

딥러닝 기반 도시가스 누출량 예측 모니터링 시스템

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An Predictive System for urban gas leakage based on Deep Learning

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● 요약 ●

In this paper, we propose a monitoring system that can monitor gas leakage concentrations in real time and forecast the amount of gas leaked after one minute. When gas leaks happen, they typically lead to accidents such as poisoning, explosion, and fire, so a monitoring system is needed to reduce such occurrences. Previous research has mainly been focused on analyzing explosion characteristics based on gas types, or on warning systems that sound an alarm when a gas leak occurs in industrial areas. However, there are no studies on creating systems that utilize specific gas explosion characteristic analysis or empirical urban gas data. This research establishes a deep learning model that predicts the gas explosion risk level over time, based on the gas data collected in real time. In order to determine the relative risk level of a gas leak, the gas risk level was divided into five levels based on the lower explosion limit. The monitoring platform displays the current risk level, the predicted risk level, and the amount of gas leaked. It is expected that the development of this system will become a starting point for a monitoring system that can be deployed in urban areas.

키워드: Gas Leakage Prediction, Monitoring System, Deep Learning

1. Introduction

The use of gas provides many conveniences in daily life, but when gas leaks, it can lead to severe damage such as poisoning, fire, or explosion. As evidenced by a recent gas explosion in a Chinese food market, which injured or killed about 150 people[1], gas leaks in real life can lead to many casualties, so a monitoring system is needed to detect gas leaks in advance and reduce the chances of explosions happening. Exaracteristics of explosions for each type of gasisting studies have analyzed comparatively the ch[2-3] or researched on systems at industrial sites that detect gas leaks and send notifications [4]. However, to the authors' knowledge, there has been no system designed that incorporates the explosive characteristics of gas types or

utilizes urban gas data.

This study creates an advanced urban gas monitoring system using empirical data. First, sensors developed to measure gas concentration were installed in gas pressure regulating stations that supply gas to residential homes, and apartment complexes that use gas. Gas concentrations were measured and a dataset was constructed from each location. Then, a deep learning-based gas leak risk prediction model was designed by linking the data of the installed sensors with the results of simulation studies related to the patterns of increasing gas concentration over time. The data collected on the server is displayed in real time on the status board of the monitoring system and is used as input

to the deep learning model to predict the total amount of leakage after one minute. A process workflow was designed to allow users and managers to quickly evacuate and respond when the gas explosion risk, calculated based on the predicted leakage amount, is expected to exceed the threshold level. The monitoring system introduced in this paper focuses on realistic and specific gas leak risk prediction based on empirical data. Through this, users can create a safer environment for using gas at home, by identifying the risk level of leaks in advance and ensuring maximum response time. It is expected that this monitoring system can be applied to multiple fields, without being limited to a specific area, so that casualties caused by gas leaks and their explosions can be minimized.

II. Preliminaries

1. Related works

Studies related to gas leaks are largely divided into studies on gas leak characteristics and studies on gas leak detection cases. Studies on gas leak characteristics mainly focus on diffusion patterns during gas leaks and explosion patterns. There is a study on how the concentration of gas in a confined space varies according to the size of the leak hole[2-3], and there is a study analyzing the explosion risk of each gas by comparing the explosion pressure and propagation speed of each of hydrogen, LPG, and LNG gas[4]. Using such data, it is possible to determine when there is a specific explosion hazard, but there have been no studies that have applied it.

In the case of a gas monitoring system, a sensor installed in an industrial site detects a leak and there is a system that sends a notification to a sensor installed in a worker's helmet[5]. However, although gas leaks can be detected in real time, the level of danger is unknown, and there is also a risk that the sensor installed on the helmet may be damaged by exposure to external shocks.

From synthesizing the analyses of existing studies, there is a need to develop a monitoring system that uses real-time data and the characteristics of gases to predict the amounts of gas leaked, and categorize the severity of the leak, based on predetermined risk guidelines. Therefore, in this paper, based on the Korea Gas Corporation standard, the gas concentration standards are divided into five stages of risk (~10%: normal, 10-15%: attention, 15-50%: caution, 50-75%: warning, 75-100%: danger), with different alerts and actions set for each risk level, and these were used to design a monitoring system that can inform users of specific risk levels and provide instructions on the emergency response.

III. The Proposed Scheme

The gas leakage and risk prediction monitoring system will

be discussed in three parts: (1) defining the environment dataset, (2) deep learning model design method comparison, LSTM, 1D-CNN model learning and evaluation, and (3) monitoring system platform configuration.

1. Environment Dataset

Due to the lack of empirical gas datasets, gas sensors and communication terminals were installed in residential homes using LNG and gas pressure regulating stations. Gas concentration data was collected for about three months from nine residential homes and six gas pressure regulating stations, and transmitted to the data management server. The locations of the 15 sensors and the collected data are shown in Figure 1, and gas concentrations were all below the "Attention" level during normal times. 200,000 data points under normal circumstances were collected.

Gas leak concentration data collected over time is difficult to obtain due to the risk of gas explosions, and the difficulty in extracting accurate concentration values. Therefore, in this study, the dataset for the gas concentration values were derived from a graph in a study simulating gas diffusion patterns in an enclosed space, according to the size of the leak hole. The Digitize program, which can extract values from the image, was used to extract data points from the graph plotting the change in gas leakage over time. 80,000 data points for gas leak circumstances were derived from this method.

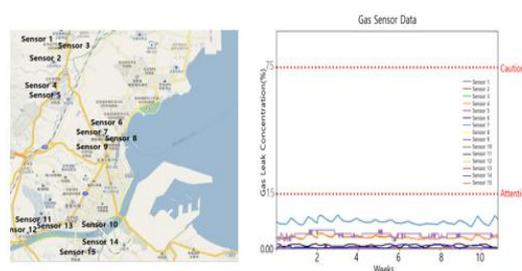


Fig. 1. Installation locations of sensors and gas concentration values measured from each sensor

2. Deep Learning based gas leak prediction model definition

2.1 Composition of Training Dataset

Gas data is collected every 10 seconds from the residential homes and gas pressure regulating stations, while the derived data extracted from the paper shows that the gas explosion lower limit is reached within two minutes. Considering these characteristics, the value of data measured every 10 seconds for up to two minutes (a total of 12 gas concentrations) was set as the input size. The input data is largely composed of the data under normal circumstances, the data at the time of

the gas leak, and the data at which the gas leak starts, in a ratio of 1:1:3 (sensor data: simulation data: sensor and simulation combined data), with the training and testing data organized in a ratio of 4:1, as summarized in Table 1.

Table 1. Composition of Dataset used to train the model

Data Type	Number	Total
Sensor	10,000	50,000
Simulation	10,000	
Sensor & Simulation	30,000	
Train	40,000	50,000
Test	10,000	

2.2 Model Comparison Analysis

Considering the time series characteristics of gas leak data and the operating environment of the real-time monitoring system, LSTM model (Long Short-Term Memory) [6] and 1D-CNN (1D-Convolutional Neural Networks) model [7] were selected, which are lightweight deep learning models. The hyperparameters and specific values used for training each network model are summarized in Table 2. Each model predicted the leakage concentration after one minute, and to determine the best model based on input-output value, two prediction methods were chosen and these are compared in Table 3: (1) to forecast gas concentration in 10 second intervals, repeated six times to obtain gas concentration after one minute, and (2) to predict gas concentration after one minute.

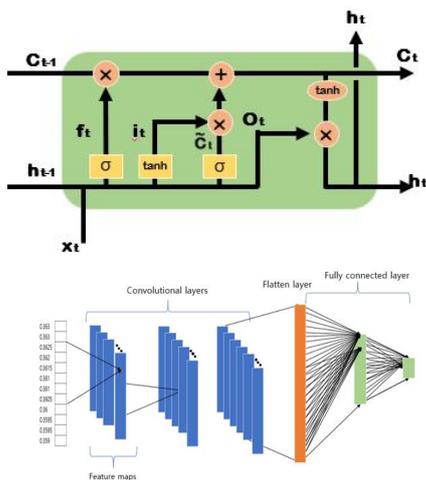


Fig. 2. Structure of LSTM and 1D CNN

Table 2. Hyperparameters applied in models

Model	Layers	Optimizer	Batch Size	Epochs
LSTM	1	Adam	100	200
1D-CNN	2	Adam	128	100

2.3 Model Performance Comparison

To evaluate the performance of each model, the accuracy calculation method using the mean squared error (MSE) and risk level was applied. The MSE is the average of the squares of the difference between the actual value and the predicted value, and the lower the value, the better the performance. The accuracy of the model prediction risk was measured by dividing the risk into five levels (Normal, Attention, Caution, Warning, and Danger), based on the gas concentration standards created for gas leak risk. Table 3 shows the model results for each model and each prediction method.

Table 3. Performance Comparison of Deep Learning Model

	1 minute after prediction in 10 second intervals		1 minute after prediction	
	MSE	Accuracy	MSE	Accuracy
LSTM	0.0833	95.56%	0.0109	98.99%
1D-CNN	0.1345	89.63%	0.0393	96.76%

As a result of the analysis, LSTM showed the highest performance in both prediction methods than 1D-CNN. It is hypothesized that this is because the input dimension is too small for the 1D-CNN model to derive the features required for learning. On the other hand, LSTM has shown that learning converges well in both prediction methods.

The performance of the LSTM model using the prediction method after one minute showed 98.99% accuracy, proving high reliability. Moreover, 89% of the errors predicted the risk level as one level higher. In addition, when checking the model, it was found that these errors occurred between the boundaries of two risk levels, with a slight error within 0.05 percentage points. The approximately 1% of inaccuracy in the model is caused by this a slight difference of 0.05 percentage points, and leads to the model conservatively predicting the higher risk level. Therefore, it was concluded that the model is suitable for the monitoring system to minimize the damage of gas leak accidents.

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3. Configuration of the Gas Monitoring System

Unlike existing gas notification systems, this system is designed

to consider the final risk level by taking into account not only the risk of the current gas leak concentration, but also the predicted risk, and provide the appropriate response to both the manager of the gas pressure regulating station, and resident using the gas.

In the case of the manager, the system was devised to allow an assessment of the situation at a glance through the gas safety dashboard (Fig. 3). The installation location and current gas concentration value of each sensor is displayed, and when the location of a sensor is pressed to check the status, the current leakage amount and risk level, and the predicted leakage amount and risk level are then displayed in real time. In addition, a front-end/back-end system that can determine whether the status is normal or a gas leak has occurred was created based on previous trends.

In the case of residents, it is designed to minimize damage by sending an alarm to the gas user to check the gas valve if the predicted leakage amount is at the level of Attention and Caution, and by sounding an alarm if it is at Warning or Danger so that user can quickly evacuate from the residence. (Fig. 4)

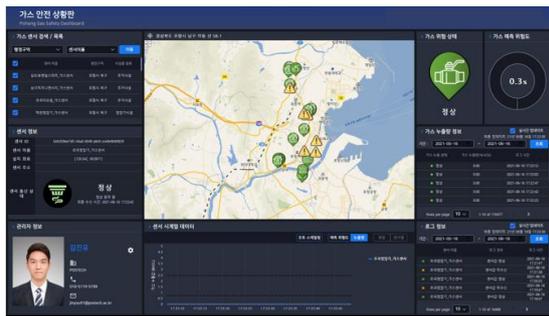


Fig. 3. Gas monitoring system status board

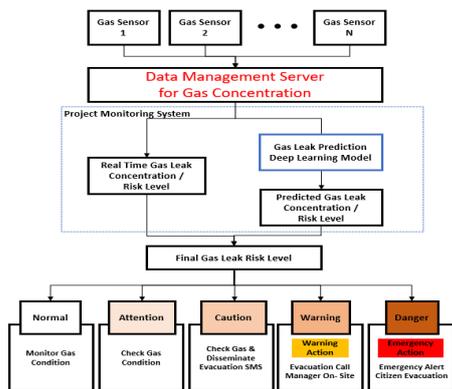


Fig. 4. Flowchart of gas monitoring system

IV. Conclusions

In this paper, a real-time gas monitoring system using the LSTM model is proposed. The accuracy of the prediction of

the model compared to the actual data leakage concentration was 98.99%, proving the reliability and excellence of the model. It is expected that the real-time gas monitoring system will be able to detect gas leaks immediately and take necessary measures to prevent consequential accidents.

ACKNOWLEDGEMENT

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning(KETEP) and the Ministry of Trade, Industry & Energy(MOTIE) of the Republic of Korea (No. 20202910100070).

This research was supported by Reginal Demand-Specific R&D Support Program from Ministry of Science and ICT(Republic of Korea) (CN20120GB001).

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