Computational Risk Assessment in Water Distribution Network

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Abstract. Water Distribution Networks (WDNs) are critical to urban infrastructure, ensuring the delivery of clean water but subject to ageing, environmental challenges, and operational pressures. This study employs a fuzzy logic-based approach using the Mamdani inference system to evaluate risks in Hashtgerd's WDN. Key risks include contamination in water wells, structural vulnerabilities in tanks, and mechanical failures in pump stations. The findings reveal an overall risk level of 69.1%, with individual contributions of 66.18% from wells, 66.87% from pump stations, and 71.9% from tanks. Recommendations include stricter zoning, improved maintenance, advanced monitoring, and enhanced security.

Keywords: Water Distribution Networks · Risk Assessment · Fuzzy Inference System · Failure Modes and Effects Analysis · Quantitative Risk Evaluation.

1 Introduction

The risk analysis framework is crucial for sustainable development, helping to identify and assess threats to water supply systems. Water Distribution Networks (WDNs) are vital to urban infrastructure, delivering clean water globally. As public infrastructure standards evolve, ensuring the safety and reliability of WDNs has become increasingly important [13]. Ageing infrastructure and environmental uncertainties necessitate an integrated approach to risk assessment and mitigation. Quantitative risk evaluation, based on historical failure data and a blend of expert and data-driven models, is key to maintaining system reliability [9]. WDNs face challenges from material degradation, environmental stress, and operational limits. Ageing pipelines are prone to failure, aggravated by corrosive soil, heavy traffic, and extreme weather [5, 14]. A typical WDN structure and purification process are shown in Fig. 1.

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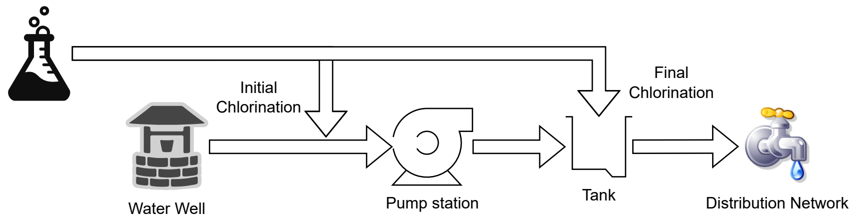

Fig. 1. Water Network Infrastructure.

This paper presents a methodology using Mamdami's Fuzzy Inference System (M-FIS) to evaluate risks in WDNs, emphasizing water contamination, structural vulnerabilities in tanks, and mechanical failures in pump stations. The objective is to combine precise evaluation with fuzzy logic's flexibility, offering recommendations to mitigate risks and improve safety. The proposed approach is evaluated based on real data from Hashtgerd's case study in Iran.

The paper is structured as follows: Section 2 reports a brief literature review on related work; Section 3 describes the methodology and the enabling techniques; Section 4 describes the application of the methodology to the case study; Section 5 ends the paper, addressing future research.

2 Related work

Quantitative risk assessment forms the backbone of modern WDN management strategies, enabling the identification and mitigation of failure risks. Advanced statistical and Machine Learning (ML) algorithms, like Cox regression, supplement WDN risk assessment based on pipe-specific traits such as diameter [8]. ML approaches have also been proven to address a wide range of WDN-related challenges. For example, Yang et al. analyse pipeline failures using Decision Tree (DT) models, showing that the elapsed time since the last failure was the most important variable explaining future failures [18]. Biganzoli et al. show that Artificial Neural Networks (ANNs) provides a powerful framework of failure predictions based on survival data and nonlinear interactions between risk factors [6]. Roozbahani et al. proposed, instead, an Integrated Fuzzy Hierarchical Risk Assessment model for Water Supply Systems (IFHRA-WSS) model for improving water supply system risk management [15]. Integrating Geographic Information System (GIS) and fuzzy logic enhances risk management, as seen in Iran's Varamin aquifer, where fuzzy models ranked subsidence risks for targeted action [12]. Furthermore, Wu et al. use GIS data, combined with Graph Neural Networks (GNNs), to predict water network leakage risk with better performance than existing methods by focusing on key factors like pipe age, material, and failure history [17]. Kaghazchi et al., instead, developed a Hybrid Bayesian Networks (HBN) model for hydraulic performance simulation and irrigation system risk assessment, achieving high accuracy [10]. Table 1 represents a first qual-

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Table 1. Comparison of Different Methods.

Criteria	(Our Method)	**Machine Learning (RF, ANN, DL)**	**Bayesian Networks (BN)**	**Markov Models**
Handling Uncertainty	Strong (which improves readability)	Needs large dataset for accurate predictions	Good (probabilistic reasoning)	Good (assumes predefined states and transitions)
Interpretability	High (rule-based and transparent)	Low (black-box models)	Medium (graph-based but complex)	Low (probabilistic but interpretable)
Computational Cost	Low (fuzzy rules are computationally simple)	High (training ML models is resource-intensive)	Medium (depends on network complexity)	Medium (state-space modelling required)
Data Requirement	Low (expert knowledge based)	High (requires extensive labeled dataset)	Medium (needs Probability estimations)	Low (can work with small dataset)
Adaptability to New Data	Limited (Rules need manual updates)	Strong (automatic pattern recognition)	Strong (can update probability tables)	Strong (adjusts to new transitions)

itative attempt to address such a classification, a sort of roadmap towards a reasoned comparison of related methods.

3 The proposed approach

This study applies a fuzzy logic-based method to assess risks in Hashtgerd's drinking water facilities using the M-FIS. Enhancing traditional Failures Modes and Effects Analysis (FMEA), it better captures the subjectivity of risk factors. The two-stage approach evaluates and aggregates risk across water wells, tanks, and pump stations. Initially, hazards are assessed via severity, occurrence, and detectability — defined respectively as potential impact, likelihood, and ease of detection. These are expressed using fuzzy linguistic terms (`low`, `medium`, `high`) to handle judgment uncertainty. Triangular membership functions model the fuzzy sets, as shown in Eq. 1 [4]:

$$\mu_A(x) = \begin{cases} 0, & \text{if } x \leq a \text{ or } x \geq c \\ \frac{x-a}{b-a}, & \text{if } a < x \leq b \\ \frac{c-x}{c-b}, & \text{if } b < x < c \end{cases} \qquad \begin{aligned} a &: \text{ lower bound} \\ b &: \text{ peak value} \\ c &: \text{ upper bound} \\ \mu_A(x) &: \text{ membership function} \end{aligned} \tag{1}$$

M-FIS computes fuzzy risk levels for each hazard, which are defuzzified via the centroid method to yield crisp risk scores. These scores guide risk ranking and prioritization, following FMEA principles tailored to water utility operations. In the second stage, average component scores inform a system-level risk assessment, using a second set of fuzzy rules. For example: *"If the Water Wells Risk is High, the Tank Station Risk is High, and the Pump Station Risk is High, then the Overall Facility Risk is Critical."*

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The final defuzzified output quantifies the overall safety level of the water facility system. As a key element of the expert system, the defuzzifier converts fuzzy values into crisp results within Fuzzy Inference System (FIS) processing. Several types exist, such as Mean Of Maximum (MOM), Centroid Of Area (COA), Largest Of Maximum (LOM), Bisector of Area (BOA), and Smallest Of Maximum (SOM), with COA being the primary method used in this study [1,3]. The centroid method is detailed in Eq. 2, where $\mu_i(x)$ denotes the membership values of each rule output.

$$R^* = \frac{\sum_i \mu_i(x) \cdot x_i}{\sum_i \mu_i(x)} \quad R^* : \text{ final risk value} \tag{2}$$

The defuzzified final score offers a clear overview of risk, supporting strategic prioritization [16]. Fuzzy logic handles subjectivity through membership functions (low, medium, high) and “if-then” rules [2] The followed approach is depicted in Fig. 2.

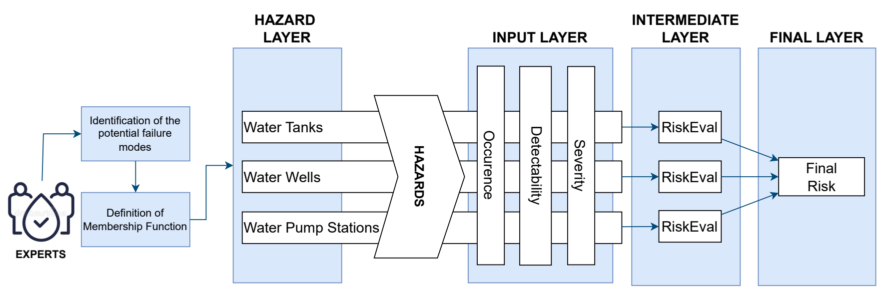

Fig. 2. Structure of the Proposed Model.

This model follows a systematic risk analysis process, beginning with expert inputs, where domain experts identify potential failure modes. Expert knowledge is embedded in the following layers[4]: (1) hazard layer, responsible for detecting the hazards related to the different considered subsystems; (2) input layer, quantifying each hazard subsystem per subsystem according to three critical risk factors: *occurrence*, *severity*, and *detectability*; (3) intermediate layer, evaluating the risk for each hazard and for each subsystem. The evaluation is carried out by RiskEval components, which are based on M-FIS and Monte Carlo Simulation (MCS); (4) final layer, which combines all the partial risk evaluations into a single final risk level for the entire WDN.

Using MCS for Risk Priority Number (RPN) computing. MCS is a technique that uses random sampling to approximate complex mathematical or physical

[4] In this context, experts are who design, maintain or operate the system and subsystems as well: mechanical, chemical, hydraulic engineers, to mention some of them.

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systems, enabling the estimation of various outcomes under uncertainty. It is widely used in risk analysis, optimization, and decision-making processes [7]. In this paper, the usage of FIS mechanism is boosted by applying the MCS technique to RPN computing. RPN computing involves estimating the RPN by modelling the uncertainty of its factors - Severity (S), Occurrence (O), Detectability (D) - using probability distributions. The formula $RPN = S \cdot O \cdot D$ describes the traditional approach in RPN computing.

In this context, MCS generates N random samples, it computes RPN values and analyses their distribution to assess and prioritize risks. The result is a probability distribution of RPN values instead of a single deterministic number, as deterministically computed by the M-FIS approach. Eq. 3 defines the formula by which the mean RPN value is computed

$$\overline{RPN} = \frac{\sum_{i=1}^{N} S_i \cdot O_i \cdot D_i}{N} \tag{3}$$

where S_i, O_i, and D_i are sampled according their probability distributions.

4 The Hashtgerd Case Study

This section describes the application of the proposed method to a case study, substituting the Hazard Layer and the Input Layer with a dataset. For the sake of the space, only the analyses related to Water Wells subsystem are shown, even if all the subsystems have been considered in the proposed case study.

Dataset. The considered dataset is related to the WDN of the 55,640 people city of Hashtgerd Alborz, in Iran in 2020 [11]. The active water facilities of Hashtgerd City include five water wells, one pumping station, two water tanks, as well as the corresponding values for the O, S, and D, which span from 0 to 10. Additionally, they describe the Risk value and Critical Level computed using the fuzzy model. Specifically, five levels of criticality have been identified: Very Very High (VVH), Very High (VH), High (H), Medium (M), and Low (L).

Water Wells. Table 2 reports the input dataset for this component (first four columns) as well as the risk computed using the Water Well Fuzzy Model, and the last column shows the level of the risk. Fig. 3 shows how the risk of water wells varies with occurrence and severity, considering the values of detectability set to its middle value. As the occurrence and severity decrease, the overall risk decreases. Conversely, an increase in either factor raises the risk. The plot demonstrates a positive correlation between risk and both the occurrence and severity of hazards. Key risks for water wells include their proximity to highways and urban areas, raising the potential for contamination from vehicle spills and hazardous discharges. Additionally, inadequate wellhead protection and poor soil conditions heightened the risk of water quality deterioration. The highest risk for water wells is placing them near highways and busy routes (92.9%), while the lowest risk is directly injecting well water into the network (33.3%).

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Table 2. Water Well — List of Hazards and Risk Evaluation.

Hazard	O	S	D	Risk	Critical Level
Wells near highways and busy routes	7	8	8	92.9	VVH
Soil conditions of the area	6	8	8	83.3	VH
Urban activities, pollution sources	7	6	8	83.3	VH
Contaminated aquifer (treated wastewater recharge-hardness/TDS)	5	7	8	83.3	VH
Intentional contamination of water through sabotage operations	4	8	8	83.3	VH
Contaminated aquifer (toxic minerals - wastewater recharge)	4	7	8	83.3	VH
Poor well maintenance, corrosion, casing issues	6	6	6	50	M
Lack of proper wellhead protection	4	7	7	83.3	VH
Insufficient perimeter and physical security	3	8	8	66.7	H
Physical attacks	6	6	5	50	M
Encroachment on buffer zone	3	5	8	50	M
Forestry and agricultural activities	3	5	8	50	M
Direct injection of well water into the network	2	5	6	33.3	L
Animal husbandry and livestock activities	1	6	7	50	M
Industrial and mining activities	1	4	7	50	M
Final Risk of Water Wells				**66.18**	**H**

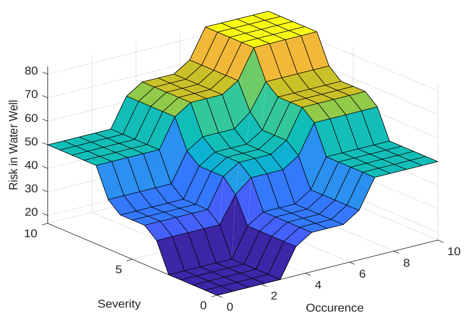

Fig. 3. MATLAB's surface view of risk related to water wells hazard.

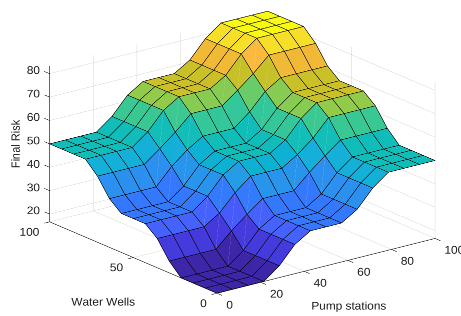

Fig. 4. MATLAB's surface view of the final risk.

Overall Risk The risk assessment of Hashtgerd's WDN found an overall risk level of 69.1%, with water wells, tank stations, and pump stations contributing 66.18%, 71.9%, and 66.87%, respectively. These results highlight the critical role of water tanks in determining the overall risk, followed by pump stations and water wells. Fig. 4 illustrates the surface plot of the final risk in a WDN: this plot is generated considering the middle value of the water tank risk.

Improving risk estimation with MCS. MCS is used to overcome the limitation of computing crisp values of risk evaluation by M-FIS evaluators. By computing the statistical distribution of RPN for each hazard, the values computed by fuzzy methods are validated by using another technique. To account for uncertainties in risk assessment, we introduced controlled variability in the O, S and D values during the MCS. Each parameter has been perturbed using a uniform distribution, $p_{Sim} = p + U(-0.5, 0.5), \quad \forall p \in \{O, S, D\}$. The MCS technique was implemented in Matlab with 10,000 for each system hazard. Sample sizes

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count 150,000 for water wells, 120,000 for pump stations, and 140,000 for water tanks. As a result of the analysis, the three highest-risk hazards, based on the mean RPN, are “Wells near highways/roads,” “Soil conditions,” and “Urban activities/pollution.” These results are concordant with the fuzzy analysis.

Discussion Here, some considerations and lessons learned are reported. To mitigate these risks, the study recommends stricter zoning, relocating critical infrastructure, and proactive maintenance—such as predictive monitoring sensors, corrosion-resistant materials, and real-time water quality systems to enable timely intervention. In particular, water tanks, with a risk of 71.9%, were found to be the most vulnerable due to their location near high-traffic areas and insufficient protection, suggesting the need for improved zoning regulations, better well-head sealing, and advanced monitoring systems. Strengthening security against sabotage is critical. M-FISs prove their effectiveness in managing uncertainties but require extensive computational resources. Future improvements could focus on streamlining data collection and enhancing the system’s applicability. Computational risk assessment of WDN is possible using various methodologies like FIS, ML, Bayesian Networks (BNs), and Markov models.

5 Conclusions

This paper presents a two-stage fuzzy inference model, which first evaluates individual risks for water wells, tanks, and pump stations, and then combines them into an overall network risk score. In addition, incorporating MCS enables probabilistic estimation of risk, giving confidence intervals for risk estimates rather than point estimates. This study identifies water tank as the most critical risk factor (71.9%), followed by pump stations (66.87%) and water wells (66.18%). Key threats include corrosion, ageing infrastructure, pressure fluctuations, and physical attacks. The proposed fuzzy-based risk assessment model can be adapted for use in other cities with different climates, water sources, and infrastructure conditions. Implementing zoning regulations, proactive maintenance strategies and security enhancements will significantly improve the resilience of Hashtgerd’s WDN. Future improvements can integrate Artificial Intelligence (AI) and Internet of Things (IoT) to enhance risk prediction by analysing real-time sensor data, detecting anomalies, and predicting failures. Testing the FIS and MCS models in different climates will assess its adaptability to environmental stressors.

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