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Early fire detection based on gas sensor arrays: Multivariate calibration and validation

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ABSTRACT

Smoldering fires are characterized by the production of early gas emissions that can include high levels of CO and Volatile Organic Compounds (VOCs) due to pyrolysis or thermal degradation. Nowadays, standalone CO sensors, smoke detectors, or a combination of these, are standard components for fire alarm systems. While gas sensor arrays together with pattern recognition techniques are a valuable alternative for early fire detection, in practice they have certain drawbacks—they can detect early gas emissions, but can show low immunity to nuisances, and sensor time drift can render calibration models obsolete. In this work, we explore the performance of a gas sensor array for detecting smoldering and plastic fires while ensuring the rejection of a set of nuisances. We conducted variety of fire and nuisance experiments in a validated standard fire room (240 m^3). Using PLS-DA and SVM, we evaluate the performance of different multivariate calibration models for this dataset. We show that calibration models remain predictive after several months, but perfect performance is not achieved. For example, 4 months after calibration, a PLS-DA model provides 100% specificity and 85% sensitivity since the system has difficulties in detecting plastic fires, whose signatures are close to nuisance scenarios. Nevertheless, our results show that systems based on gas sensor arrays are able to provide faster fire alarm response than conventional smoke-based fire alarms. We also propose the use of small-scale fire experiments to increase the number of calibration conditions at a reduced cost. Our results show that this is an effective way to increase the performance of the model, even when evaluated on a standard fire room. Finally, the acquired datasets are made publicly available to the community (doi: 10.5281/zenodo.5643074).

1. Introduction

Indoor fires involve materials that undergo smoldering reactions which often develop very slowly. Compared to flaming fires, smoldering fires are considered low-intensity fires and release relatively small amounts of energy [1] but, on the other hand, after the onset of fire, smoldering produces significantly higher concentration levels of gas and volatile organic compounds (VOCs) [2,3]. Additionally, fire emissions may contain irritant gases that decrease the escape probability. For example, in under-ventilated conditions, fires produce substantial amounts of asphyxiants, such carbon monoxide and hydrogen cyanide. Released toxic volatiles and asphyxiants may endanger occupants before dense smoke and open flames appear. The accumulation of carbon monoxide is likely to be incapacitating before smoke fills the room completely [4]. In fact, inhalation of toxic fire effluents is the main cause of death in involuntary fires, higher even than burns [5,6]. In the last 30 years, the use of synthetic materials in building materials, furniture, and electrical insulation covering has risen dramatically. These materials produce more toxic effluents, especially in the presence of flame retardants [7,8]. Proper detection of toxic compounds may lead to faster

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fire detection and higher levels of safety and security for the occupants of buildings.

Obviously, saving human lives is the major concern but early fire detection is also key in minimizing economic losses. Here we would like to focus our attention on fire protection for data centers. Data centers are essential for today's communication infrastructure and its importance is growing as more and more services and applications operate from the Cloud. Underwriter Laboratories recently reported on data collected for diverse electrical fires in data centers in the period 2014–2015 [9]. It has been estimated that each downtime incident has a cost of 700,000 USD. While there are many reasons underlying data center outages, unexpected fires can have a major impact on the infrastructure leading to high service outage costs. In most cases, these fires were initiated by overheating of electronic components or cables. It is well-known that the plastic materials in general use in electronics, and the insulating materials for cabling, start the emission of volatiles when overheated by the process of thermal degradation or pyrolysis. These flammable gases emitted may enter into combustion themselves if a high enough temperature is achieved. Two other phenomena leading to the emission of gases are polymer melting and charring. It is important to note that in pyrolysis the amount of CO generated is very low [10]. Under such conditions, the use of sensors for other gases may be a research avenue for earlier fire detection and enhanced protection of critical information technology infrastructure, including data centers.

In recent years, to provide fast and reliable fire alarm systems that can detect fire in its incipient stage, different sensing and detection technologies have been explored [11]. For example, in order to incorporate additional information to smoke or obscuration sensors, CO sensors have been coupled to smoke-based systems. Very recently, Wu et al. proposed a back-propagation neural network to discriminate fire from nuisances in residential fire settings using smoke, CO and temperature sensors [12]. They used a dataset made available by the National Institute of Standards and Technology that provides data from 27 experiments (fire and nuisances) including smoke obscuration measure, carbon monoxide, carbon dioxide and oxygen readings, and different types of smoke alarm systems [13] Here, we aim at unspecific gas sensors to allow us detect the wider range of volatiles that may be released at early stages of fires. Systems based on arrays of unspecific gas sensors are particularly well-suited for fast fire detection since they are sensitive to the early emissions of effluents and toxic compounds. Hence, in contrast to widespread smoke-based fire detectors, gas-based fire detectors can provide additional safety to occupants [2,14]. On the other hand, gas-based fire detectors show low specificity since they respond to volatile compounds from sources not directly related to fire conditions (nuisances that yield false alarms). Even though the use of pattern recognition algorithms can increase the robustness of the gas-based fire detectors, the fire alarm market is still primarily served by smoke detectors.

The most promising route to improving false alarm immunity for gas-based fire detectors is the use of machine learning techniques to build robust calibration models that differentiate between sensor signatures induced from fire or nuisance scenarios [2]. These strategies are data-driven, and the systems need to be exposed to different fire types and nuisance scenarios during the calibration phase. The acquisition of a proper calibration dataset requires extensive and time-consuming efforts since fire conditions and nuisance scenarios can be extremely diverse.

The definition of a consistent set of calibration conditions to ensure reliable fire detection is further challenged by the absence of standards that define the requirements for fire alarms based exclusively on gas sensor arrays. Current standards for fire detectors determine the specifications for ionization and light scattering smoke detectors, UV and IR flame detectors, the combination of CO sensor with smoke detectors, and standalone CO detectors. The standards detail the procedures to perform test fires, the dimensions of the test room, the position of the detectors, and the necessary instrumentation to run the tests. Standard norms also determine the fire conditions in terms of smoke density [μl/l] or light obscuration [dB/m] and stopping criteria for the experiment. Parts of the standards describe the conditions for point fire detectors based on carbon monoxide sensors such as the EN 54 standard part 26 [15]. ISO7240 part 6 [16] lays out the specifications for CO fire detectors using electrochemical cells, setting a threshold for the alarm level in the range from 25 ppm to 60 ppm. It also details the exposure to a set of interfering volatiles that must keep detector compliance within specification. Additionally ISO 7240- part 27 considers the combination of carbon monoxide sensors and smoke sensors [17]. The standards UL 217 [18] and UL 268 [19], very recently incorporated a cooking nuisance test to increase the reliability of fire alarms and avoid system manipulation (de-activation) by the user because of their high false alarm rate.

Previous studies that incorporate arrays of unspecific gas sensors for fire alarm systems, have built and evaluated calibration models using different datasets. In the late-nineties, fire and nuisance tests were conducted in a $3.6 \times 3.6 \times 2.4$ m^3 room at the University of Maryland (College Park, MD, USA). A multi-sensor system including a gas sensor array and an obscuration detector was placed in the test room and a total of 87 tests were performed [20–23]. Specifically, the tests performed included flame fires (heated liquids), smoldering fires (including paper, cotton, polystyrene, pine, cardboard) and nuisances (including disinfectant, cooking aerosols, ammonia-based window cleaner and boiling water). Based on a set of observed rules, the multi-sensor system showed faster fire response than a smoke fire alarm, but it also showed greater susceptibility to false alarms. More recently, early fire detection was also explored using gas sensor arrays placed in a conventional $4.5 \times 2.8 \times 2.6$ m^3 office room [24]. The system included six gas sensors coupled to a particulate matter sensor and temperature and humidity sensors. Ten different fire types that included different common fire sources (paper, plastic, foam, cotton, cardboard, wire and PVC) and building materials (wood, brick and gypsum board) were placed in an $0.8 \times 0.55 \times 0.65$ m^3 oven, while temperature increased up to 250 °C. The generated volatiles were introduced to the room using a vacuum pump. The authors showed that the system was able to identify the fire source using probabilistic Neural Networks [25] or a fuzzy K-nearest neighbor (fuzzy k-nn) [26]. However, in this study, no nuisances were included in the measurement regime.

Other studies explored fire detection and fire emissions in setups specific to particular applications. For example, the Naval Research Laboratory studied different sensor technologies for fire detection to enhance damage control in ships [27,28]. Sensors were placed in a $4.1 \times 6.5 \times 3.6$ m^3 room, where 24 fire types and 12 nuisances were investigated. Fires included, among others, liquids, smoldering fires such as mattress, pillow, and electrical cable and propane fires. Nuisances included cooking activities and common workshop activities. Results showed that gas sensors provide additional useful information for a reliable and early fire detection. Nuisance rejection improved by up to 25% when gas sensors were combined with smoke detectors. Chen et al. explored the performance of a fire detection system to reduce false alarms of fire detection systems located in aircraft cargo compartments [29]. The system was based on a smoke detector coupled to carbon monoxide and carbon dioxide sensors. The dataset was acquired in a $2.2 \times 1.4 \times 4$ m^3 room, where smoldering fires (HDPE beads, PVC clad wire, mixed fabrics and green canvas), flame fires (heptane, toluene, methanol and mixed plastics), and nuisances (dry ice, insecticide aerosol, halon, water, methanol, ethanol, acetone, and ammonia) were carried out. The system was able to reject all the tested nuisances. Wang et al. employed three commonly-used spacecraft materials (cotton lamp wick, Nomex fabric, and acrylic glass) to evaluate gas emissions for spacecraft safety [30]. The fire experiments were performed in an 8 m^3 chamber. The combustion samples were placed on a hotplate that heated the surface to 450 °C, whereas flaming fires were initiated with a propane torch [31]. Gas sensors inside the chamber and reference instrumentation measured the evolution of the gas emissions. Results showed that fuel-based emissions of CO and particle matter are higher for smoldering fires than for flaming fires. Other scenarios explored included mobile robot platforms to detect indoor smoldering fires using customized gas sensor arrays [32–35]. These scenarios represent a much greater challenge due to the sensor response speed required to navigate efficiently throughout the experimental arena.

In summary, the number and type of fires and nuisances explored in previous works is large and diverse. Some of the studies combine chemical sensing with conventional smoke detectors to reduce false alarms. Additionally, previous studies performed system calibration and test in the same experimental setup and, sometimes, over a relatively short period of time. It is our understanding that more demanding validation is needed in order to prove that a fire detection system based on chemical sensors is a valuable technology for fire detection.

In this research, we describe the development of a fire detector based exclusively on chemical sensors, together with the required multivariate calibration models. These systems were tested for their response to smoldering plastic and electrical fires, with a portfolio of relevant nuisances. The dataset was acquired in a validated standard fire room (240 m^3). To expand the dataset and develop machine learning algorithms able to capture the discriminant signatures of diverse fires while being immune to nuisances, we propose a strategy to increase the number of calibration conditions by using a small-scale set-up. Finally, to explore the time stability of the system, its performance was evaluated over different measurement campaigns spanning more than a year (15 months). Hence, since the captured datasets contain data from different setups and were acquired over time, our data enable the study of common limitations, such as high calibration costs [36–39] and sensor drift [40–42] in low-cost gas sensors. Finally, the datasets are made publicly available—to the best of our knowledge this represents the first public dataset for fire detection using gas sensor arrays.

The remainder of the paper is organized as follows. Section 2 presents the devolved gas sensor array for fire detection. Section 3 and Section 4 describe the standard fire room and the small-scale setup, and the measurement campaigns, respectively. Then, we present the calibration models (Section 5) and the results (Section 6), followed by our conclusions (Section 7).

2. Gas sensor array for fire detection

We developed a standalone system for fire detection based on an array of gas sensors that include several sensing technologies. Governed by the particular fire conditions, smoldering fires involve different gas emissions which can include several volatiles which include carbon monoxide, carbon dioxide, hydrogen, methane, nitrogen oxides (NO_X) and wide range of VOCs [6]. The sensor selection was performed to target the main combustion products and to capture other volatiles that may help to discriminate fire from nuisances. Additionally, the sensors were selected to enable the detection and monitoring of the most health-threating toxic emissions in the fires.

The customized system we developed is based on a sensor board and a control and acquisition board. The sensor board includes 12 off-the-shelf sensors and integrates all the required signal conditioning electronics. Specifically, it includes an electrochemical gas sensor for CO detection, a non-dispersive IR (NDIR) sensor for CO_2 detection, and a photoionization detector (PID) and eight metal oxide (MOX) sensors for VOC detection. The system also includes temperature and humidity sensors. Table 1 lists the sensors included in the prototype.

The sensor board interfaces directly with the control and acquisition board that hosts the microcontroller for data management. It is based on an Arduino DUE platform due to its popularity, and the rapid development and features built on the 32-bit ARM core. All analog signals are sampled at 10 Hz using the built-in 12-bit analog-digital converters. The analog output of the sensors is adapted to the operating voltage of the Arduino platform by means of LM117 (Texas Instruments) voltage regulators. The control and acquisition board, in turn, communicates with an external computer for data storage and real-time data visualization. Fig. 1 shows the block diagram of the prototype developed for fire detection.

Table 1
Sensors included in the prototype.

Sensor type	Reference and manufacturer	Number of units
MOX	*AS-MLV,* ams	2 (*)
MOX	*AS-MLC,* ams	2 (*)
MOX	*AS-MLX,* ams	2 (*)
MOX	*AS-MLN,* ams	2 (*)
Electrochemical	CO-B4, Alphasense	1
NDIR	NDIR-A1, Alphasense	1
PID	PID-A1, Alphasense	1
Temperature and humidity	SH-75, Sensirion	1

*Each copy of the MOX sensor operates at a different temperature (259 °C and 446 °C).

2.1. MOX sensors

The sensor board includes eight MOX gas sensors to detect a wide range of volatiles. All the MOX sensors were provided by AMS [43], and the system included four types of sensors (two copies of each type): *AS-MLV*, *AS-MLC*, *AS-MLX,* and *AS-MLN,* that targeted volatile organic compounds, carbon monoxide, methane, and nitrogen dioxide, respectively. The sensors were heated to operation temperature by a Pulse-Width Modulation (PWM) signal at 1KHz applied to the built-in sensor heater. To add diversity to the sensing system, the sensors of the same type operated at a different temperature. Specifically, the induced temperatures were 259 °C and 446 °C, which corresponded to a power consumption of 37 mW and 73 mW, respectively. Hence, the MOX sensor array is composed of 8 sensing elements with a unique configuration (sensor type and operating temperature) in each channel.

The control electronics for the MOX sensors include the PWM controller circuit. A current amplifier circuit based on N-MOSFET (BUK954- NXP Semiconductors) transistor was built to drive the signal to the sensor heaters. In addition, in order to attenuate noise and the capacitive coupling of the PWM signal in the sensor dielectric membrane, a low-pass filter (5 Hz cut-off frequency) was implemented at the output of each MOX sensor using operational amplifiers (MCP6004 provided by Microchip).

2.2. NDIR sensor for CO_2

Carbon Dioxide is produced in most organic combustions. High concentration levels of CO_2 can, however, also be achieved due to high occupancy in buildings [44]. However, the combination of the CO_2 signal with other sensor signals should provide relevant information to discriminate non-fire scenarios from fire scenarios.

Non-Dispersive Infrared Sensors (NDIR) are the technology of choice for CO_2 detection. This sensing principle results in a highly selective and sufficiently sensitive sensor, with long-term stability. We selected the NDIR-A1 from Alphasense, which is based on an infrared thermopile detector. This sensor provides the active output and a reference output that is used to compensate for drift in the sensor, such as changes in the intensity of the infrared light due to lamp aging. The IR lamp is modulated at 3 Hz and the sensor requires an operation current of 300 mA, which is supplied by means of a N-MOSFET (BUK954- NXP Semiconductors) transistor. A bandpass resonator filter (second order Butterworth filter) was applied to both output signals to match the output range with the input voltage range of the analog-digital converters integrated into the Arduino platform. The filter added a 36 dB gain in the central frequency (3 Hz). The filters were implemented in a unipolar configuration using a LM117 regulator (Texas Instruments).

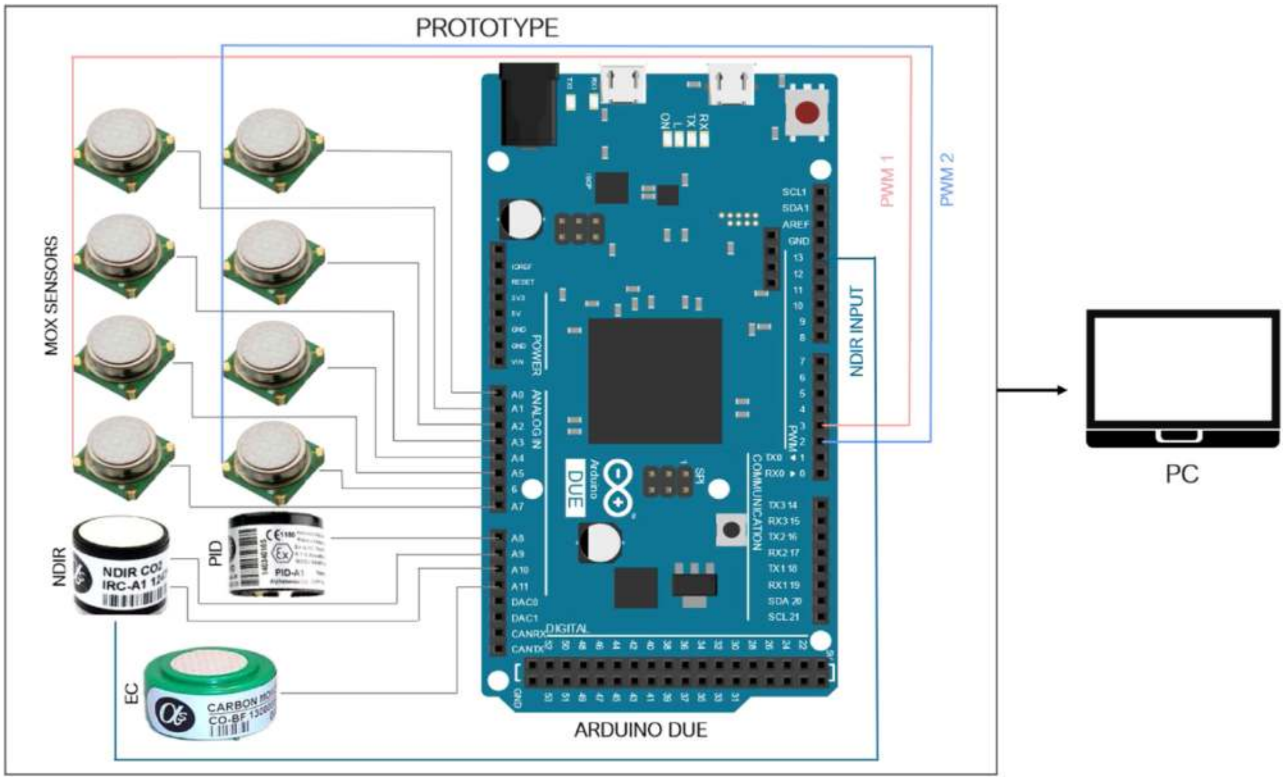

Fig. 1. Block diagram of prototype developed for fire detection. The system includes 12 different sensors and the signal conditioning electronics, the signal acquisition platform based on an Arduino DUE, and a desktop computer for data storage and real-time signal visualization.

2.3. Electrochemical sensor for CO

To monitor CO concentration levels, we selected the electrochemical sensor CO-B4, from Alphasense. We implemented a potentiostat circuit to stabilize the potential between the counter and the reference electrodes based on the LMP91000 Programmable Analog Front-End (AFE) potentiostat for Low-Power Chemical Sensing Applications (Texas Instrument). The AFE uses a trans-impedance amplifier (TIA) configuration to convert the current generated by the electrochemical sensor into voltage. The gain of the TIA, and the bias, can be programmed using an I2C communication protocol, which was implemented on the Arduino platform. In particular, we selected the recommended values of 22 K for gain and 300 mV for bias voltage.

2.4. Photoionization detector

A photoionization detector (PID) was also included as a broadband sensor for VOCs. We selected the PID-A1 sensor, provided by Alphasense, with a 50-ppm resolution in the range of 2000 ppm (isobutylene equivalent). The sensor uses a 10.6 eV lamp and was operated such that the power consumption was 85 mW. We added a barrier/segregation resistor at the output of the sensor to acquire the PID sensor signal output. We also included a 120 mA fuse to limit the input current.

2.5. Temperature and humidity

Only subtle temperature changes are expected at the onset of smoldering fires. Nevertheless, we also added temperature and humidity sensors to the standalone prototype. Specifically, we selected the Sensirion SH-75 sensor.

3. Experimental setups

We performed fire and nuisance experiments in a standard fire room according to the standard EN54. The standard fire room is located at Minimax GmbH in Bad Oldesloe, Germany. We additionally designed and implemented a scaled-down setup to perform experiments at a lower cost and to circumvent the time-consuming routine of the experimental protocol required in the standard room.

3.1. Standard fire room

We performed our measurements in a standard fire room, assembled following the EN-54 standard, and we extended the conditions tested to evaluate gas-based fire detectors.

The test room has dimensions of 10 m × 6 m × 4 m (L × W × H) and, hence, an inner volume of 240,000 l. The required burning materials were placed next to the ignition system in the center of the experimental area. Two circular mounting brackets of different diameter (5.5 m and 6 m) and 31 supports installed in the center of the ceiling enabled the placement of the sensing platforms. To heat up the combustion materials, a hotplate was placed in the center of the experimental area, 23 cm from the flat floor. Following the standard, the hotplate had a diameter of 220 mm and a thermocouple (type K) is attached to monitor the temperature of the substrate. A window enabled visual inspection of the measurement from a control room, where the electronic instrumentation is located, and from which the experiment in progress could be monitored. Fig. 2 shows a scheme of the standard fire room and the contiguous control room. Finally, the developed sensor array was placed on the ceiling, over the 6 m circle, centered in the vertical axis of the combustion material.

The fire room integrates reference instrumentation to monitor environmental conditions and air composition during the experiments. Specifically, the room is equipped with a DKRF400 temperature and humidity sensor (Driessen+Kern GmbH), a Jumo pressure sensor (model 668-3024), along with the required instrumentation to measure smoke density. All this instrumentation was installed on ceiling brackets in the experimental area. The environmental signals were collected using

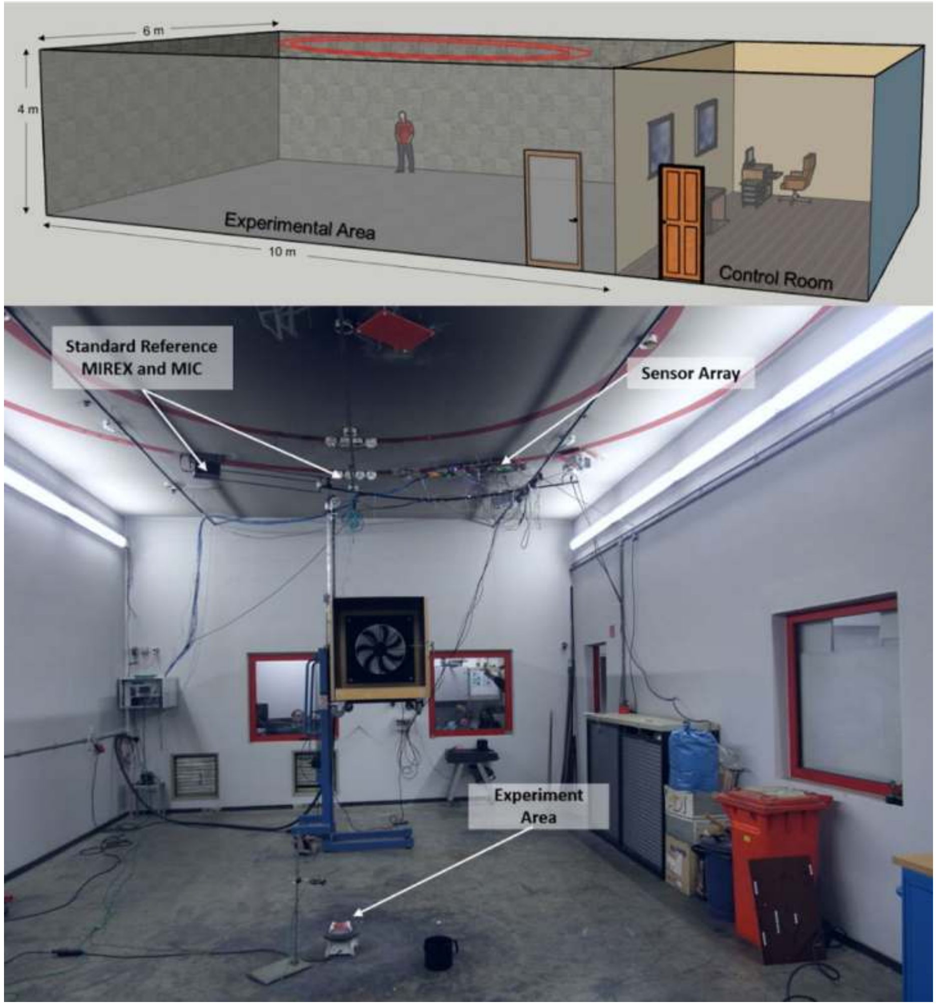

Fig. 2. EN-54 Standard fire room adapted to test gas-based fire alarm systems. Visual inspection of the experiment is performed from a contiguous control room.

dedicated software developed by Minimax that takes one sample per minute for each sensor. This software allows the visualization of the signals in real time and enables time synchronization between all installed sensors and the reference instrumentation.

Two smoke density measurement systems were installed in the standard fire room. These were an ionization smoke detector and a light scattering smoke detector both of which conform to the EN-54 standard. The ionization smoke detector (MIC) EC-912, was provided by Delta (Horsholm, Denmark) and the light scattering smoke detection MIREX EC-911 (1 Hz sampling frequency) was also from Deltaware. The placement of two reference instruments with different sensing principles constitutes a powerful reference system since most commercially available smoke detectors operate on one of these two principles. In accord with the EN-54 standard, and depending on the smoke production, the ionization and the light scattering measures were used to indicate the end of a fire event.

3.2. Small-scale setup

The second setup corresponded to a customized measurement test chamber. The dimensions of the chamber were $55 \times 55 \times 90$ cm ($L \times W \times H$), for a total inner volume of 272 l. The bottom, top and upper part of the walls (50×35 cm) were made of aluminum. Glass panels embedded into the lower part of the lateral walls (50×50 cm) allowed visual inspection of the experiments. Air flow from the outside of the chamber was favored to maintain oxygen concentration and avoid fire suffocation. Hence, 25-mm apertures were opened along the chamber, between the top and bottom lids and the lateral walls. Finally, one of the glass panels was enabled as door for an easy access to the inner volume of the chamber.

For a safe operation, the measurement chamber was placed inside a fume hood, which was equipped with an exhaust system to facilitate the evacuation of the smoke and volatiles generated inside the chamber. While the extraction system was switched on, a flow meter measured air flow in the chamber. Induced air speed was 1.5 m/s at the lower region of the chamber and 0.2 m/s at the top of the chamber. Fig. 3 shows a picture of the small chamber located inside the fume hood (left) and the dimensions of the customized chamber (right). The chamber also incorporates a heater with a plate to heat up samples and initiate fire/nuisance experiments.

The gas sensor array developed was placed inside the chamber, fixed on the inner side of the top lid. The customized measurement chamber also included reference instrumentation and commercially available fire alarm systems based on smoke detection. Such systems enable a comparative study of different technologies in respect to sensitivity and time response. The complete instrumentation included the necessary hardware for signal acquisition, which was synchronized and stored.

Inside the measurement chamber, next to the sensor array, a commercially available smoke detector based on photoelectric/heat detection (SLR-24H, provided by Hochiki) and a detector based on ionization detection (S250, provided by NOVA-500) were also installed. These smoke and particles detectors sent data directly to the CPU (host PC) by means of proprietary software provided by the respective manufacturers, or by means of a data logger (Data Taker DT800 –

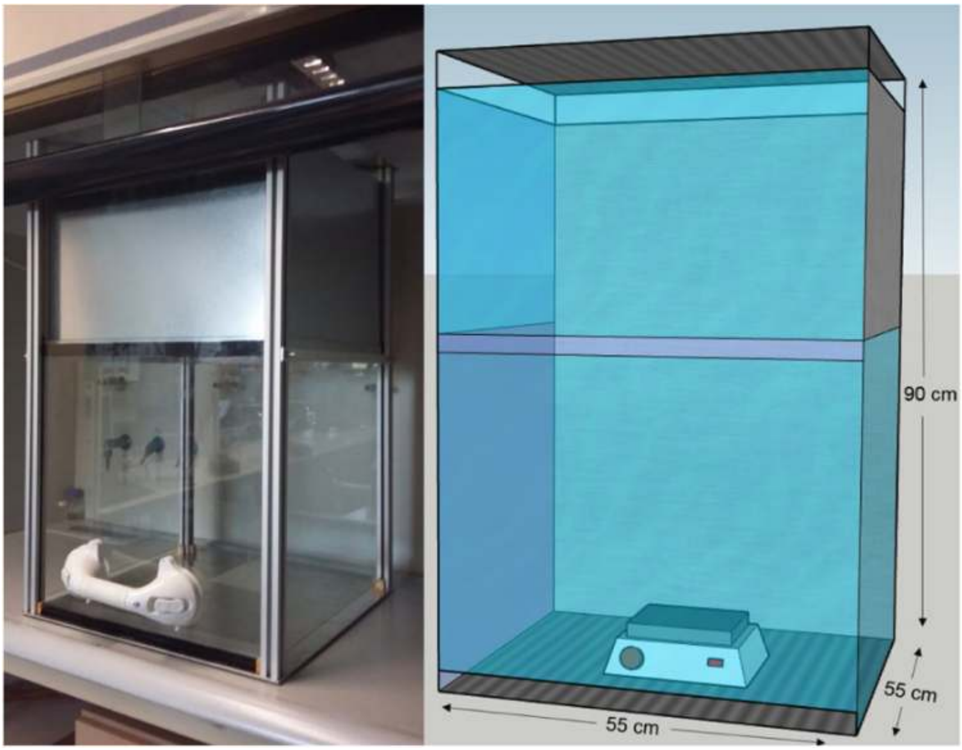

Fig. 3. Small-scale setup developed to perform faster and cost-efficient experiments. A heater is integrated into the base of the chamber to control the temperature of the combustion products.

ThermoFischer) that interfaced the sensor with the CPU at a 1 sample/second frequency.

Hence, the customized measurement chamber and the integrated sensors configured a setup inspired by the standard fire room, but at a smaller scale and with reference instrumentation to monitor the gas composition and smoke density of the environment. The smaller scale of this set up largely speeds up undertaking calibration experiments.

4. Fire and nuisance experiments

As mentioned in the introduction, we focused our efforts on smoldering fires and plastic fires rather than open flaming fires because gas sensors are particularly well suited for the detection of combustion products released in smoldering fires. Within this scope, we carried out four different measurement campaigns in the standard fire room and the small-scale setup.

There is no standard that regulates the requirements for fire detectors based exclusively on multiple gas chemical sensors. Nevertheless, EN-54-26 standard defines tests for CO-based fire detectors. Hence, we selected smoldering fire types included in the EN-54-26 standard, namely smoldering wood (TF2) and smoldering cotton (TF3). These two types produce high concentrations of CO, the smoke production is very slow, and the temperature increase is very gentle. We included fire scenarios additional to the EN-54-26 standard that should have significant gas emissions and are of particular interest due to the increasing popularity of plastic materials in household furnishings and growing presence of electronic equipment in home settings and offices. In particular, we added plastic smoldering fires (PVC and PET) and electronic equipment overheating (cable and electric).

Cross sensitivities produced by volatiles found in indoor settings challenge the robustness of fire detection. However, no suitable test sets for gas-based detectors were found in the standards for fire alarm evaluation. Nevertheless, to test the reliability of the systems, we also included nuisance scenarios in the datasets. In particular, scenarios that readily found in offices, houses or industries were selected according to the high level of volatility of the chemical compounds and their potential to be detected by gas sensors—these included cleaning products, fuels, and alcohols.

All the experiments performed in the small-scale setup were inspired by the experiments performed in the standard fire room. The materials were scaled down to adapt the experiments to the reduced setup. The main criterion when adjusting the material quantities was that the resultant sensor signals had similar amplitudes to those from the fire room experiments.

4.1. Standard fire room

Detailed fire room protocols were defined to perform the experiments (fire and nuisance scenarios) and record the sensor signals. For the fire experiments described in the EN-54 standard, we followed the requirements it details. Each experiment consisted of a three-step process, during which the sensors signals were continuously acquired. The first step corresponded to the baseline condition. Initially, the room was empty and with no residuals from the previous experiment. The required elements and materials were introduced into the room and correctly positioned in their starting positions. The second step corresponded to the volatile release, which was performed differently for to each experiment. For experiments that relied on gas evaporation, the experiment started when the engineer left the room, and the door was closed. In the case of experiments that required heating the sample, the experiment was controlled by means of a hot plate remotely accessible from the control room. The experiment was considered to finish when fire conditions were achieved according to the EN-54 standard, in terms of smoke density or light obscuration. In the case of nuisances, the experiment finished 15 min after the beginning of the gas release. Finally, the last step corresponded to room cleaning, in which ventilation system was turned on to extract combustion products and emanated volatiles until baseline conditions were recovered.

4.1.1. Fire experiments

4.1.1.1. Standard fires. TF2a is a slow-starting smoldering fire and, typically, it generates white smoke and a small temperature increase, making it a common test for fire detectors. TF2a also provides a significant rise in the concentration of CO, CO_2, hydrogen, and CH_4. To perform a TF2a experiment, four sticks of beechwood ($75 \times 20 \times 20$ mm, each) were placed on the hotplate that was heated so that the temperature reaches 600 °C after 10 min. Before the experiment, the sticks were dried to reduce its moisture content to 5%. The experiments finished when the measured smoke attenuation reached 2 dB/m or the smoke detectors generated an alarm signal. Typically, the duration of a TF2a experiment is around 45 min (excluding room cleaning for the following experiment).

TF3a is another smoldering fire, which, according to the EN-54 standard, is initiated by means of a flame. Reduced TF3a for smoldering cotton experiments were performed in the standard fire room. Each TF3a fire consisted of burning 30 pieces of 80-cm long braided cotton wicks. The cotton wicks were hung in a 10 cm non-combustible ring suspended 1 m above the floor. The ignition of the cotton wick ends was performed with a torch and methylated spirits, while ensuring that no flame was generated on the cotton. The experiment started when the wicks began to glow. As for TF2a, the experiment finished when the measured smoke attenuation reached 2 dB/m, or the smoke detectors generated an alarm signal.

4.1.1.2. Non-standard fires. Besides the standard fires, we also performed four non-standard smoldering fire experiments in the standard fire room. The non-standard fires consisted of heating up a combustion element so that volatiles were generated. The four experiments included different quantities of the following plastic materials and electronic components:

(i) *Smoldering PVC* required 10 pieces of a PVC tube. Each piece of PCV was 5 cm long, with a 4 cm diameter;
(ii) *PET smoldering fire* included 10 g of PET plastic deriving from plastic bottles;
(iii) *Smoldering cable fire* required 15 pieces of 10-cm electronic cable;
(iv) *Smoldering electronics* consisted of a populated 8×8 cm^2 Printed Circuit Board (PCB).

The same hot-plate and temperature profile required for TF2a were used to heat up the required materials for the non-standard fires. A $20 \times 20 \times 5$ cm^3 aluminum plate with flat base was placed on top of the hotplate to ensure high thermal conductivity and enable easy surface cleaning between experiments. The experiments started when the engineer left the room, and the temperature of the hotplate started to increase. The experiments concluded either 30 min after switching on the hotplate or, if earlier, when the burning materials were totally consumed.

4.1.2. Nuisance experiments

We adapted the experimental protocol defined for fire experiments to test six nuisance scenarios in the standard fire room.

The first set of four nuisances shared the same experimental setup and protocol since they relied on the evaporation from a substance in liquid form. The same aluminum plate that was used for non-standard fire tests was placed in the experimental area of the fire room, in the same position in which the fires are started. First, 100-ml of liquid was poured inside the plate. The experiment started once the liquid was in the container and had started to evaporate. The total duration of the experiment was 15 min, which is considered long enough for the sensors to respond to the evaporated volatiles. The tested nuisances included products that are commonly found in cleaning, aromatizing products, or ones with high volatility, specifically, gasoline, vinegar, ethanol, and turpentine.

The other set of tested nuisances required human intervention; hence the methodology was adapted. The nuisance designed to test the interference of air fresheners was carried out with the help of a volunteer who, from the center of the room used a commercially available *Airwick spray*. The volunteer used the spray twice to each of the four cardinal points and twice to the top of the fire room, for a total of 10 spray uses. The volunteer quietly left the fire room shutting the door. The experiment lasted for 15 min until the door was opened for air ventilation. Similarly, window cleaning nuisances were tested by using a common cleaning product (*Putz-Meister cleaner*). In this case, the volunteer used the spray 6 times on one window of the fire room adjacent to the control room and then cleaned the room using a towel. Next, the volunteer repeated the same process on the second window and left the fire room with the door shut. The experiment also lasted 15 min.

4.2. Small-scale setup

In order to reproduce as closely as possible all the fire and nuisance experiments performed in the standard fire room, we appropriately scaled down all the materials for experiments carried out in the small-scale setup.

Following a similar protocol to that of the fire room, every experiment in the smaller setup consisted of three stages. During the first stage, which constituted the baseline for the acquisition of the sensor signals, the chamber remained empty, without any test material except for one that do not release volatiles at room temperature. The second stage started with volatile release which corresponded to the introduction of the products such as air freshener, floor cleaner, ethanol presentation and vinegar cleaner that have high volatility at room temperature. For the remaining experiments, heating of the material was performed to force volatile release. Materials placed on the hotplate were heated up to 280 °C by switching on the hotplate to full power. Stage two finished 15 min after switching on the hotplate if commercial smoke detectors had not already triggered the alarm signal. For the experiments that did not require temperature increase, stage two lasted for 10 min. Finally, the last stage corresponded to baseline recovery, in which chamber doors were opened to renew air composition and recover the baseline conditions for starting a new experiment.

4.2.1. Fire experiments

We performed four different types of fire in the small-scale chamber. TF2a and TF3a, namely beechwood and cotton fire, were adapted to the smaller chamber. We also conducted a variation of wood fire using pinewood and a final variation for electrical fire.

Specifically, we used 4 sticks of beechwood ($75 \times 20 \times 20$ mm) and 1 stick of pinewood ($100 \times 20 \times 9$ mm) for the adapted TF2a and pinewood fires. The EN-54 standard requires a low moisture content in the wood samples. Hence, all the wooden sticks were placed in an oven at 85 °C for 24 h before being used in the experimental tests. The wooden sticks were placed on top of the hotplate to control the temperature rise. For the adapted TF3a fire, we used 4 cotton wicks, with 10 cm length each. As detailed in the standard, the smoldering fire was induced by ignition of the end of each cotton wick, blowing out any flame. The experiment was considered to start when the wicks began to glow. Finally, we also performed a cable fire, that consisted in heating up 10 pieces of flat cable ($100 \times 12 \times 0.5$ mm) with PVC insulation.

4.2.2. Nuisance experiments

Six nuisances were induced inside the measuring chamber. The three nuisance experiments that use products with high volatility at room temperature share the same experimental protocol. For these, ethanol (1.2 ml), vinegar-based cleaning product, or floor cleaner were placed on a square-shaped ceramic plate inside the chamber.

Another nuisance experiment consisted of raising the humidity content inside the chamber. This was performed by introducing 100 ml of water in a glassware beaker and placing it on the hotplate. Turning on the hotplate induced high levels of humidity. It is well known that MOX sensors are humidity dependent so the alarm used should be sufficiently robust to high humidity levels. In fact, the generated steam increased the obscuration level of the chamber also posing problems to light scattering based smoke detectors. Humidity is also a problem for ionization detectors since they can be responsive to water aerosols [45]. Due to the small dimension of the chamber, heat transfer from the hotplate may cause a noticeable rise of temperature in the small chamber. Hence, we added an additional nuisance scenario which consisting in turning on the hotplate with no material on it.

Finally, the nuisance with air freshener was performed with an electronic *Airwick* air freshener, which was turned on during stage two of the experimental protocol (15 min in total).

4.3. Measurement campaigns

We performed four measurement campaigns using the described setups and experimental protocols. Each measurement campaign (LD1, LD2, LD3 and SD1) constituted a different dataset, with different number of fire and nuisance types and repetitions. LD1, LD2, and LD3 were acquired in the standard fire room, and SD1 was generated using the small-scale setup.

LD1 contained 27 experiments; 6 types of smoldering fires, and 6 types of nuisances. LD2 contained 18 experiments; 5 types of smoldering fires and 5 types of nuisances. LD3 contained 25 experiments; 5 types of fires and 6 types of nuisances. Finally, SD1 included 34 experiments; 4 types of fires and 6 different nuisance scenarios. Each measurement campaign had a duration of 4–5 days and the experiments were performed in random order such that no fire or nuisance scenario of the same type was performed on the same day. Table 2 details all the fire and nuisance scenarios included in the different datasets, with the corresponding number of repetitions.

It is important to note that each measurement campaign was performed months apart, enabling thereby the study of system stability over time. In particular, SD1 was performed in March of 2016, 8 months before LD1, performed in November of 2016, which in turn was acquired 3 months before LD2, February of 2017. Finally, LD3 was acquired 4 months after LD2, in June of 2017.

Table 2
The number of repetitions included in each dataset. LD1, LD2, LD3 were acquired in the standard fire room. SD1 was acquired in the small-scale setup. N: Nuisance; F: Fire.

			Number of repetitions			
Name	Material	Type	LD 1	LD2	LD3	SD1
Temperature rise	Hotplate blank	N	0	0	0	2
Air freshener	Air freshener	N	3	2	2	4
Ethanol	Ethanol	N	3	1	2	4
Boiling water	Humidity rise	N	0	0	1	4
Floor cleaner	Floor cleaner	N	0	0	0	3
Vinegar	Vinegar cleaner	N	1	0	0	3
Turpentine	Turpentine	N	3	2	3	0
Gasoline	Gasoline	N	3	1	2	0
Window Cleaner	Window Cleaner	N	3	2	2	0
TF2a	Beechwood	F	2	2	4	0
TF3a	Braided cotton	F	3	2	2	0
Beechwood	Beechwood	F	0	0	0	4
Braided cotton	Braided cotton	F	0	0	0	2
Pinewood	Pinewood	F	0	0	0	4
Electrical fire	Electronic components	F	2	2	3	0
Cable fire	Cables	F	2	2	2	4
Plastic Fire, PVC	PVC	F	1	2	2	0
Plastic Fire, PET	PET	F	1	0	0	0
Total			27	18	25	34

5. Calibration models

We explored different methodologies designed to address two main challenges of fire detection using gas chemical sensors: the robustness against nuisances and the increased calibration cost required to guarantee reliability. For the first, we built multivariate calibration models for a gas sensor array to provide robust calibration and reliable fire detection. For the second, we explored the use of experiments performed at a smaller scale to reduce calibration costs.

Simple signal pre-processing was carried out before building the calibration models. In order to remove noise, sensor signals were filtered using a median filter and decimated into 1-second segments (the initial sampling frequency was 10 Hz). On the other hand, MOX sensor signals were transformed from voltage to conductance. Moreover, due to the changing environmental conditions and pollution remnants in the fire room, sensor baselines were corrected using the sensor signal at the beginning of each experiment. On the other hand, to assess the variability between campaigns due to different environmental conditions, we measured the temperature and humidity during each experiment. We found that temperature and humidity changes between experiments are moderate: lower than 5 °C and 13%, respectively. Hence, the impact of cross-sensitivity to environmental background conditions is subtle with respect the experimental variability and the intrinsic fire evolution.

First, exclusively using measurements performed in the standard fire room, we built calibration models to discriminate between fire and non-fire situations. We built the calibration models using two different classifiers, a linear Partial Least Squares Discriminant Analysis (PLS-DA) model, and a non-linear, Support Vector Machines (SVM) model. For the SVM algorithms we selected a radial kernel and explored different values of gamma (from 0.1 to 0.9) and cost (from 1 to 1000). We simulated production conditions, in which the calibration dataset was acquired once, after which the system was placed in continuous operation. Specifically, we selected the first two measurement campaigns LD1 and LD2 to train the calibration model, and the LD3 dataset was then used to assess the quality of the predictions.

The calibration dataset (LD1 and LD2) was divided into two sets: training and internal validation. Specifically, 80% of the measurements were used to train the models, and the remaining 20% were used to optimize the model. The training set included 17 fires and 19 nuisance experiments, while the internal test set consisted of 4 fire and 5 nuisance experiments. Random subsampling was applied, and the procedure was repeated 50 times such that all the experiments were included once in the validation set. The hyperparameters of the models were optimized for maximum accuracy of the classification rates in the internal validation set. Finally, the models were evaluated with the LD3 dataset to provide a quantification of the performance of the models on an external validation dataset. Using datasets acquired 7 and 4 months before the test set, it is possible to assess the prediction power of the models and their robustness across time.

Second, to provide robust calibration models at a lower cost, we made use of calibration examples acquired in the small-scale setup to increase the number of calibration examples and expand the calibration conditions. To evaluate the benefits of a model that combines experiments from a standard room and a small-scale setup, we built a model with experiments from the fire room only (LD1 dataset), another model from the small-scale setup only (SD1 dataset), and a third model that combined calibration examples from both setups (LD1 + SD1). For this task, the calibration models were based on PLS-DA. The number of latent variables was selected after a leave-one-out methodology in the training set, i.e., each complete experiment was used once as internal validation. The three resulting calibration models were evaluated with the experiments acquired in the fire room during an independent measurement campaign (LD2). To test the statistical significance of the results, we used a permutation test where the models were trained with permuted labels 500 times. We tested that the experimental accuracy does not belong to the null hypothesis, with 95% confidence. Additionally, we computed a binomial test to acquire the confidence interval of the different figures of merit values (specificity, sensibility and classification rate). Finally, we computed the Area Under the curve of the different models.

6. Results

6.1. Data visualization

To gain some insights on the variance distribution of the datasets and visualize the separability of fire and nuisance experiments, we plotted all the experiments and repetitions for a measurement campaign in a reduced subspace using Principal Component Analysis (PCA) projections. The constructed datasets included all the gas sensors integrated in the developed prototype. Temperature and humidity sensors were excluded since temperature and humidity are expected to change at a later stage in smoldering fires in the large standard room. Fig. 4 shows that all the measurements included in LD1 and LD2 dataset appear to overlap, confirming thereby the complexity of the data.

All the experiments start in the same region (background-position) of the PCA space. Each trajectory (representing a different experiment) follows a different path, reaching different areas of the space that depend on the volatiles released during the event. Some fire experiments and nuisance experiments appear close to each other, thereby confirming the challenge of building a robust and reliable fire alarm system. In addition, there are repetitions of the same type of experiment that presented significantly different trajectories due to the intrinsic variability of the experiment. Moreover, different experiments (TF3a and TF2a fires, for instance) presented similar starts but reach different regions. Nevertheless, trajectories start from the same initial region and some of the fires travel to areas far away from the experiments' origin, showing favorable behavior for a fire/non-fire discrimination model. Differences due to the experimental protocol and environmental conditions could produce different sensor responses in the same fire type. In Fig. 5 the sensor responses corresponding to two different TF2 experiments are shown. One can observe a similar behavior in MOX sensors, CO_2 and CO sensors. However, the PID sensor showed different between the LD2 and LD3 experiments. Repetitions of the same type of fire or nuisance one can observe significant variations in sensors values due to the experimental variability and fire/nuisance evolution (slight variation on the gas plume may affect the sensor signal significantly). In particular, in Fig. 5, one can observe a factor of 5 in the MOX and CO signals. This probably indicates that one fire experiment resulted in a prominent gas release and a gas plume hitting the sensors more directly.

6.2. Calibration using standard fire room data

We explored two types of calibration models, based on PLS-DA or SVM. For both models, the LD1 and LD2 datasets are used as training set, and the corresponding model performance is evaluated with the LD3 dataset, which was acquired 7 months after LD1 and 4 months after LD2. Internal validation was used to select the hyperparameters for each model. In order to prevent a high number of false alarms due to spurious activations, the final algorithm requires that the classification model predicts "fire alarm" for at least ***t*** seconds, where ***t*** is the length of a post-processing window. We explored three different post-processing time windows: 15, 30, 60 s. With this constraint, incidental and brief fire alarm predictions are not considered as such. The use of longer time windows adds reliability at the expense of a slower time response for the fire detector.

In particular, after internal validation, 4 latent variables and 60-second windows were selected for the PLS-DA calibration model. Similarly, a cost of 500, a gamma of 0.5 and a 15-second window were selected for the SVM model. The models showed different performance when evaluated with the test dataset. In particular, Table 3 and Table 4 show the confusion matrices for the PLS-DA and SVM based classifiers, respectively. The PLS-DA model is capable of rejecting all the nuisance (100% false positive rate) and provides 85% of true fire positive alarms. The PLS-DA model misclassified PVC fire experiments, which feature high levels of VOC emissions with a low production of CO and CO_2.

On the other hand, the SVM-based model algorithm is capable of detect 77% of the fires, this being two repetitions of an electrical fire and one repetition of a TF3 fire classified as non-fire situations. The model is capable of rejecting 91% of the nuisances—only one repetition of a window cleaning experiment is recognized as fire.

Fire detection with gas sensors is expected to provide faster response than smoke-based fire alarms. Hence, we investigated the time response of the different calibration models and compared their performance with commercially available smoke-based fire alarms. Fig. 6 shows the different time responses of the commercial fire alarm systems and the response time of the gas-based system for the evaluated models (models performance were evaluated using LD3 dataset). This confirms that gas chemical-based fire detection can provide faster fire detection than smoke-based alarms since, for certain fire types, volatiles appear at an earlier fire stage than do airborne particles. In particular, the SVM-based model provides a consistently faster response than the PLS-DA model

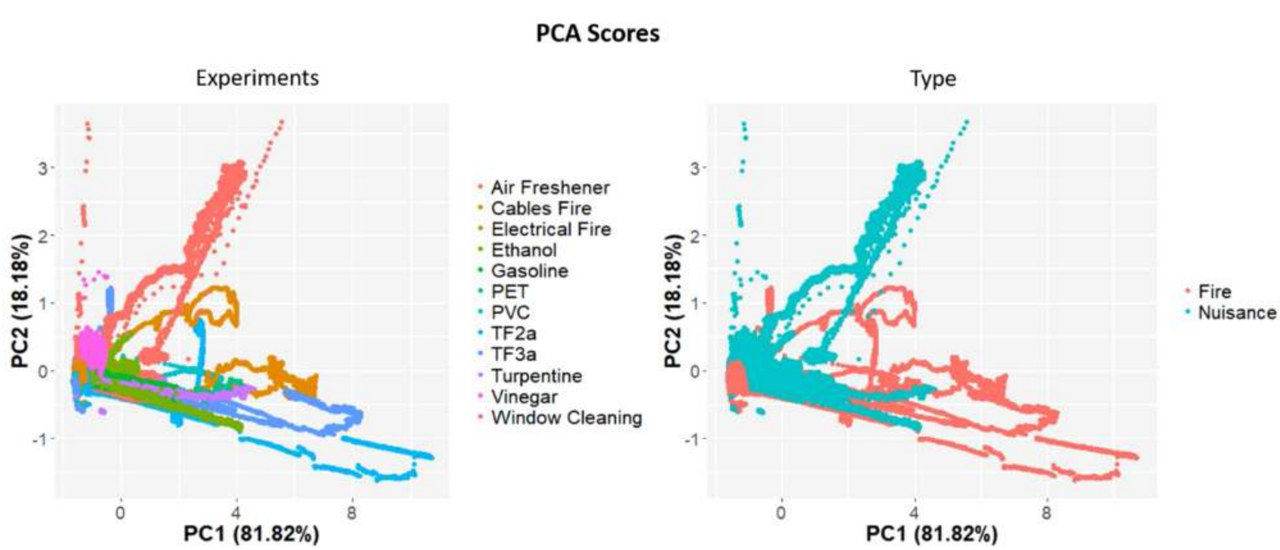

Fig. 4. PCA Scores of the LD2 dataset. The scores are colored according to the experiment type (left) or according to fire/nuisance experiment (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

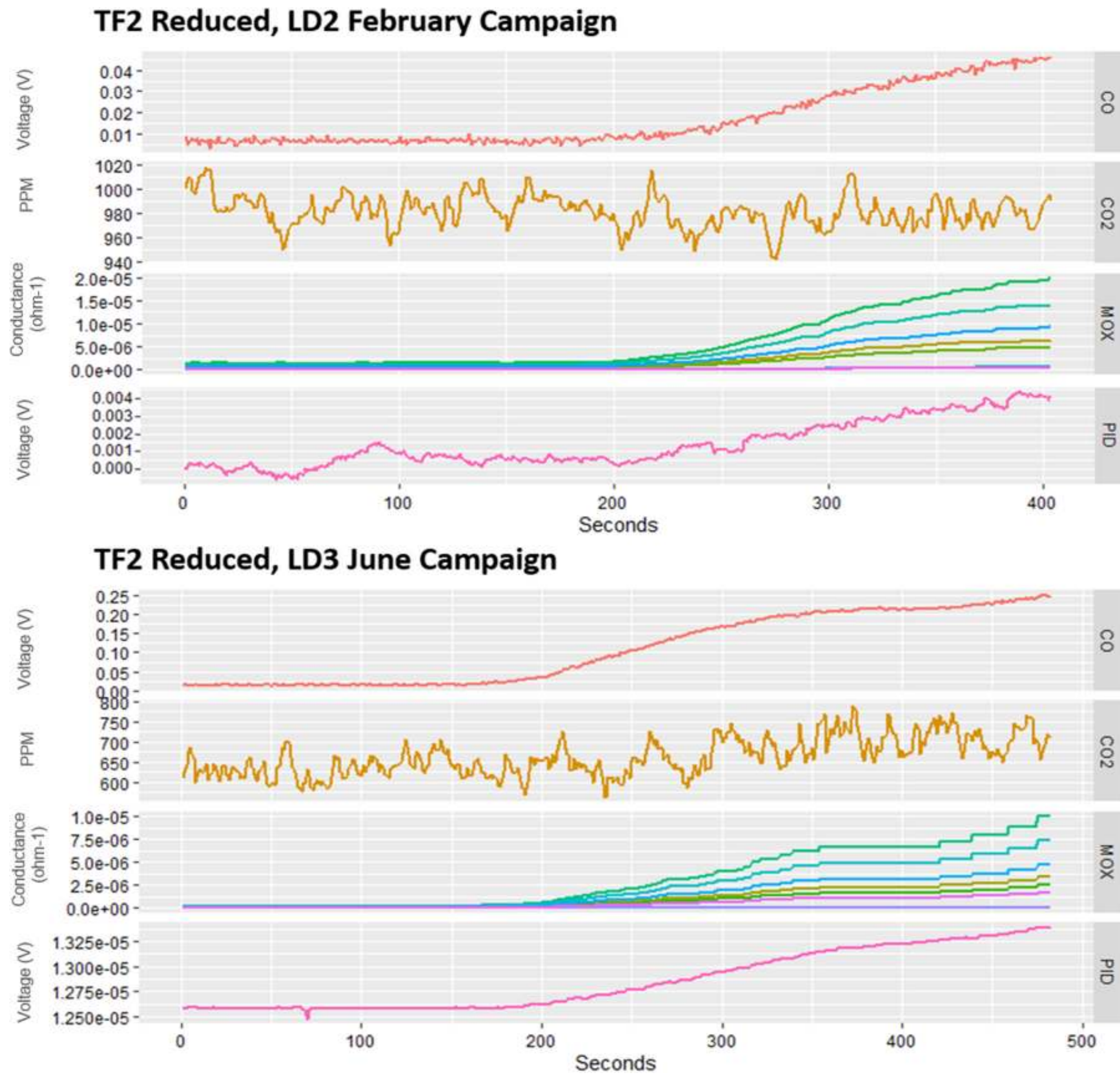

Fig. 5. Sensor signals of a TF2a fire experiment. In the top plots, a repetition of the experiment performed in LD2 campaign. In the bottom plots, a repetition of the TF2a fire performed in the LD3 campaign.

Table 3
Confusion matrix for the PLS-DA model trained with the LD1 and LD2 dataset and evaluated with the LD3 dataset.

		Predicted	
		Fire	Non-fire
Actual	Fire	11	2
	Non-fire	0	12

Table 4
Confusion matrix for the SVM model trained with LD1 and LD2 dataset and evaluated with LD3 dataset.

		Predicted	
		Fire	Non-fire
Actual	Fire	10	3
	Non-fire	1	11

and the commercial smoke detector, even though specificity is reduced. Our results reproduce a common trade-off, whereby faster systems provide higher numbers of false alarms.

Moreover, data projection using the PLS-DA model enables the study of each sensor's contribution and the correlation between sensors. In particular, Fig. 7 shows the test data (LD3 dataset) projected over the PLS-DA model built with the training data (LD1 + LD2 datasets). One can confirm that all the experiments (fires and nuisances) start in the same region, and the trajectories travel to other regions of the space, according to the volatile compounds released during the corresponding experiment. Moreover, sensor saturation results in straight lines in the projection. Fire experiments with trajectories close to nuisance scenarios are challenging and may result in the misclassification of the experiment. For example, some of the fire scenarios are characterized by gas emissions that do not produce CO emissions. This represents a major challenge to hybrid fire alarms that combine smoke detectors with CO-specific sensors. This suggests using different gas sensors for the detection of fires that produce VOCs or other combustion gases beyond CO at early stage of fire. Also, in the biplot (Fig. 8), the CO and CO_2 sensors provide similar directions, which in turn are orthogonal to the set of MOX gas sensors. TF2a and TF3a produce significant amounts of CO and CO_2 at an advanced stage of a fire. However, PID and MOX sensors react before CO and CO_2 sensors and so can be used to provide a faster response to fire.

Finally, to represent the relevance of each sensor to the PLS-DA

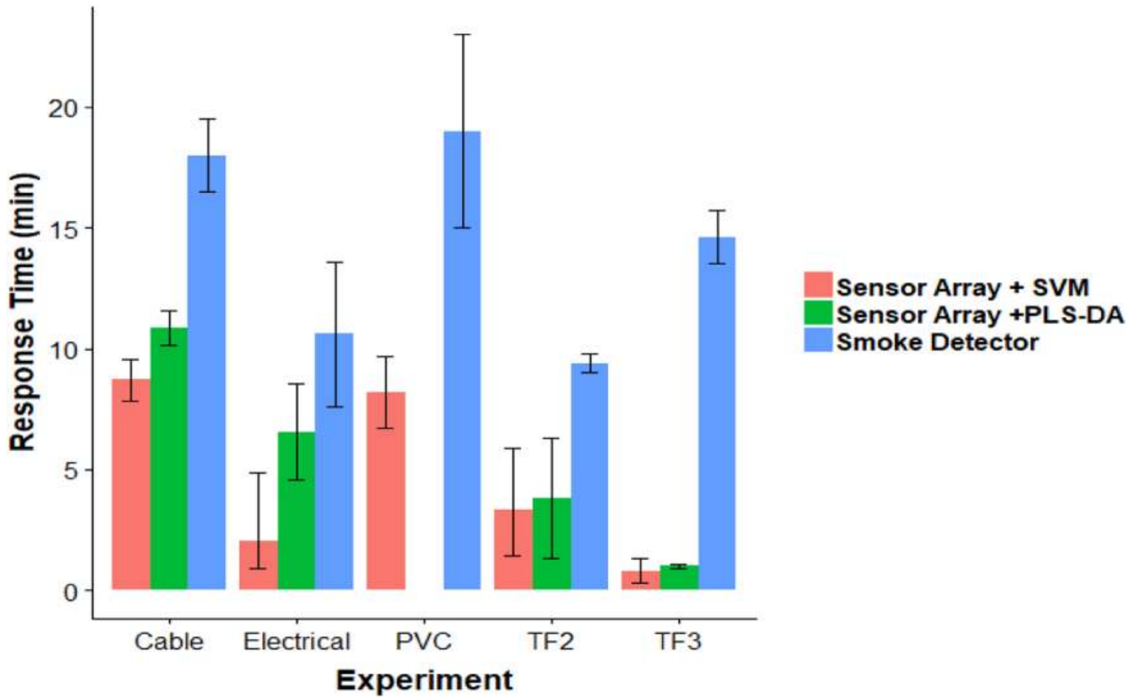

Fig. 6. Time response of a commercially available fire alarm based on smoke detection and the time response of the gas-based fire alarm system we developed, for the PLS-DA model and the SVM model. Time responses of the Sensor array were calculated in prediction, using the LD3 measurements.The different fire types were performed in a standard fire room. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

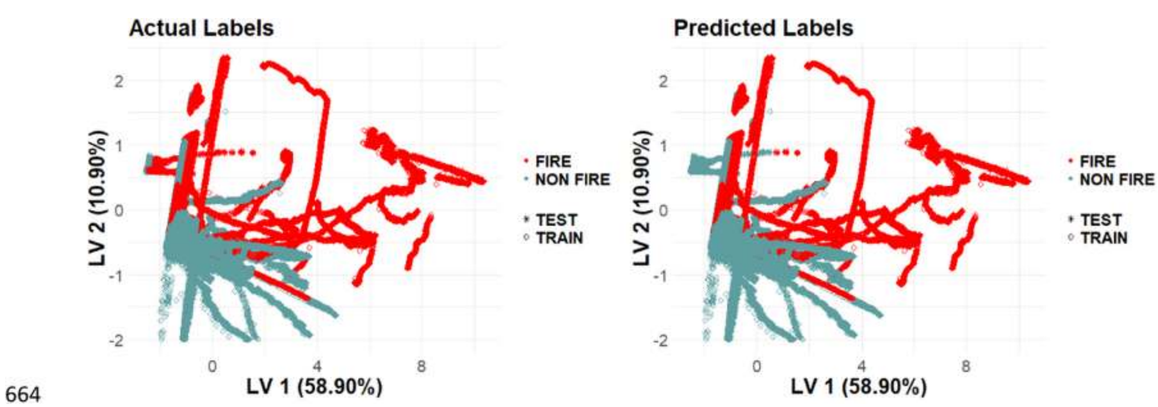

Fig. 7. PLS-DA projection of the test dataset (LD3) using the model built with the calibration dataset (LD2). Data is colored according to the actual labels (left) and according to the model predictions (right). Training/Test data is also presented, showing the good generalization of the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

calibration model, we performed a Variable Importance in the PLS projection (VIP). This enables studying the contribution of each sensor to discriminate fires from nuisances. Fig. 9 shows that the CO and CO_2 and PID sensors are the most important sensors for correct classification. This result is supported by a high production of CO and CO_2 in smoldering fires. MOX sensors show similar contributions to the model, the MLX and MLV sensors performing slightly better than the other MOX sensors (MLC and MLN). Nevertheless, MOX sensors are still relevant useful for their sensitivity to broad range of volatiles released during the fire and non-fire events.

6.3. Calibration with small-scale setup data

The calibration of fire alarms in standard fire rooms is time consuming, leading to a small number of calibration examples. Small calibration datasets may result in prediction models with insufficient discrimination power. Datasets in small setups are however faster to acquire, with reduced experimental costs. In this way, datasets acquired at small scale setups may expand training data for calibration and result in more robust predictions. Here, we considered training a dataset acquired in the fire room with limited calibration measurements (LD1 dataset), another calibration dataset acquired in the small-scale setup (SD1), and a test dataset to evaluate the performance of the models (LD2) acquired in the fire room. Despite the different dynamics and amplitude of the captured signals (see for example Fig. 10), data from small-scale setups may still have its place in increasing the reliability of fire detection models. Actually, a PCA projection of the 3 datasets considered shows sensor space overlaps in this projection (see Fig. 11), confirming thereby that small-scale data may be beneficial for increasing calibration data.

Specifically, we built three calibration models. The first model ***LD1 Data*** (fire room model***)***, was trained using data from the *LD1;* the second model ***SD2 data*** (small-scale model***)***, used as training set data from the *SD1;* and finally, the third model ***SD1*** + ***LD1 data*** (data fusion model***)***,

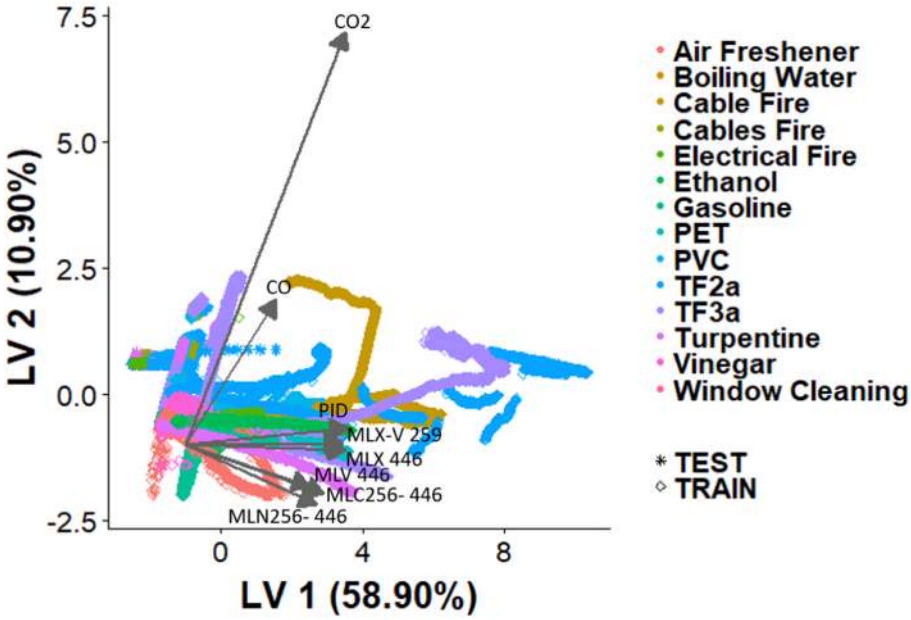

Fig. 8. Biplot of the training and test PLS-DA projection. Scores are colored according to experiment type. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

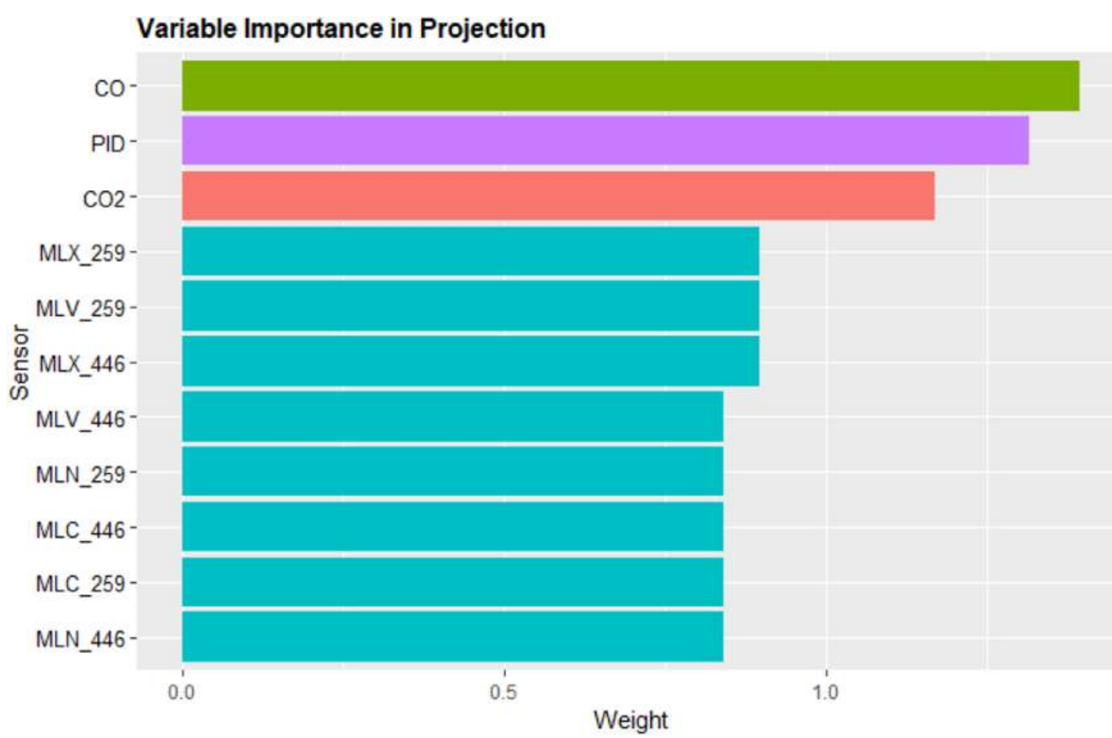

Fig. 9. Variable importance of projection of the PLS-DA model.

used the combination of LD1 and SD1 for training. All the models were evaluated using data from the standard fire room (LD2).

Fig. 12 and Table 5 shows the performance of the models, in particular, their classification rate, sensitivity, specificity, and Area Under the ROC Curve, AUC. The confidence intervals are computed assuming the binormal distribution. Results show that a calibration model built only with data from the fire room showed a high number of false alarms, resulting in an unreliable fire alarm. However, most of the fires presented in the training set are correctly classified. The low robustness of the model in rejecting nuisances can be considered a consequence of the reduced number of experiments contained in LD1. On the other hand, the model trained only with data from the small-scale setup improves the ability to reject nuisances, with an 88% specificity. The fire prediction performance, however, decreases to 60%. The reduced ability to predict fires can be attributed to some of test fires (PVC and Electronics) not being present in the training set. Even though the training set contains Flat Cable fire experiments, in which the cable isolation is based on PVC, the amount of gas emission is much lower and slower than in the fire room. As a result, the model finds difficulty in generalizing the dynamics of the sensors to the plastic-based fires.

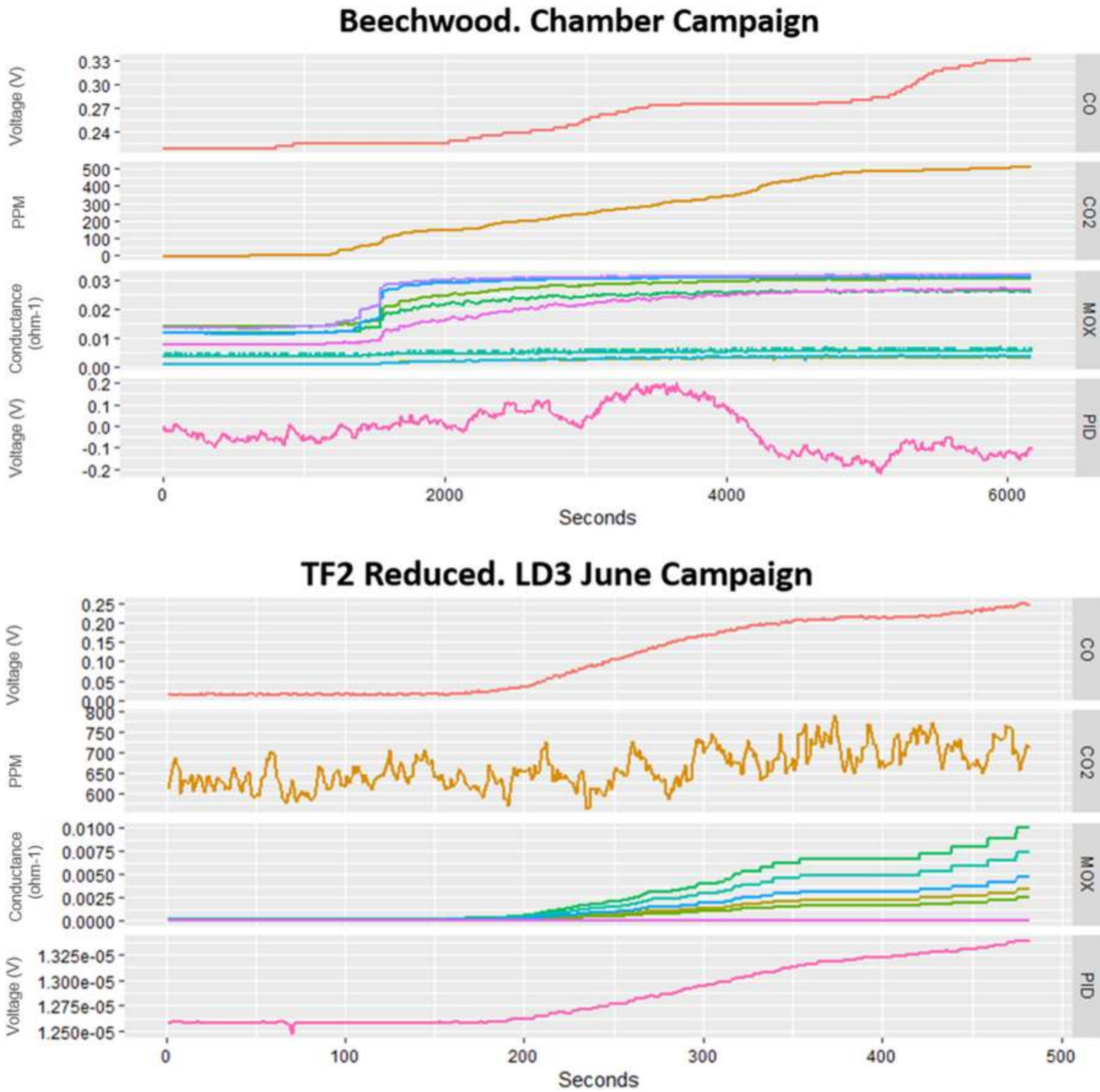

Fig. 10. Sensor signals of a TFa2 fire, performed in the small-scale setup (top) and in the standard fire room (bottom).

Finally, the model that combines data from the standard fire room and the small sale setup improves fire sensitivity and the ability to discriminate nuisances (specificity). This model presented only 3 false alarms and one fire was undetected. This is confirmed by the larger AUC shown by the third model. The model that combines data from both setups takes advantage of the larger number of calibration samples and the different dynamics of the setups, resulting in a more reliable and robust prediction model.

7. Conclusions

Gas sensor arrays together with pattern recognition techniques are a valuable alternative for early fire detection in smoldering and plastic fires, which are characterized by early emissions of gas. In contrast to widespread smoke-based fire alarm systems, a fire alarm that relies on gas emission detection can provide faster response. It can also provide additional safety to the occupants since released volatiles are very often toxic and asphyxiant in environments with new building and plastic materials.

We studied the three factors, fire sensitivity, robustness to nuisances, and performance stability over time, that constitute major limitations for the commercialization of gas-based fire alarms system. We designed and implemented a system that holds an array of unspecific gas sensors, specifically selected for fire detection. We built multivariate calibration models using datasets acquired in a validated standard fire room, where different smoldering fire types and nuisances were generated. Our results show that, four months after calibration, the system still retains 85% sensitivity and 100% specificity. The results also show the importance of including larger number and wide spectrum of training examples, trying to cover the space of fire/nuisance scenarios. Since this is costly in the fire room, training examples from a scaled-down setup are also beneficial to increase the robustness of the classifier. While the results are promising, more research needs to be performed to counteract sensor drift and ensure higher sensitivity several months after calibration. This could be performed in a cost-efficient way making use of calibration transfer or calibration update strategies applied to the sensor array. We also found that systems based on gas detection are sensitive to early gas emissions in fires, and they provide faster detection than smoke-based fire alarms. Time response is an especially important feature for fire alarm systems since fast response is essential to save lives and reduce damage.

To facilitate the path to market, we propose the combination of small-scale setup data with calibration data from a standard fire room. The reduced experimental setup benefits from using less combustion

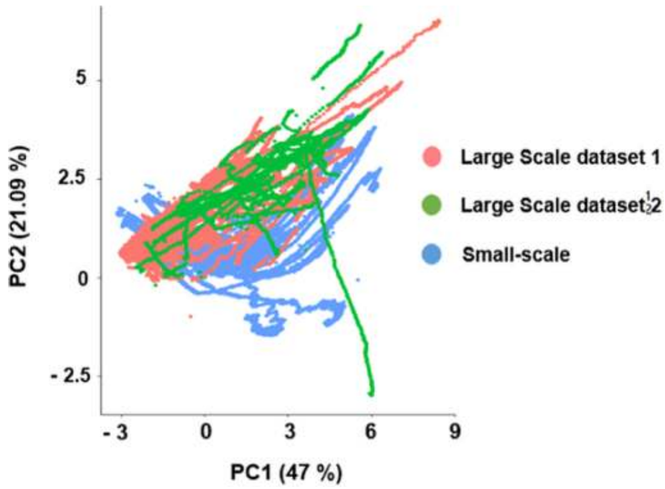

Fig. 11. PCA projection of datasets acquired in the fire room (LD1 and LD2) and acquired in the small-scale setup (SD1). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

products and has a much easier ventilation procedure to clean the room between experiments. Our results show that, despite the different size and gas dynamics of the two datasets, data from the small-scale setup can improve the performance of the calibrated system in a cost-efficient manner.

In certain scenarios, especially those of slow-starting smoldering fires, fire alarm systems based on gas sensors can be better suited than the commonly encountered systems based on smoke detection Gas sensor arrays can help to detect fire scenarios with low smoke production, these being particularly challenging for common smoke detection systems. Nevertheless, before gas sensor arrays can completely replace smoke detectors, their sensitivity and specificity may need to be improved, necessitating further research on sensor selection and model calibration. To contribute to further research efforts, we have made all the datasets generated in this work publicly available. To the best of our knowledge, this is the first public dataset for fire detection systems acquired with unspecific sensor gas arrays, whether in a standard fire room or in a customized experimental setup.

CRediT authorship contribution statement

Jens Eichmann: Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Supervision, Project administration, Funding acquisition. **Jordi Fonollosa:** Conceptualization, Formal analysis, Writing – review & editing, Supervision, Project administration. **Santiago Marco:** Conceptualization, Methodology, Formal analysis, Resources, Writing – review & editing, Supervision, Funding acquisition. **Ana Solórzano:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Luis Fernández:** Methodology, Software, Formal analysis. **Bernd Ziems:** Validation, Investigation, Resources. **Juan Manuel Jiménez-Soto:** Investigation.

Table 5
Values of the Figures of merit computed in each model. Confidence intervals are calculated using a binomial test.

Model	Classification rate	Sensitivity	Specificity	AUC
LD1 Data	52% [32,72]	82% [48,98]	32% [11,58]	0.6
SD1 Data	70% [49,86]	60% [32,83]	88% [61,98]	0.7
SD1 + LD1 Data	88% [71,98]	90% [60,99]	81% [54,96]	0.89

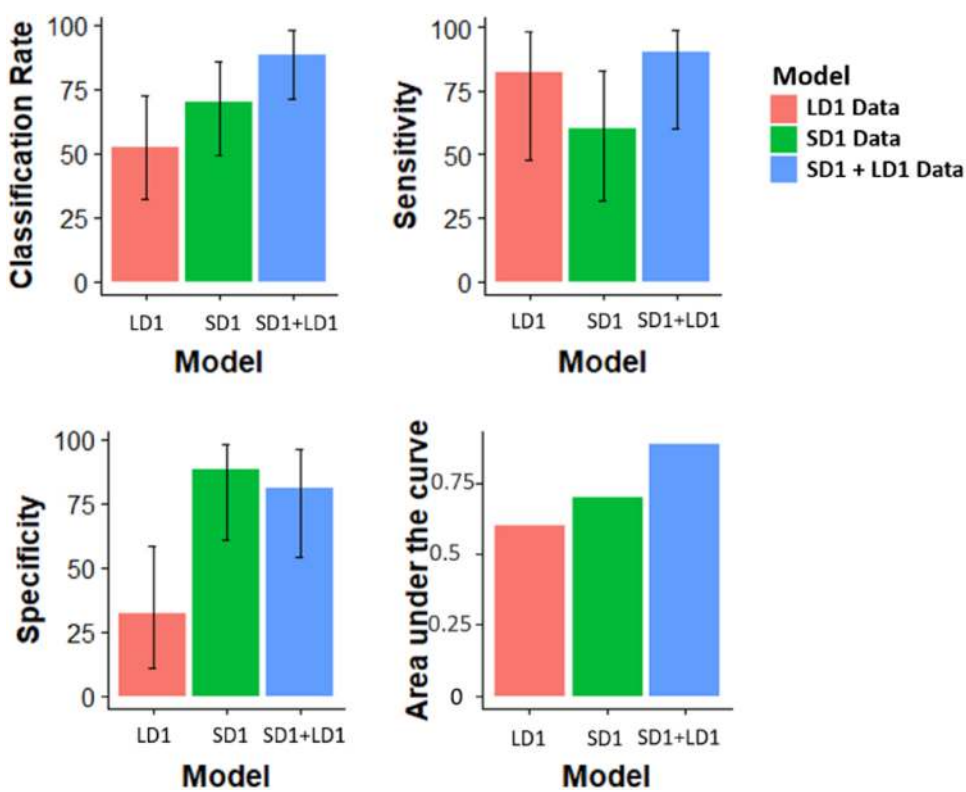

Fig. 12. Classification Rate, Sensitivity, Specificity and AUC for a model trained with data from the fire room (LD1, red), data from the small-scale setup (SD1, green), and combining data from both setups (LD1 + SD1, blue). Error bars indicates the standard deviation of the different figures of merit. Figures of merit are evaluated using data from fire room (LD2). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: A. M. Solorzano, J. Eichmann and B. Ziems are employees of Viking-Minimax, a company with commercial interest in fire detection.

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