Deep Neural Network Anomaly Detection and Statistical Estimation of High Pressure Liquefied Natural Gas Pipe

Dabin Yang[1], and Jongsoo Lee[2]

[1,2]*Department for Mechanical Engineering, Yonsei University, Seoul, 03722, Korea*
lucy423star@yonsei.ac.kr
jleej@yonsei.ac.kr

ABSTRACT

Anomaly detection method using neural network is performed for diagnosis. Liquefied natural gas pipeline is designed using finite element method. To consider abnormal condition, a damage was applied to the model. Then failure mode and effect analysis are performed to determine if the location of damage is acceptable. The designed system was validated through literatures and showed that the model is suitable to replace the actual model. Data collection was done by changing each design variables in certain range from the designed model. Designable generative adversarial network was used for data augmentation and anomaly detection with adversarial network was used for anomaly detection. The performance of anomaly detection of the proposed model showed 95% of accuracy before data augmentation and 99% of accuracy after data augmentation. The result provides statistical estimation of diagnosis range for each design variables, which clearly showed the difference of performing data augmentation. By diagnosis result, the variables are used back to the designed model for validation of the result and showed accuracy of 85%.

1. INTRODUCTION

Demand of liquefied natural gas (LNG) with low carbon dioxide emission is increasing. The amount of supply must be increased accordingly, but high flow rate and pressure of the natural gas can damage the pipelines carrying LNG. Pipeline maintenance must be performed since even a small damage can cause fatal effects. Currently in actual field, in-line pigging method is used which is a post-maintenance technique and the gas supply is stopped for applying this method. By development of artificial intelligence, Aljameel, Alomari, Alismail, and Khawaher (2022) performed anomaly detection of pipelines based on machine learning technique, but there are limitations of clear identification of the anomalies in the system.

The procedure for this study is shown in Figure 1. Simulation model is constructed by finite element method (FEM), and the result of the analysis is compared and validated through literature. Then failure mode and effect analysis (FMEA) of actual pipeline is considered and analyzed. By comparing FEM results and FMEA, the validity of the simulation model was performed. For accurate diagnosis and anomaly detection of the pipe, deep neural network was applied for the data augmented and anomaly detection. The contributions of this study are as follows:

1. Applicability of the simulation model was validated through literature to find main anomality in pipe.
2. Anomaly detection was performed, and the result showed the suitability of the diagnostic results.

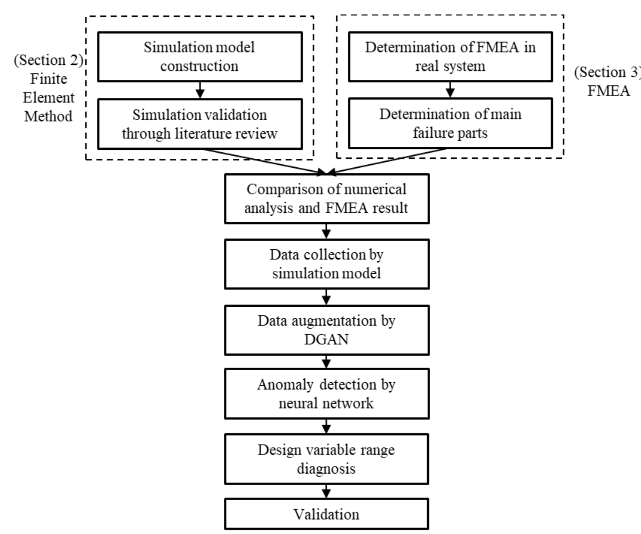

Figure 1. Flowchart of the process.

2. Finite Element Method

ANSYS software was used for FEM of high pressure liquefied natural gas pipe. API 5L Gr.X65 material property was applied for the model. Total length of 4600mm with diameter of 762mm main pipe was designed as T-shaped as Figure 2a). Also, 200mm length branch pipe with diameter of 66mm are welded with fittings to the main pipe for supply and detailed view of the branched pipe is shown in Figure 2b). The parameters of the pipe and fluid characteristics are adopted from real work scenarios to consider actual working conditions. The gas enters the pipe through the inlet and is discharged through two different outlets. FEM was done in the process of flow, structural, vibration and fatigue analysis to determine the behavior and tendency of the pipe due to high pressurized LNG flow.

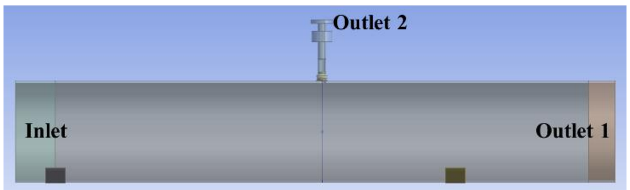

Figure 2a). Pipe model.

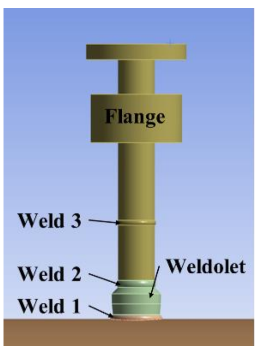

Figure 2b). Branched pipe.

2.1. Flow Analysis

For quick supply of the gas, high flow rate of 20 m/s was applied. k-ε turbulence model was applied for analysis due to high Reynolds number of 8.52×10^7. By analysis, turbulence flow was found around the branch pipe, where literature research was focused to define this tendency. Sierra, Bates, and Doherty (2000) found that the formation of vortex shape in the branched pipe due to turbulent kinetic energy of the main pipe. Jo, Kim, Jo, and Hwang (2015) also determined that the maximum pressure occurs inside the branch pipe, close to the vortex.

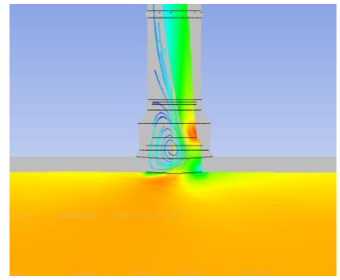

Figure 3. Flow around branched pipe.

2.2. Structural Analysis

Stress concentration due to flow pressure was considered at this stage. It was determined that the maximum stress occurs at the welds of the branch pipe. Among the welds, maximum stress was occurring at the connection between the main pipe and the branch pipe. Figure 4 shows three points, where point A and C corresponds to clutch and point B as saddle. For the inner surface of the weld, clutch points had the lowest stress and in contrast, the saddle point had the highest stress. The stress at the saddle was the location of stress concentration happening throughout the whole pipe system. Shin, Yoon, and Kim (2006) determined the stress distribution of T-shaped branch pipe and deriving the same result and distributions.

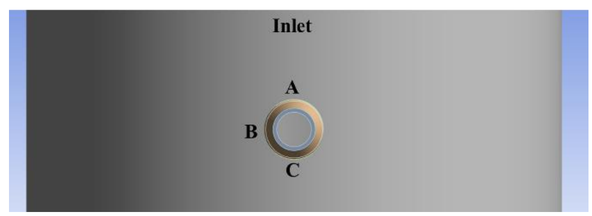

Figure 4. Top view of the pipe.

2.3. Vibration Analysis

Mode analysis and harmonic analysis was performed to analyze dynamic characteristics of the pipe. By structural analysis, stress concentration occurs in the weld connecting the main pipe and the branch pipe. Based on this result, damage applied to this weld is considered to cause most critical failure to the system. Sine wave and natural frequency was derived and stress occurring by fluid induced vibration was determined.

2.4. Fatigue Analysis

Based on stress-strain curve of the material and derived vibration signal, fatigue analysis was applied for fatigue failure determination. Without small crack on the system, no fatigue failure occurs. However, when there is a small crack applied, the pipe fails after 3.3 years of operation. The analysis result as Figure 5. shows the stress occurred from the crack propagates to the outer surface of the weld, which affects the fatigue life of the pipe. By applying damage to the system, the maximum stress and vibration signal from previous steps increased, which caused the fatigue life to decrease.

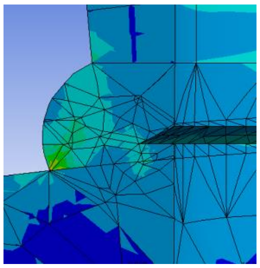

Figure 5. Stress propagation from crack.

3. Failure Mode and Effect Analysis

Failure mode and effect analysis was established by literature analysis. The main consideration of the establishment was the pipeline components on the system, where non-designed parts from simulation was omitted. From various of literatures Jeong, Park, Koo, Kim, Yoo, and Jo (2018), Animah & Shafiee (2020), and Yuhui, Shiyu, Lijing, and Tao (2013) pointed out that pipe leakage is found to be the most critical mode, and the cause of failure is by welding defect or internal/external corrosion. FMEA from literatures shows that the maintenance of the weld is important, where FEM result also showed the stress concentration occurrence in the weld connecting main and the branch pipe. For damage prevention, scrutiny needs to be done around the region with high probability of failure. The result of stress concentration at the weld of the pipe shows that the simulation process is suitable to replace the actual pipe.

4. Anomaly Detection

By performing sensitivity analysis, five relevant design variables most related to stress were selected. For sensitivity analysis, Pearson correlation coefficient was applied. Damage of crack is considered as abnormality and 83 data is collected by changing design variables. 69 data from the dataset is considered as normal data since the maximum stress does not excess the construction threshold. Yoo, Jung, Han, and Lee (2021) performed designable generative adversarial network (DGAN) which augments data and determines the variable information of the augmented dataset. DGAN was applied for the pipe dataset and total 498 data are collected by augmentation. Widely used classification method of support vector machine (SVM) showed low accuracy of 79% and 82% before and after data augmentation, respectively. To improve the accuracy of the model, the input data type and overall structure of the model was considered. As a solution, anomaly detection method, of neural network-based method is performed. The used method is based on unsupervised anomaly detection, where the discriminator of the model is only trained with normal data. Table 1 shows the minimum and maximum value of the variable for initial 83 data. The accuracy of anomaly detection of the model was 95% before augmentation. F1 score before data augmentation was 0.857, with recall score of 0.75 and precision score of 1. Table 2 shows the statistical estimation of the design variables by 95% confidence interval range of the detected result. Before augmentation, the average value of healthy range and faulty range is similar and the range of 95% confidence interval is also similar with each other. Anomaly detection accuracy after data augmentation was 99% and the variable range is shown at Table 3. Additionally, the F1 score after data augmentation was 0.960, where recall score of 0.923 and precision score of 1. The result shows that the healthy and faulty range for variables x1, x3, x5 is separated from each other, where variables x2 and x4 did not clearly converge.

Table 1. Initial variable range

Variable	Minimum [mm]	Maximum [mm]
x1	48.285	59.015
x2	2.7	3.3
x3	1.44	1.76
x4	28.8	35.2
x5	33.75	41.25

Random values of variables are selected from healthy range. For variables x2 and x4 which does not have clear differences, the average value which has high probability density function of the distribution was selected. The variable values are applied back to simulation for validation. Weighted integrated factor (WIFac) was used and the comparison of the result of validation is shown in Figure 6. In Figure 6, the simulation data is plotted as blue line and the generated data from DGAN is shown in black dashed line. Main importance in this plot is that the peak values of the augmented data and actual simulation data is like each other, and the result is acceptable.

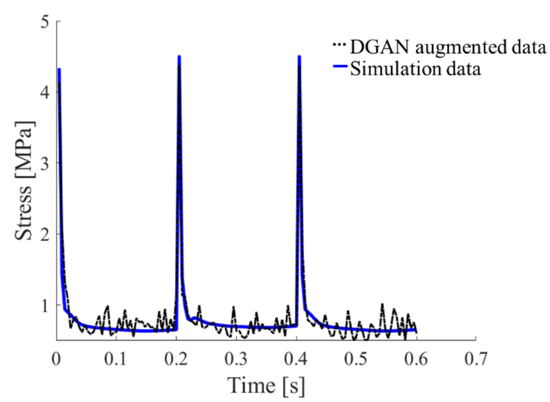

Figure 6. WIFac validation (WIFac = 0.85714)

Table 2.95% confidence interval before augmentation.

Variable	Healthy		Faulty	
	Average	Range	Average	Range
x1	53.4167	[44.3204 62.5130]	54.0332	[43.3327 64.7337]
x2	3.0348	[2.5356 3.5340]	2.8071	[2.3602 3.2541]
x3	1.6	[1.3256 1.8744]	1.5657	[1.2801 1.8513]
x4	31.496	[26.4118 0.5712]	32.6857	[26.9732 38.3982]
x5	37.3913	[30.9638 43.8188]	38.8393	[32.5251 45.1535]

Table 3. 95% confidence interval after augmentation.

Variable	Healthy		Faulty	
	Average	Range	Average	Range
x1	50.462	[49.9705 55.9584]	58.80595	[53.8322 63.7797]
x2	2.9202	[2.6563 3.1841]	2.925855	[2.7390 3.1128]
x3	1.5941	[1.5034 1.6847]	1.43858	[1.28 1.5972]
x4	30.4140	[28.42 32.4079]	31.98105	[29.9073 34.0548]
x5	36.5214	[33.9113 39.1314]	29.33085	[22.1333 36.5284]

5. Conclusion

High pressure liquefied natural gas pipeline has designed by FEM and validated. The existence of damage in the weld connecting the branch pipe and main pipe was analyzed as the location where stress concentration occurs. It was able to analyze that the designed model was used to replace the actual model. By applying neural network, it was able to achieve variable information and perform high accuracy of anomaly detection. The result provides statistical estimation of the design variables which enables to perform diagnosis of the designed model. In future study, considering more failure modes or components will enable to perform more precise diagnosis in high pressure LNG pipeline.

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References

Aljameel, S. S., Alomari, D. M., Alismail, S., Khawaher, F., Alkhudhair, A. A., Aljubran, F., & Alzannan R. M., (2022). An Anomaly Detection Model for Oil and Gas Pipelines Using Machine Learning. *Computation*, 10(8), pp. 138. doi: 10.3390/computation10080138.

Animah, I., & Shafiee, M., (2020). Application of risk analysis in the liquefied natural gas (LNG) sector: An overview. *Journal of Loss Prevention in the Process Industries*, 63. doi: 10.1016/j.jlp.2019.103980.

Jeong, W., Park, G., Koo, Y., Yoo, S., & Jo, Y., (2018). City Gas Pipeline Pressure Prediction Model. *The Journal of Society for e-Business Studies*, 23(2), pp. 33-47. doi: 10.7838/jsebs.2018.23.2.033.

Jo, C., Kim, M., Jo, S., & Hwang. S., (2015). A Study on Internal Flow Characteristics of T Branch using CFD Analysis. *The Korean Hydrogen and New Energy Society*, 26(5), pp. 438-444. doi: 10.7316/KHNES.2015.26.5.438.

Shin, K., Yoon, K., & Kim, Y., (2006). Reference Stress Based Stress Analysis for Local Creep Rupture of a T-pipe. Transactions of the Korean Society of Mechanical Engineers A, 30(8), pp. 873-879. doi: 10.3795/KSME-A.2006.30.8.873.

Sierra, E. F. Z., Bates, C. J., & Doherty, T. O., (2000). Turbulent flow in a 90° pipe junction: Part 2: Reverse flow at the branch exit. *Computers and Fluids*. 29(2), pp. 215-230. doi: 10.1016/S0045-7930(99)00005-5.

Yoo, Y., Jung, U., Han, J., & Lee, J., (2021). Data Augmentation-Based Prediction of System Level Performance under Model and Parameter Uncertainties: Role of Designable Generative Adversarial Networks (DGAN). *Reliability Engineering and System Safety*, 206. doi: 10.1016/j.ress.2020.107316.

Yuhui, Z., Shiyu, L., Lijing, Z., & et al., (2018). Natural Gas Pipeline Network Risk Assessment Based on FMECA-Fuzzy Comprehensive Analysis. *IEEE International Conference of Safety Produce Informatization (IICSPI)*. Dec 10-12, Chongqing, China. doi: 10.1109/IICSPI.2018.8690464.

Dabin Yang received B.S in Mechanical Engineering at Wrocław University of Science and Technology, Wrocław, Poland in 2020. She is currently pursuing the Combined M.S/Ph.D degree in Mechanical Engineering at Yonsei University, Seoul, South Korea. Her research interests include multi-physics design optimization (MDO), reliability-based robust optimization, prognostics and health

management (PHM), and industrial artificial intelligence of data augmentation with applications to structures, fatigue, lifetime prediction and safety.

Jongsoo Lee received B.S. and M.S. in Mechanical Engineering at Yonsei University, Seoul, Korea in 1988 and 1990, respectively and Ph.D. in Mechanical Engineering at Rensselaer Polytechnic Institute, Troy, NY in 1996. After a research associate at Rensselaer Rotorcraft Technology Center, he has been a professor of Mechanical Engineering at Yonsei University since 1997. His research interests include multi-physics design optimization (MDO), reliability-based robust optimization, virtual product design and development, model-based system engineering (MBSE), prognostics and health management (PHM), and industrial artificial intelligence of data augmentation, transfer learning, domain adaptation, domain generalization and domain randomization with applications to structures, fatigue/durability, lifetime prediction, noise and vibration problems.