Optimal Sensor Network Design in the Real-Scale Pipeline System Subjected to Physical and Measurement Uncertainties

C. Kim[1], H. Oh[1*] and B. Jeon[2,3]

[1]School of Mechanical Engineering, Gwangju Institute of Science and Technology, Gwangju, 61005, Korea
[2]Aero Technology Research Institute, Air Force Logistics Command, Daegu, 41052, Korea
[3]18th Fighter Wing, Republic of Korea Air Force, Gangneung, 25618, Korea

[*]Corresponding author: hsoh@gist.ac.kr

1. Introduction

Pipeline systems are widely used in petrochemical, power and offshore plants. Leakage and fracture in the pipeline systems can lead to catastrophic consequences (i.e., economical loss to human loss). Therefore, numerous studies on damage detection of the pipeline systems were conducted. For example, visual inspection, mathematical modeling-based, and signal processing approaches were employed to detect the damage [1-3].

The signal-processing approach analyzes sensor signals such as vibration, acoustic emission, and pressure. With the increase of computing power and the rise of artificial intelligence technology, the signal-processing approach received attentions to detect pipeline damages. Nevertheless, it is clear that, without high quality sensor data, high performance cannot be achieved. Therefore, this paper presents an optimal sensor network design for the detection of fracture in pipeline systems. A general framework is depicted in Fig. 1. This study focuses on a probabilistic simulation model with physical and measurement uncertainties.

This paper is organized as follows. The simulation model with uncertain parameters is described in Section 2. The formulation of the optimal sensor network design problem is shown in Section 3. Results and discussion follow in Section 4. Finally, conclusions and future works are shown in Section 5.

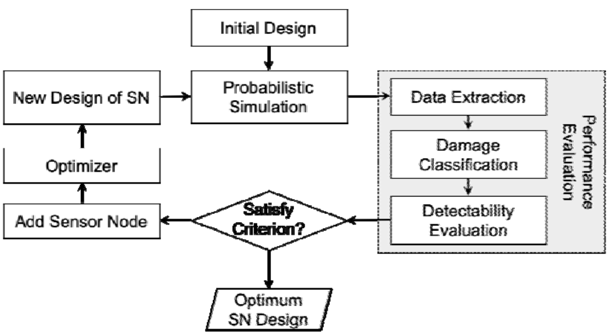

Fig. 1 Framework for optimal sensor network design

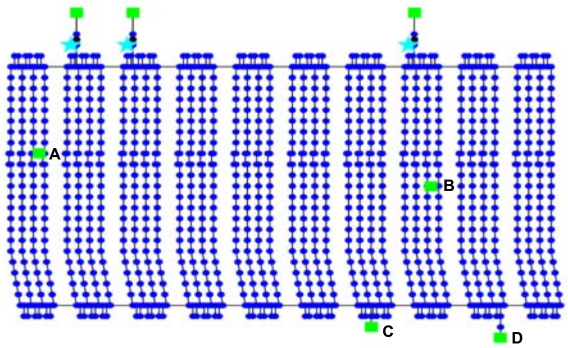

Fig. 2 Simulation model of real-scale pipeline system

Table 1 Uncertainty in input parameters

Uncertain Parameter	Value
Roughness coefficient	$X_1 \sim N(150, 15)$
Minor loss coefficient	$X_2 \sim N(0.05, 0.005)$
Measurement error	$\varepsilon \sim N(0, 033)$

Table 2 Damage scenarios

	A	B	C	D
Scenario 1	F	F	F	F
Scenario 2	F	F	F	N
Scenario 3	F	F	N	F
Scenario 4	F	F	N	N
Scenario 5	F	N	F	F
Scenario 6	F	N	F	N
Scenario 7	F	N	N	F
Scenario 8	F	N	N	N
Scenario 9	N	F	F	F
Scenario 10	N	F	F	N
Scenario 11	N	F	N	F
Scenario 12	N	F	N	N
Scenario 13	N	N	F	F
Scenario 14	N	N	F	N
Scenario 15	N	N	N	F
Scenario 16	N	N	N	N

F: fracture condition, N: normal condition

2. Simulation model and performance evaluation

The simulation model consists of water tanks, pumps, and pipelines as shown in Fig. 2. The water is transported from tanks (indicated by stars) to the pipeline systems. Spots A, B, C, and D (indicated by green rectangles) are susceptible to fracture. Input parameters including roughness coefficient, minor loss coefficient, and measurement errors are assumed to be uncertain as shown in Table 1. The uncertainty is propagated by a random sampling method. Damage scenarios is a combination of fractures at individual spots as shown in Table 2. For a given combination of sensor locations, Mahalanobis distance (MD) is calculated. The MD measures the distance between points considering covariance. A small MD value indicates that the points are close. The potential condition of the pipeline is classified using the MD [4]. Then, the detectability, the probability of correct classification, is calculated. If the detectability exceeds a predefined threshold, the sensor network design is terminated. Otherwise, a new design of sensor networks is conducted by adding another sensor. This process is iterated until the detectability exceeds a predefined threshold.

3. Optimal sensor network design

The optimization problem is formulated.

$$\begin{aligned} &\text{Maximize} && \sum_{i=1}^{N_{Sc}} D_i(X_{LOC}) \\ &\text{subject to} && X_{LOClb} \le X_{LOC} \le X_{LOCub} \end{aligned} \qquad (1)$$

where N_{Sc} is the quantity of sensors; D_i is the detectability; X_{LOC} is the location of sensors; X_{LOClb} and X_{LOCub} are the lower and upper bounds of the sensor locations, respectively. The optimization problem is mixed-integer nonlinear. Genetic algorithm (GA) was employed to solve the problem. The GA finds a set of the optimal sensor locations under a given number of sensors. Another sensor is added until the target detectability is satisfied with the given quantity of sensors. Finally, a set of the sensor locations can be obtained satisfying the target detectability with the minimum quantity of the sensors.

4. Results and discussion

With the probabilistic simulation model, an optimal sensor network could be designed. The target detectability was set to be 90% for all damage scenarios. In this study, five sensors were sufficient to achieve the detectability of 90%. As expected, the results showed that the sensor network with additional sensors can achieve the higher detectability. However, adding more sensors requires more resources for data acquisition and processing. Therefore, a tradeoff between available resources and detectability is required.

5. Conclusion

A framework for an optimal sensor network design was described in this paper. A simulation model was built considering two hydraulic uncertainties and measurement error. By propagating the uncertainties through the simulation model, the detectability was calculated as a probabilistic measure to evaluate the performance of the designed sensor networks. The mixed-integer nonlinear optimization problem was formulated. Then, a genetic algorithm was used to solve the problem. Finally, an optimal set of sensor network design with five sensors was obtained satisfying the target detectability of 90%. In the future, the design will be verified with experimental results from a testbed that emulates real pipeline systems.

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