Optimal Proactive Seismic Rehabilitation of Gas Pipeline Networks

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ABSTRACT

Critical infrastructure systems, such as gas pipeline networks, are essential to the modern community's survival. In severe seismic hazard zones, earthquakes can cause catastrophic damages to gas pipeline networks. The damages disrupt the gas supply, resulting in various direct and indirect losses to the utilities that serve the community. Resource constrained proactive rehabilitation of these pipelines under seismic uncertainty presents a challenge for gas utilities. Existing seismic susceptibility assessment models of gas pipeline networks have evaluated connectivity loss (CL). However, there is limited research that determines the optimum rehabilitation policy that minimizes connectivity loss within resource constraints. This study aims to identify critical pipes of a gas pipeline network for rehabilitation minimizing the network's connectivity loss when only a limited length of pipes can be rehabilitated. With this aim in mind, four specific tasks are completed: (1) characterization of spatial seismic hazards in terms of peak ground velocity, (2) determination of pipe repair rate using the empirical fragility curves, (3) evaluation of gas pipeline network's connectivity loss, and (4) minimization of the expected value of connectivity loss using a genetic algorithm (GA). A simulation-based approach is used to evaluate the seismic hazard, network-level seismic susceptibility assessment, and evaluation of the gas pipeline network's connectivity loss while accounting for relevant uncertainties. Monte Carlo simulations were carried out to emulate the stochastic nature of the damages to the gas pipeline network. The methodology's application has been illustrated on a reference network to identify the critical pipelines of that gas pipeline network. The outcomes were compared with the rehabilitation policies determined from a length-based rehabilitation approach. The comparison demonstrated significant improvement in connectivity loss while using GA-based rehabilitation approach. The proposed approach is expected to assist the gas utilities in making rehabilitation decisions to reduce connectivity loss of the gas pipeline networks.

INTRODUCTION

Utility networks such as gas pipeline networks that are crucial for communities are known as lifelines. Although earthquakes are infrequent, their impact on the performance of a gas pipeline network can be substantial (FEMA 1992; O'Rourke and Palmer 1996; Cavalieri et al., 2014). Past earthquakes (e.g., the San Fernando and Kanto earthquakes) revealed the vulnerability of gas pipeline networks (Esposito et al. 2015). The primary purpose of a gas pipeline network is to supply gas to the end users via buried pipelines, reduction stations, and demand nodes. When a thermoelectric power station's connection is compromised, it can impair daily life by preventing energy flow to households. In addition, the damage has the potential to start cascading disasters like fires and explosions. Therefore, it is essential to accurately estimate the seismic susceptibility of gas pipeline networks.

The behavior of a gas network can be idealized by a topological connectivity-based analysis or a flow-based analysis. Topological connectivity-based analysis approaches are limited to graph theory. Both simulation-based (Cimellaro et al. 2013; Esposito et al. 2015) and non-simulation-based analysis (Chang and Song 2007; Kim and Kang 2013; Lim et al. 2015) can be used for seismic susceptibility assessment of gas pipeline networks. Several simulation-based works in the literature analyze gas pipeline networks from a topological point of view, whether they are independent or interdependent with other crucial infrastructures (Poljanšek et al. 2012; Liu et al. 2018).

For a gas pipeline network, one possible system-level performance index from a topological point of view is the connectivity loss (CL). Existing seismic susceptibility assessment models of gas pipeline networks have evaluated CL employing a topological connectivity-based analysis and using a simulation-based approach (Poljanšek et al. 2012; Esposito et al. 2015; Cavalieri 2020). However, limited research determines the optimum rehabilitation policy that minimizes connectivity loss within resource constraints. This paper aims to identify the optimum set of critical pipes of a gas pipeline network for rehabilitation minimizing the network's connectivity loss under resource constraints.

METHODOLOGY

The optimization problem is formulated. Then it is solved using a genetic algorithm (GA). The proposed GA-based rehabilitation approach integrates four different models illustrated in Figure 1.

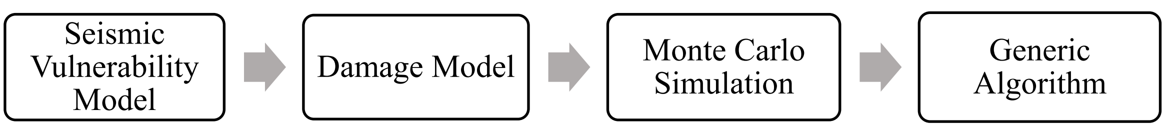

Figure 1. Integrated models of the proposed GA-based rehabilitation approach

Gas distribution network data, and seismic intensity data are required to integrate the various models. The seismic vulnerability model includes seismic repair rate calculation, a damage model for connectivity analysis, Monte Carlo simulation for evaluating objective function, and a genetic algorithm (GA) for identifying an optimal solution.

Model Formulation

The objective function is the minimization of the expected value of connectivity loss (E[CL]) of a gas pipeline network when a limited length of the pipeline is allowed for rehabilitation. The optimization problem is formulated as Equation 1.

$$\min_{n \in N} E\,[CL(n)] \tag{1}$$

Subject to,

$$L \leq x\% \text{ of } L$$

where N is the policy set to choose from, n denotes a policy including a set of pipes selected for rehabilitation, L denotes the total length of the gas pipeline network, and x% denotes a percentage of the overall pipeline length that can be rehabilitated. We looked at 10%, 20%, and 30% of the total pipeline length that was allowed for rehabilitation in order to illustrate the proposed approach.

Expected Connectivity Loss (E[CL])

Connectivity loss quantifies the average decline in sink nodes capacity to receive flow from source nodes because of a hazard (Poljanšek et al. 2012). In other words, it measures the decline in the number of source nodes connected to a sink. The network's topology and, to some extent, potential ideal flow patterns are taken into consideration while calculating this parameter. Each sink is assumed to be linked to every source in the initial state. The number of sources linked to the k^{th} sink in both the original network, $N^{k}_{source,original}$, and the damaged network, $N^{k}_{source,damaged}$, must be first counted. Finally, using Equation 2, CL is determined.

$$CL = 1 - \langle \frac{N^{k}_{source,damaged}}{N^{k}_{source,original}} \rangle \tag{2}$$

where ⟨⟩ means taking an average across all sink vertices. Equation 3 gives a general formula for determining the expected connectivity loss (E[CL]).

$$E[CL] = \frac{1}{MCS * V} * \sum_{mcs=1}^{MCS} \sum_{v=1}^{V} CL_{v}^{mcs} \tag{3}$$

where MCS is the predetermined number of Monte Carlo simulations for a particular gas pipeline network, and V is the number of peak ground velocity (PGV) fields generated for a scenario earthquake.

Seismic Vulnerability Model for Evaluation of Seismic Repair Rate

A seismic deaggregation analysis is used to select a scenario earthquake (Adachi and Ellingwood 2008; Pudasaini and Shahandashti 2020a). A PGV field was generated for the selected earthquake scenario (Abrahamson and Silva 2007; Sharveen et al. 2022). The formula for determining PGV is demonstrated in Equation 4.

$$\log_{10} (PGV_{uv}) = f(M_u, R_{uv}, \theta_u) + \sigma_B v_u + \sigma_w \varepsilon_{uv} \tag{4}$$

where PGV_{uv} is the peak ground velocity for site v from source u at R_{uv} distance; M_u represents the earthquake magnitude; θ_u denotes the geological parameter that identifies the source of the scenario earthquake; the interevent and intra-event residuals are denoted by $\sigma_B v_u$ and $\sigma_w \varepsilon_{uv}$ respectively. Then, for the particular earthquake scenario, the seismic repair rate is calculated. The seismic repair rate is the number of repairs required for every 1,000 meters of pipe (Pudasaini and

Shahandashti 2021; Roy et al. 2022). Equation 5 illustrates the general formula for calculating seismic repair rate, which was established using post-disaster information from previous earthquakes in the United States and Mexico (O'Rourke and Ayala, 1993).

$$RR_m = \frac{(PGV_{m,V})^{2.25}}{10{,}000} \tag{5}$$

where RR_m denotes the repair rate for one thousand meters of pipe m. $PGV_{m,V}$ is the peak ground velocity in cm/sec for the m^{th} pipe, and V^{th} PGV field.

Damage Model for Connectivity Analysis

The ability to estimate the mean break occurrence rate makes the repair rate (RR) effective for describing the likelihood of pipeline ruptures. A wide variety of damage mechanisms, such as breaks or leaks, are included in repair rates. Typically, 15–20% of such mechanisms are breaks, with the remaining 85-80% being leaks (Hwang et al. 1998).

The probability that the number of pipe breaks equals b within a specified pipeline segment length L is estimated using a spatial Poisson process (Dueñas-Osorio, 2007). Equation 6 illustrates the general formula for estimating the probability of b number of breaks in a pipeline.

$$P\ (Break = b) = \frac{(RR_m * L)^b}{r!}\ e^{-RR_m * L} \tag{6}$$

It is assumed that a pipeline segment's operation will be compromised by the occurrence of at least one break. As a result, the probability of a pipeline break reduces to as Equation 7.

$$P(Break>0) = 1 - P\ (Break = 0) = 1 - e^{-RR_m * L} \tag{7}$$

Then, for each pipeline, a random number between 0 and 1 is generated. A pipeline is damaged if the value from Equation 7 is larger than the randomly generated number. Each damaged pipeline is eliminated from the gas pipeline network. Then network analysis is performed to determine which nodes remain connected in the damaged network. Finally, the connectivity loss of the gas pipeline network is evaluated using Equation 2.

Genetic Algorithm for Identifying Optimal Solution

The workflow of GA based rehabilitation approach for identifying optimal seismic rehabilitation policies for gas pipeline networks is illustrated in Figure 2, and each operator of the algorithm is described below (Pudasaini et al. 2017; Pudasaini and Shahandashti 2018).

Initialization operator: N_{pop} random policies within the rehabilitation length constraint are selected as the current generation. N_{pop} is the number of populations in the current generation.
Evaluation operator: The values of the objective functions are evaluated for the selected rehabilitation policies.
Selection operator: Ranking is done based on E[CL] value. The policy with the lowest E[CL] value will have the highest ranking. Then the two policies with the lowest E[CL] value is selected as the parent rehabilitation policies.

Crossover operator: A two-point crossover is applied to generate one new offspring rehabilitation policy for the selected parent rehabilitation policies. Each parent pair produces an offspring rehabilitation policy.
Mutation operator: The genetic algorithm's initial mutation rate is 100%. In every generation, the rate of mutation is reduced by 2%. Every offspring rehabilitation policy’s 20% of the binary strings are randomly mutated. Repeated crossover and mutation operations were performed until the rehabilitation length constraint was met.
Termination operator: When the algorithm's maximum generation is reached, it is terminated. Otherwise, the current generation is updated each time. From the last generation the solution with the lowest E[CL] is the optimum rehabilitation policy.

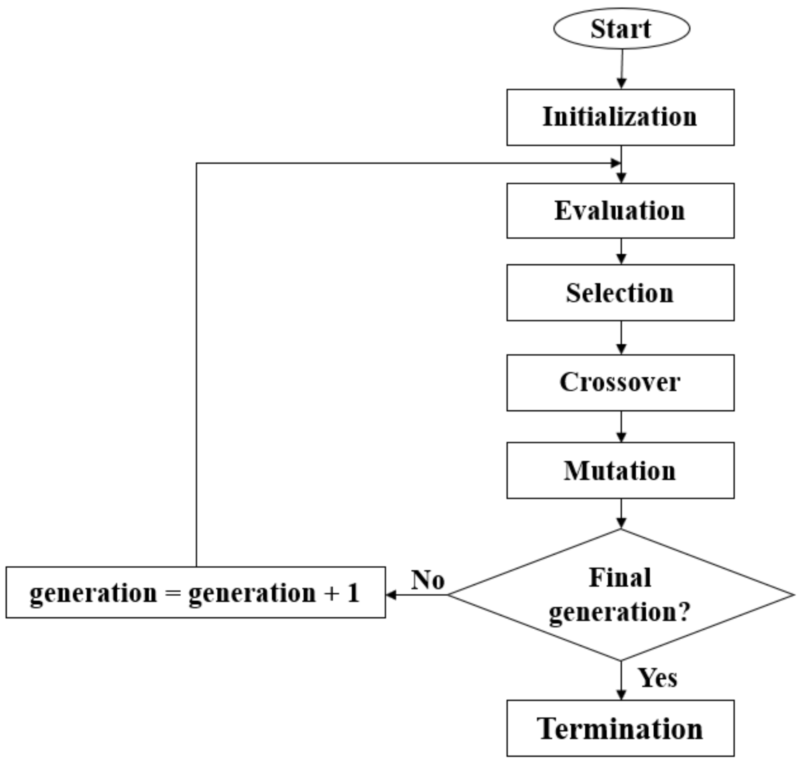

Figure 2. The workflow of GA-based rehabilitation approach for identifying the optimal seismic rehabilitation policies for gas pipeline networks

APPLICATION AND RESULTS

For testing and comparing the proposed modeling approach, the GasLib, which contains publicly available gas transport network instances is used (Schmidt et al. 2017). The GasLib-134 network was subjected to the proposed methodology for seismic susceptibility assessment of the network. The network comprises of 86 pipes, 45 short pipes, 3 entry, 45 exits, and 86 inner nodes. The gas pipeline network has a total length of 1412 km, and its pipeline diameter ranges from 254 to 914.4 mm to include transmission and distribution links. The network was centered in Pasadena, California. Figure 3 depicts the GasLib-134 network. After deaggregation analysis, a 7.12 magnitude earthquake originating at the Raymond fault was chosen as the scenario earthquake (Pudasaini et al. 2017; Roy et al. 2021).

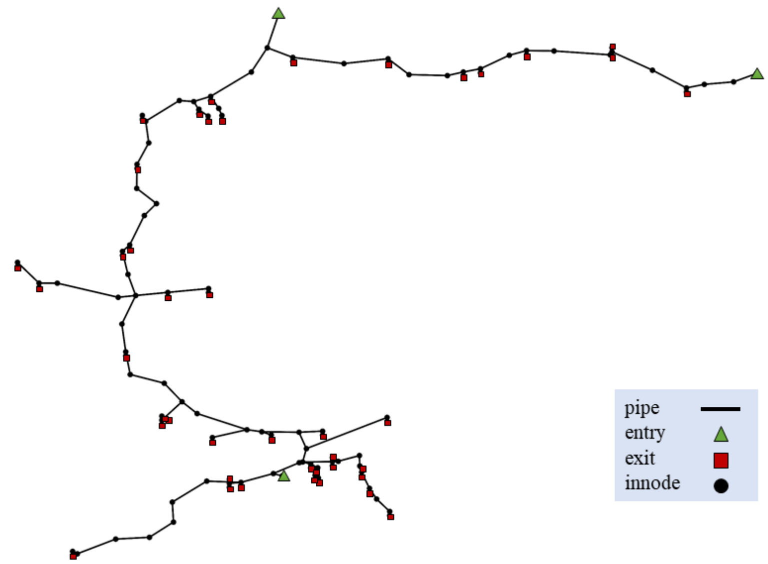

Figure 3. GasLib-134 network

A convergence analysis on the GasLib-134 network was done to find an appropriate number of Monte Carlo simulations (Shahandashti and Pudasaini 2019; Pudasaini and Shahandashti 2020b). The scenario earthquake was applied to the selected network without any rehabilitation. According to the convergence analysis, 400 Monte Carlo runs were sufficient (Figure 4). The expected connectivity loss of the GasLib-134 network without any rehabilitation was estimated at 0.6990, applying 400 Monte Carlo simulations.

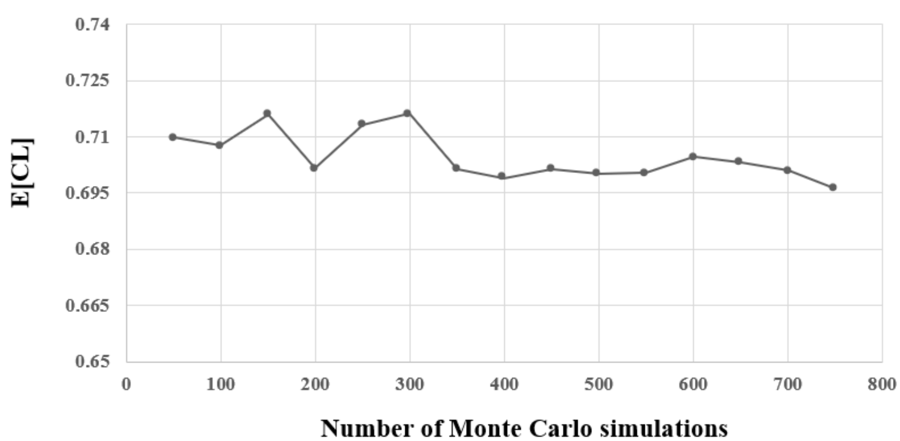

Figure 4. Convergence analysis to find an appropriate number of Monte Carlo simulations for the Gas-Lib 134 network

Table 1 displays the parameters of the genetic algorithm for determining the seismic susceptibility of the gas pipeline network. At first, fifty random rehabilitation policies within the length constraint are selected as the current generation. In the first generation, the mutation rate is set to 100%. Fifty rehabilitation policies from the first generation were evaluated and ranked according to their E[CL] values. The two policies with the lowest E[CL] values in the first generation were chosen to produce an offspring rehabilitation policy. The two-point crossover was selected as the crossover method to create an offspring rehabilitation policy. Repeated crossover and mutation operations were performed on the offspring rehabilitation policy until the length constraint was met. In the first generation, the rehabilitation policy having the highest E[CL] value was then substituted by the offspring rehabilitation policy. This substitution resulted in a new current generation. The mutation rate was reduced by 2% for the following generation. For each new generation, the genetic operations were repeated for 30 generations. The policy with the lowest E[CL] value in the final generation represents the optimum rehabilitation policy.

Table 1. Genetic algorithm parameters

Single objective GA Parameters	Values
Maximum Generation	30
Number of policies in each Generation	50
Maximum Monte Carlo Simulations	400
Type of Crossover	Two- point crossover
Initial Mutation Rate	100%
Mutation Rate Reduction	2% every generation
Number of Strings Mutated	20% of the binary strings

The outcomes of the suggested GA-based rehabilitation approach for various rehabilitation length constraints for the GasLib-134 network are listed in Table 2. The identified critical pipelines from the proposed GA-based rehabilitation approach are highlighted in bright red in Figure 5.

Table 2. The outcomes of the proposed GA-based rehabilitation approach for various rehabilitation length constraints for the GasLib-134 network

Policy ID	Rehabilitation length constraints (%)	Rehabilitation length constraints (km)	Total pipeline rehabilitated (km)	E[CL]	Variance of E[CL]
G_{10}	10	144.7022	126.6884	0.6011	0.049941
G_{20}	20	289.4045	286.8107	0.5430	0.062821
G_{30}	30	434.1067	430.6717	0.4817	0.073650

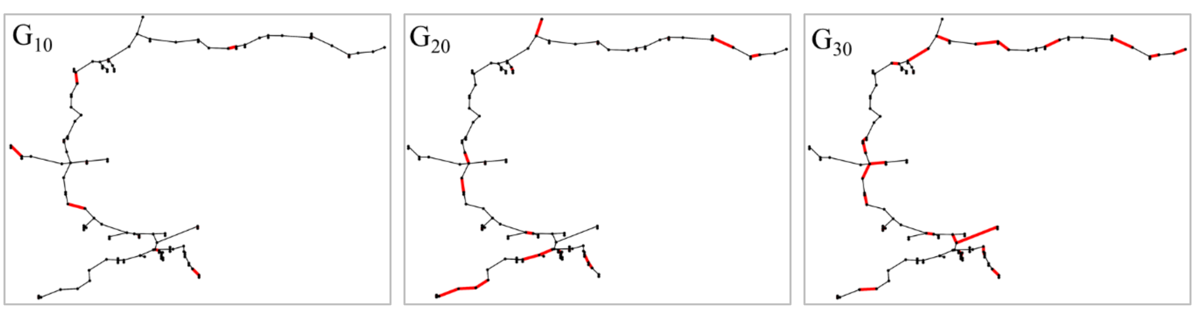

Figure 5. Critical pipelines identified by proposed GA-based rehabilitation approach for GasLib-134 network

The proposed approach was compared with the outcomes of a simple length-based rehabilitation approach. In this approach, rehabilitating longer pipelines such that the total pipeline rehabilitated stays within the constraint set by the available resources. The longest unrehabilitated pipe was rehabilitated first. This process is repeated until the total pipe length for rehabilitation is less than the rehabilitation length constraint. Table 3 summarizes the outcomes of length-based rehabilitation approach for GasLib-134 network. Figure 6 highlights the critical pipes in bright red that were identified by the length-based rehabilitation approach for GasLib-134 network.

Table 3. The outcomes of a length-based rehabilitation approach for various rehabilitation length constrain for GasLib-134 network

Policy ID	Rehabilitation length constraints (%)	Rehabilitation length constraints (km)	Total pipeline rehabilitated (km)	E[CL]	Variance of E[CL]
L_{10}	10	144.7022	116.3667	0.6794	0.041833
L_{20}	20	289.4045	261.6027	0.6548	0.054019
L_{30}	30	434.1067	433.0187	0.6341	0.036696

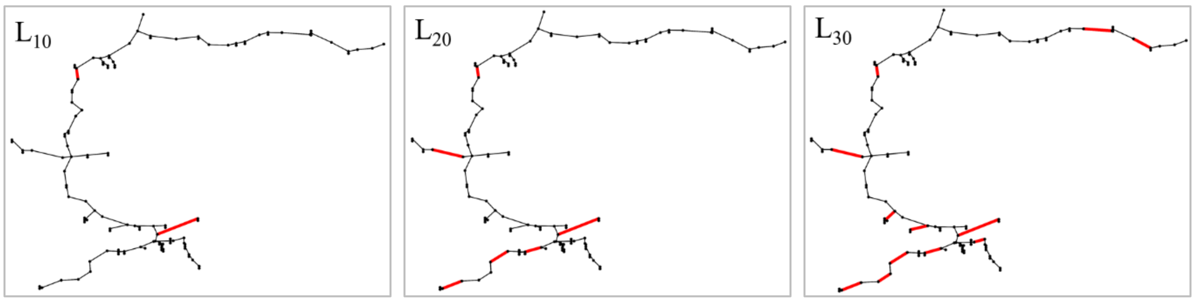

Figure 6. Critical pipelines identified by a length-based rehabilitation approach for GasLib-134 network

Figures 5 and 6 show that some of the identified critical pipes are different in the GA-based rehabilitation approach from the length-based rehabilitation approach. Figure 7 compares the E[CL] values obtained from the two approaches - GA-based rehabilitation and length-based. When compared to the solution set produced by the length-based rehabilitation approach, the solution from the GA-based rehabilitation approach generated 7-15% lower E[CL] values for the specified network and the scenario earthquake.

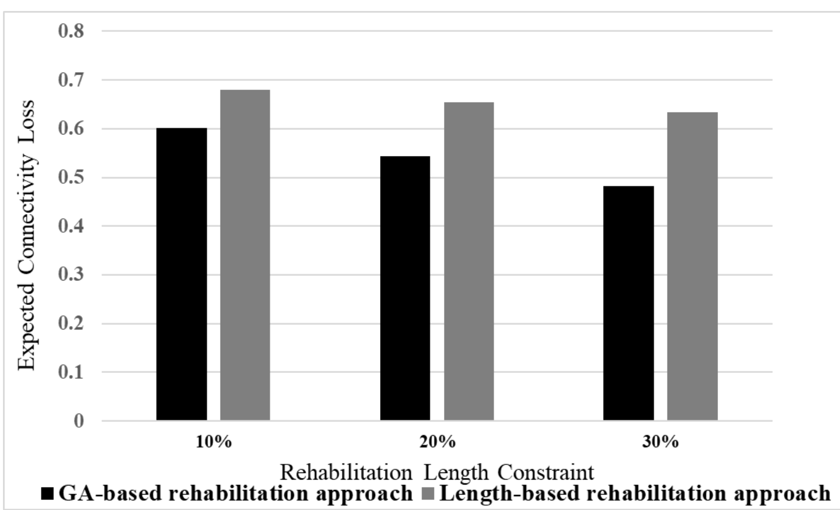

Figure 7. Comparison of the E[CL] values of the rehabilitation policies found using the GA-based rehabilitation approach and the length-based rehabilitation approach for the GasLib-134 network

CONCLUSION

Various methodologies for seismic susceptibility assessment of gas pipeline networks have been proposed, but there is limited research identifying the critical pipelines for seismic rehabilitation of gas pipeline networks. This was addressed by creating a GA-based rehabilitation approach and integrating it with a network-level seismic susceptibility assessment model. The proposed approach reduced the expected connectivity loss in a gas pipeline network by considering resource constraints. The outcomes of GA-based rehabilitation approach were then contrasted with the outcomes recommended by a simple length-based rehabilitation approach. The comparison revealed that, compared to the latter, the suggested methodology identified rehabilitation policies that yield much reduced expected connectivity loss. When adopting a GA-based rehabilitation approach, the comparison showed a 7–15% improvement in connectivity loss. It is anticipated that the suggested approach will help the gas utilities in their decision-making regarding rehabilitation to reduce the expected connectivity loss of the gas pipeline network.

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