Heliyon 9 (2023) e12964

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Recognition of IoT-based fire-detection system fire-signal patterns applying fuzzy logic

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A R T I C L E I N F O

Keywords:
IoT-based fire-detection system
Unwanted fire alarm
False alarm rate

A B S T R A C T

Article history: In Korea, the use of fire-detection systems applying IoT technology to existing analog fire-alarm systems has increased owing to the communication technology convergence, the world's best Internet network, and the proliferation of Internet of Things (IoT). Its use can be expected to increase worldwide in the future. For IoT-based fire-detection systems to exhibit the requisite reliability (based on a low false-alarm rate), research related to the analysis of detection signals should be actively promoted and conducted. However, there has been no research activity based on actual operational data, apart from the research that has been conducted in laboratory environments. The primary reason for this state of affairs has been that the installation and use of IoT-based fire-detection systems on a large scale has been rare, worldwide. Consequently, with respect to the fire-signal characteristics of IoT-based fire-detection systems, related data in this study were obtained by investigating actual fire accident cases, using fire alarm data that occurred over a period of 5 years. Based on the signal pattern analysis results using these field data, a fuzzy logic system for recognizing fire signal patterns was developed and verified. As a result, in the actual fire accidents examined, an "alarm" condition—corresponding to the high possibility of fire among the five fire alarms—was determined 30 s before the actual fire alarm. Moreover, it was also found that approximately 80% of non-fire alarms could be reduced in the actual fire alarms that occurred at Institute *K* during the 5-year period examined.

1. Introduction

When a fire occurs, smoke, flames, and rising temperatures inevitably occur due to the burning of combustibles. Fire-alarm systems detect these phenomena, swiftly notifying related personnel that a fire has occurred, enabling people to be evacuated and the fire to be quickly extinguished.

According to the Korean National Fire Agency statistics, over the past 10 years there have been an average of 42,332 fires and 2215 casualties in South Korea, both of which continue to increase [1]. This phenomenon is accelerating due to increasing urban densities. In such a densely concentrated and integrated society, a reliable fire-alarm system becomes essential to ensure public safety.

According to the Seoul Metropolitan Fire and Disaster Headquarters (2019), the annual false fire-alarm rate from 2015 to 2019 ranged from 2.2 to 7.6%, which could be considered to be high. As this data were based on fire department dispatch statistics, the actual false-alarm rate was estimated to be considerably higher [2].

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https://doi.org/10.1016/j.heliyon.2023.e12964
Received 24 July 2022; Received in revised form 6 January 2023; Accepted 10 January 2023
Available online 20 January 2023

To prevent administrative loss and damage due to false fire alarms, numerous studies have been conducted on improving the reliability of fire-alarm systems. Moreover, studies are underway on new types of fire-alarm systems, as distinct from existing analog fire-alarm systems.

Advances in IT have enabled researchers to realize digital fire-alarm systems applying IoT technology. The smoke and temperature detection accuracy of analog fire-alarm systems in the event of a fire have traditionally been measures of reliability. However, in digital fire-alarm systems applying IoT technology—that is, in IoT-based fire-detection systems—how the output signal of a detector is analyzed to classify fires and false alarms can now be a measure of reliability. Consequently, research on the analysis techniques and signal characteristics of detectors is important for IoT-based fire-detection systems.

However, despite the changes in fire-alarm systems, such studies have not been conducted as, worldwide, there have been only a few cases of large-scale IoT-based fire-detection systems installed and operated.

Accordingly, this study analyzed the fire-signal characteristics in a fire accident that occurred where an IoT-based fire-detection system was installed, using the measured data and fire alarm data generated over five years to analyze the false fire-alarm signal characteristics of Institute *K*, which operates South Korea's largest IoT-based fire-detection system.

To distinguish genuine fire and false fire-alarm signals, this study examined how to determine whether a fire had actually occurred by applying fuzzy logic to the output signals of detectors, thereby improving reliability.

2. Review of related work

To overcome the limitations of existing analog fire-alarm systems, research on new types of fire-alarm systems that are faster, more accurate, and convenient, while also reducing the false-alarm rate is being conducted or developed. CCTV-based fire-detection systems [3–6] detect flames and smoke by applying image preprocessing methods, applying deep learning-based convolutional neural network (CNN) models. However, while such fire-alarm systems can be used to prevent forest fires in public places or mountainous areas that can be difficult to access, they can be of limited use in the urban context including in private areas. In particular, it can be more difficult in countries that strongly protect individual freedom and rights—such as in Korea with its Personal Information Protection Act. Conversely, IoT-based fire-detection systems [7–9] that apply IoT technology to existing analog fire-alarm systems can be expected to be increasingly used worldwide due to their scalability and integrability, allowing them to be linked to smartphones and CCTV system, amongst others. For IoT-based fire-detection systems to exhibit the requisite reliability—based on their low false-alarm rates—research related to the analysis of detection signals must be actively conducted.

Rachman et al. [10] reported a fire detection system using a wireless multi-sensor (consisting of flame sensor, smoke sensor, and temperature sensor) network based on fuzzy logic rules. The experiment uses eight multi-sensor nodes and 60 × 50 × 50 cm prototype room.

Sowah et al. [11,12] reported the design and development of a fuzzy logic based multi-sensor fire detection system and a web-based notification system. Experimental results were obtained using candle (flame), burning a paper (smoke) and using hair dryer (temperature).

Devi et al. [13] applied fuzzy logic to data obtained from temperature and gas sensors and conducted an experiment to detect fire through web monitoring.

Although laboratory-scale studies have been conducted, their experimental results have limitations as they do not include various real-world site variables.

Once installed, the fire detection system is used for more than 10 years and consists of dozens to thousands of detectors depending on the size of the building. Consequently, various unexpected variables may occur and cause false alarms. Therefore, research based on actual operation cases rather than experimental cases is required.

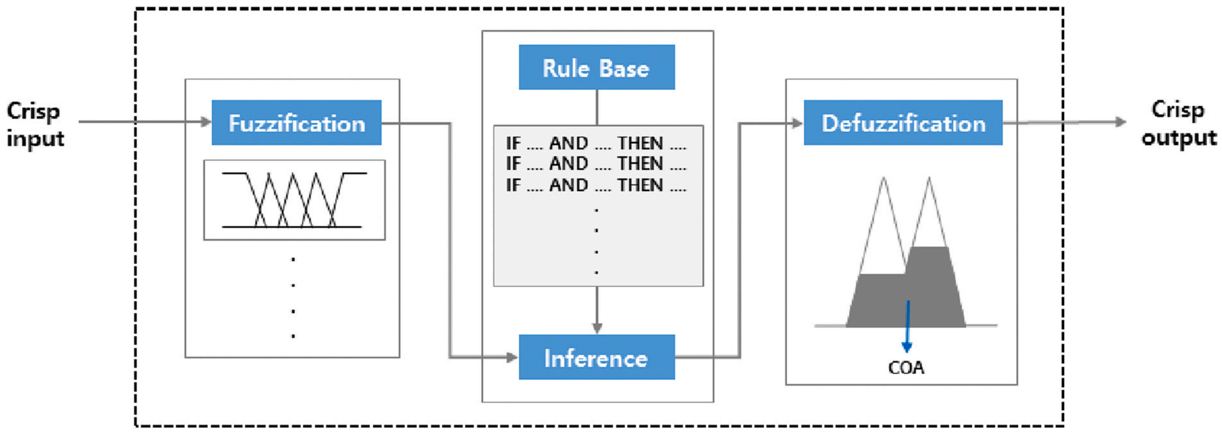


Fig. 1. Fuzzy logic structure.

3. Theoretical formulation for fire detection using fuzzy logic

Fuzzy logic attempts to express unclear standards with ambiguities, such as 'large' and 'hot.' In existing mathematical logic, if the value of a formula can be expressed as *0* or *1*, fuzzy logic can be extended for ambiguity to obtain values between *0* and *1*, moving away from the binary logic of "*true*" or "*false*".

Fig. 1 shows a schematic of a fuzzy logic structure, comprising fuzzification, inference rules, and defuzzification.

Fuzzification is the process of converting the crisp values of an input variable into a fuzzy set, which involves converting the fuzzy variables of the input values determined beforehand into an entire set to facilitate fuzzy calculations for the values measured from each detector sensor. The fuzzy membership function refers to a subset randomly divided based on the range. Although there can be various shapes, trapezoids and triangles have the advantage of being convenient and were used in this study [14].

The inference rules are linguistic rules stating that "if a specific condition is satisfied, then a specific result will be obtained," which establishes the relationship between an input variable and output variable. Typically, all rules consist of several multiple input and output fuzzy conditional statements [15]. For example,

IF Temperature is Low AND Duration is Low THEN Fire possibility is Low.

⁞

n.

In this way, the reasoning process proceeds using *n* inference rules and fuzzy input variables. In this study, Mamdani's max–min method [16,17]—which is typically used as an inference method—was used.

Defuzzification is the process of converting the membership function of a linguistic output variable into a defuzzified manipulated variable—that is, a crisp value. Of the various defuzzification methods, this study applied the modified center of area (CoA) method, the most widely used method [18,19]. The centroid method defuzzification calculates the size of the area of a fuzzy set, to find the geometric center of the two-sided area (Fig. 2). In this study, LABVIEW was used for the design and calculation of the fuzzy system.

4. System design and methodology

The composition of an IoT-based fire-detection system used in Korea was investigated. Additionally, to obtain realistic results related to the recognition of fire-signal patterns in the IoT-based fire-detection system, field data were obtained from actual operational cases—as opposed to experimental data generated in laboratory conditions—and used in this study.

Regarding the fire-signal characteristics of the IoT-based fire-detection system, related data were obtained by examining actual fire-accident cases. In relation to the false-alarm signal characteristics, Institute *K*—operating the largest IoT-based fire-detection system in Korea—was examined. This study was conducted using annual fire-alarm data. Based on signal-pattern analysis of the field data, a fuzzy membership function was selected, and an improved system based on it was designed.

4.1. IoT-based fire-detection system in South Korea

IoT-based fire detectors in South Korea can be easily connected to the Internet, even in typical households. This is partly because the country has the world's best Internet network but is also due to the popularity of user-friendly products such as AI-based smart-speakers and CCTV.

A fire accident at the Seomun Market in Daegu, South Korea on November 30, 2016, burned down all 839 stores handling inflammable products such as clothes and bedding, causing massive property damage of $31.25 million [20]. This accident became a social issue in South Korea. As part of follow-up measures, the government has been promoting the installation of fire-alarm facilities in traditional markets since 2018.

Traditional markets in South Korea have numerous problems, including aging and complex structural problems related to the dense concentration of shops in maze-like alleys. Consequently, there can be many restrictions to the installation of wired analog fire-alarm systems. Accordingly, by adopting a wireless IoT-based fire-detection system, this study sought to address such structural limitations, enable automatic reporting to the fire department when a fire alarm occurred, and solve the problem of firefighter insight via security CCTV integration.

The comprehensive regulatory transition policy announced by the Korean government in 2019 permits new types of fire-alarm facilities using new information and convergence technologies—such as the IoT—expands limited product concepts, and enhances the flexibility of rigid classification systems. This encouraged the entry of companies with IoT expertise into the firefighting industry

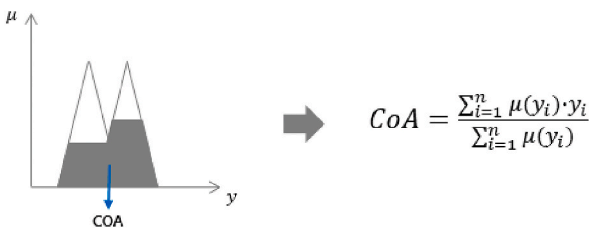


Fig. 2. The defuzzification process.

and the implementation of new technologies by existing companies [21].

Fig. 3 shows the configuration of a typical IoT-based fire-detection system.

The communication between a receiver and detector makes use of low-power long-range (LoRa) wireless communication, capable of relatively long distance transmission (1–2 km). The system connects the receiver to the server, control room, and fire station using an Internet-based communication network. Moreover, additional equipment—such as CCTV and speakers—can be connected to the system.

In IoT-based fire-detection systems, when a detector's measurement exceeds a specified threshold, a real-time detection signal is stored on the server every few seconds from this point until the measurement falls below the threshold. The detector transmits the measured analog signal to the receiver as an 8-bit digital signal—that is, a data communication unit, as a number from 0 to 225. This

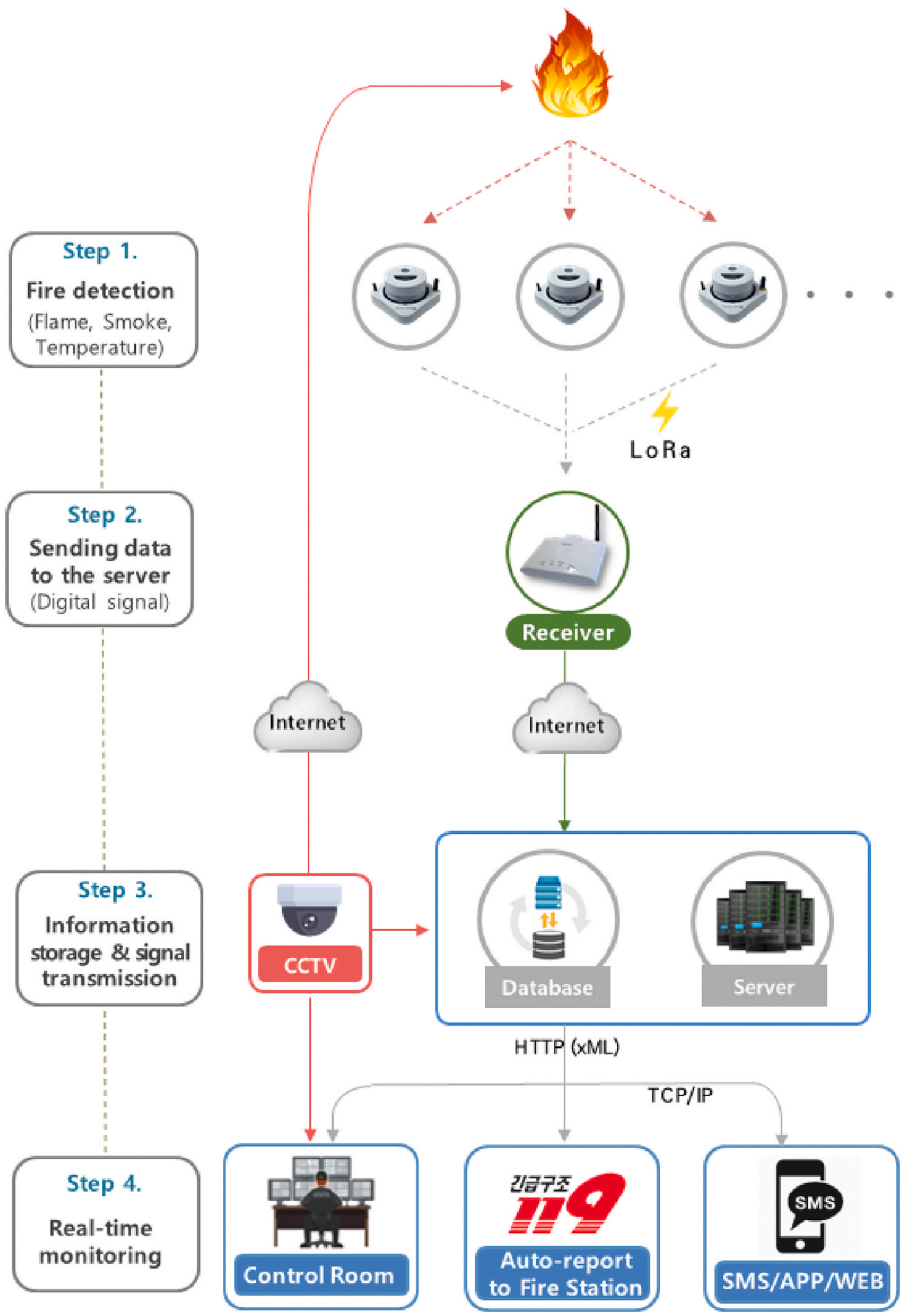


Fig. 3. Configuration of a typical IoT-based fire-detection system.

detection signal can be expressed in data communication units, so the value itself does not use units of flame, smoke, or temperature but is a percentage, ratio, or relative number.

4.2. Fire-signal characteristics

In South Korea, IoT-based fire-detection systems have been installed in various places, including traditional markets, energy storage systems (ESSs), and cultural asset venues. This study investigated places where actual fires occurred, the data being stored on a server. Based on the results, there were seven fire accidents between 2020 and 2021, all of which occurred in traditional markets. The fire signal characteristics were analyzed using the server data of the accident site.

Table 1 shows whether the fire signals were detected by the three sensors built into the complex detector in the seven fire accidents. As shown, all three sensors—that is, flame, smoke, and temperature—were used in four of the cases, and only two sensors—that is, smoke and temperature—were used in the remaining three cases. Consequently, it is evident that the conditions of an installation site should be considered when installing a single-type detector.

Fig. 4 shows *Fire Accident 1*, which occurred at a seafood shop. The detector (Fig. 4a**)** was destroyed 1 min and 20 s (Fig. 4b**)** after the fire had started. Based on CCTV footage (Fig. 4c**)** and the detector locations at the time of the fire, the detector was likely to have been destroyed, as many Styrofoam boxes used for seafood packaging burned rapidly. The detector at an adjacent side dish shop also measured the large volume of smoke generated by the fire. Flame values were detected later than the smoke and temperature values because the fire from an outside distribution board penetrated and spread inside the store.

In *Fire Accident 5* (Fig. 6), an inflection point (Fig. 6b) of the smoke values occurs when the shop door was opened to extinguish the fire. A similar change was observed in four fire accidents including *Fire Accident 2* (Fig. 5).

In *Fire Accidents 5, 6* and *7*, the flame sensor did not operate. A flame sensor works by detecting UV rays generated by flames. As shown in Fig. 6, the UV detection was blocked due to obstacles (Fig. 6a) within the store.

The smoke and temperature sensors operated normally in all fire situations. Rapid changes in the slopes of the temperature and smoke values are evident in the graph of the seven fire accidents—the graphs consisting of the detected values and times, showing the correlation between components. In a graph of the seven fire accidents, the fire-detection signal exhibits two characteristics. The first is variability. The values change sharply over time until the detection limit is reached. The second is continuity. Over time, there is a continuous detection signal until the detection function is lost or the fire is extinguished.

In the seven fire accidents, data—such as the location of the site of the fire, the location of the detector, and the measurements—were combined to analyze and infer the situation during the fire. Consequently, if IoT-based fire-detection systems become universal in the future, they are expected to have high utility in the field of fire accident investigation.

4.3. Unwanted fire alarm signal characteristics

Institute *K*, which operates South Korea's largest IoT-based fire-detection system, has 3648 complex detectors comprising flame, smoke, and temperature sensors. Firefighters are stationed in shifts 24 h-a-day responding immediately when a fire alarm occurs at the site. The reliability of data and the history of false alarms is high. Accordingly, this study used the fire and false alarm data of *K* over a period of five years, from 2016 to 2020.

The smoke and temperature sensor measurements above a specified threshold are stored on a server, as in the fire accident cases analyzed earlier. For the flame sensors, however, the measurements above the threshold are stored as 0 and 1, rather than on the server. This simple format indicates that the flame's UV rays either exceeded the threshold and were detected or were not detected. As the signal characteristics analysis was limited, this study analyzed *K*'s smoke and temperature fire alarms over a period of five years.

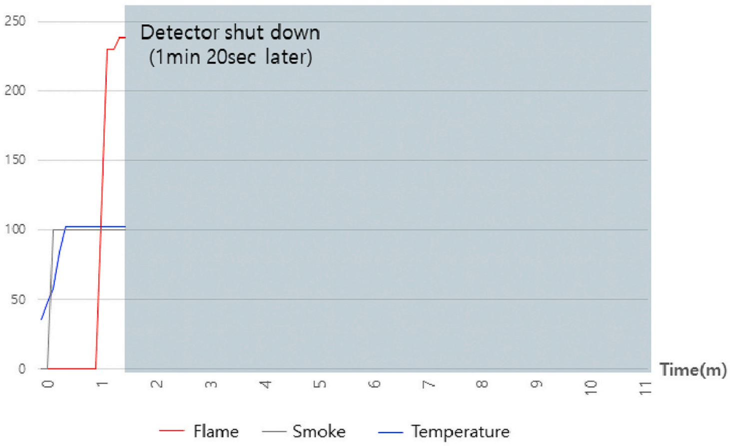
Institute *K* had 233 smoke and temperature fire alarms over the five-year period. As shown in Table 2, the alarms were classified into "unwanted fire alarms" and "normal operation" based on the results of dispatches to the site when a fire alarm occurred in the 24-h fire control room. Alarms for which the cause of detector operation was not confirmed were classified as "unwanted fire alarms"—including cases where the detector malfunctioned or was operating normally but the cause was not confirmed when personnel were dispatched to the site.

Alarms for which the cause of detector operation was confirmed were classified as "normal operation." Institute *K is* a nuclear-related research institute that runs approximately 600 laboratories. Consequently, these alarms were cases when the detector operated due to smoke or high temperatures from experiments or other activities. Additionally, two fire accidents occurred during the five-year period, and the corresponding fire alarms were classified as "normal operation." Table 3 shows the classification based on

Table 1
Fire accident at places where IoT-based fire-detection system were installed.

	Flame	Smoke	Temperature
Fire accident 1	Detection	Detection	Detection
Fire accident 2	Detection	Detection	Detection
Fire accident 3	Detection	Detection	Detection
Fire accident 4	Detection	Detection	Detection
Fire accident 5	None	Detection	Detection
Fire accident 6	None	Detection	Detection
Fire accident 7	None	Detection	Detection

(a) Detector position & fire point



(b) Flame, smoke, and temperature sensing values

(c) CCTV screen

Fig. 4. Fire accident 1, (a) Detector position & fire point. (b) Flame, smoke, and temperature sensing values. (c) CCTV screen.

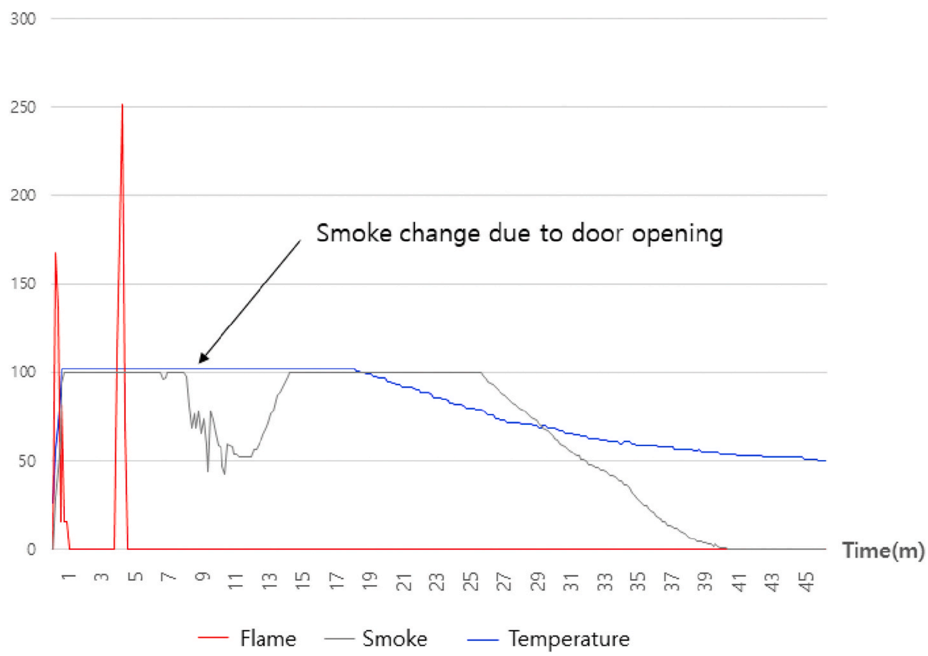


Fig. 5. Fire accident 2.

variability and continuity, which are characteristics of the fire accident graph.

Variability is represented by V-Signals and continuity by C-Signals. Cases of simultaneous variability and continuity are denoted as VC-Signals.

Figs. 7–9 show graphs of the V-Signals, C-Signals, and VC-Signals of the smoke fire alarms, respectively.

Fig. 9 shows the smoke alarm detection values for the two fire accidents that occurred in *K*; the first fire accident is denoted by the blue dotted lines, and the second by the red dotted lines. In both cases, there was no temperature alarm because the fires were extinguished early, before they could spread into large fires.

Figs. 10–12 show graphs of the V-Signals, C-Signals, and VC-Signals of the temperature fire alarms, respectively.

The C-Signals shown in Fig. 11 are mostly concentrated around 50°. Since the threshold of the constant temperature sensor was set to 50°, these are cases where the temperature inside the building rose to near the threshold due to the summer heat wave or the detectors were normally triggered by high temperatures due to experiments or other activities.

Over the five-year period of fire alarms (233 cases) that occurred at *K*, the fire signal characteristic VC-Signal occurred in 31% (55 cases) of smoke alarms and 30% (17 cases) of temperature alarms. As the flame alarm measurements were not stored on the server, the signal characteristics could not be distinguished. However, considering that the fire signal characteristics of VC-Signals from the seven fire accidents in traditional markets and Institute *K* use the same complex detectors comprising flame, smoke, and temperature sensors, the signal patterns are presumed to have similar shapes. Nevertheless, there is uncertainty since no actual data were analyzed.

4.4. *Application of fuzzy logic*

Based on the signal characteristics analysis, the fire signals appeared as VC-Signals. Input and output variables were composed to apply fuzzy logic to the 233 smoke and temperature fire alarms at *K* and the seven fire accidents at traditional markets.

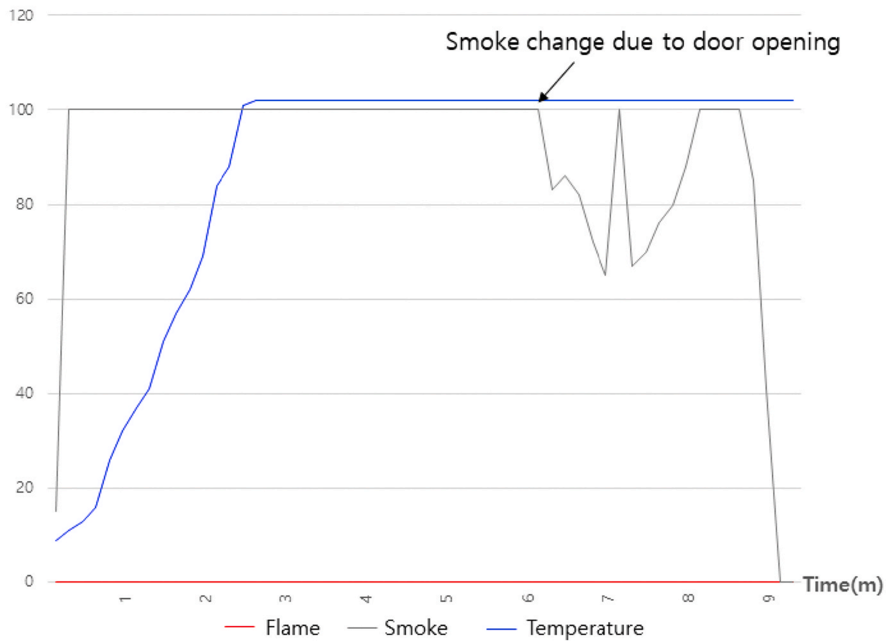
Duration and photosensitivity—which are indicative of the smoke concentration—were used as the input variables of the smoke fire alarms, and duration and detected temperature were used for the temperature fire alarms. Duration refers to the length of time the detector's measured value remains above the specified threshold. The output variable was expressed as the possibility of fire.

4.4.1. *Input variables*

The linguistic variables of the input signal were expressed as *Low, Medium,* and *High*. The "Technical Standards for Type Approval and Product Inspection of Fire Extinguishing Agents" established by the Korean National Fire Agency was referenced for the composition of the membership functions [22]. Table 4 shows the values of the input variables of smoke, temperature, and duration, and Figs. 13–15 show the corresponding graphs.

The photosensitivities detectable using the photoelectric smoke detectors are 7.5% (Type 1), 15% (Type 2), and 22.5% (Type 3). Accordingly, *Medium* was designated as 7.5–22.5%, *Low* as 5–15%, and *High* as 15–25% based on the 15% detectable rate of Type 2 being the most versatile. As the measurements were stored as 8-bit communication units in the server of Institute *K*, they were converted and displayed, as shown in Table 4 and Fig. 12.

(a) Detector position & fire point



(b) Flame, smoke, and temperature sensing values

Fig. 6. Fire accident 5. (a) Detector position & fire point. (b) Flame, smoke, and temperature sensing values.

Table 2
Fire alarms from IoT-based fire-detection system in Institute *K*.

	Alarms	Unwanted fire alarms	Normal operation
Smoke	176	152	24
Temperature	57	49	8
Total	233	201	32

Table 3
Classification of fire alarm signals.

	V-Signals	C-Signals	VC-Signals
Smoke			
Unwanted fire alarms	103	18	33
Normal operation	0	0	22
Temperature			
Unwanted fire alarms	9	23	17
Normal operation	0	8	0

Table 4
Linguistic values of smoke, temperature, and duration.

	Low	Medium	High
Smoke (%)	5–15	7.5–22.5	15–25
Conversion (8 bit)	13–38	19–57	38–64
Temperature (°C)	55–70	60–80	70–90
Duration (s)	10–25	20–30	25–40

The nominal operating temperature of the constant temperature sensor is 60–150 °C. However, since the maximum value that can be expressed in *K*'s IoT-based fire-detection system is 101 °C, the singleton of *High* was set to 90 °C, and given that most of the C-Signals in Fig. 10 are concentrated around 50 °C, the singleton of *Low* was set to 55 °C. *Medium* was set to 60–80 °C based on the 70 °C constant temperature sensor, which is the most commonly used.

The most sensitive photoelectric detector (Type 1) has an operating time of 30 s. Also, the most sensitive constant temperature sensor (60 °C) has an operating time of 30 s. Therefore, for duration, the singleton of *High* was set to 40 s based on 30 s and an error range from the communication traffic and consideration of the fact that *K*'s IoT-based fire-detection system communicates in 10-s units, the singleton of *Low* was set to 10 s. *Medium* was set to 20–30 s to receive the detection value 2–3 times.

4.4.2. Output variables

The linguistic variable of fire possibility was divided into five levels and expressed as a number from 0 to 100. Level 1 (*Ignore*) indicates that the possibility of fire is low, for which the singleton was set to 15 and the maximum value to 25. Level 2 (*Concern*) indicates that the possibility of fire is low and was set to 20–50. Level 3 (*Caution*) indicates that there is a possibility of fire and was set to 40–70. Level 4 (*Danger*) indicates that the possibility of fire is high and was set to 60–90. Level 5 (*Alarm*) indicates that the possibility of fire is high, for which the minimum value was set to at least 80 and the singleton to 85. Fig. 16 shows the above configurations.

4.4.3. Inference rules

The inference rules were based on the single-type detector, which is the most commonly used in the market. The inference rules were set for the relationship between smoke and duration for the first case and between temperature and duration for the second case.

Fig. 17 shows the inference rules of the smoke detector and Fig. 18 shows the inference rules of the temperature detector. Although there is variability, as shown in Fig. 7, considering unwanted fire alarms having the characteristic of discontinuity, the inference rules in Fig. 17 were set to output *Ignore* if the duration was *Low*.

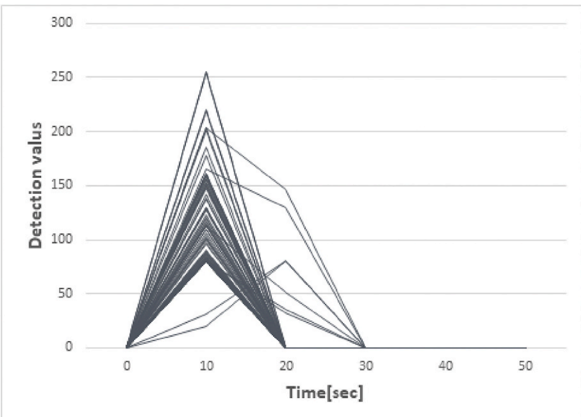


Fig. 7. V-Signals of smoke.

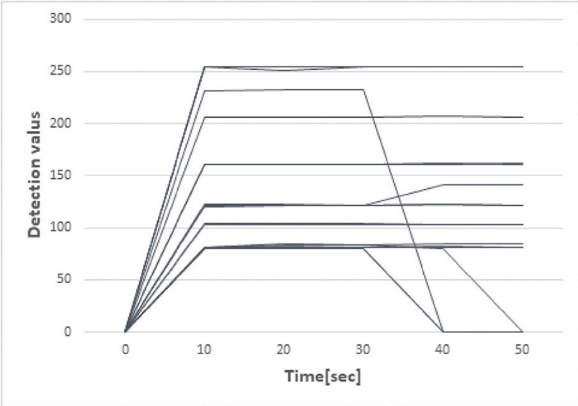


Fig. 8. C-Signals of smoke.

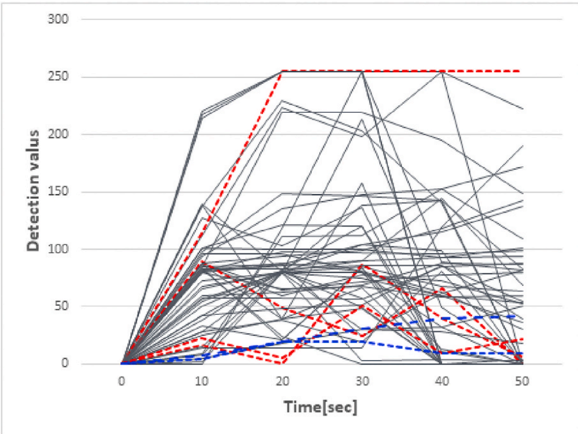


Fig. 9. VC-Signals of smoke.

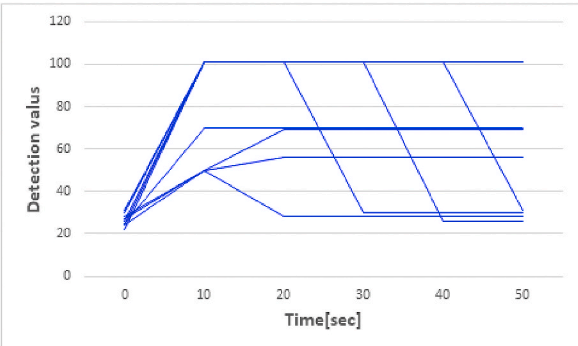


Fig. 10. V-Signals of temperature.

5. Results: system implementation and testing

5.1. System implementation

There may be various ways to recognize the fire signal pattern using the server. However, considering the characteristics of firefighting equipment used in the past, it could be considered to be inappropriate to apply a load to the server using complicated calculations needing additional computing resources.

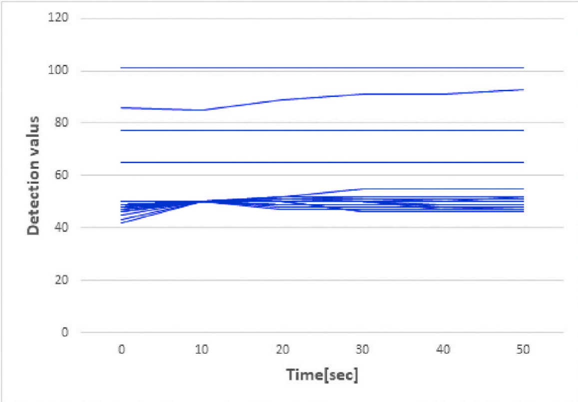


Fig. 11. C-Signals of temperature.

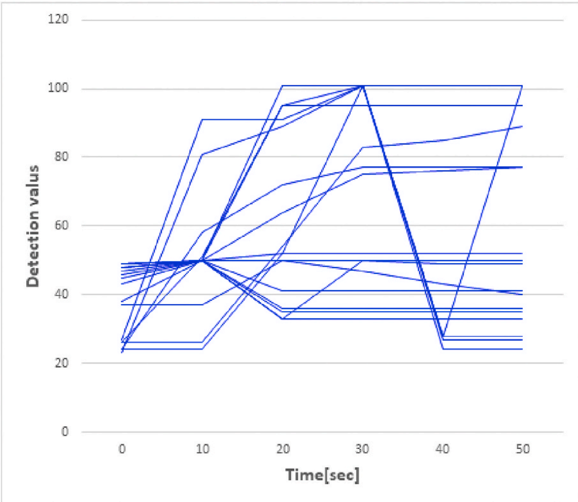


Fig. 12. VC-Signals of temperature.

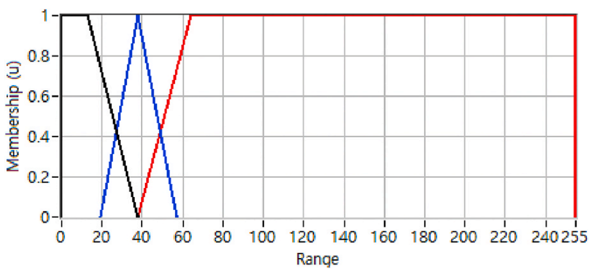


Fig. 13. Input variable membership function for smoke.

Table 5 shows the recommended service life of analog-type fire-alarm system components specified by the Korea Fire Protection Industry Cooperative and the Korea Fire and Fire Society [23].

In an IoT-based fire-detection system, the server managing operations and information storage can have its service life impacted by the increased heat generation of semiconductor devices such as its CPU and RAM, which are core components of the server, compared to the recommended service life of the analog fire-alarm system. It can be considered that durability of at least 10 years is required even if in the context of matters such as shortened life spans and reduced reliability [24–26].

The system was designed, as shown in Fig. 19, to recognize the fire-signal pattern as a minimum considering the server lifespan.

The IoT-based fire-detection system comprises a network structure. In the case of Institute *K*, unique MAC addresses were assigned

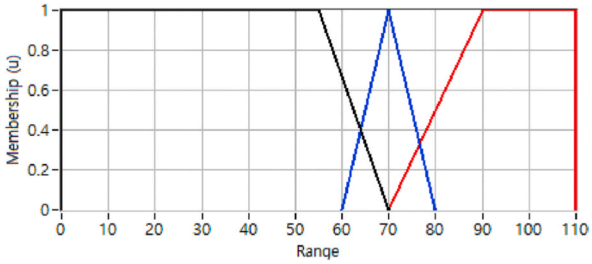


Fig. 14. Input variable membership function for temperature (°C).

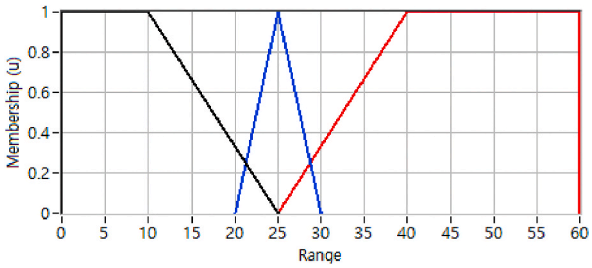


Fig. 15. Input variable membership function for duration (s).

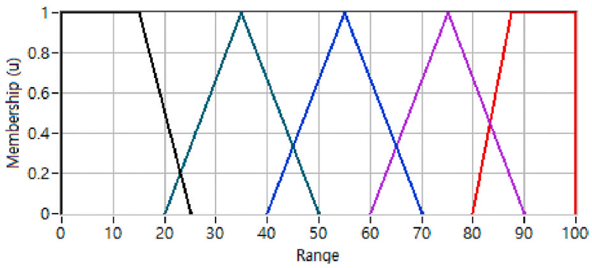


Fig. 16. Output variable membership functions.

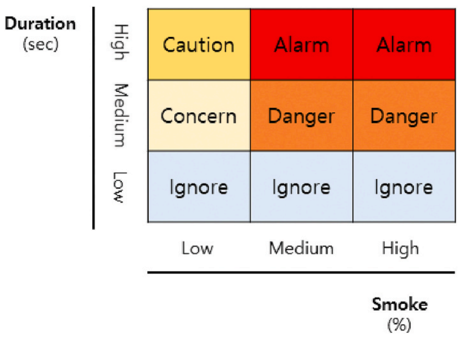


Fig. 17. Fuzzy inference rules for the smoke and duration.

to 3648 detectors, 97 receivers were connected via a wireless communications network, and the fire-detection signal data were stored on the server.

Fig. 19 shows the storage format of the transmitted data in units of the detector MAC address. In a normal state, the detector communicates with the receiver every 10 min to transmit general information (G-Info) indicating the state of the detector. If there are signs of fire, when the detection value exceeds a certain threshold, a detection signal is transmitted. Information is communicated every 10 s until the detection value is lower than the threshold value. Data above the threshold are indicated as '*Detect*' in Fig. 19.

The detection signal (*Detect*) is calculated based on the input variable, output variable, and inference rules specified in the '4.4

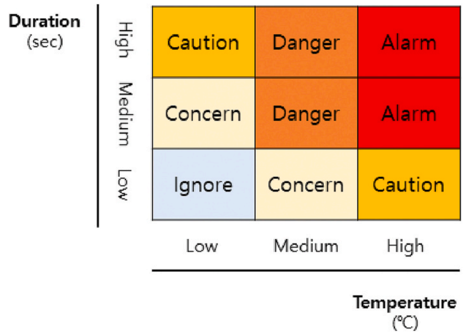


Fig. 18. Fuzzy inference rules for temperature and duration.

Table 5
Recommended service life of components of automatic fire-detection equipment.

Detector	Manual fire alarm box	Alarm bell	Transmitter	Receiver
10–15 years	20 years	20 years	15 years	15–20 years

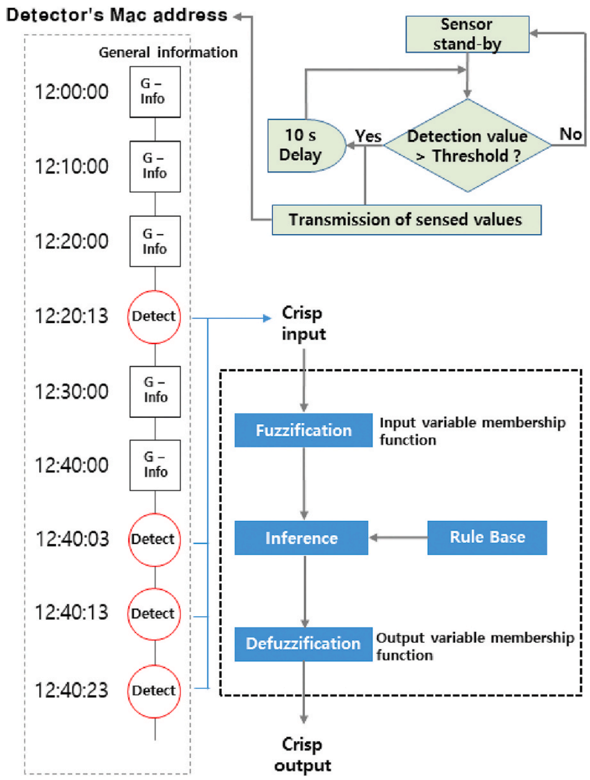


Fig. 19. System design for the recognition of fire signal patterns.

Application of Fuzzy Logic' standard and is communicated as a five-stage fire possibility.

5.2. Results and discussion

The system design shown in Fig. 19 was applied to seven real fire cases. Based on the results, all reached Level 5 (*Alarm*) before 30 s, indicating the possibility of fire to be high. This satisfies the standard for the most sensitive detector in the "Technical Standards for Type Approval and Product Inspection of Fire Extinguishing Agents" established by the Korean National Fire Agency.

The inference rules shown in Fig. 19 were similarly applied to the 233 alarms that occurred over five years at Institute *K*, the results of which are shown in Table 6.

For smoke alarms, out of 176 cases, it output 0 *Danger* cases and 32 *Alarm* cases (18.2%), which could be considered to be actual fires.

For temperature alarms, out of 57 cases, it output 4 *Danger* cases (7%) and 10 *Alarm* cases (17.5%), which could be considered to be actual fires.

The inference rules shown in Fig. 19 were also applied to the two fire accidents that occurred at Institute *K*. based on the results, both reached Level 5 (*Alarm*) before 30 s, indicating the possibility of fire to be high.

The blue dotted lines shown in Fig. 9 denote the first fire accident, where smoke alarms were generated from two fire detectors. Level 5 (*Alarm*) was output for the detector closest to the site of the fire, and Level 3 (*Caution*), indicating the possibility of a fire, was output for the other.

The red dotted lines shown in Fig. 9 denote the second fire accident, where smoke alarms were generated from five fire detectors. As in the first fire accident, *Alarm* was output for two detectors, *Caution* for two detectors, and *Ignore* for the remaining detector, in proportion to their distance from the fire site. *Ignore* was output because, although the threshold was exceeded while extinguishing the fire, the duration was short due to the door opening and ventilation.

5.3. Limitations

This study is the first to apply a method to recognize only reliable signals as fire alarms in a large-scale IoT-based fire-detection system. However, owing to the absence of on-site data related to flame sensors, only smoke and temperature sensors were considered, and the application of fuzzy logic to minimize the computational overhead of the server needs supplementary research in future.

In addition, in this discussion, since the subject of the application of the research results was limited to Institute *K*, it was not possible to deal with problems that may have arisen from difference in data communication systems from various manufacturers. In future research on data and communication standards and follow-up studies on fire signal pattern recognition, it is expected that the installation and use of IoT-based fire-detection systems could increase throughout residential and industrial areas.

6. Conclusions

This study analyzed the fire-signal characteristics of a fire accident that occurred where an IoT-based fire-detection system had been installed and analyzed the false alarm signal characteristics of Institute *K*, which operates South Korea's largest IoT-based fire-detection system. Fuzzy logic was applied based on the signal-characteristic results, and the following conclusions were reached.

1. Using the location of the site of the fire, the detectors, and the flame, smoke, and temperature measurements from the IoT-based fire-detection system, it was possible to infer the situation during the fire. By analyzing seven fire accidents, the VC-Signal characteristic showing both continuity and variability in the detection values over time was evident in the fire signals.
2. The fire signal characteristic VC-Signal was also evident in two fire accidents that occurred at Institute *K*, and of the 233 fire alarms that occurred over five years, VC-Signal occurred in 31% (55 cases) of the smoke alarms and 30% (17 cases) of the temperature alarms.
3. Fuzzy logic was developed and applied to identify the VC-Signal, a fire signal characteristic. All seven fire accidents that occurred at traditional markets and both fire accidents that occurred at Institute *K* reached Level 5 (*Alarm*) before 30 s, indicating the possibility of fire to be high. This satisfied the standard in South Korea for the most sensitive fire detector.

Table 6
Results of applying the fuzzy inference rules to Institute K.

	Smoke	Temperature
V-Signal	103	9
Ignore	103	1
Concern	–	–
Caution	–	4
Danger	–	1
Alarm	–	3
C-Signal	18	31
Ignore	3	10
Concern	–	–
Caution	–	16
Danger	–	1
Alarm	15	4
VC-Signal	55	17
Ignore	14	6
Concern	–	–
Caution	9	6
Danger	–	2
Alarm	32	3

4. Fuzzy logic was applied to the 233 fire alarms at Institute *K*; *Alarm*—indicative of a very high possibility of fire—was output for 18.2% (32 cases) of the smoke alarms and 17.5% (10 cases) of the temperature alarms, and *Danger*—indicative of a high possibility of fire—was only output for 4% (7 cases) of the temperature alarms. Consequently, based on the case of Institute *K*, this study demonstrated that by applying fuzzy logic to an IoT-based fire-detection system, unwanted fire alarms could be reduced by approximately 80%.

Author contribution statement

Seung Hwan Park: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Doo Hyun Kim: Analyzed and interpreted the data; Wrote the paper.

Sung Chul Kim: Conceived and designed the experiments; Wrote the paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

Data will be made available on request.

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