently, some effort have been made to evaluate the condition of WDS considering interdependence effect of the road network (e.g., Shahata and Zayed 2016; Elsawah et al. 2016). These studies, however, have some limitations. For example, identification of critical components of a complex network (graph) system is often ignored during the decision-making process. Other limitations include the lack of consideration of the propagation of system disruption, risk updating, etc. (Ismaeel and Zayed 2018). Fuzzy-based hierarchy structure and network centrality analysis can overcome these limitations.

The main focus of the current study is to formulate an integrated decision-making framework that considers the interdependence between WDS and the road network for facilitating rehabilitation planning. The integrated decision-making framework combines the condition rating and centrality analysis results of WDS. The proposed framework is presented in the next section.

2. PROPOSED FRAMEWORK

In order to formulate a comprehensive decision-making tool, the current study integrates road factors that influence the performance of WDS. Figure 1 illustrates procedures and components of the proposed framework. The proposed framework uses Water Network Tool for Resilience (WNTR) to perform water hydraulic and network centrality analysis (Klise et al. 2017). Identified risk factors values are transferred into the fuzzy scale and Mamdani type input-output rules are applied for risk quantification in the fuzzy hierarchical inference. The outputs from fuzzy inference and network centrality analysis are combined using Geographic Information System (GIS) tool to generate decision alternatives. The output of this decision-making tool can be used for prioritizing preventive maintenance actions.

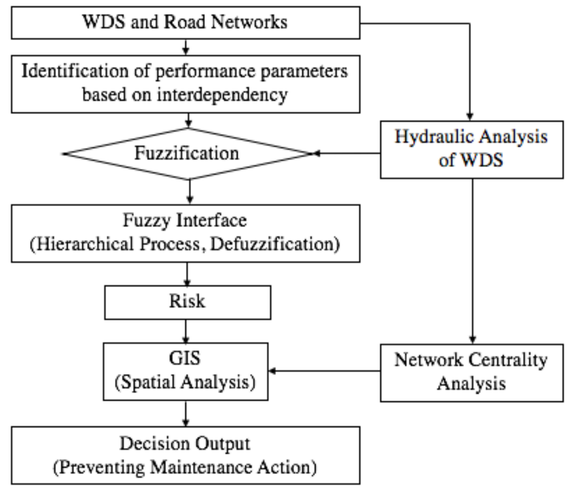

Figure 1: Proposed decision-making framework

3. PERFORMANCE INDICATORS

Water distribution pipelines typically run under road networks and failures in WDS often leads to failures in road systems and vice versa. Integrated consequence due to failure in any of these two systems needs to be considered in risk assessment. A comprehensive literature review has been performed towards the identification of important parameters that are responsible for the failure and interdependency consequence of both infrastructures. A comparison of contributing risk factors used in past research for evaluating the performance of WDS is presented in Table 1. Past risk assessment methods considered the potential consequence of failure in the system in terms of direct and indirect losses (Fares and Zayed 2010). Past methods classified risk factors into various performance classes such as physical, hydraulic, operational, etc. The current study uses 14 risk factors that are responsible for the integrated performance of WDS.

Table 1: Performance parameters of WDS

Reference	Parameters												Net.
	D	t	M	ST	RT	NL	LU	TL	d	A	AC	RF	
Elsawah et al. (2016)	√	√	√	√	√	√	√	√	√	X	√	X	W, R, S
Shahata and Zayed (2016)	√	√	√	√	√	√	√	√	√	X	√	X	W, R, S
Ismaeel and Zayed (2018)	√	√	√	√	X	X	√	X	√	√	X	√	W
Fares and Zayed (2010)	√	√	√	√	X	X	√	√	X	√	X	X	W
Kabir et al. (2015)	√	√	√	√	√	X	√	√	X	√	X	X	W

**W: water network; R: road network; S: sewer network; D: diameter; t: thickness; M: pipe material; ST: soil type; RT: road type; NL: no. of lanes; LU: land use; TL: traffic load; d: burial depth; AC: accessibility; A: age; RF: roughness*

4. FUZZY MEMBERSHIP

In WDS performance evaluation problems, the probability of various performance indicators is represented vaguely and imprecisely (Sadiq et al. 2007). Zadeh (1965) provided a fuzzy set theory to overcome the problem associated with crisp and imprecise representation of probabilities. Fuzzy logic is a useful technique to transfer qualitative human knowledge into numerical reasoning (Demartinos and Dritsos 2006). The fuzzy-based technique is preferable in many decision-making models as it is capable of incorporating human jurisdiction whenever a database is incomplete.

Fuzzy membership can be defined in various ways, such as triangular, trapezoidal, Gaussian, singleton, etc. The risk parameters are transformed into fuzzy membership ranges [0, 1]. The membership function of each parameter can be defined based on the available information, knowledge, literature review, contribution to the risk of failure, etc. The integrated risk of failure can be determined if vulnerability and consequence are identified. Based on the literature review, 14 parameters are classified into four vulnerability indices (physical strength, hydraulic, environmental and road) and one consequence index depending on their influence to the failure and consequence.

4.1. Physical Strength Index

The physical strength index parameters are pipe diameter, age, thickness, and material type (see Table 2). Past research shows that large diameter pipelines experience lesser number of breaks compared to smaller diameter pipelines. This is because larger diameter pipelines have stronger beam strength than comparatively smaller diameter pipelines (Najafi 2005). Pipeline wall thickness is a vital strength performance indicator for metallic pipes. Most buried water mains in the USA are metallic and the relatively thicker pipes are more resistant to failure (Mazumder et al. 2018). Many researchers have identified pipe age as the most important factor that determines the likelihood of failure (Kleiner and Rajani 2001). Pipe material is also an indicator of pipe strength. Flexible pipelines (e.g. PVC) are capable of tolerating more deflection than rigid pipelines (e.g. Concrete) as they can transfer ground overloads to the surrounding soil beneath it (Potter 1985; Zhang et al. 2016). Cast iron pipelines have experienced more breaks in the past (Mazumder et al. 2018).

4.2. Hydraulic Index

The hydraulic index parameters include water pressure and roughness. Water pressure at demand nodes is a measure of the hydraulic performance of WDS (Kabir et al. 2015). Higher surplus head at a node indicates more resiliency in the system especially during minor and moderate head losses (Todini 2000). Roughness is typically represented by the Hazen-William Coefficient (C-Factor). Higher roughness degrades the hydraulic performance of WDS (Al-Barqawi & Zayed 2008).

4.3. Environmental Index

The environmental index parameters are soil corrosivity and freezing factor. Soil type is a key factor in the corrosion behavior of metallic pipelines (Al-Barqawi & Zayed, 2008). The soil corrosion characteristics are influenced by different chemical characteristics (e.g. pH, resistivity, etc.) of the surrounding soil (Fares and Zayed 2010). Temperature drops impose excessive pressure on pipelines and frost loading can increase the failure risk of water mains (Mazumder et al. 2018). Literature reveals that underground pipes experience relatively higher rate of failure during cold temperatures (Moser and Folkman 2001). Freezing factor can be used as a surrogate measure to account for cold weather effects on water pipe failures (Kabir et al. 2015).

4.4. Road Index

The road index parameters include pipe buried depth, pavement type, number of lanes, and traffic load. Heavy traffic load induces higher stress on pipelines and high-speed vehicles induce dynamic loads on pipelines (Potter 1985; Zhang et al. 2016). The number of lanes is an important measure of the redundancy of roadways and the type of pavement indicates the condition of roadways (Al-Barqawi & Zayed 2008; Fares & Zayed 2010). Effect of traffic load on pipelines decreases with higher burial depth. Buried pipelines located in shallow depths are more prone to damage due to combined traffic and underground loads. Increase in burial depth reduces the effect of imposed forces on the pipeline (Zhang et al. 2016).

4.5. Consequence Index

The consequence index of water mains failure includes a number of parameters. In the current study, pipe diameter, pipe type, burial depth, neighbourhood land use, and population density are considered to determine the consequence of failure. The consequence due to larger water mains failure is expected to be higher than the consequence of the failure of smaller water mains (Sahata and Zayed 2016). Type of pipe material is an important indicator of replacement cost. The cost of replacing concrete and metallic pipes is higher than the cost of replacing PVC pipes. The cost of rehabilitation and replacement increases with the burial depth. Losses can vary significantly due to the pattern of usage of the nearby area in case of a water main failure. For example, the impact in an industrial area will be more than the impact of the same failure in an agricultural area (Francisque et al. 2009). Population mass density is measured by the number of people living in a square kilometer. More people will be affected in densely populated regions (Kabir et al. 2015).

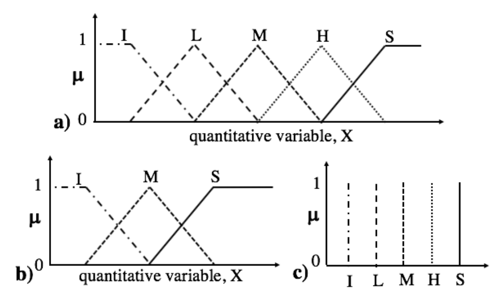

Figure 2: Fuzzy membership; a) diameter, age, roughness, indices b) thickness, water pressure, soil corrosivity, freezing factor, burial depth, traffic load, population density and c) material type, pavement type, land use

4.6. Fuzzy Membership Functions

Five standard membership functions are used, and their corresponding score is evaluated from 0 to 1 corresponding to a rating of insignificance and severity, respectively. Figure 2 shows the fuzzy membership representation of triangular, trapezoidal and singleton functions. The granularity fuzzy membership functions (singleton, triangular and trapezoidal are used in the current study) for risk factors are given in Table 2.

Table 2: Risk factors analyzed

Item	Unit	I	L	M	H	S
Strength Index						
Pipe diameter	mm	[600 600 500 400]	[500 400 300]	[400 300 200]	[300 200 100]	[200 100 0 0]
Pipe age	year	[0 0 10 20]	[10 30 50]	[30 50 70]	[50 70 90]	[70 90 100 100]
Pipe thickness	mm	[50 50 30 20]	-	[30 20 10]	-	[20 10 0 0]
Pipe material	-	PVC		Asbestos/Corrugated Steel		Steel, CI, DI/ Concrete
Hydraulic Index						
Water pressure	m	[100 100 90 70]	-	[90 70 50]	-	[70 50 30 30]
Roughness	C	[150 150 130 110]	[150 130 110]	[130 110 90]	[110 90 70]	[70 50 30 30]
Environmental Index						
Soil corrosivity	-	Low	-	Moderate	-	High
Freezing factor	-	[0 0 0.5 1.0]	-	[0.5 1.0 1.5]	-	[1.0 1.5 2.0]
Road Index						
Buried depth	m	[12 12 8 5]	-	[8 5 3]	-	[5 3 0 0]
Pavement type	-	Reinforced	Asphalt	Seal	Footpath	Unpaved
No. of lanes	-	≥4	-	2	-	1
Traffic load	-	Low	-	Moderate	-	Heavy
Consequences						
Pipe diameter	mm	[0 0 100 200]	[100 200 300]	[200 300 400]	[300 400 500]	[400 500 600 600]
Pipe material	-	-	PVC	Asbestos/ Corrugated Steel	Steel, CI, DI	Concrete
Burial depth	m	[0 0 3 5]	-	[3 5 8]	-	[5 8 12 12]
Land use		Open space/Agricultural		Residential		Industrial
Population density	ppl/ km^2	[0 0 500 1000]	-	[500 1000 1500]	-	[1000 1500 2500 2500]
Intermediate Layer Variables (SI, HI, EI, RI, Vul, CI)						
Index	-	[0 0 1 0.3]	[0.1 0.3 0.5]	[0.3 0.5 0.7]	[0.5 0.7 0.9]	[0.7 0.9 1.0 1.0]

*I=Insignificant; L=Low; M=Moderate, H=High; S=Severe, ppl=population

5. FUZZY HIERARCHICAL INFERENCE

In the current study, the risk factors are categorized into five classes depending on their influence on the overall risk. The risk factors are evaluated through fuzzy hierarchical inference for risk aggregation, as shown in Figure 3.

In the fuzzy inference system, risk parameters are classified into five classes and range values from 0 to 1. The knowledge-base (using literature) technique is used to develop the fuzzy rules. Mamdani fuzzy input-output rules system is applied in this fuzzy inference. Mamdani fuzzy inference uses simple rules based on if and then relationship and is easy to understand (Mamdani 1976; Fares and Zayed 2010). A typical form of the fuzzy rule can be expressed as below;

$$IF\ (Antecedent)\ THEN\ (Consequence)$$

$$R^i = IF\ (x_1 is\ A_1^i\ and\ x_2 is\ A_2^i\ and\ \dots\dots.\ and\ x_n is\ A_n^i)\ THEN\ (y\ is\ B^j);\quad i,j=1,2,\dots.,n \qquad (1)$$

where R^i is the i-th rule; A_1^i is input subsets; B^j is output subsets.

The rule-base fuzzy system typically requires a large number of inputs to account for the fuzzy behaviour of all possible ranges of input variables. The fuzzy inference process allows for determining consequent functions based on the antecedent functions. The fuzzy rules use 'and' operator to get the consequence function depending on output values. Then the fuzzy consequence value is obtained using the minimum operator, as shown below (Fares and Zayed 2010);

$$\mu_R\,(x_1, x_2 \dots\dots, x_n, y) = \wedge_{i=1}^{n}[\mu_R{}^j(x_1, x_2 \dots\dots, x_n, y)] \qquad (2)$$

where ∧ represents the minimum operator. The consequence values of fuzzy rules are aggregated by using the maximum operator, as expressed in the equation below;

$$\mu_R\,(x_1, x_2 \dots\dots, x_n, y) = \vee_{i=1}^{N}[\mu_R{}^j(x_1, x_2 \dots\dots, x_n, y)] \qquad (3)$$

where ∨ represents the maximum operator and R denotes the consequent membership functions defining a range from insignificant to severe.

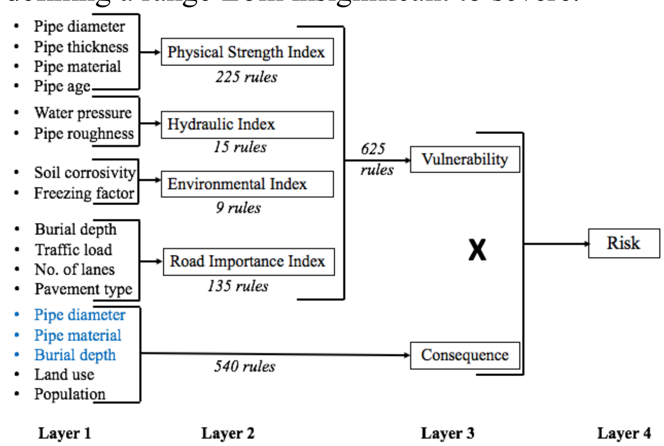

Figure 3: Fuzzy hierarchical structure

Each hierarchical layer uses the defuzzification process to convert fuzzy output numbers into crisp values. The centroid of area method is applied in this study to determine the crisp number. The final layer quantifies the overall risk by multiplying vulnerability and consequence values. The five qualitative risk functions are evaluated on a quantitative scale [0, 1], as shown in Table 3.

Table 3: Risk scaling

Risk Score	Likelihood of failure	Letter Grade	Description
≥ 0.9	Severe	S	Severe impact on the performance and consequence
0.7	High	H	Highly influence the performance and at risk
0.5	Moderate	M	Moderately affect the system component
0.3	Low	L	Minor impact on the performance
≤ 0.1	Insignificant	I	No or very little influence on the performance

6. NETWORK CENTRALITY ANALYSIS

WDS is often large and inherently complex due to its nature, topology and operation. Condition rating alone is not sufficient to prioritize maintenance decisions. Network centrality analysis, along with risk analysis explained in previous sections, can be a useful tool to prioritize maintenance decisions by utility managers under budget constraints and resource limitation. A WDS can be represented by a graph G (n, e) composed of a collection of n junctions (e.g. node) connected by e edges (e.g. pipeline). In a WDS, a node is defined as a consumer point or source (pump, tank, reservoir) and an edge represents transmission or distribution mains (Hawick 2012). A graph can be either directed or undirected depending on the representation of edge direction. A graph is said to be undirected if a node can be reached from any other nodes whereas in directed graph, nodes can be reached by following directed edges only. For simplicity of analysis, all of the graphs are assumed to be undirected in this study.

6.1. Node Degree (ND)

The simplest centrality measure is called degree centrality. ND refers to the number of nearest neighbours. A higher importance is given to a node that is connected to more nodes. ND is expressed as (Barthélemy, 2011);

$$N_D(i) = \sum_{j \subset n} a_{ij} \tag{4}$$

where n is the number of nodes and a_{ij} denotes the matrix elements.

6.2. Betweenness Centrality (BC)

In a graph, a node may not be important locally but may be important globally if many access flows need to pass through it (Hawick 2012). BC measures the number of shortest pathways that passes through each node or edge (Barthélemy, 2011). BC is calculated by the following equation;

$$B_C(i) = \sum_{s \neq t \neq v \in V} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}} \tag{5}$$

where σ(υ) is the number of connecting paths that pass-through node υ, σ is the total number of shortest paths from node s to node t.

6.3. Closeness Centrality (CC)

This measure is calculated as the reciprocal of the sum of the length of shortest pathways from a node to all other nodes in the network. Hence, the node is said to be more central if it is closer to other nodes. CC, normalized by the sum of minimum possible distances, is defined as (Barthélemy, 2011).;

$$C_C(i) = \frac{n-1}{\sum_{v=1}^{n-1} d(v,u)} \tag{6}$$

where n is the number of nodes in the graphs and d(υ,u) represents the shortest path distance between the node υ and u.

7. ILLUSTRATIVE EXAMPLE

The WDS of Modena city, Italy, taken from the Centre for Water Systems at the University of Exeter is used to demonstrate the proposed framework. The network consists of 268 nodes (junctions), 317 elements (pipes) and 4 reservoirs (sources), as shown in Figure 4a. However, due to the unavailability of actual data of the risk parameters, desired values of risk parameters are randomly generated. The water pressure is calculated using EPANET and the maximum pressure of end nodes is considered for a particular pipeline. Table 4 shows a part of 14 risk parameters data of the Modena WDS.

Table 4: Risk parameters of Modena WDS

ID	Diameter (mm)	Thickness (mm)	Age (yr)	Material Type	Pressure (m)	C-Factor	Freezing Factor	Soil Corrosivity	Burial Depth	Pavement	Traffic Load	No. of Lanes	Lan Use	Pop Density (ppl/km)
1	510	7	84	CI	59.9	105.7	1	Low	4.7	Asphalt	Low	4	Ind	1731
2	576	12	92	PVC	57.5	97.2	2.5	Mod	0.6	Asphalt	Low	4	Ind	1338
3	598	7	100	DI	42.2	80.2	1	High	1.5	Unpav	Low	2	Ind	652
4	403	9	86	DI	56.5	133.5	1.5	High	6.2	Asphalt	Low	4	Ind	1352
5	470	8	48	CI	45.4	76.1	1	Low	2.8	Asphalt	Low	2	Ind	1394
6	507	12	59	PVC	51.2	134.8	1.5	Mod-Low	6.7	Unpav	Low	2	Res	617
7	550	12	41	CI	42.7	43.0	1	Low	1.1	Asphalt	Low	4	Res	1609
8	594	11	82	PVC	27.7	84.1	1	Low	5.6	Seal	Low	1	Res	1113
9	539	12	98	CI	56.3	110.1	2.5	Low	1.5	Asphalt	Low	1	Ind	2004
10	454	11	84	Steel	40.6	110.3	1	High-Mod	3.2	Asphalt	Low	1	Res	2157
11	591	12	84	CI	60.0	91.0	1	Low	2.7	Reinforced	Low	1	Ind	1054
12	582	8	50	CI	35.1	101.2	2.5	Mod-Low	7.4	Footpath	Low	1	Ind	1103
13	491	11	61	PVC	28.2	114.6	2.5	Mod-Low	6.7	Seal	Low	2	Ind	757
14	547	10	75	DI	49.2	120.1	2	Low	5.0	Reinforced	Hev-Mod	4	Res	1834

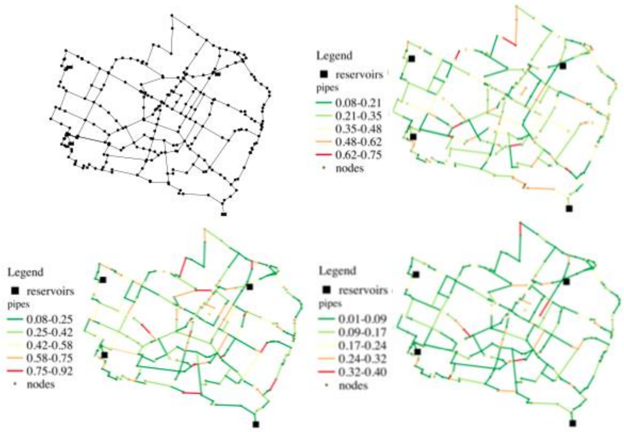

Figure 4: WDS of Modena, Italy; a) Network model; b) Vulnerability; c) Consequence and d) Risk

The vulnerability and consequence of Modena WDS obtained from fuzzy hierarchical process are represented in GIS, as shown in Figure 4b and Figure 4c, respectively. The final risk of a component is obtained by multiplying the vulnerability and consequence scores, as shown in Figure 4d. Network centrality analysis is performed to identify critical components of the network. Figure 5 shows various centrality measures of Modena WDS. This figure shows the relative importance of components in the WDS. Components marked with red colors in Figure 5 are more critical than other components of the WDS.

Based on centrality analysis, criticality rating (1.0, 1.05, 1.1, 1.15 and 1.2) is assigned to a component based on its relative criticality importance (higher value is assigned to highly critical component). Then the final decision output is obtained by multiplying the risk analysis result by the criticality rating. Figure 6 shows different priority groups (priority group 1 to priority group 5) for maintenance decision of WDS components. Components with higher priority should be maintained before those with lower priority.

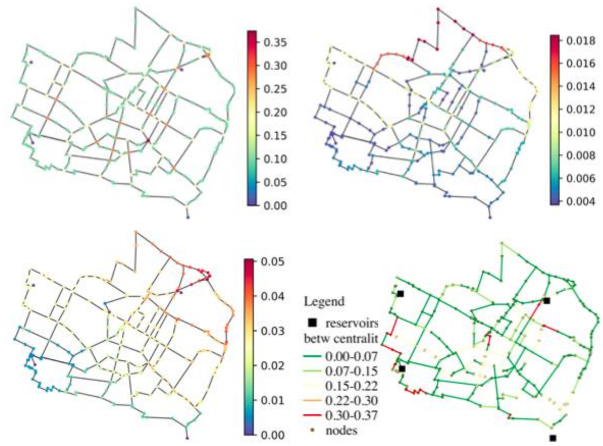

Figure 5: Network centrality measures of Modena WDS; a) normalized ND, b) normalized BC of nodes, c) CC of nodes and d) BC of pipes

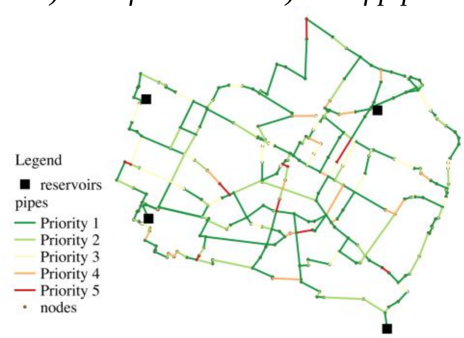

Figure 6. Decision support output

8. CONCLUSION

In the current study, integrated decision-making tool is developed utilizing fuzzy inference and network centrality analysis. A number of risk parameters that influence the performance of WDS are identified through rigorous literature review. The risk parameters are classified into four vulnerability classes and one consequence class in order to perform fuzzy hierarchical inference analysis. At the same time, topological vulnerability or the critical component of WDS is identified through network centrality analysis. The proposed concept is illustrated for the WDS of Modena, Italy. However, due to unavailability of real data, hypothetical data was generated randomly for the purpose of demonstration. Final decision support map was generated combining the outputs from fuzzy inference and network centrality analysis.

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