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Asset Management Decision Support Model for Water Distribution Systems: Impact of Water Pipe Failure on Road and Water Networks

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Abstract: Failure of a buried water pipeline can have an adverse effect on neighboring infrastructure, especially road networks. The impact of the failure of water pipelines on road networks and water distribution systems (WDSs) significantly increases the economic and social consequences of such failure. This paper presents a risk-informed decision support framework for WDSs considering the risk and the criticality of components to aid maintenance prioritization. The probability of water pipe failure is estimated using a physical probabilistic approach. The economic, operational, environmental, and social consequences of the failure of the integrated water and road segments are evaluated using 14 factors. The economic, operational, environmental, and social consequences are combined using fuzzy hierarchical inference to determine the overall consequence of the failure of each integrated segment (road and water network sharing the same geographical space). The risk of assets is determined by utilizing two approaches: risk equation and risk matrix. A shortest path–based network efficiency metric is then used to identify the impact of the failure of water pipelines on both infrastructure systems. The final decision alternatives are prepared by combining the outputs from the risk analysis and the network efficiency metric to prioritize maintenance tasks. A geospatial model is used to identify dependent road and collocated water segments sharing the same geographical space. The water and road networks of the Rancho Solano Zone III area of the city of Fairfield, California, are used to illustrate the proposed framework. The results show that the failure of a critical segment can have a significant impact on the efficiency of both networks. In the considered case study, the failure of a critical segment can result in about 7.5% and 9.6% system efficiency loss in the water and road networks, respectively. The proposed model is expected to assist in integrated municipal asset management decision-making. **DOI: 10.1061/(ASCE)WR.1943-5452.0001365.**

Introduction

The performance of water distribution systems (WDSs) is typically linked to other neighboring infrastructures due to physical proximity, functional dependency, shared resources, and so on. (Atef and Moselhi 2013; Ng and Cai 2013; Rinaldi et al. 2001). Zimmerman (2004) analyzed a set of previous failures of interdependent infrastructure systems and concluded that failures in water networks are the most damaging to other infrastructures, especially road networks. This is because most water pipelines laid underground often follow road networks. As such, failures in water mains often led to cascading failures to road networks resulting in huge economic losses, and vice versa (Atef and Moselhi. 2014; Ostfeld 2014). 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 of failure because a majority of water pipelines are old, with many of them running beyond their expected life. Each year, about 240,000 water main breaks occur throughout the United States, and roughly $2.1 trillion is required to replace all of the existing pipelines. It will cost about $1 trillion over 25 years to replace only the most urgent pipelines (ASCE 2017; AWWA 2012). Hence, many municipalities need to prioritize maintenance under financial constraints and identify the riskiest pipelines.

In the current literature, integrated asset management decision models considering the interdependency between water and road networks are rare. Most of the studies on WDS performance evaluation are performed separately from other infrastructure systems (e.g., Al-Barqawi and Zayed 2008; Fares and Zayed 2010; Phan et al. 2018). Recently, some effort has been made to evaluate the condition of WDSs, considering interdependency with road networks. Abu Samra et al. (2017) developed a multiobjective decision support tool for intervention activities for integrated road and water networks. The multiobjective framework considered four aspects (physical state, life-cycle cost, user cost, and replacement value) and analyzed six parameters of the road and three parameters of the water network for developing an intervention scheduling and rehabilitation alternatives. Shahata and Zayed (2016) developed a comprehensive risk assessment framework for municipal infrastructures (sewer, water, and road). The Delphi-based analytical hierarchy process was used to assign weights to 18 risk factors, and a risk matrix was formulated by combining the probability of failure and consequence of failure for rating overall risk of integrated

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Note. This manuscript was submitted on May 13, 2020; approved on November 15, 2020; published online on March 10, 2021. Discussion period open until August 10, 2021; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496.

segments. Similarly, Elsawah et al. (2016) formulated a criticality index for water and sewer networks for prioritizing the infrastructure intervention under budget limitation and resource constraints. The authors accounted for 13 social, economic, and environmental factors for consequence quantification. Most of these studies classified a branch of parameters (e.g., pipe age, diameter, type of road, soil type, etc.) into physical, operational, environmental, and economic factors, among others, for determining the failure likelihood of water mains and potential failure consequences. However, while determining the risk and developing decision alternatives, none of these methods quantifies the importance of pipelines based on topological and hydraulic measures to determine the performance of complex WDSs.

WDSs are typically complex and composed of a large number of subsystems. As such, rehabilitation decisions based on standalone structural or hydraulic analysis often cannot capture the importance of an individual component's contribution to system performance. Along with risk assessment, identification of criticality of the components in a network based on graph theory can provide a meaningful alternative in the decision-making process. Graph theory has been extensively used in previous research for identifying critical components and system reliability of a complex network. In the reliability analysis problem, incorporating isolation valves and removing a segment from a WDS need to be accounted for adequately when evaluating system reliability after pipe failure (Walski 2020a, b). Despite its importance, the role of isolation valves was often ignored in previous analyses, especially for estimating the reliability of a partially failed system (Walski 2020a, b). Isolation valves, located along pipelines, need to be closed to remove failed segments from the system. Although incorporating an isolation valve would be useful to develop a better decision model, it is often not possible due to a lack of available information (e.g., valve location, characteristics). Many valves are not operable in most WDSs due to many reasons, such as misaligned box, presence of debris, and so on (Walski 2020b). When valve location and characteristics are not known, graph theory–based measures can still be useful to support decision-making (Balekelayi and Tesfamariam 2019).

Topological matrices have been studied to identify the critical components of various network systems (Crucitti et al. 2005; Latora and Marchiori 2001; Duenas-Osorio and Vemuru 2009; Campbell et al. 2015). Yazdani and Jeffrey (2012) investigated the relationship between structural configuration and functionality of WDSs utilizing network-based theory to measure the system vulnerability and robustness. Torres et al. (2017) explored a WDS's topological effects by developing a large set of lattice-like pipe networks. The authors found a strong correlation between graph theory–based matrices and performance measures of WDSs. Giustolisi et al. (2017) used a topology-based neighborhood centrality metric for classifying WDS infrastructure. Balekelayi and Tesfamariam (2019) aggregated four topological metrics results and compared them with a WDS's hydraulic performance. The author used the Bayesian belief network-based data fusion technique to improve the accuracy of topological metrics. Giudicianni et al. (2020) used various centrality matrices, such as betweenness centrality and Katz centrality, to place sensors in a WDS without performing hydraulic analysis.

Atef and Moselhi (2014) modeled the functional interdependency between water, sewer, and road networks using four centrality measures (betweenness centrality, neighborhood centrality, relative closeness centrality, and significant point of variance). Boeing (2017) analyzed complex street networks by developing an open-source OSMnx Python tool. Other studies (Su et al. 1987; Shinstine et al. 2002; Yannopoulos and Spiliotis 2013; Mazumder et al. 2019) applied the adjacent matrix method and minimum cut sets approach to determine the system reliability of water networks. Although previous studies utilized graph theory for identifying the critical components and reliability measures, only a few of them integrated network analysis results in a decision-making problem.

The objective of this paper is to develop a risk-informed decision support framework for WDSs, considering the criticality of components within a network. The aim is to support utility managers to prepare an asset management plan by identifying the impact on the infrastructure systems due to failure of water segments on the basis of expected pipe failure, integrated consequences, and system topological performance metric. The decision support model also accounts the effect of water pipeline failure on road networks to aid maintenance prioritization. The proposed framework is expected to help utility managers with rehabilitation planning and maintenance decision-making. The proposed framework is presented in detail in the next section.

Research Framework

The proposed framework consists of three modules: (1) risk assessment, (2) dependency analysis, and (3) decision-making. In the risk assessment module, the riskiest segments of the water and road networks are identified utilizing a risk equation and a risk matrix, as subsequently described in the paper. The risk equation and the risk matrix are formulated based on the pipeline fragility and the consequences of failure. The time-variant failure probability of individual pipelines is estimated using a physical probabilistic pipe failure method. Fourteen factors are incorporated in this research through rigorous literature review for determining the consequence of the failure of integrated water and road segments. Consequence factors are mapped into fuzzy membership functions, and a Mamdani-type input–output rule-based fuzzy hierarchical inference system is used for consequence quantification. Infrastructure assets are categorized into five risk groups, depending on their performances.

In the decision-making module, due to budget constraints and resource limitation, utilities often need to prioritize their assets even among components with the same risk level. Hence, using the complex network theory, criticality of a component in a network or graph is identified using a shortest path–based network efficiency metric. The NetworkX Python tool is used to determine the network efficiency of infrastructure systems (Hagberg et al. 2008). The output of the risk analysis and topological analysis are combined to generate decision alternatives for determining critical segments for prioritizing maintenance tasks.

In the dependency analysis module, the dependency of the functionality of the road network on WDSs is modeled. The geospatial interdependency is evaluated by analyzing the geometry and location of assets in a geographical information system (GIS) environment to recognize water and road segments that share the same corridor in an overlapping buffered layer. It is assumed that the functionality of collocated road segments will be affected by the failure in water mains. The probable cascading effect in the neighboring road network due to failure in the integrated water and road segments is presented using the OSMnx tool (Boeing 2017). The impact on WDSs and road networks due to water pipe failure is analyzed using a network efficiency metric.

Fig. 1 illustrates the conceptual framework of the proposed decision support model.

Risk Analysis

The integrated risk of failure can be determined if the probability of failure (likelihood of failure) and the consequences of failure are known (Baah et al. 2015). In this study, the failure probability of a

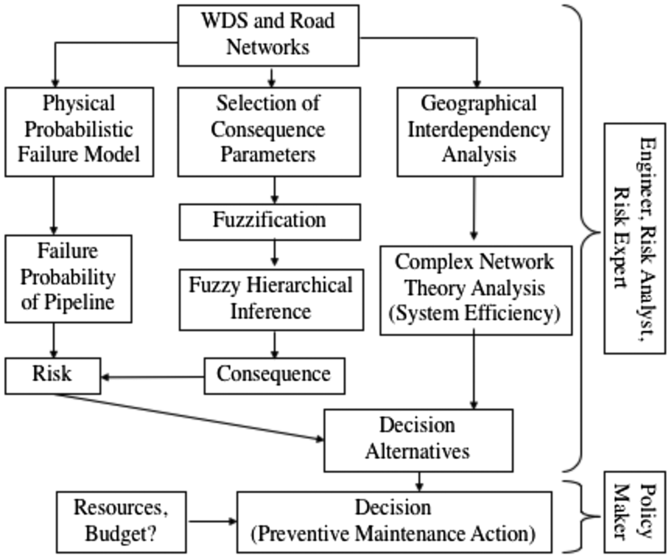


Fig. 1. Conceptual framework of proposed decision support model.

pipeline is estimated as a fragility function and the consequence of the failure is determined through a fuzzy hierarchical process.

Fragility of Pipelines

The failure probability of water pipelines is typically determined either using physics-based or statistical methods. Statistical methods analyze previous failure data to predict the future trend of failure, whereas physics-based approaches estimate the likelihood of failure by comparing failure stress and resistance of pipe (Rajani and Kleiner 2001). The physics-based approach is relatively more accurate compared to the statistical approach if all the necessary information is readily available (Mazumder et al. 2019). A number of methods are available for determining the failure probability of buried pipelines using the physics-based approach. Since the majority of US water mains are made of cast iron (CI) (Kirmeyer et al. 1994), the physical probabilistic pipe failure model for CI pipelines developed by Ji et al. (2017) is used in this study. Another advantage of using a physics-based model is that it accounts for time-dependent stress variation by incorporating the gradual reduction of pipe wall thickness over time due to corrosion. The failure probability of a pipeline, P_f, is defined by comparing the maximum stress (σ) on the pipeline with the tensile strength of the pipe material as given by Eq. (1)

$$P_f(T) = P[\sigma_y \leq \sigma(T)] \tag{1}$$

where σ_y is the tensile failure strength of the pipeline material, T is the elapsed time in years, and $\sigma(T)$ is the time-dependent stress on the pipeline. Stress on the CI pipeline is estimated based on the model developed by Robert et al. (2016). Details of the stress calculation model are discussed in "Fragility Analysis Results" section.

Consequence of Failure

Water distribution pipelines typically run under road networks, and failure in the WDS often leads to failures in the road network. Integrated consequence due to failure in the WDS needs to be accounted for in risk assessment. Risk assessment methods typically consider potential consequences in the form of direct and indirect losses (Muhlbauer 2004; Fares and Zayed 2010). Parameters influencing the failure consequence include both qualitative and quantitative parameters. A comprehensive literature review has been performed to identify parameters that potentially influence consequences after a failure event. Some recent studies considered the integrated consequence of failure in water mains on other infrastructure. A comparison of the contributing consequence factors used in previous research is presented in Table 1.

Most studies classified the consequences into various categories, such as economic, operational, and environmental, among others. Based on the literature review, the current study considers 14 factors for consequence quantification. These consequence parameters are grouped into economic, operational, environmental, and social consequence classes.

Economic Consequences

The economic consequences of water mains failure are determined on the basis of factors that influence asset utility and society in monetary terms (e.g., repair cost, loss of revenue, etc.). Factors considered in the economic consequences are pipe diameter, material type, burial depth, land use pattern, type of road, and degree of accessibility.

Pipe diameter: The consequence due to the failure of larger water mains is expected to be higher than the consequence due to the failure of smaller water mains (Shahata and Zayed 2016). Rehabilitation cost is higher for relatively larger diameter pipelines regardless of the type of technique used (Zhao and Rajani 2002).

Material type: The 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 (Shahata and Zayed 2016).

Burial depth: The cost of rehabilitation and replacement increases with the burial depth because more excavation will be required (Baah et al. 2015; Shahata and Zayed 2016).

Table 1. Consequence parameters

References	Pipe diameter	Pipe material	Type of soil	Type of road	No. of road lanes	Land use	Average daily traffic	Buried depth	Accessibility	Proximity to other asset	Network(s)
Al-Barqawi and Zayed (2008)	√	√	√	X	X	√	√	X	X	X	W
Fares and Zayed (2010)	√	√	√	X	X	√	√	X	X	√	W
Atef and Moselhi (2013)	√	√	√	√	X	√	√	X	√	√	W, R, S
Kabir et al. (2015)	√	√	√	√	X	√	√	X	X	X	W
Baah et al. (2015)	√	X	X	√	X	√	X	√	X	√	S
Elsawah et al. (2016)	√	√	√	√	√	√	√	√	√	X	W, R, S
Shahata and Zayed (2016)	√	√	√	√	X	√	√	√	√	X	W, R, S
Abu Samra et al. (2017)	√	√	X	X	√	X	√	X	X	X	W, R
Ismaeel and Zayed (2018)	√	√	√	X	X	√	X	√	X	X	W

Note: W = water network; R = road network; and S = sewer network.

Land use pattern: Losses can vary significantly depending on the pattern of usage of the nearby area in the case of a water main failure. For instance, the impact in an industrial area will be more than the impact due to the same water main failure in an agricultural area (Francisque et al. 2014).

Type of road: The economic consequence of water main failure will differ based on the type of roadway. Failure of a water main under an expressway will have higher consequences compared to failure beneath a local municipal roadway (Shahata and Zayed 2016). The maintenance cost of an expressway is typically higher than the maintenance cost of a municipal roadway.

Degree of accessibility: Limited accessibility to infrastructure can potentially delay the repair process and cause greater damage to surrounding assets. Accessibility can be hampered by the lack of easement, deep infrastructure, and limited vehicle access (Shahata 2013).

Operational Consequences

Operational consequences occur due to the loss of the operational ability of infrastructure assets and associated surroundings (e.g., loss of production, loss of hydraulic functionality, etc.). Hydraulic performance, business disruptions, number of lanes, and damage possibility to the nearby asset are parameters used for evaluating the extent of operational disruption.

Hydraulic performance: The hydraulic performance of a WDS is determined to know if the system has an excessive capacity to provide adequate water to consumers under partially-failed conditions. A system with lower hydraulic performance is likely to have a higher consequence of failure that may lead to an inadequate water supply to the consumers, lower firefighting capacity, and so on (Kabir et al. 2015; Fares and Zayed 2010). The impact on the system hydraulic excessive capacity due to the failure of each pipeline separately is estimated using Todini's resilience (Todini 2000). Pressure-dependent hydraulic simulation is performed using the water network tool for resilience (WNTR) for estimating Todini's resilience (Klise et al. 2017). Todini's resilience provides information about system hydraulic excessive capacity of a WDS [interested readers are referred to Todini (2000) for further details].

Business disruption: Nearby business areas may need to close due to the failure of a water main. The operational impact is higher for important business zones (e.g., health service, industrial production zone, etc.) (Shahata 2013).

Number of lanes: The possibility of the complete shutdown of a road increases with the decrease in road width. The number of lanes is an important measure of the redundancy of roadways (Al-Barqawi and Zayed 2008; Fares and Zayed 2010).

Possible damage to nearby assets: The level of damage to surrounding assets is a good indicator of the functionality of surrounding infrastructure including gas, utilities, cables, electricity (Shahata and Zayed 2016).

Environmental Consequences

Failure in water pipelines may impact habitats, water bodies, service areas, and archaeological sites, among others (Shahata and Zayed 2016). Parameters influencing environmental consequences include soil type, sensitive area proximity, and average traffic volume.

Soil type: Soil type is a key factor in the corrosion behavior of metallic pipelines. Soil can be classified based on the presence of corrosive characteristics in soil media. The environmental consequence is likely to be higher if the surrounding soil is highly aggressive (Shahata 2013).

Proximity to a sensitive area: The water pipelines traveling near industrial areas and environmental areas will have a higher environmental impact due to the failure of the water main (Baah et al. 2015).

Average daily traffic: A road with heavy traffic volume will have higher environmental consequences due to water main failure (Shahata 2013). Utility and road construction after a water pipe failure often results in a partial or complete road closure, leading to significant traffic delay and forcing traffic to take detours. Increased travel distance and reduced speed in the utility construction zone may increase fuel consumption and negatively impact the environment with higher carbon emission (Matthews et al. 2015).

Social Consequences

Social consequences refer to the impact on society as a result of inconvenience to public life due to service disruption, traffic delays, and so on (Salman and Salem 2011). Social factors included in this study are the type of service area, average daily traffic, and population density (Elsawah et al. 2016; Shahata and Zayed 2016).

Type of service area: Social impact may vary depending on the type of service area affected due to water main failure. For instance, longer service disruption in medical facilities and industrial areas will have a higher social impact compared to residential areas (Elsawah et al. 2016; Shahata and Zayed 2016).

Average daily traffic: Average daily traffic is a good measure of social impact. The shutdown of a road with high traffic volume will redistribute higher traffic loads to the neighboring roads. Traffic delay is expected in the utility construction zone (Matthews et al. 2015). As such, a road with higher average daily traffic is likely to have a higher social consequence if the road needs to be closed due to water main failure (Elsawah et al. 2016; Shahata 2013).

Population density: Population density (number of populations per km^2) is a good indicator that measures social impact by recognizing population size within a pipeline's dissemination area that is likely to be out of water supply after a water pipe failure. The social consequence is typically higher in densely populated areas (Kabir et al. 2015).

Fuzzy Membership Functions

In integrated water and road systems, data of various consequence parameters (e.g., soil type, traffic volume, etc.) are uncertain and imprecisely presented (Sadiq et al. 2007). One of the major challenges in dealing with linguistic or qualitative parameters is that the contribution of the parameters to the consequences is difficult to estimate and categorize into hazardous groups. Zadeh (1965) introduced fuzzy set theory to overcome the problem associated with the crisp and imprecise representation of probabilities. Fuzzy logic is a useful technique to transfer qualitative human knowledge or linguistic scale into numerical reasoning toward a conclusion or decision-making (Demartinos and Dritsos 2006). The fuzzy-based technique is preferable in many decision-making models because it is capable of incorporating human jurisdiction whenever the database is incomplete and unavailable.

Fuzzy membership functions can be defined in various ways, such as triangular, trapezoidal, Gaussian, and singleton, among others. The real data of the consequence parameters (e.g., diameter, material type) is transformed into fuzzy membership ranges $[0, \quad 1]$ using the membership functions. The fuzzy membership functions for each consequence parameter are defined based on information adapted from literature review, range of the parameter's attribute, characteristics of the parameter, effect of parameter on consequences, engineering judgment, and so on (e.g., Sadiq et al. 2007; Fares and Zayed 2010; Kabir et al. 2015). The consequence of failure is classified into five consequence levels.

The development of fuzzy membership functions for one parameter from each consequence class is explained here. In the

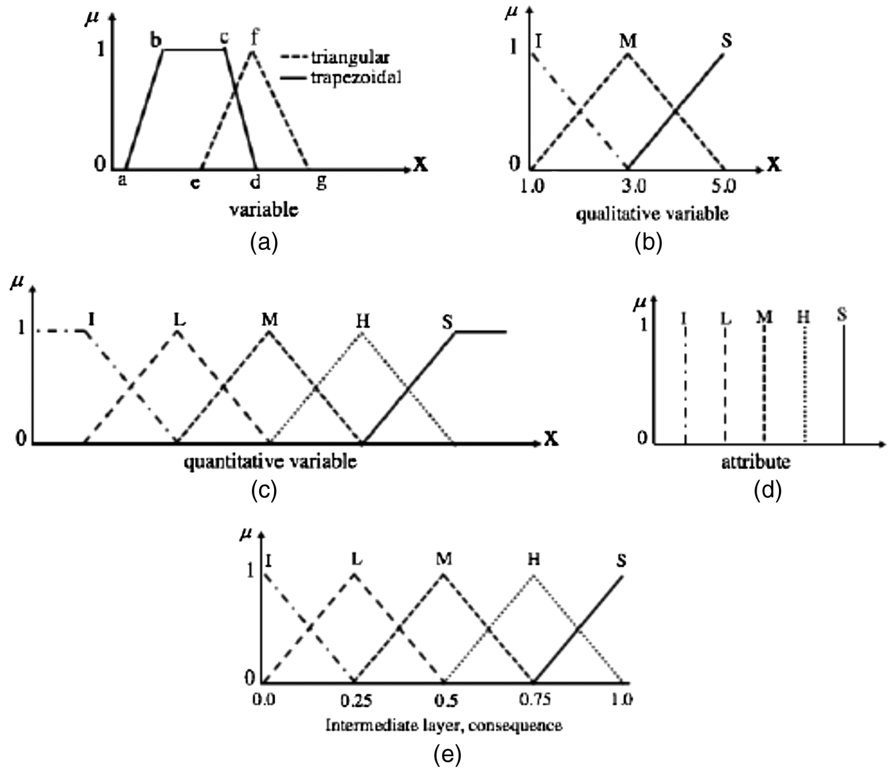


Fig. 2. Fuzzy memberships: (a) generalized triangular and trapezoidal functions; (b) accessibility, soil type, and average daily traffic; (c) diameter, buried depth, hydraulic performance, possible damage to nearby asset, proximity to sensitive area, and population density; (d) material type, road type, land use, business disruption, number of lanes; and (e) input/output in second and third layers.

economic consequences, previous studies (e.g., Shahata and Zayed 2016; Baah et al. 2015; Kabir et al. 2015) classified the pipe diameter into various consequence classes where the level of consequence increases with the diameter size. For instance, Kabir et al. (2015) classified pipe diameter into five consequence levels: (1) very small: 0–50 mm, (2) small: 50–200 mm, (3) medium: 200–400 mm, (4) large: 400–600 mm, and (5) very large: ≥600 mm. Phan et al. (2018) classified pipes into four performance class: (1) class 1: <300 mm, (2) class 2: 300–600 mm; (3) class 3: 600–900 mm, and (4) class 4: >900 mm. Based on the knowledge gained from previous studies and the range of diameter considered in this study, the pipe diameter is grouped into three consequence levels: (1) small: <100 mm, (2) medium: 100–400 mm, and (3) large: >400 mm. In the operational consequences, sudden failure of the water main may damage surrounding assets (e.g., structure, utility, road), leading to operational disturbance to other systems. The extent of such damage depends on the proximity of the asset to the water main. For instance, Phan et al. (2018) classified possible impact of failure into three categories depending on the proximity of an asset to a water main: (1) high: distance <5 m, (2) moderate: distance 5–10 m, and (3) low: distance >10 m. Other studies (Vanrenterghem-Raven 2007; Fares and Zayed 2010; Baah et al. 2015; Shahata and Zayed 2016) also classified the consequence of damage into three to five levels depending on the proximity of the asset to the water main where a comparatively nearby asset has a higher likelihood of damage than the farther asset. In the current study, in light of this discussion, possible damage to nearby assets is classified into three groups: (1) severe: distance <5 m; (2) moderate: distance 5–15 m; and (3) insignificant: distance >15 m.

In the environmental consequence, the presence of corrosive characteristics in surrounding soil of pipeline may impact the environment adversely in the case of a water main's failure. The environmental consequence is likely to be high if the surrounding soil is highly aggressive. Fares and Zayed (2010) classified soil type into five groups on a scale of 0–10 depending on the soil corrosivity, where highly corrosive soil has a higher level of environmental consequence. Shahata (2013) rated soil type depending on the corrosiveness of soil into four categories: (1) nonaggressive: 1; (2) moderate: 2; (3) high: 3; and (4) highly aggressive: 5. Based on the information gained from these studies, soil type is classified into three classes (low, moderate, and high) on a scale of 1–5 depending on the corrosive of soil. In social consequences, the water main's failure is typically impacting the community as service disruption experienced by the population within the pipeline's dissemination area. Population density is used in previous studies to determine the level of possible social consequences. Kabir et al. (2015) classified social consequences into five classes depending on the impacted population density (person/km^2): (1) very low: <415; (2) low: 415–595; (3) medium: 595–830; (4) high: 830–1,195; and (5) very high: >1,195. Similarly, the current study classifies population density (person/km^2) into five categories: (1) insignificant: <100; (2) low: 100–500; (3) moderate: 300–700; (4) high: 500–900; and (5) severe: >1,200.

Other parameters are also classified into various consequence levels, as expressed in Figs. 2(a–e). For example, business disruption is classified into three classes depending on the pipe failure location: (1) other (e.g., residential, open space); (2) commercial (e.g., small shop); and (3) major clinic/user (e.g., industrial) (Fares and Zayed 2010). Average daily traffic is used as an indicator for both environmental and social consequences. Road closure due to water pipe failure may result in traffic delay, leading to an increase in fuel consumption that negatively affects the environment. At the same time, traffic delay increases inconvenience to

Table 2. Fuzzy membership functions

Parameter	Unit	I	L	M	H	S
Economic consequences						
Pipe diameter	mm	Small [0 0 100 250]	—	Medium [100 250 400]	—	Large [250 400 500 500]
Buried depth	m	[0 0 1 3]	—	[3 4 5]	—	[3 4 5 5]
Accessibility	—	Good [1 1 3]	—	Moderate [1 3 5]	—	Low [3 5 5]
Pipe material	—	PVC	—	Asbestos/Corrugated Steel	—	Steel, CI, DI/Concrete
Road type	—	Local	Collector	Arterial	Custom	Highway
Land use	—	Agricultural/Open Space	Park	Residential	Educational/ Commercial	Industrial
Operational consequences						
Hydraulic performance	—	[0 0 0.05 0.1]	—	[0.05 0.1 0.15]	—	[0.1 0.15 1 1]
Business disruption	—	Other	—	Commercial	—	Health Clinic/Major Users
Number of lanes	Numbers	—	—	≥3	2	1
Possible damage to nearby assets	m	[10 15 20 20]	—	[5 10 15]	—	[0 0 5 10]
Environmental consequences						
Soil type (corrosivity)	—	Low [1 1 3]	—	Moderate [1 3 5]	—	High [3 5 5]
Proximity to sensitive area	m	[10 15 20 20]	—	[5 10 15]	—	[0 0 5 10]
Average daily traffic	—	Low [1 1 3]	—	Moderate [1 3 5]	—	High [3 5 5]
Social consequences						
Type of service area (land use)	—	Agricultural/Open Space	Park	Residential	Educational/ Commercial	Industrial/Medical/Emergency
Average daily traffic	—	Low [1 1 3]	—	Moderate [1 3 5]	—	High [3 5 5]
Population density	ppl/km^2	[0 0 100 300]	[100 300 500]	[300 500 700]	[500 700 900]	[700 900 1200 1200]

Note: I = insignificant; L = low; M = moderate; H = high; S = severe; and ppl = population.

society. Hence, a road with higher average daily traffic is expected to experience higher environmental and social consequences. As classified in previous studies (Vanrenterghem-Raven 2007; Fares and Zayed 2010; Kabir et al. 2015; Shahata 2013; Elsawah et al. 2016), average daily traffic is classified into three categories: (1) low; (2) moderate; and (3) high, on a subjective scale of 1–5, depending on the traffic volume.

Fuzzy membership functions are defined for the consequence classes depending on the characteristics of a variable. Singleton, triangular, and trapezoidal membership functions are defined in this study, as provided in Table 2 and Figs. 2(a–e). Generalized triangular and trapezoidal membership functions presented in Fig. 2(a) are expressed by the following equations:

$$Trapezoidal;\ \mu(x) = \begin{cases} 0; & x < a \\ \dfrac{x-a}{b-a}; & a \le x \le b \\ 1; & b \le x \le c \\ \dfrac{x-d}{c-d}; & c \le x \le d \\ 0; & x > d \end{cases} \tag{2}$$

$$Triangular;\ \mu(x) = \begin{cases} 0; & x < e \\ \dfrac{x-e}{f-e}; & e \le x \le f \\ \dfrac{x-g}{f-g}; & f \le x \le g \\ 0; & x > g \end{cases} \tag{3}$$

where $\mu(x)$ is the fuzzy membership value on a scale of [0,1] mapped on the vertical axis, x (horizontal) axis represents the fuzzy universe of discourse, a is the minimum value, b and c are the two values that define the interval of the most likely range, and d is the maximum value of a trapezoidal membership function. Similarly, e, f, and g are the minimum, the most likely, and the maximum values of a triangular membership function, respectively. The membership functions of trapezoidal and triangular members are expressed by $[a \quad b \quad c \quad d]$ and $[e \quad f \quad g]$, respectively, as provided in Table 2.

The level of consequence is rated as from insignificant to severe, depending on the corresponding contribution to the consequence. A maximum of five consequence levels is considered: Insignificant, Low, Moderate, High, and Severe tagged as I, L, M, H, and S, respectively. Among the selected 14 consequence parameters, a few qualitative parameters (accessibility, soil type, average daily traffic) are evaluated on a scale of 1–5, and triangular membership functions are used to define three consequence levels (I, M, and S) for these qualitative parameters, as shown in Fig. 2(b). The quantitative parameters (except number of lanes) are evaluated on the range of parameter universe [min, max]. Both trapezoidal and triangular membership functions are used to define consequence levels for these quantitative parameters. For quantitative parameters, the level of consequence remains the same after limiting values (below a lower limit and above an upper limit). Hence, trapezoidal membership functions are used to define I and S consequence levels, and triangular membership functions are used to define intermediate consequence levels (L, M, and H), as shown in Fig. 2(c). As previously discussed, the number of consequence levels (three or five) for a parameter is selected based on the information obtained from available literature, range of parameter universe, and engineering judgment (Tesfamariam and Saatcioglu 2008a, b; Fares and Zayed 2010).

To further explain how the fuzzy membership function is defined for a quantitative parameter, consider pipe diameter as an example. Three consequence levels and their corresponding membership functions are defined for pipe diameter under the economic consequences. Membership functions for pipe diameter are defined over a range of 0 to 500 mm. It was assumed that a diameter value of less than or equal to 100 mm will have the same level of I consequence. Similarly, a diameter value of 400 mm or more will have the same level of S consequence. Hence, the trapezoidal membership function is used to define I and S consequence levels as $[0 \quad 0 \quad 100 \quad 250]$ and $[250 \quad 400 \quad 500 \quad 500]$, respectively. Fuzzy numbers in the parenthesis $[0 \quad 0 \quad 100 \quad 250]$ represent trapezoidal fuzzy membership function of the I consequence level where 0 is the minimum, interval 0–100 is the most likely range, and 250 is the maximum value of trapezoidal membership function. The fuzzy membership value of I consequence, μ, at any point between 0 and 250, is calculated using Eq. (2). Intervals of midlevel consequence levels (L, M, and H) are equally distributed using triangular membership functions. The fuzzy numbers in the parenthesis $[100 \quad 250 \quad 400]$ represent a triangular membership function of M consequence level where 100, 250, and 400 denote the minimum, the most likely, and the highest values, respectively. The fuzzy membership value of M consequence, μ, at any point between 100 and 400, is calculated using Eq. (3).

Other qualitative and quantitative parameters are evaluated for standard five consequence levels based on their characteristics and relative effect to the consequence. Singleton fuzzy membership functions are used to define these parameters, as presented in Fig. 2(d) and Table 2.

However, it should be noted that number of consequence levels, the interval between different consequence levels of a particular parameter, fuzzy membership type can be modified or changed based on expert opinion. For instance, the pipe diameter is classified into three categories based on the understanding of previous literature, and both trapezoidal and triangular membership functions are used to define corresponding consequence levels. The number of consequence levels and type of membership functions can be modified and changed by the user based on the specific context (Sadiq et al. 2007). Two parameters, *land use* and *average daily traffic*, are used twice for estimating the consequences. Average daily traffic is used for estimating environmental and social consequences because it contributes to both. Similarly, the type of land use or service area is considered for estimating economic and social consequences.

Figs. 2(a–e) shows the fuzzy membership functions used in this study for consequence quantification.

Fuzzy Hierarchical Inference

The hierarchical fuzzy inference is developed to aggregate the consequences of parameters for each pipe segment, as shown in Fig. 3. The indirect knowledge acquisition approach (e.g., expert in-person interview, literature review, engineering judgment) is applied to develop a knowledge base fuzzy hierarchical model for consequence quantification due to water pipeline failure. The consequence parameters are categorized into four consequences depending on their type of contribution to the consequence. The parameters associated with consequence evaluation are decomposed into three hierarchical levels. In the first layer, all parameters are classified into four consequences and the corresponding consequence values are obtained through a Mamdani-type inference. In the economic consequences, the selected six parameters are subgrouped into major economic contributor (Eco1) and minor economic contributor (Eco2). These subgroups are performed because (1) the four parameters in the Eco1 class contribute more to the economic consequence than the parameters in the Eco2 class and (2) consideration of the six economic parameters in a class results in a large number of fuzzy combinations (rules) that potentially increase computation time significantly. Subclassifying the economic parameters increase computational efficiency in the analysis. Similar to the input membership functions, input–output variables in the second and third layers are mapped into I, L, M, H, and S consequence levels over a range from 0 to 1. Intervals of five consequence levels are equally distributed on a scale of $[0, \quad 1]$ (Sadiq et al. 2007), Hence, fuzzification used for variables in the second and third layers is $(I; L; M; H; S) \Rightarrow ([0 \;\; 0 \;\; 0.25]; [0 \;\; 0.25 \;\; 0.5]; [0.25 \;\; 0.5 \;\; 0.75]; [0.5 \;\; 0.75 \;\; 1.0]; [0.75 \;\; 1.0 \;\; 1.0])$.

The most commonly used Mamdani-type input–output fuzzy model is used to estimate the consequence of each integrated section (Mamdani 1976). Mamdani fuzzy inference has an advantage over the Sugeno fuzzy system, because the rules of the Mamdani model are easily understandable, well suited for a knowledge-based expert system, and consequents are expressed in fuzzy sets (Sugeno 1985; Jin 2003). Mamdani fuzzy inference uses simple rules based on the *IF* and *THEN* relationship of antecedent and consequent parts (Mamdani 1976; Fares and Zayed 2010), as expressed by Eq. (4). The fuzzy inference process determines the consequent (output) based on the antecedent (inputs). Input parameters in the antecedent part convey the characteristics of consequent. For instance, environmental consequences (consequent/output) in the second layer is obtained based on three input parameters (antecedent) in the first layer. The attribute of input parameters is evaluated on fuzzy memberships, and consequent value is obtained through fuzzy rules. A typical form of *IF/THEN* rules can be expressed as

$$IF\ (Antecedent)\ THEN\ (Consequent)$$

$$\begin{aligned} &R^i = IF\ (x_1\ is\ A_1^i\ and\ x_2\ is\ A_2^i\ and\ \cdots\cdots\cdots\ and\ x_m\ is\ A_m^i) \\ &THEN\ (y\ is\ B^j) \end{aligned} \tag{4}$$

where R^i is the ith rule, $A_j^i (i = 1, 2, \ldots, N; j = 1, 2, \ldots, m)$ is the fuzzy subsets of inputs, N is the total number of rules, m is the total number of input variables, and B^j is the fuzzy subsets of outputs. An example of fuzzy rules generation is explained in the supplemental materials.

This rule-based fuzzy inference typically has a large number of rules to account for all possible combinations of input variables (Tesfamariam and Saatcioglu 2008a). The Mamdani method is based on simple minimum function, and logical operator "and" is used for the minimum function, as expressed by Eq. (5) (Demartinos and Dritsos 2006; Fares and Zayed 2010). Hence, the fuzzy rules presented in Eq. (4) can be reexpressed as (Jin 2003)

$$\mu_{R^i}(x_1, x_2 \ldots \ldots, x_m, y) = \mu_{A_1^i} \wedge \mu_{A_2^i} \wedge \cdots\cdots\cdots \wedge \mu_{A_m^i} \wedge \mu_{B^i} \tag{5}$$

where $\wedge$ is the minimum operator, $\mu_{A_j^i}$ is the membership function of parameter j for the ith rule, μ_{B^i} is the membership of output parameter for the ith rule, and μ_{R^i} presents the fuzzy relationship for the ith rule. The consequent is evaluated on a scale of $[0, \quad 1]$. After knowledge base fuzzy rules are evaluated, the consequent values of fuzzy rules are aggregated by using the maximum operator, as follows (Jin 2003):

$$\mu_R(x_1, x_2 \ldots \ldots, x_m, y) = \bigvee_{N}^{i=1} [\mu_{R^i}(x_1, x_2 \ldots \ldots, x_m, y)] \tag{6}$$

where $\vee$ is the maximum operator and μ_R is the aggregated membership function for consequents. Eqs. (5) and (6) perform the maximum of minimum approach $[\max\{\min()\}]$ to obtain aggregated consequent numbers for insignificant to severe consequence levels. This approach is used to obtain the maximum value of any consequent membership functions used to determine a crisp value of consequence in the defuzzification process.

Defuzzification

The defuzzification process converts fuzzy outputs into a crisp value in each hierarchy level. There are several ways to perform the defuzzification process (e.g., the centroid of the area, weighted average). The centroid of area method is applied in this study to determine the crisp number of each output. Eq. (7) estimates the centroid of each truncated consequent function and averages them by their areas for determining the crisp value. This approach has the advantage of being easier to program, computationally efficient, and providing reasonable outcomes (Fares and Zayed 2010). The crisp value of each consequence is determined on a quantitative scale $[0, \quad 1]$, as follows:

$$C_f = \frac{\sum_{i=1}^{n} \bar{A}_i \times c_i}{\sum_{i=1}^{n} \bar{A}_i} \tag{7}$$

where C_f is the consequence of failure, $\bar{A}_i$ is the truncated area of the ith part, and c_i is the centroid of the ith part.

Defuzzification is performed for economic (Eco1, Eco2), operational, environmental and social consequences to obtain a crisp number using fuzzy consequent membership functions. The weighted sum method is used to integrate the overall consequence from the different consequences. Weights of consequences in the decision-making process can be derived from information available in the literature and/or expert's pairwise comparison between parameters. The relative importance of consequences/parameters can be estimated at each hierarchical layer through the analytical hierarchy process. Shahata and Zayed (2016) studied the integrated consequence of water, sewer, and road assets where 18 factors are grouped under economic, operational, environmental, and social consequence indexes. Since the current study also classified consequence parameters into four consequence indexes in a similar way, for the water and road assets, weights of four consequence classes are adapted from Shahata and Zayed (2016). However, for assigning weights of parameters for a particular context, readers are referred to Tesfamariam and Saatcioglu (2008b) for a detailed descript of analytical hierarchy–based weights estimation from expert judgment. The final consequence is also evaluated on a scale of 0–1. The fuzzy inference system, as presented in Fig. 3, was built and analyzed in the MATLAB program.

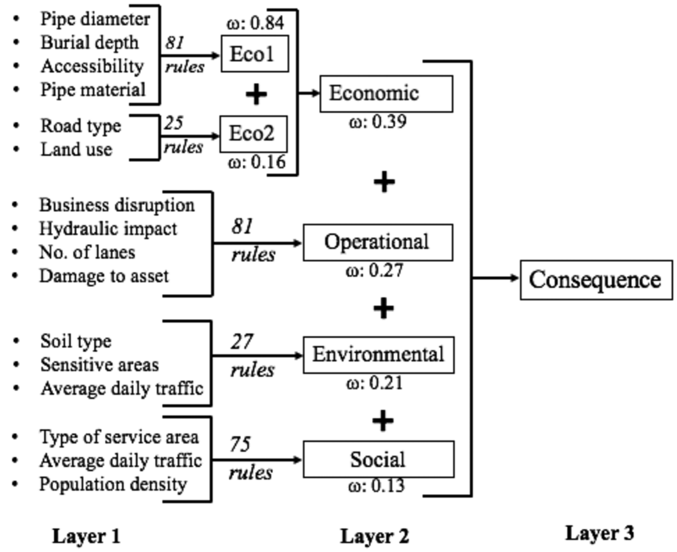


Fig. 3. Fuzzy hierarchical structure.

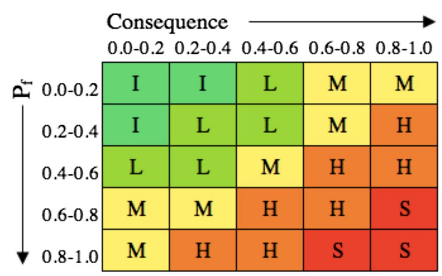


Fig. 4. Risk matrix.

Risk Estimation

Risk Equation

The overall risk (R_f) is the combination of the probability of failure (P_f) and the consequence (C_f) due to the failure of an asset to meet the performance objective. A widely used concept to quantify the risk is multiplying the probability of failure with the consequence of failure (Vladeanu and Matthews 2018) as follows:

$$R_f = P_f \times C_f \tag{8}$$

This approach determines the riskiest components based on the numerical values of the probability of failure and the consequence of failure.

Risk Matrix

The risk matrix is a square matrix where the columns and rows of the matrix denote the consequence of failure and the probability of failure, respectively, as shown in Fig. 4 (Vladeanu and Matthews 2018). Previous research on condition rating of infrastructure assets (Elsawah et al. 2016; Shahata and Zayed 2016; Vladeanu and Matthews 2018) used a similar risk matrix for decision-making. In this research, both the consequence of failure and the probability of failure are classified into five levels, as shown in Fig. 4. Finally, five qualitative risk levels are assigned based on the combination of the level of the consequence of failure and the level of likelihood of failure, as shown in Fig. 4 and Table 3.

Table 3. Risk scaling

Risk level	Likelihood of failure	Letter grade	Description
5	Severe	*S*	Severe impact on the performance and consequence
4	High	*H*	Highly influence the performance and at risk
3	Moderate	*M*	Moderately affect the system component
2	Low	*L*	Minor impact on the performance
1	Insignificant	*I*	No or very little influence on the performance

Dependency Analysis

Modern infrastructure systems are highly interconnected and becoming increasingly interdependent due to physical proximity, shared resources, and functionality, among others. Existing research classified dependency and interdependency among infrastructures in various ways (Ouyang 2014). Infrastructure dependency refers to a unidirectional relationship among the infrastructure systems where the state of one system is dependent on the state of another system. On the other hand, infrastructure interdependency refers to a

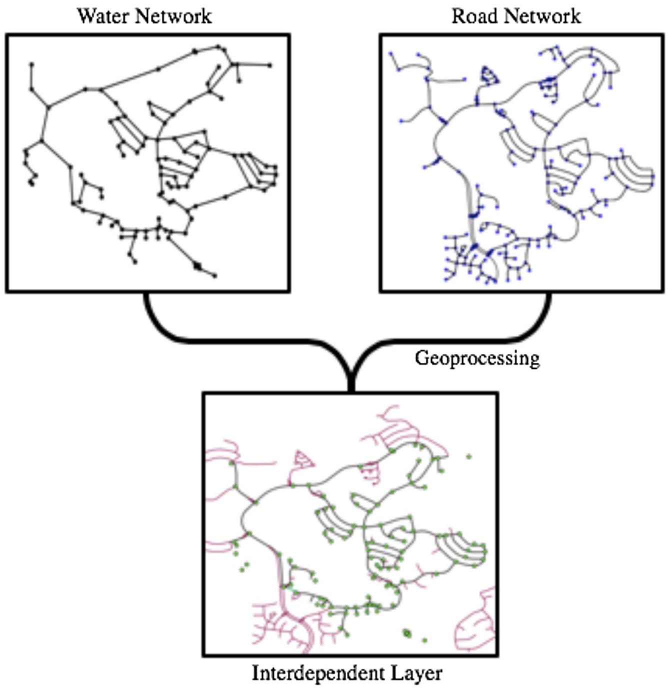


Fig. 5. Geospatial dependency analysis.

bidirectional relationship among the infrastructure systems where the state of one system is dependent on the state of the other and vice versa (Rinaldi et al. 2001).

The current study modeled the dependency of road networks on water infrastructure assets as a geospatial dependency. Infrastructure systems are spatially dependent or interdependent when the performance of one is affected by another in the same geographical space (Atef and Moselhi 2014). Road networks collocated in the paths of water pipelines are likely to suffer catastrophic consequences in the event of a failure in the water network. Hence, the geospatial dependency of road networks on WDSs is performed to identify the road and water network segments that are collocated in the same geographical space.

Geospatial analysis can be performed utilizing the geoprocessing tool of a GIS software. ArcGIS geoprocessing toolbox is used to analyze the data set of the two infrastructure systems to identify a new data set with collocated assets. This is achieved by generating a buffer around each link in the two systems. A buffer is a dynamic or static geometric boundary generated around the selected feature, and it encapsulates the study zone (Atef and Moselhi 2014). If any feature falls within that boundary, it is considered as a collocated feature. For example, if a buffer of 10 m is assumed from the centroid of a water pipeline, then the intersection of a buffered layer of water pipes and road links are considered as collocated assets. The width of the buffer can be varied dynamically or statically depending on the decision maker's preference. Using the selection query and union module, the dependent road links and collocated water pipelines can be identified. Fig. 5 shows an example of spatial data analysis used for identifying dependent road and collocated water segments.

Network Criticality Analysis

After quantifying the risk to the infrastructure assets, decision makers need to know how failure of a component affects the performance of the system. Criticality of a component is estimated by identifying the change of network efficiency before and after the failure of that component. Complex network theory is used to determine the network efficiency of a network. Road and water networks are typically a complex representation of graphs consisting of vertices and edges embodied in a geographical space that can be modeled as a graph $G(n, e)$ composed of a collection of n vertices (e.g., node, junction, intersection, tank) connected by e edges (e.g., pipeline, road links). A graph can be either directed or undirected, depending on their representation of edge direction. A graph is said to be undirected if a vertex can be reached from any other vertices, whereas in a directed graph, vertices can be reached by following directed edges only. It should be noted that the topological metrices are determined for an undirected graph using the NetworkX tool (Latora and Marchiori 2001; Brandes 2008; Hagberg et al. 2008).

Edge Betweenness Centrality

In a water or road network graph, an edge (pipe or road link) may not be important locally but maybe important globally if many access flows need to pass through it (Hawick 2012). Edge betweenness centrality (EBC) is defined as the number of shortest paths based on the length that passes through an edge in a network or graph (Barthélemy 2011). Pipeline failure and road closure are common phenomena in the WDS and road networks, respectively. EBC of edge (pipe or road link) provides information about the possible flow path disruption if the edge fails. Failure of a pipeline/road link with high EBC is likely to significantly affect the connectivity of the system (Giustolisi et al. 2019).

The EBC of an edge, l (pipe or road link), for vertices s and t, is calculated by the following equation (Brandes 2008; Giustolisi et al. 2019):

$$C_e(l) = \sum_{\substack{s \neq t \varepsilon V \\ l \varepsilon E}} \frac{\rho_{s,t}(l)}{\rho_{s,t}} \tag{9}$$

where $C_e(l)$ is the EBC of edge l, $\rho_{s,t}(l)$ is the number of connecting shortest paths that pass-through edge l from vertex s to vertex t, $\rho_{s,t}$ is the total number of shortest paths from vertex s to vertex t, and V and E are sets of vertices and edges, respectively. For an undirected graph, the normalized form of the EBC is expressed as (Brandes 2008)

$$C_e^*(l) = \frac{2}{(n-1)(n-2)} C_e(l) \tag{10}$$

where $C_e^*(l)$ is the true EBC of edge l and n is the number of vertices in a WDS or road network. The EBC is a good measure to identify the most influential edges that control the performance of the system.

Network Efficiency

Failure in the water pipeline will not only affect the dependent road network but also will affect the WDS. Since failure of a component of a network (both indirectly and directly, cascading failure) triggers a change in the connectivity between some vertices and the rest of the network, the shortest path–based network efficiency can be a useful measure to analyze the effectiveness of connectivity-based functionality of a network. The efficiency of a road network and WDS is measured by the following expression (Latora and Marchiori 2001; Guidotti and Gardoni 2018)

$$\eta(G)=\frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{\substack{j=1\\ i\neq 1}}^{n}\frac{1}{d_{ij}} \tag{11}$$

where $\eta(G)$ is the efficiency of a network graph G, d_{ij} is the shortest path between vertex i and vertex j, and n is the number of vertices in the network. When vertex i is disconnected from vertex j, d_{ij} is equal to infinite (∞). The efficiency metric is recently applied for functionality analysis of infrastructure networks after localized attack (Hu et al. 2016) and can be used as a measure to determine the extent of loss of system connectivity of a road network and WDS.

The impact on network due to the failure of a particular pipeline/road segment is evaluated as follows:

$$I_\eta(l)=\frac{\eta(G)-\eta(\bar{G})}{\eta(G)} \tag{12}$$

where I_η is the network impact index due to failure of pipeline/road segment l, and $\eta(\bar{G})$ is the efficiency of a network graph $\bar{G}$, where $\bar{G}$ is the subgraph of graph G after removing the failed pipeline/road segment from the network.

Decision-Making

Both the risk equation and the risk matrix are used to assign the risk to components. Decision alternatives are generated using the risk equation and risk matrix separately. After determining the risk level of an individual asset, the utility manager needs to understand how a component plays a role in keeping the system functional. To prioritize assets within a system, results from the risk assessment and network impact index are used in the decision-making process. In this study, two decision-making approaches are followed. In the first approach, decision alternatives are generated by combining the outcomes from the risk equation and the combined I_η for both road network and WDS. The concept of compromise ranking method (Opricovic and Tzeng 2004; Asadi et al. 2019) is utilized to rank the components as follows:

$$\begin{aligned}\mathrm{DI} &= \text{Weight of Risk}\times\text{Normalized Risk}\\ &\quad+\text{Weight of } I_\eta\times\text{Normalized } I_\eta\end{aligned} \tag{13}$$

$$\mathrm{DI}=\omega_R\cdot\frac{Rf-R_f^{\min}}{R_f^{\max}-R_f^{\min}}+\omega_{I_\eta}\cdot\frac{I_\eta-I_\eta\min}{I_\eta\max-I_\eta\min} \tag{14}$$

where DI is the decision index, R_f is the risk value obtained from the risk equation, $R_f^{\min}$ is the minimum of R_f, $R_f^{\max}$ is the maximum of R_f, I_η is the combined impact index, $I_\eta^{\min}$ is the minimum of I_η, $I_\eta^{\max}$ is the maximum of I_η, ω_R is the weight of the risk, and $\omega_{\mathrm{I}\eta}$ is the weight of the I_η. This approach provides a number of scenarios based on various relative weights between risk output and network criticality analysis (NCA) output. The decision maker can accept or reject a decision based on their goals. In the second approach, components are classified first into different risk levels using the risk matrix. Then components are prioritized for maintenance actions depending on their I_η values obtained from the NCA. This is the simplest way to prioritize components for maintenance or renewal works.

Case Study

Network Description

In the current study, the water distribution system and road network of Zone III of the Rancho Solano area of the city of Fairfield, California, is used as a case study. The EPANET compatible water network data file is obtained from the ASCE task committee on research databases repository of the University of Kentucky (Jolly et al. 2013; WDST 2019). The water network is composed of 111 nodes (junctions), 126 elements (pipes), and 1 elevated water tank, as shown in Fig. 6(a). The road network of Rancho Solano is retrieved from OpenStreetMap using the OSMnx Python tool (Boeing 2017). The road network consists of 205 vertices (junctions) and 267 edges (road segments), as shown in Fig. 6(b). Network topology, hydraulic model, diameter, material type, road types, and number of lanes are readily available.

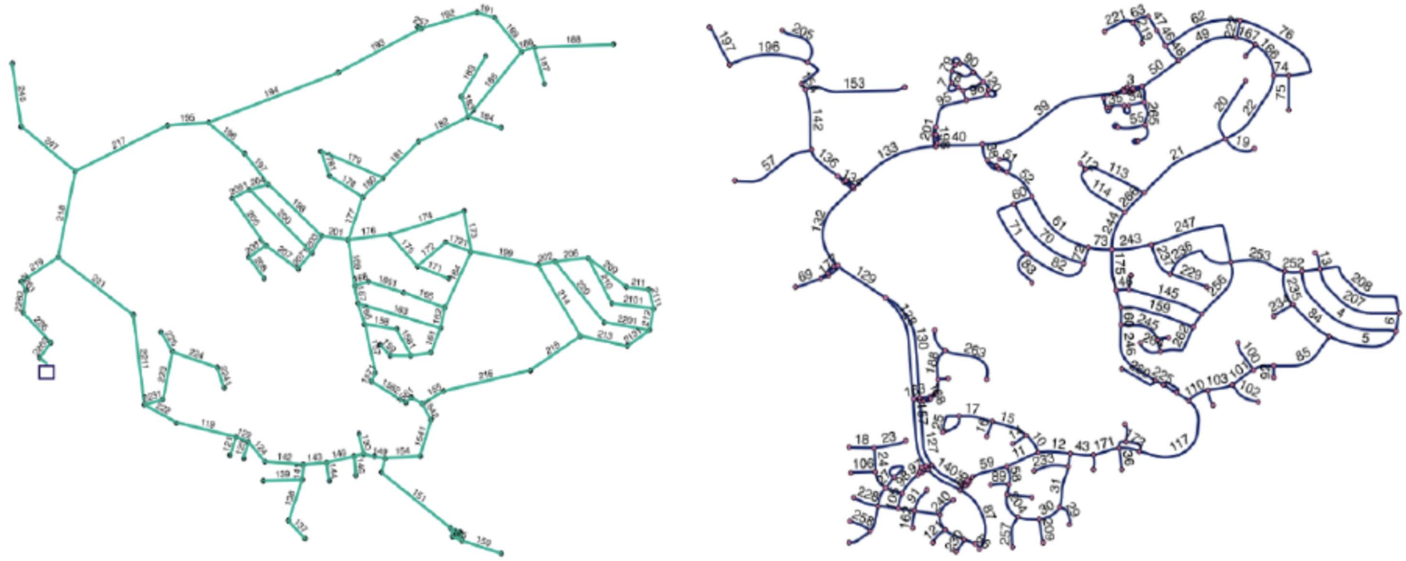
For the simplicity of the fragility analysis, three types of pipelines are assumed. The hydraulic performance of WDS is measured by utilizing the WNTR (Klise et al. 2017). Other parameters are randomly generated within a reasonable limit and assigned to illustrate the proposed framework. Table 4 provides a sample data set of consequence parameters. Criticality of pipelines in a WDS graph are identified using NetworkX (Hagberg et al. 2008).

Fragility Analysis Results

In this case study, only the physical failure of the water pipeline is considered, and it is very likely that physical failure in water pipelines will affect the traffic flow in the dependent road segments. Hence, it is assumed that the dependent road will be fully closed due to the failure of collocated buried water pipelines. Since the majority of water pipelines in the United States are made of CI, the current WDS is assumed to be composed of CI pipelines. Three types of pipes are considered (type 1: $D=300$ mm, $t=12$ mm; type 2: $D=350$ mm, $t=15$ mm; type 3: $D=450$ mm, $t=16$ mm). An evenly distributed real random number was generated over a range from 70 to 100 years for assigning the age of pipelines (since most of the gray CI pipes were produced before 1948 until ductile iron was introduced) (Rajani and Kleiner 2001). The fragility curves are determined using the physics-based limit state approach expressed by Eq. (1) where stress, $\sigma(T)$ is calculated using the following equation (Robert et al. 2016):

$$\begin{aligned}\sigma(T)&=\left[\frac{W+\gamma_s D^2H}{D^2}\right]\alpha_1\left(\frac{E_P}{E_S}\right)^{\beta_1}\left(\frac{E_S}{\gamma_s H}\right)^{\beta_2}\\&\quad\times\left[\alpha_2\frac{\left(\frac{P_O}{E_S}\right)^{\beta_3}}{\left(\frac{\tau(T)}{D}\right)^{\beta_4}\left(\frac{W}{\gamma_s D^2H}+1\right)^{\beta_5}}\right.\\&\quad\left.+\alpha_3\frac{\left(\frac{\tau(T)}{D}\right)^{\beta_6}\left(\frac{W}{\gamma_s D^2H}+1\right)^{\beta_7}}{\alpha_4\left(\frac{E_P}{E_S}\right)+\alpha_5\left(\frac{P_O}{E_S}\right)+\alpha_6\left(\frac{H}{D}\right)+\alpha_7\kappa}\right]\end{aligned} \tag{15}$$

where α and β are model coefficients and can be found in Robert et al. (2016). Monte Carlo simulation with 100,000 sampling points, was performed to obtain the time-variant failure probability of the CI pipelines based on the random variables adapted from Mazumder et al. (2019) and Ji et al. (2017). Definition of other parameters in Eq. (15) and their statistical distributions are provided in Table 5. The Rajani et al. (2000) corrosion model is used considering two types of corrosive soil environments (moderate



(a) (b)

Fig. 6. Rancho Solano (a) WDS; and (b) road network.

Table 4. Sample data set of consequence parameters (10 out of 126 pipes)

Pipe ID	Dia. (mm)	Depth (m)	Mat	Degree of access.	Road type	Land use	BD	HP	# of Lanes	PA (m)	Soil type	Prox. sensitive area (m)	Avg. daily traffic	Pop./km^2	Age
119	300	4.1	CI	2.4	Collector	Agr	Health	0.010	2	6	Mod	5	Low	767	70
121	350	2.8	CI	1.5	Collector	Res	Health	0.000	2	20	Mod	19	Low	576	80
122	300	4.0	CI	4.7	Collector	Park	Com	0.008	2	4	Low-Mod	13	High	412	70
123	350	3.1	CI	1.3	Collector	Com	Other	0.000	2	14	Mod	18	Low	992	90
124	350	1.4	CI	1.1	Arterial	Res	Com	0.006	2	6	Low-Mod	10	Low	345	70
125	450	1.2	CI	2.3	Collector	Ind	Other	0.003	2	7	High	13	High	689	70
126	350	2.0	CI	1.3	Arterial	Ind	Major	0.003	2	9	Low-Mod	4	High	212	90
127	350	2.4	CI	4.1	Collector	Agr	Com	0.003	2	6	Low-Mod	19	High	386	90
130	300	3.5	CI	3.2	Collector	Agr	Health	0.001	2	12	Low-Mod	14	Low	685	70
137	450	4.3	CI	3.6	Collector	Ind	Health	0.000	2	20	Mod	4	High	1039	90

Note: Dia = diameter; access. = accessibility; BD = business disruption; HP = hydraulic performance; PA = proximity to asset; Avg. = average; and Pop. = population.

and high). Figs. 7(a and b) show the fragility curves of pipelines for moderate and high corrosive environments, respectively. More details on the fragility analysis can be found in Mazumder et al. (2019).

Risk Analysis Results

The risk of WDS is determined by combining the probability of failure of pipeline and the consequence of failure. Fig. 8(a) shows the failure probability of pipelines in the network. Since the youngest pipeline age is randomly assigned as 70, the lowest value of the failure probability is equal to 0.2. However, the probability of failure does not only depend on the pipeline age. As shown in Eq. (15) and Table 5, the probability of failure depends on various factors, such as pipe wall thickness and operating pressure inside pipelines. Corrosion growth deterioration significantly dominants the pipe's performance. Increment of corrosion pit growth over time reduces pipe wall thickness, leading to potential pipe failure (Robert et al. 2016; Mazumder et al. 2019). The integrated consequence is evaluated on a scale of 0–1 using the fuzzy hierarchical inference system. The consequence refers to the potential impact due to the failure of the water pipeline. Integrated consequence due to failure of water pipes is estimated for the closely collocated road and WDS segments only. Parameters associated with the road network are opted out while estimating the consequence of water pipelines that are not collocated with the road network. For instance, in addition to low

Table 5. Statistical parameters and distributions

Parameters	Mean	COV	Unit	Distribution type
Wall thickness, t	12, 15, 16	—	mm	Deterministic
Pipe diameter, D	300, 350, 450	—	mm	Deterministic
Surface traffic loads, W	70	0.3	kN	Normal
Buried depth, h	0.8	0.25	m	Normal
Elastic modulus of soil, E_S	25	0.3	MPa	Lognormal
Unit weight of soil, γ	20	0.1	kN/m^3	Lognormal
Tensile strength, σ_y	100	0.15	MPa	Normal
Model coefficient, κ	1.0	0.15	—	Normal
Operating pressure, P_O	1000	0.15	kPa	Normal
Elastic modulus of pipeline, E_P	100000	—	MPa	Deterministic

Note: COV = coefficient of variation.

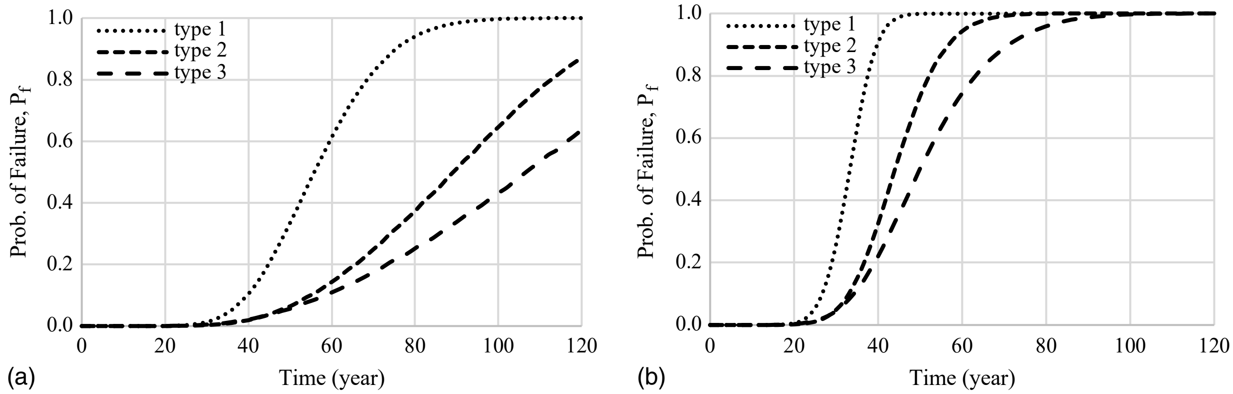


Fig. 7. Fragility curves of pipelines considering: (a) average; and (b) high corrosion models.

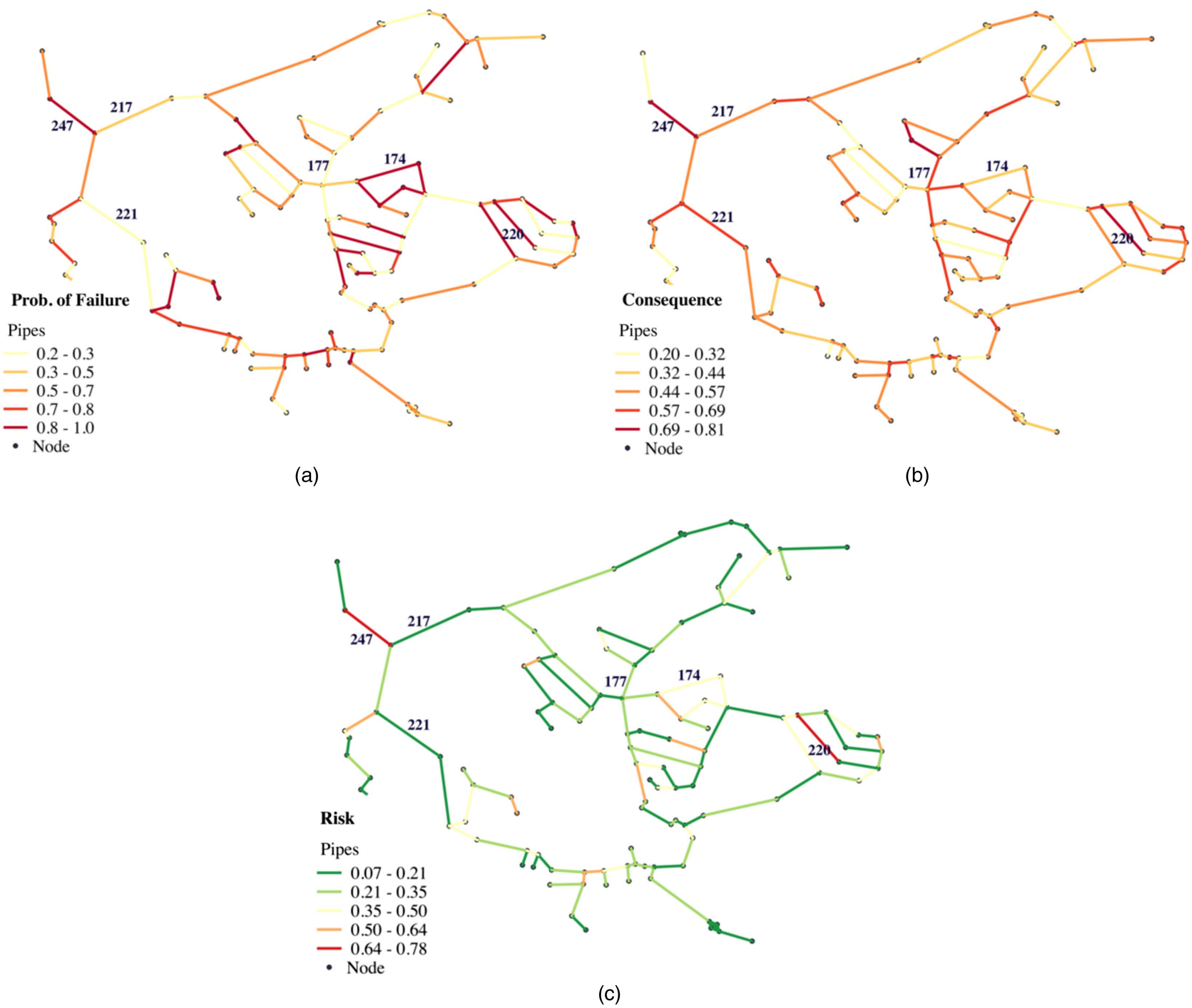


Fig. 8. Risk estimated based on risk equation: (a) probability of failure; (b) consequence of failure; and (c) risk.

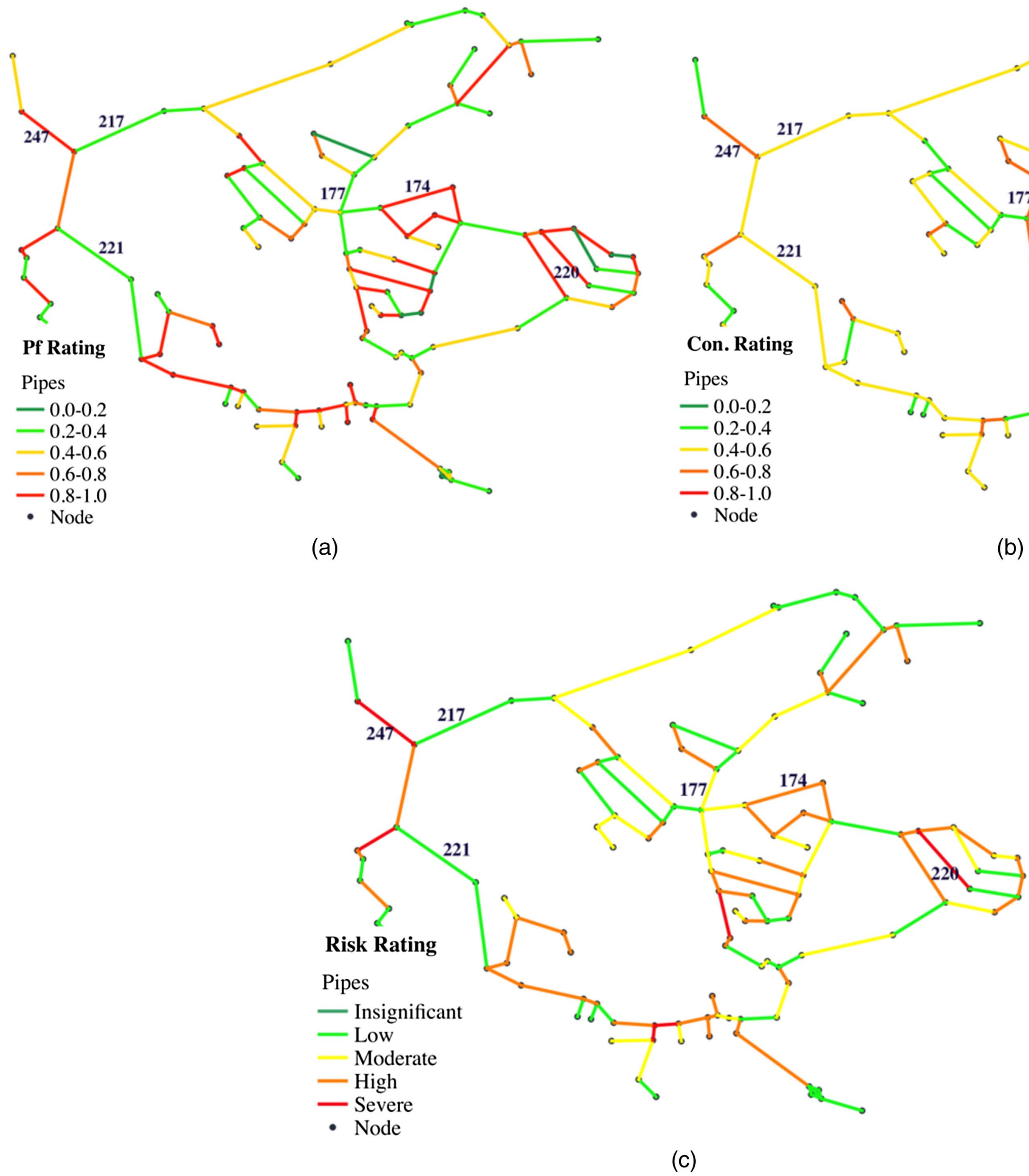


Fig. 9. Risk estimated based on risk matrix: (a) probability of failure; (b) consequence of failure; and (c) risk.

failure probability, pipe #150 is not dependent to the water pipeline, leading to a very low consequence for this pipe. Fig. 8(b) represents the consequence of failure obtained through fuzzy hierarchical inference. The nearness of the road and other assets to the water main potentially increases the consequence. Some factors related to a dependent asset, such as nearby assets and traffic volume are considered to account for determining consequences on dependent assets. The economic consequence is the dominant consequence class that contributes higher than other consequences to the total consequences. This is because the weight of economic consequences is considered relatively larger than the weights of other consequences. Fig. 8(c) shows the risk estimated by utilizing the risk equation. Pipe #220 and #247 have the highest level of risk because they have the highest level of consequence and the highest failure probability. On the other hand, pipe #221 has a low-risk level because it has a lower probability of failure and moderate consequence.

As previously mentioned, the risk information obtained through the risk equation is unable to differentiate between components with a low probability of failure and higher consequence of failure and those with a higher probability of failure and lower consequence of failure. Hence, the risk matrix is applied to assign risk levels based on the combination of the probability of failure and consequence of failure. Using the risk matrix, the decision maker will be able to differentiate between pipelines having low failure probability and high failure consequences and pipelines having high failure probability and low failure consequences. The risk matrix is popular within utility agencies for combining the consequence of failure and the condition of pipes to determine the risk of failure (Miles et al. 2007). Figs. 9(a–c) show the assigned rating for the failure probability of pipelines, the consequence of failure, and the risk of components obtained utilizing the risk matrix, respectively. It can be seen that pipe #174 has a lower consequence of failure (level 2) and a high probability of failure (level 5) that made the pipe at high risk (level 4). On the other hand, pipe #177 has a lower probability of failure (level 2) and moderate consequence of failure (level 3) that made the pipe at moderate risk (level 3).

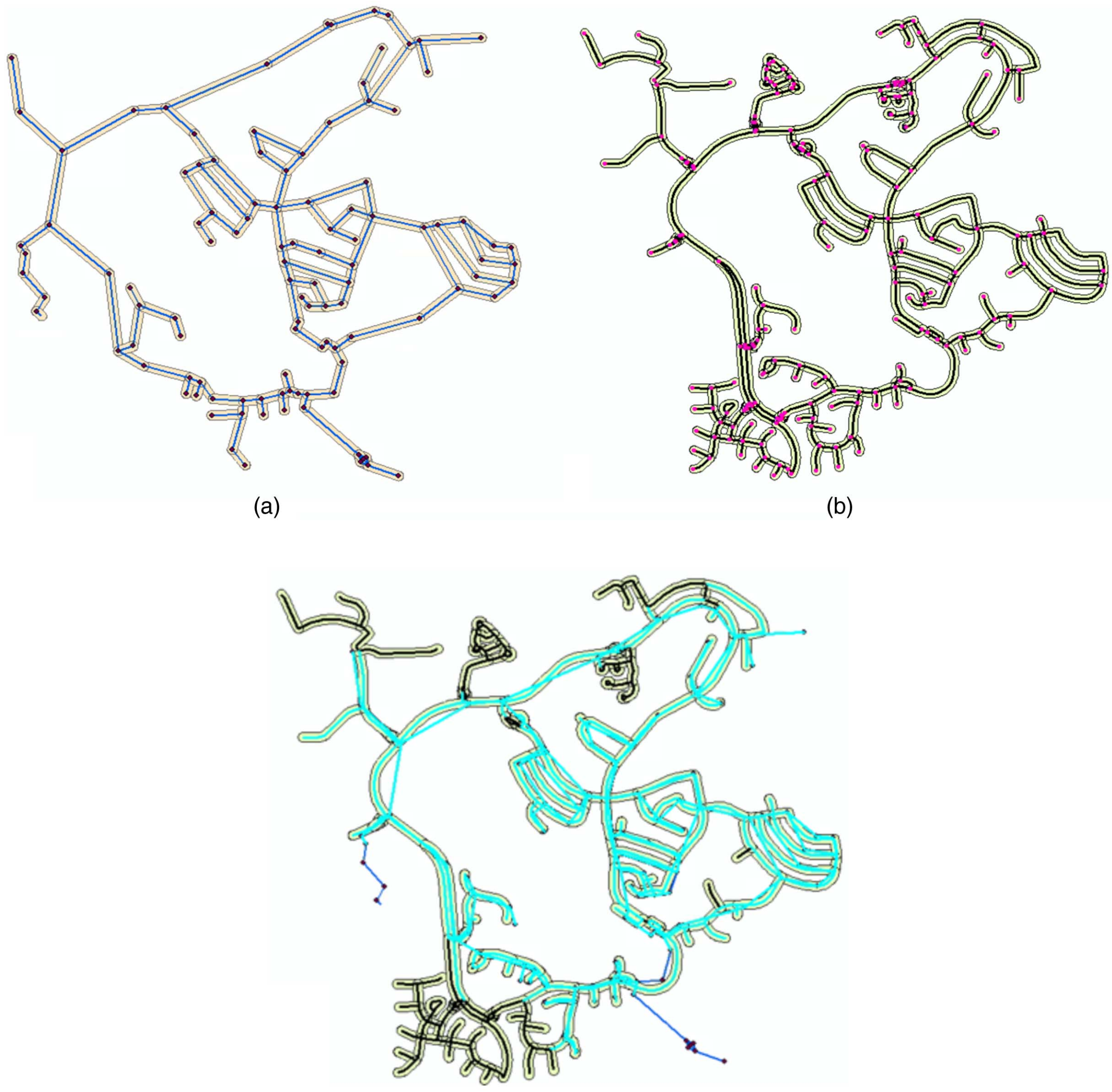


Fig. 10. Dependency analysis: (a) WDS; (b) road network; and (c) collocated segments.

Figs. 8(a–c) and 9(a–c) show that the risk levels of various components vary notably if different risk approaches are used. For example, if the risk matrix is used instead of the risk equation, pipe #174 moves from moderate risk level to high risk level. In the risk equation approach, the multiplication of a higher failure probability value by a lower failure consequence value resulted in a moderate risk level for pipe #174. On the other hand, the risk matrix first classifies the failure probability and the consequence of failure to severe and low levels, respectively, which resulted in a high risk level for pipe #174. The number of components with higher risk levels in Figs. 9(a–c) (using risk matrix) is relatively higher than the number of components with higher risk levels in Figs. 8(a–c) [using risk Eq. (8)].

Dependency Assessment Results

The relationship of the geospatial dependency of the road network on the WDS is modeled using the geometry and asset location in a GIS environment. The geospatial dependency is modeled by creating a buffer layer to all the assets. A 10-m offset buffer was generated from the centerline of the roads for determining the intersecting water asset within the buffer zone. Buffer layers of water and road segments are presented in Figs. 10(a and b), respectively. Fig. 10(c) shows spatially collocated components. Out of 126 water pipelines, 111 are identified as closely interdependent with the road network. In other words, dependent road segments will be impacted due to the failure of any of these 111 pipelines.

Network Criticality Analysis Results

Impact on Networks

Vehicles typically follow the shortest travel distance between origin and destination points. In a road network, the road links associated with a high EBC value hold a high number of shortest paths and will carry a higher volume of traffic flow than other parts of the network. In case there is a road segment closure in the shortest travel path, a vehicle is likely to travel a longer distance to reach its destination. Fig. 11(a) shows the vulnerability of the pipelines. The failure of the most vulnerable pipelines will have a significant impact on the network. For instance, if there is a failure in pipelines #217 and #218, this will potentially affect the dependent road

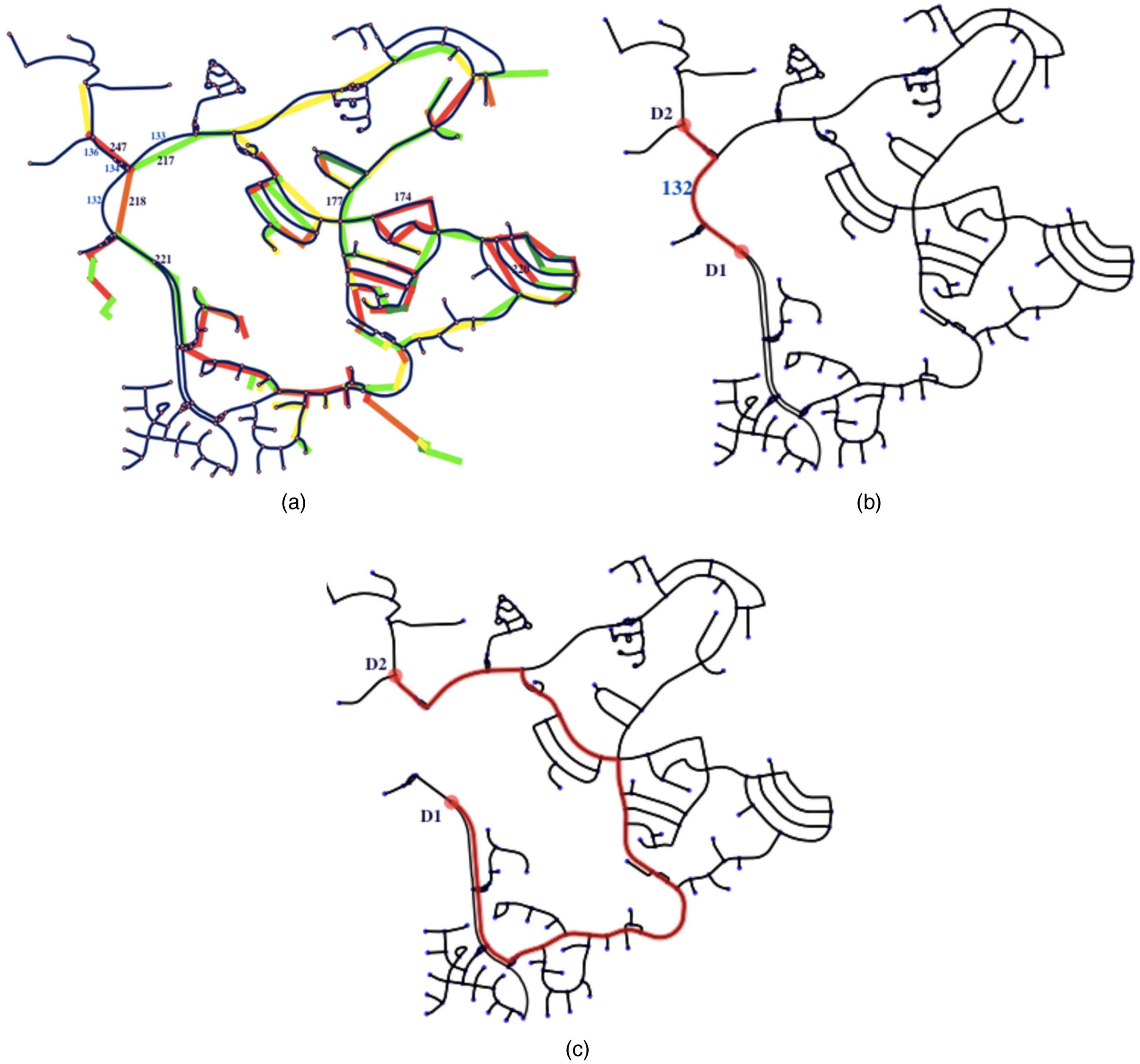


Fig. 11. (a) Probability of failure of pipelines, the shortest path from point D1 to point D2; (b) before; and (c) after closure of road #132.

segments #132 and #133. Since these roads (#132 and #133) have a high EBC, their closure will significantly affect the other parts of the road network and will force traffic to take a detour to a longer travel path. If there is a closure of road segment #132 due to the failure of pipe #217, the shortest distance from point D1 to point D2 in Fig. 11(b) increases significantly, as shown in Fig. 11(c).

Due to the failure in a water pipeline, the road segment above the damaged pipeline is likely to be interrupted. This process can be illustrated by analyzing the EBC and shortest path efficiency of the network. To illustrate the dependency phenomena, a random failure sequence is assumed based on the failure probability of pipelines. Pipelines with higher failure probability, #218, #196, and #166, are assumed to fail in a cascading sequence. It is assumed that failure will initiate in pipe #218 (state-II) followed by cascading failure in pipelines #196 (state-III) and #166 (state-IV), as shown in Fig. 12. At the initial stage (state-I in Fig. 12), the network efficiencies [using Eq. (11)] of the WDS and road network are estimated to be 0.146 and 0.115, respectively. At state-II, due to the failure of water pipe #218 and dependent road segment #132, the network efficiencies of WDS and road network are decreased by 7.5% and 9.6%, respectively. For the cascading failure state-III, due to the failure of pipe #196 and collocated road segment #38, the network efficiencies of WDS and the road network will be further reduced by 2.7% and 3.8%, respectively. If failure further propagates to pipe #166 and collocated road segment #160 at state-IV, network efficiencies of the WDS and road network will again drop by 2.1% and 2.9%, respectively. As a whole, for the assumed cascading sequence, failure in pipelines and road links would reduce network efficiencies of the WDS and road network by 16.3% and 12.3%, respectively.

Fig. 12 shows how the EBC of the networks at different states change and redistribute the vulnerability in the network systems. For instance, due to the failure in pipe #218 and dependent road segment #132, traffic flow is likely to change significantly. As such, the EBC changes in a way that road segments with the highest EBC at state-II (e.g., road segment #117) will experience the highest volume of traffic and will be more prone to having traffic disruption. Similarly, due to the change in the EBC of pipelines, the WDS will experience a similar impact in terms of connectivity, as shown in Fig. 12. To develop an effective emergency response plan, the

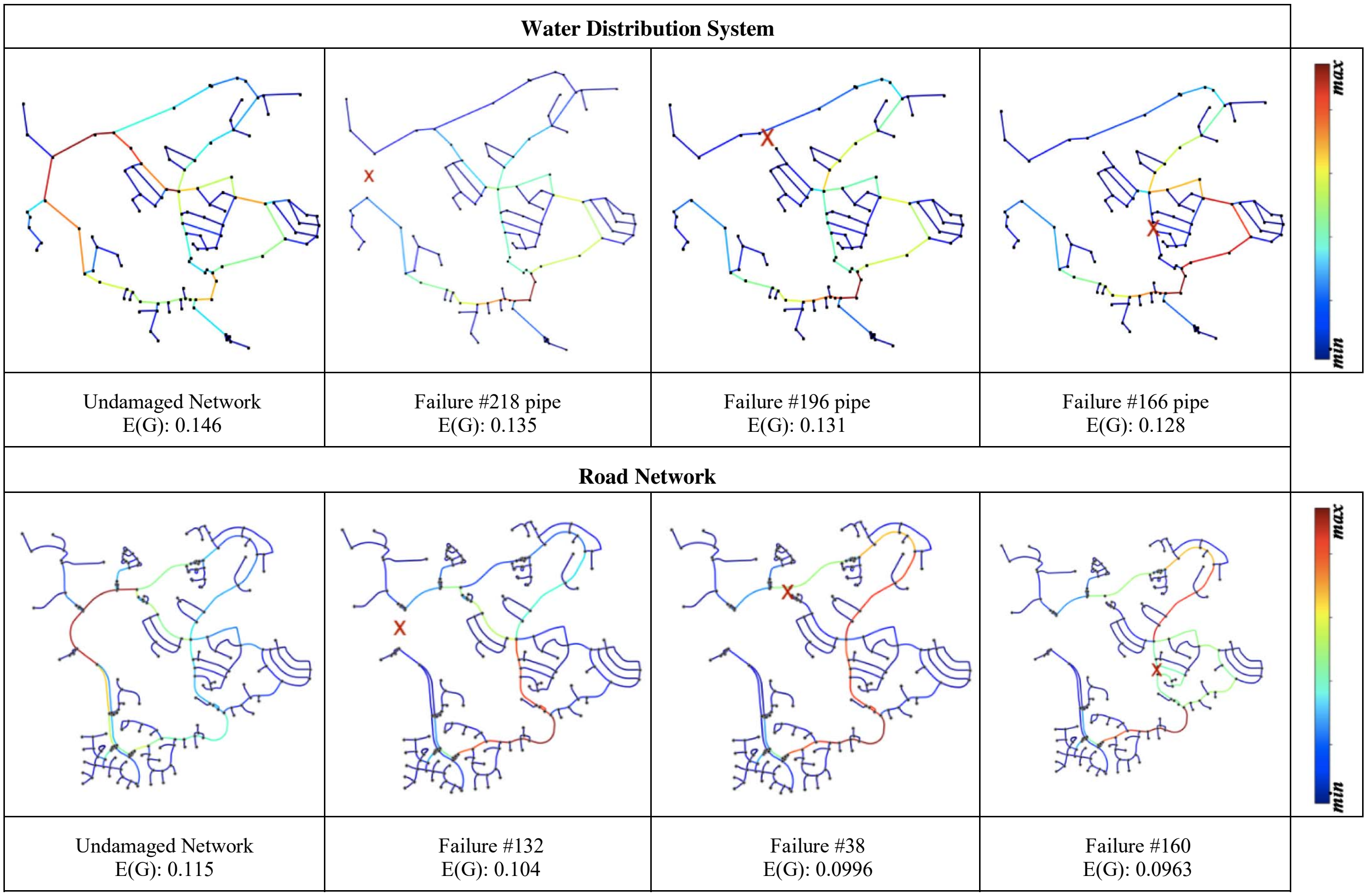


Fig. 12. Impact assessment of WDS and road network.

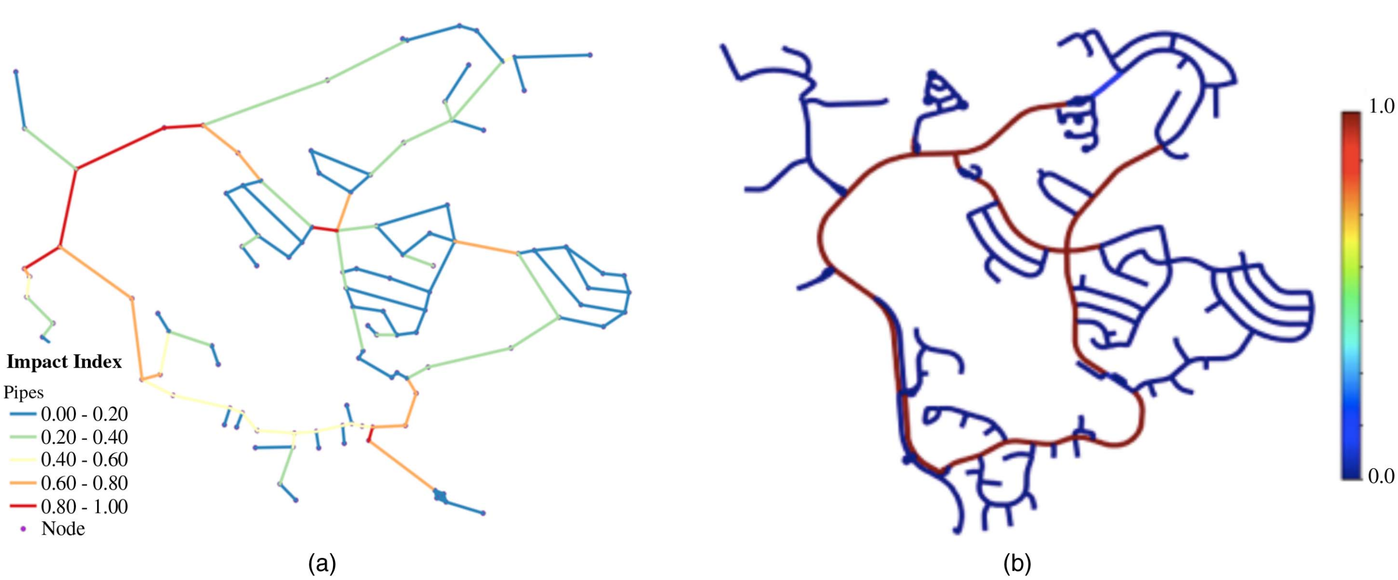


Fig. 13. Normalized network impact index: (a) Rancho Solano WDS; and (b) road network.

shortest path can be utilized by repair crews to travel from the repair station (origin) to the failure point (destination). Hence, any potential travel delay to initiate the repair process can be avoided. If driving speed limit of roads is known, then the fastest path can be determined by assigning "driving speed" as a weight to road segments. The failure of a pipeline and dependent road interruption increases the travel burden to other parts of the road system. Changes in traffic patterns may result in excessive traffic loads on buried pipelines under the road segment and, therefore, increases the vulnerability of pipelines (Liu et al. 2018).

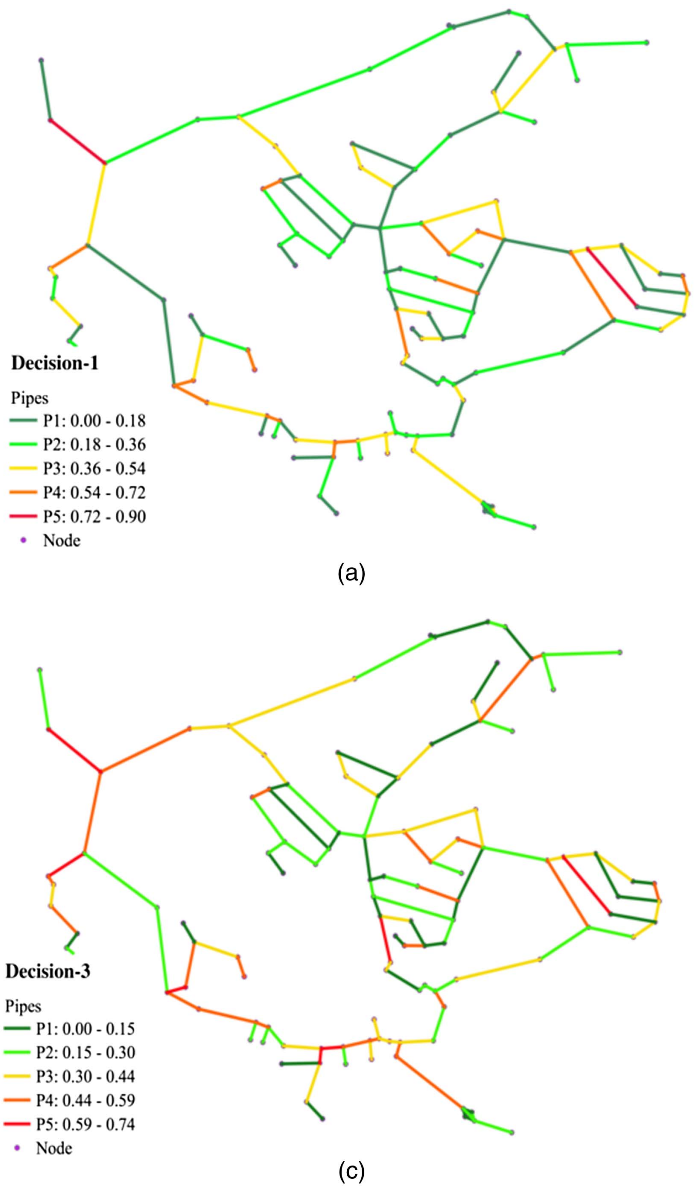


Fig. 14. Decision alternatives: (a) Decision-1 (ω_R:0.9, $\omega_{I\eta}$:0.1); (b) Decision-2 (ω_R:0.8, $\omega_{I\eta}$:0.2); (c) Decision-3 (ω_R:0.7, $\omega_{I\eta}$:0.3); and (d) Decision-4 (from risk matrix).

Criticality of Components

Figs. 13(a and b) show the normalized impact index obtained for both Rancho Solano WDS and road network, respectively. This impact is determined by removing pipelines or road segments separately from the network, as expressed in Eq. (12). The pipeline and road segment with higher values in Figs. 13(a and b) are more critical for the system because failure of these components will highly impact the network.

Decision-Making Results

Four decision scenarios are then generated following two decision-making approaches. The first three scenarios are generated following the first approach [using Eq. (14)], and the fourth scenario is developed following the second approach. A combined impact index for the water pipeline and corresponding dependent road segment are linearly added and further normalized while developing decision alternatives.

The three decision scenarios using the first approach are generated using different combinations of weights of the risk and the network impact index. The corresponding weights of the risk and the network impact index, I_η, for decision-1, decision-2, and decision-3 are taken as $\{\omega_R$:0.9, $\omega_{I\eta}$:0.1$\}$, $\{\omega_R$:0.8, $\omega_{I\eta}$:0.2$\}$, and $\{\omega_R$:0.7, $\omega_{I\eta}$:0.3$\}$, respectively. These combinations are chosen based on expert opinions obtained through in-person interviews. Then, the final decision index is estimated as per the combination expressed by Eqs. (13) and (14). Figs. 14(a–c) show the results of decision scenarios 1, 2, and 3, respectively. The fourth decision scenario is generated by utilizing the risk matrix and the $\omega_{I\eta}$. In addition to the assigned risk rating to an individual component, the I_η value is linearly added to the risk values for prioritizing assets. Fig. 14(d) indicates the criticality of the components. The most critical components should be repaired first, followed by the least critical components.

It can be seen from all the decision alternatives that pipe #247 has the highest decision index and hence needs to be rehabilitated first. It can also be seen that pipes #217 and #221 belong to priority class P2 in decision scenarios 1 and 2. However, the priority level increases from P2 to P3 if decision scenario 3 is chosen. This is because decision scenario 3 gives a higher relative weight to EBC than the other two scenarios. It should be noted that the priority class P5 in Figs. 14(a–c) refers to the highest priority, and the priority class P1 refers to the lowest priority for maintenance.

Conclusions

This paper presents a risk-informed decision support framework for integrated water and road infrastructure asset management. The proposed framework utilizes a physics-based pipe failure method, fuzzy hierarchical inference, geoprocessing tool, and complex network theory for generating the decision index of each individual component.

In civil infrastructure management, decision makers are interested to know the impact of component failure on system performance. Hence, along with the risk assessment outputs, topology-based network efficiency is used for developing meaningful and better decision alternatives, which is an advancement to the existing decision-making models. Also, the network efficiency of the WDS and road network is estimated to measure the impact on a damaged system separately due to the failure of a collocated segment. The framework uses a number of Python tools (e.g., WNTR, NetworkX, OSMnx) that are computationally efficient to analyze large networks within a relatively short time.

The proposed model was implemented for the water and road infrastructures of the Rancho Solano Zone III of the city of Fairfield, California. Four decision scenarios are developed, combining outputs from the risk analysis and the NCA. The case study showed that the identification of critical components provides useful information about the post-failure consequence at the system level. For instance, due to the failure in the water pipeline and subsequent closure of collocated road segments, the shortest path length between two different points can be significantly increased, which may result in traffic delay and other consequences. It was observed that due to the failure of a single segment (one of the riskiest pipelines and dependent road links) in the critical part, the network efficiencies of the WDS and road network might drop by 7.5% and 9.6%, respectively.

Although a medium-sized network is considered in this case study, the proposed framework can be applied to any network size if the required parameters are available. The framework is expected to assist utility decision makers in identifying the most critical segments for prioritizing maintenance tasks.

The decision-making process allows a decision maker to select a decision alternative for optimizing the maintenance actions. It should be noted that a decision maker may accept or reject any alternatives based on their goals, available resources, and budget. The decision-making process can be updated by including a renewal cost analysis, and multicriteria analysis can be performed for selecting a decision from the decision alternatives. While estimating the impact on both road and water networks, geospatial interdependency analysis is performed to determine the dependent road segment.

This study also has other limitations that need to be addressed in future research. The effect of dependency was modeled, assuming that water pipeline failure will trigger a failure in both systems. Consequence factors are only classified depending on their significant contribution to a specific consequence. Potential aspects of these factors' contribution to other consequences are ignored. In the future, the effect of failures in road networks on water networks can be considered explicitly. Also, in the WDS, only the failure of the pipelines was considered. Effect of failure of other components of WDSs, such as pressure reducing valves, isolation valves, water pumps, reservoirs, and joints, need to be considered in future research. Correlation among the parameters in a consequence class and consequence classes is not accounted for in the consequence analysis. The effect of correlation between consequence parameters on consequences should be analyzed in future research. Dependency analysis technique can be further updated by accounting for other factors, such as burial depth, traffic volume, and flow-based metric.

Data Availability Statement

The following data and code generated during the study are available from the corresponding author by request including consequence parameters data and MATLAB codes for fuzzy inference analysis.

Acknowledgments

This research was supported, in part, by the National Science Foundation (NSF) Critical Resilient Interdependent Infrastructure Systems and Processes (CRISP) under Grant No. NSF–1638320. This support is thankfully acknowledged. The authors also acknowledge Cleveland Water Department, particularly its commissioner Mr. Alex Margevicius, for their support of this project. However, the writers take sole responsibility for the views expressed in this paper, which may not represent the position of the NSF or their respective institutions.

Supplemental Materials

An example of fuzzy rules generation (Fig. S1 and Table S1) is available online in the ASCE Library (www.ascelibrary.org).

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