*International Journal of Advanced Smart Convergence Vol.12 No.4 378-385 (2023)*
*http://dx.doi.org/10.7236/IJASC.2023.12.4.378*

**IJASC 23-4-46**

# A Study on a Method for Detecting Leak Holes in Respirators Using IoT Sensors

Woochang Shin

*Professor, Dept. of Computer Science, Seokyeong University, Korea*
*wcshin@skuniv.ac.kr*

### *Abstract*

*The importance of wearing respiratory protective equipment has been highlighted even more during the COVID-19 pandemic. Even if the suitability of respiratory protection has been confirmed through testing in a laboratory environment, there remains the potential for leakage points in the respirators due to improper application by the wearer, damage to the equipment, or sudden movements in real working conditions. In this paper, we propose a method to detect the occurrence of leak holes by measuring the pressure changes inside the mask according to the wearer's breathing activity by attaching an IoT sensor to a full-face respirator. We designed 9 experimental scenarios by adjusting the degree of leak holes of the respirator and the breathing cycle time, and acquired respiratory data for the wearer of the respirator accordingly. Additionally, we analyzed the respiratory data to identify the duration and pressure change range for each breath, utilizing this data to train a neural network model for detecting leak holes in the respirator. The experimental results applying the developed neural network model showed a sensitivity of 100%, specificity of 94.29%, and accuracy of 97.53%. We conclude that the effective detection of leak holes can be achieved by incorporating affordable, small-sized IoT sensors into respiratory protective equipment.*

Keywords: Air Pressure, IoT Sensors, Leak Holes, Machine Learning, Neural Network, Respirator

## 1. Introduction

The imperative of wearing respiratory protective equipment (RPE) has gained unprecedented significance in the context of the COVID-19 pandemic. As a highly contagious respiratory virus, SARS-CoV-2 has underscored the critical role that RPE, such as masks and face shields, plays in mitigating transmission risks. Recent studies have highlighted the efficacy of RPE in reducing viral spread, particularly in crowded public spaces [1-4].

For RPE to effectively fulfill its respiratory protection function, the Inward Leakage and Fit Factor of the RPE are crucial. Inward leakage represents the ratio of the exchange of external and internal air when wearing the respirator, indicating the degree of air leakage while the respirator is worn. On the other hand, the Fit Factor measures the tightness between the face and the respirator, illustrating how well the respirator conforms to the

Manuscript Received: November. 4, 2023 / Revised: November. 10, 2023 / Accepted: November. 15, 2023
Corresponding Author: wcshin@skuniv.ac.kr
Tel: +82-2-940-7755
Professor, Dept. of Computer Science, Seokyeong University, Korea

facial contours. A higher Inward Leakage suggests a lower protective efficacy of the respirator, while a higher Fit Factor indicates an increased level of protection.

It was found that the Inward Leakage of a respirator is greatly influenced by the filtration efficiency of the filter mounted on the respirator, while the Fit Factor is more influenced by the shape of the wearer's face or the design of the respirator [5]. The Occupational Safety and Health Administration (OSHA) in the United States conducts facial fit tests to assess the leakage through the sealing surface when RPE is worn. This practice is not exclusive to the U.S.; it is also legislatively mandated in countries such as Australia, Canada, and New Zealand, requiring all workers who wear RPE to undergo fit testing at least once annually. This regulatory measure underscores the importance of evaluating the effectiveness of respiratory protection by ensuring a proper fit and minimizing leakage through the facial interface, promoting the safety and well-being of workers in various occupational settings [6, 7].

Even if a respirator has successfully undergone fit testing in a laboratory setting, the occurrence of improper respirator donning by the wearer, respirator damage, or sudden movements by the wearer in the actual work environment can lead to the formation of leak holes in the RPE. The presence of leak holes in RPE, imperceptible to the wearer, poses a critical challenge to the intended protective function. Leak holes compromise the integrity of the respiratory barrier, allowing the ingress and egress of airborne particles, including potentially infectious respiratory droplets.

Real-time detection of leak holes in RPE emerges as an imperative aspect of ensuring the reliability and efficacy of these safety measures. Traditional methods of RPE inspection, often relying on visual or manual checks, may not promptly identify subtle defects or leak holes caused by wearer issues. Consequently, a proactive approach utilizing advanced technologies for real-time leak hole detection becomes crucial for maintaining the integrity of the protective barrier.

In this paper, we introduce a method for real-time detection of respirator fit problems by attaching an IoT sensor inside a full-face respirator and measuring pressure changes inside the mask according to the wearer's breathing activity. We train a machine learning model on pressure changes inside the mask with good-fit or with leak holes. The trained model can then be used to detect leak holes in real time.

Section 2 reviews related works. Section 3 describes the structure of the leak hole detection system for respiratory protection, and designs experimental scenarios. It also describes how the pressure inside the respirator changes due to the breathing activity of the wearer. Section 4 acquires the respiratory data of the wearer of the respirator according to the experimental scenarios and analyzes it. We also implement a neural network model for leak hole detection, train the neural network model using the acquired experimental data, and evaluate its performance. Finally, Section 5 summarizes and concludes this paper.

## 2. Related Works

In recent years, research on the detection of leaks in respirators has seen significant advancements, reflecting the growing recognition of the critical role that leak prevention plays in ensuring the effectiveness of such equipment.

Y. Liu et al. developed the Respirator Seal Integrity Monitor (ReSIM), a low-cost, portable device to monitor the concentration of aerosol particles inside the wearer's respirator mask and alert the wearer when the seal is broken and aerosol particles enter the mask [8].

A workshop on respirator sensors was held at the National Institute of Standards and Technology (NIST) on May 1, 2009. The objective of this workshop was to discuss and document the need for real-time monitoring of the respiratory intake of emergency responders [9]. In this workshop, Michael Sailor presented on the development of a microsensor that detects the passage of organic vapors through a filter bed to indicate the end of life of a respiratory protection filter. Dr. Benkstein presented data showing how to use a microhotplate with a metal oxide sensing film to detect hazardous industrial chemicals such as ammonia and hydrogen cyanide in environments containing non-target chemicals such as paint fumes, window cleaners, etc., which are further complicated by humidity [9].

Dr. William King reported the preliminary results of a study to detect leaks by measuring the ultrasonic sound emission associated with the flow field of the mask to monitor internal leaks in respirators. Ultrasound is a frequency range of sound pressure that is outside the human audible range and has not been confirmed to be a health hazard. It can be used to detect leaks. this study showed that the leak inside the respirators can be monitored by attaching an ultrasonic sensor to the mask regardless of temperature and humidity. However, there appears to be a performance variation issue based on the attachment location and the number of sensors for ultrasound [9].

Other studies on respirator leakage include Floyd et al., which evaluated the effects of beard length and area density on seal leakage, and Arnoldsson et al., which developed an aerosol challenge method for assessing the performance of the interface between a respirator and a protective suit hood [10, 11].

Most respirator leakage detection research focuses on monitoring the safety of respiratory protection worn by firefighters and soldiers in hazardous situations using sensors that react to toxic gases. However, this approach cannot detect pathogen infections such as COVID-19.

While there is ongoing research exploring the use of ultrasound as an alternative approach to directly detect leakage points in respirator, demonstrating the feasibility of this technology, the developmental outcomes of RPE incorporating this technique have not been officially reported as of yet.

## 3. System Architecture and Experimental Scenario Design

The overall architecture of the system developed in this study is illustrated in Figure 1. Pressure sensors are attached inside the non-powered hood RPE, and the pressure data within the respirator is measured while the wearer breathes. This data is then transmitted to a smartphone. The smartphone's app, upon receiving the data, analyzes it to determine the presence of a leak hole within the respirator. If a leak hole is detected, an alarm is triggered. Figure 2 shows the respirators and devices used in the development.

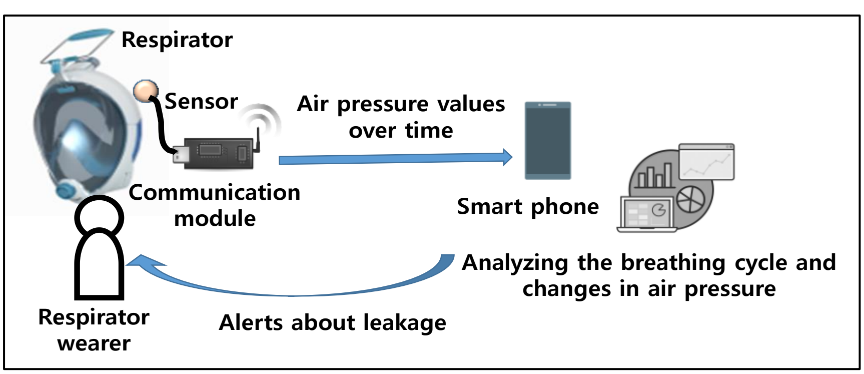



Figure 1. Overall architecture of the system

Figure 2. Respirator

### 3.1 Respirator with Air Pressure Sensor

In our previous study, we developed a system using the Bosch Sensortec BME680 pressure sensor and the Espressif System's ESP32 communication module to measure the respiratory rate of a wearer of RPE [12-14]. We programmed the ESP32 device using the Arduino IDE, where the program instructs the BME680 to measure pressure every 20 milliseconds and transmits the pressure data to a smartphone app via Bluetooth communication. The smartphone app stores the transmitted pressure data in a local file and analyzes it to measure the wearer's respiratory rate [12].

For the measurement of leak holes in RPE in this study, we utilize the same hardware developed in the previous research. The pressure values transmitted from the respirator are stored, and the range of pressure change according to the wearer's respiratory cycle is calculated using it to judge whether there is a leak hole.

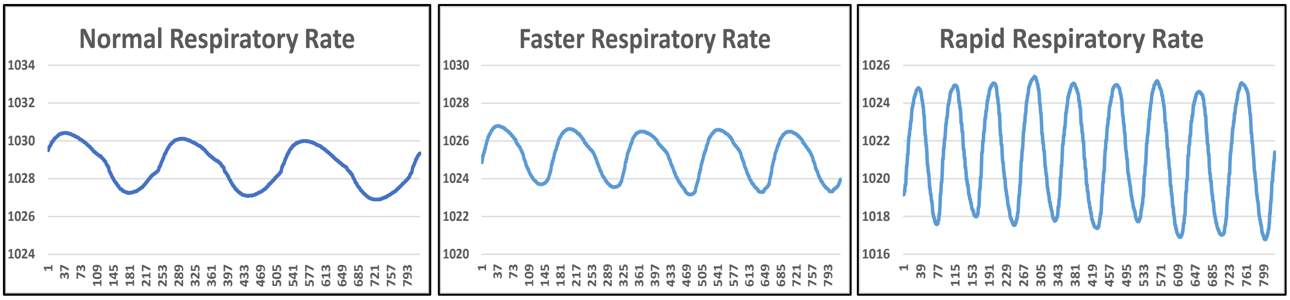
### 3.2 Experiment Scenario

We prepare three types of RPE: one with a normal airtight seal (without leak holes), another with a small-sized single leak hole, and a third with two small-sized leak holes. The participants wear each respirator and engage in breathing for approximately 2 minutes while measuring the pressure values within the respirator. Considering that the speed of breathing may influence the pressure change range within the respirator, the participants conduct breathing experiments at three different speeds: normal speed, slightly faster speed, and very fast speed.

Normal breathing speed is set to achieve a breathing rate of approximately 4-5 seconds per breath when the wearer is in a calm state. The slightly faster breathing speed was set to be about 3 seconds per breath, which is the situation where the wearer is breathing in a slightly strenuous state. The very fast breathing speed is for measuring the state where the wearer has a high oxygen demand due to activities such as running. The pressure values inside the respirator are measured for about 2 minutes immediately after the wearer runs for 10 minutes. In conclusion, each participant wears three respirators with different degrees of tightness, and experiments are conducted according to a total of 9 experimental scenarios, tailored to the 3 breathing speeds.

To intentionally create a leak hole within the respirator, we use a straw with a diameter of 6mm. For a small-sized leak hole, we insert one straw into the mask filter, creating an intentional hole with an area of 28.27mm$^2$. To create a slightly larger leak hole, we use two straws, resulting in an intentional hole with an area of 56.54mm$^2$ in the mask filter

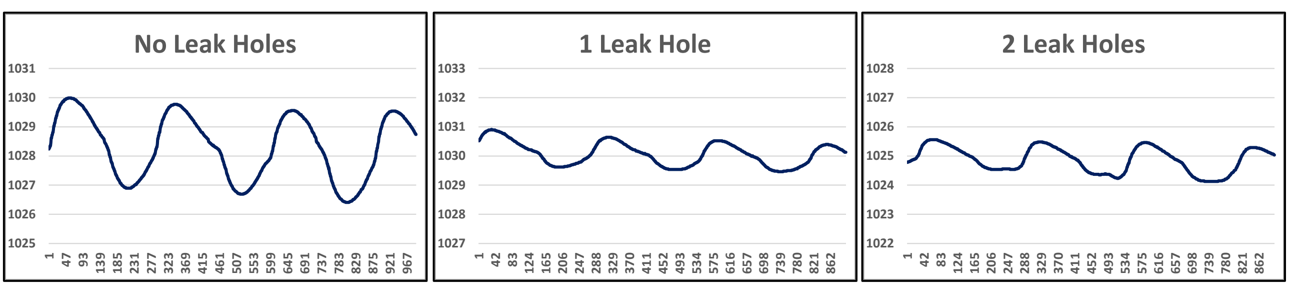
Figure 3 illustrates the pressure changes within the respirator as the participant wears a respirator without a leak hole and breathes at three different speeds. The graphs shown in Figure 3 have been adjusted to have the same pressure range and time range for ease of comparison. These graphs show that the pressure in the respirator changes depending on the wearer's breathing activity. When comparing the calm state in Figure 3-(a) with the slightly faster breathing speed in Figure 3-(b), it can be observed that, despite the shortened breathing cycle, the amplitude of pressure change does not vary significantly. In contrast, for the measurement taken after 10 minutes of running, as shown in Figure 3-(c), both the breathing cycle significantly shortens, and the amplitude of pressure change noticeably increases.




(a) Normal respiratory rate (b) Faster respiratory rate (c) Rapid respiratory rate

**Figure 3. Pressure changes within the respirator based on breathing speed**

Figure 4 illustrates the pressure changes within the respirator for scenarios with no leak hole, one small-sized leak hole, and two small-sized leak holes, respectively. As shown in Figures 4-(a) and 4-(b), the amplitude of pressure change within the respirator is significantly larger in the case without a leak hole than in the case with one leak hole. However, contrary to initial expectations, as shown in Figures 4-(b) and 4-(c), there was not a substantial difference in the amplitude of pressure change between the cases with one leak hole and two leak holes.




(a) No leak holes (b) 1 leak hole (c) 2 leak holes

**Figure 4. Pressure changes within the mask according to the size of the leakage hole**

## 4. Experiments

### 4.1 Experimental Data

The following steps are taken to process the pressure data from an IoT respiratory protection:

(a) Remove abnormal values (noise) and duplicate values from the pressure data.
(b) Remove local maxima and minima from the pressure data.
(c) Calculate the "breathing cycle time" as the distance between the maxima, and the "pressure change range" as the pressure difference between the maxima and minima.

For each breath of a respirator wearer, the "breathing cycle time" and "pressure change range" are measured. These measurements are then analyzed to determine whether the respirator has a leak hole. The number of breathing data measured, the average breathing cycle time, and the average pressure difference for each of the 9 experimental scenarios are shown in Table 1.

In general, the faster the breathing speed, the greater the pressure change range in the respiratory protection. However, in the case of "2 leak holes", the pressure change range was 1.02 hPa at normal breathing speed, but 0.87 hPa at fast breathing speed, showing unexpected results. This is thought to be because the speed of breathing does not have a significant impact on the pressure change range in the respirator when the respirator wearer is in a calm state.

**Table 1. Data measured according to 9 scenarios**

| | Normal breathing | | | Fast breathing | | | Rapid breathing (after running) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Number | Cycle time (seconds) | Pressure difference | Number | Cycle time (seconds) | Pressure difference | Number | Cycle time (seconds) | Pressure difference |
| No leak hole | 81 | 4.26 | 2.75 | 138 | 2.32 | 2.77 | 186 | 1.31 | 6.44 |
| 1 leak hole | 78 | 4.11 | 1.19 | 93 | 2.52 | 1.53 | 189 | 1.17 | 3.45 |
| 2 leak holes | 99 | 3.86 | 1.02 | 138 | 2.61 | 0.87 | 204 | 0.96 | 1.72 |
| Total | 258 | | | 369 | | | 579 | | |

### 4.2 Experimental Results

In this study, a neural network model was constructed using TensorFlow and Keras to detect leak holes in IoT respirators. The developed neural network model takes two real-valued inputs (breathing cycle time and pressure change amplitude) and is structured with one hidden layer containing 32 units, another hidden layer with 16 units, and an output layer with a single unit indicating the output values (0: no leak, 1: leak).

Out of a total of 1206 respiratory data samples, 80% were used to train the neural network model, and the remaining 20% were utilized as the test set. Up to 300 epochs were trained, and the change in loss value according to epoch progress during training is shown in Figure 5. The smallest loss value was shown at the 55th epoch, where the loss value of the test set was 0.05927 (5.93%) and the accuracy value was 0.9753 (97.5%).

In Figure 6, the confusion matrix for the test dataset run on the neural network model trained with the 55th epoch is presented. The probability of detecting an actual leak hole in the respirator was 100%, and the accuracy of correctly identifying the absence of a leak hole when there was none was 94.29%. However, there was a 5.71% occurrence of false positives, indicating a detection of a leak when there was no actual leak hole.

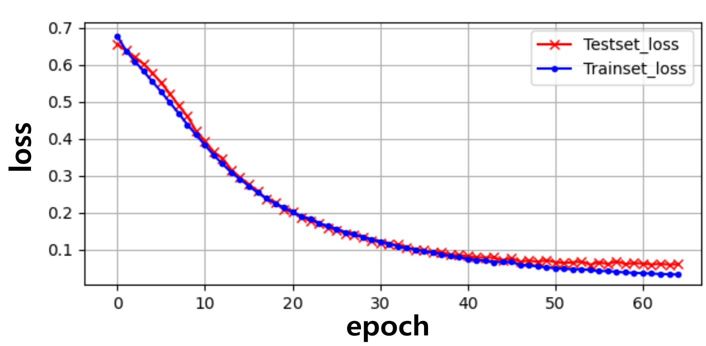



**Figure 5. Change of loss value**

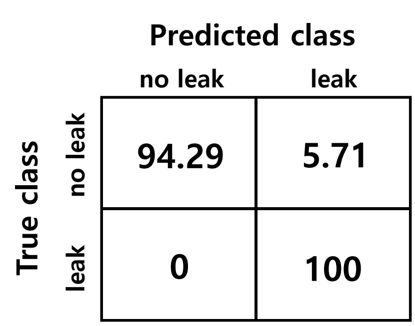



**Figure 6. Confusion matrix**

While the neural network model accurately detected the presence of a leak hole when it was actually present, the instances where the model incorrectly identified a leak hole despite its absence might be attributed to the wearer breathing more gently in specific respiratory situations.

Table 2 presents the performance metrics of the leak hole detection system developed in this study. The experimental results demonstrate that the breathing cycle time and pressure variation of the wearer can be effectively utilized to detect the leak hole in the respirator.

**Table 2. Performance metrics for the leak hole detection**

| F1-Score (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Accuracy (%) |
|---|---|---|---|---|
| 97.87 | 100 | 94.29 | 95.83 | 97.53 |

## 5. Conclusion

In this paper, we propose a method to detect leak holes in full-face respiratory protection by attaching a pressure sensor inside the respirator and measuring the pressure changes inside the respirator according to the breathing activities of the wearer.

We designed a total of 9 experimental scenarios by varying the degree of leakage holes in the respirator and the breathing cycle time. We acquired respiratory data of the wearer of the respirator according to these scenarios. Additionally, we analyzed the respiratory data to find the duration and pressure change for each breath, using them as training data for the neural network model to detect leak holes in the respirator.

The probability of detecting actual leak holes in the RPE was 100%, and in cases where there were no real leak holes, the output correctly indicated no leakage in 94.29% of instances. However, there was a 5.71% probability of falsely detecting leakage when there were no actual leak holes. These probabilities are based on the results for a single breathing cycle. Increasing the number of respiratory cycles used for leak hole detection to more than three is expected to enhance the system's accuracy in detecting the presence or absence of leak holes in the RPE.

## Acknowledgement

This Research was supported by Seokyeong University in 2022.

## References

[1] H. Ueki, Y. Furusawa, K. I. Horimoto, M. Imai, H. Kabata, H. Nishimura, and Y. Kawaoka, "Effectiveness of Face Masks in Preventing Airborne Transmission of SARS-CoV-2," *mSphere*, Vol. 5, Issue 5, e00637-20, 2020. DOI: https://doi.org/10.1128/mSphere.00637-20

[2] T. M. Cook, "Personal protective equipment during the coronavirus disease (COVID) 2019 pandemic – a narrative review," *Anaesthesia, Association of Anaesthetists*, Vol.75, Issue 7, pp.920-927, July 2020. DOI: https://doi.org/10.1111/anae.15071

[3] R. E. Shaffer and S. Rengasamy, "Respiratory protection against airborne nanoparticles: a review," *Journal of Nanoparticle Research*, Vol. 11, pp. 1661–1672, 2009. DOI: https://doi.org/10.1007/s11051-009-9649-3

[4] U.S. Department of Health & Human Services, Personal Protective Equipment. *https://chemm.nlm.nih.gov/ppe.htm*

[5] J. Y. Jeong, *Performance Evaluation of Face Masks : Inhalation Resistance, Fit Factor, Total Inward Leakage and Respiratory Burden*, Master's Thesis. Seoul National University, Seoul, Korea, 2018.

[6] Occupational Health and Safety Act (OSHAct), *Respiratory protection*, 2011.

[7] National Institute for Occupational Safety and Health (NIOSH), *Guide to industrial respiratory protection*, 1987.

[8] Y. Liu, J. Corey, M. V. Yermakov, B. Wu, and S. A. Grinshpun, "Preliminary Development of a Real-Time Respirator Seal Integrity Monitor With Low-Cost Particle Sensor," *in IEEE Transactions on Industry Applications*, Vol. 54, No. 4, pp. 3928-3933, July-Aug. 2018.
DOI: https://doi.org/10.1109/TIA.2018.2816907.

[9] K. Butler, M. Nyden, and R. Bryant, *Real-Time Monitoring of Total Inward Leakage of Respiratory Equipment Used by Emergency responders: Workshop Proceedings*, National Institute of Standards and Technology, Gaithersburg, MD, Sep. 2010.
DOI: https://doi.org/10.6028/NIST.SP.1113-BFRL

[10] E. L. Floyd, J. B. Henry, and D. L. Johnson, “Influence of facial hair length, coarseness, and areal density on seal leakage of a tight-fitting half-face respirator,” *Journal of Occupational and Environmental Hygiene*, Vol. 15, Issue 4, pp. 334-340, 2018.
DOI: https://doi.org/10.1080/15459624.2017.1416388

[11] K. Arnoldsson, S. Danielsson, and M. Thunéll, “A method for evaluating aerosol leakage through the interface between protective suits and full-face respirators,” *Journal of Occupational and Environmental Hygiene*, Vol. 13, Issue 5, pp. 315-324, 2016.
DOI: https://doi.org/10.1080/15459624.2015.1117616

[12] W. C. Shin, “A Study on the Measurement of Respiratory Rate Using a Respirator Equipped with an Air Pressure Sensor,” *The International Journal of Advanced Smart Convergence, IIBC*, Vol. 11, No. 4, pp. 240-246.

[13] Bosch Sensortec, BME680 – Datasheet. *https://www.bosch-sensortec.com/products/environmental-sensors/gas-sensors-bme680*

[14] Espressif Systems, ESP32 Overview. *https://www.espressif.com/en/products/socs/esp32*