

École polytechnique de Louvain

Analysis of Early Indicators for Fire Detection using a Multi-Sensor System

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Abstract

This thesis investigates the potential of a multi-sensor system for enhancing early fire detection by monitoring key emissions during the early stages of combustion. Traditional fire detectors primarily focus on smoke particles, often leading to delayed alarms in smouldering fires where toxic gases accumulate to dangerous levels. This research explores whether the combination of sensors measuring carbon dioxide (CO₂), Volatile Organic Compounds (VOCs) and particulate matter (PM) can enhance early fire detection.

A prototype sensor node was developed to monitor these emissions in real-time. Controlled burn experiments were conducted using common household materials such as rubber, plastic, wood, and paper, to analyse the behaviour of the indicators. The study also explored the optimal placement of sensors within indoor environments to enhance detection efficiency. A second experiment was realised to assess the effectiveness of the multi-sensor system in enhancing early fire detection through a real-time monitoring system based on the MQTT protocol.

The results demonstrate that multi-sensor systems can significantly improve early fire detection compared to conventional smoke detectors. Emissions in CO₂, VOCs, and PM were detected within minutes of fire ignition, with higher detection efficiency at elevated sensor heights. The research highlights the potential of these indicators to provide a more comprehensive fire detection system.

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Acronyms

CO Carbon Monoxide

CO₂ Carbon Dioxide

H₂ Hydrogen

I²C Inter-Integrated Circuit

MCU Micro Controller Unit

MQTT Message Queuing Telemetry Transport

NDIR Non-Dispersive Infrared

NO_x Nitrogen Oxides

PM Particulate Matter

PM₁ Particulate Matter with an aerodynamic diameter smaller than 1 µm

PM₁₀ Particulate Matter with an aerodynamic diameter smaller than 10 µm

PM_{2.5} Particulate Matter with an aerodynamic diameter smaller than 2.5 µm

PM₄ Particulate Matter with an aerodynamic diameter smaller than 4 µm

TCP/IP Transmission Control Protocol/Internet Protocol

VOC Volatile Organic Compound

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Introduction

Worldwide, fires constitute one of the main sources of public health problems, responsible for many deaths and injuries, as well as being a leading cause of property damage, and economic disruption. Each year, a large number of fire incidents across the world cause devastation [1, 2]. The main causes of fires in buildings are cooking, smoking, short circuit, electrical sources, etc [3]. Compartment fires, in particular, pose significant threats both to financial assets and human lives, making continuous monitoring and quick response to fire situations within buildings essential. [4].

Nowadays, fire detection systems are widely used around the world to protect lives and property. However, current detectors have limitations in terms of detection speed and reliability. They respond to only a few fire parameters, such as smoke particles, while not considering other important indicators, such as gaseous products [5]. Conventional smoke detectors refer exclusively to the detection of fire particulates, without including gas emissions. The two commonly used methods for fire detection - photoelectric detectors, which rely on light scattering, and ionisation detectors - both lack sensitivity to toxic emissions. This limitation can result in inadequate protection during smouldering fires, where the delayed response may allow dangerous levels of toxic gases to accumulate, reaching life-threatening concentrations before the alarm is triggered [6].

Indoor fire detection using gas chemical sensing has been studied since the early nineties. This approach leverages the fact that, for certain types of fire, volatile chemicals appear before smoke particles, enabling chemical sensing systems to provide faster alarm responses than conventional smoke-based detectors. Main fire indicators are surrounding heat, flame, air quality, smoke, and air-track [3]. Gas-based fire detection offers an additional level of safety to building occupants, and even systems relying exclusively on gas sensors have been explored. Multi-sensor systems have been developed over the years, combining various sensor types to enhance detection accuracy. In recent years, multi-sensor technology has become a highly active field, particularly in real-time fire detection applications [6, 3].

Combustion processes release a significant amount of gases and volatile during the pyrolysis and oxidation phases. Understanding the physicochemical processes

occurring in the early stages of a fire is crucial to identifying the emissions produced during combustion. Additionally, the behaviour of these volatile emissions requires special attention to ensure that fire detection system operates effectively and comprehensively.

This thesis aims to evaluate whether a multi-sensor system, designed to detect specific emissions during the early stages of a fire, can improve fire detection. The sensors were chosen based on physicochemical processes of fire and relevant studies, with an emphasis on capturing the key emissions generated in the initial combustion phase. The primary focus is on monitoring carbon dioxide (CO₂), Volatile Organic Compounds (VOCs), particulate matter (PM), Nitrogen Oxides (NO_x), temperature, and humidity in real-life indoor environments during fire events to assess the performance of the multi-sensor system in a building context. These indicators are subsequently analysed based on the results obtained from experiments. As a next step, the research aims to investigate whether the selected parameters, when combined and monitored in real time, can improve early fire detection compared to traditional smoke detectors.

Furthermore, a wide variety of materials are found nowadays inside occupied buildings. During the open burning of household solid waste, which often includes plastics, the emissions can vary significantly as the combustion releases different combustion products, namely aerosols and gases [7, 8]. Consequently, this study examines different materials and their emissions to observe how fire parameters behave. Additionally, the work explores how multi-sensor measurements respond at different distances and height from the fire source, with a focus on enhancing early fire detection.

In summary, this thesis explores how real-time multi-sensor systems can enhance early fire detection compared to traditional smoke detectors by focusing on the primary emissions released during the initial stages of combustion. The research assesses the effectiveness of monitoring CO₂, VOCs, PM, NO_x, temperature, and humidity in small-scale experiments and real-life indoor environments. By analysing how these indicators fluctuate during fire tests, the study aims to determine when they appear and how they behave as early fire indicators across different materials and distances from the fire source.

Structure

Chapter 1 The first chapter covers the chemical processes and combustion phases that occur during a fire, along with the gas emissions produced at early stages. An overview of the existing research in the field of fire detector using multi-sensors is provided, along with their potential to detect emissions appearing in the early stages of a fire, compared to traditional smoke detectors.

Chapter 2 The prototype sensor node, which will be used in the subsequent experiments, is introduced, along with a detailed explanation of the sensors selected for this study.

Chapter 3 A set of experiments is conducted and aims to observe the behaviour of emissions during fire events over time for different distances and heights. Analyses of the results obtained during the combustion of different materials help determine when key indicators appear during combustion and to assess their potential for early fire detection.

Chapter 4 Another aspect of this work involves using real-time monitoring for early fire detection. The fundamental principles underlying the system, based on the MQTT protocol, is thoroughly explained.

Chapter 5 A second experiment is realised to assess the effectiveness of the multi-sensor system in enhancing early fire detection through a real-time monitoring system based on the MQTT protocol. The experience involves determining the typical baseline readings of CO₂, PM and VOCs under normal environmental conditions. The system's response to a series of fires involving different materials is tested and compared to the response of conventional smoke detectors, using simple fire detection rules based on the previous analyses.

Chapter 6 The final chapter outlines the limitations and interesting issues encountered during the research, offering insights into potential areas for future research.

Conclusion The conclusion of this work highlights the essential findings.

Chapter 1

Physicochemical aspects of fires and Related Works

To effectively enhance fire detection, it is essential to have a thorough understanding of fire from a physico-chemical perspective. Section 1.1 covers the chemical processes and combustion phases that occur during a fire, along with the gas emissions produced at early stages, which can differ depending on whether the combustion is flaming or smouldering. Section 1.2 provides an overview of the existing research in the field of fire detector using multi-sensors and their potential to detect emissions appearing in the early stages of a fire. It also points out the challenges encountered with single-sensor detectors, as conventional smoke detectors.

1.1 Chemical processes and Emissions during fire

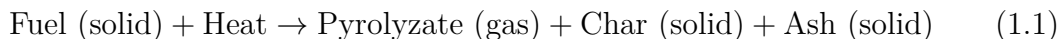
A fire can only occur when what is known as the fire triangle - fuel, oxidiser (often oxygen) and a source of ignition - come together [9]. Heat must be delivered to the initial fuel source and any nearby fuel in order for the fire to expand and spread. Fire spreads due to heat's ability to remove, by evaporation, the moisture from the adjacent fuel, making it easier for it to ignite or move. Fuel burns by reacting with the oxygen from the surrounding air, releasing heat and producing combustion products including smoke, particles, and gases [10].

The core of any combustion process is a global exothermic reaction that results in the release of heat, and both gaseous and solid products. Whether smouldering or flaming will be the dominant mode is dictated by which chemical species is oxidised. If the oxidation takes place in the solid phase, smouldering is dominant, and if the oxidation is in the gas phase then flaming dominates. The global reactions of a solid fuel combustion may be divided into several chemical processes:

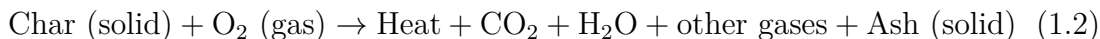
distillation/drying, pyrolysis (thermal decomposition) followed by oxidation. Fires progress through these stages with varying behaviours depending on the materials involved. Improving fire detection requires understanding these stages [4]. SFPE Handbook of Fire Protection Engineering [11] details each phases that are resumed below.

Distillation involves volatilisation of compounds stored in liquid pools as the fuel is heated. Distillation has been observed to emit a variety of Volatile Organic Compounds (VOC). The drying follows with evaporation, emitting water vapour and leaving behind dry fuel [11].

Pyrolysis is the initial step of a combustion process and is defined as “a process of simultaneous phase and chemical species change caused by heat” [6]. It is the thermal decomposition of materials at high temperatures in the absence of oxygen or under low oxygen conditions. The fuel is heated to high temperatures, causing it to decompose into smaller molecules, including gases (pyrolyzate) and solid char. These products can then combust in the presence of oxygen. The main components of the gas produced by pyrolysis are hydrogen (H_2), hydrocarbon gases (C1-C4), carbon monoxide (CO), carbon dioxide (CO_2), and Hydrogen sulfide (H_2S) [12]. Another solid residue left after the fire is ash. Pyrolysis process is given in Equation 1.1.

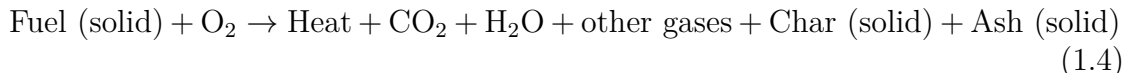


Oxidation is an exothermic reaction of the solid char and the gas pyrolyzate with oxygen from the air. Char oxidation leads to smouldering combustion. Gas-phase oxidation involves the oxidation of of air-suspended pyrolyzate in the gas phase and leads to flaming combustion. Char oxidation and gas oxidation processes are detailed in Equation 1.2 and Equation 1.3, respectively.



Combustion is “a chemical process of oxidation that occurs when a combustible is oxidised, at a rate fast enough to produce temperature rise and usually light, either as glow or flame” [6]. Combustion and pyrolysis are distinct processes, but pyrolysis is often a preliminary step to combustion. In the chemical reactions (1.1, 1.2 and 1.3), the end result of the processes can be summarise without detailing

the intermediate steps. The direct combustion of the solid fuel in the presence of oxygen is therefore often given as follows in Equation 1.4.



During a fire event, the complex thermal degradation processes — distillation, pyrolysis, char oxidation and oxidation of the resultant gas products — occur simultaneously and often in close proximity. This makes it difficult, if not impossible, to tell them apart. However, in the context of emissions characterisation, fire behaviour is generally described in terms of the presence or absence of an open flame: "flaming" or "smouldering" combustion. This taxonomy is imperfect, but it provides a basis for objectively describing the fire behaviour associated with emissions measurements. [13].

Flaming combustion The flaming combustion process produces gas-phase emissions that are dominated by highly oxidised compounds as it tends to complete thoroughly with high temperatures increasing the levels of gases like CO₂, Nitrogen Oxides (NO_x) and Sulphur Dioxide (SO₂) [8]. Consumption of the fuel leads to a reduced rate of pyrolysis and eventual cessation of the open flame [13].

Smouldering combustion After flaming combustion has ceased due to the reduced rate of pyrolysis, heat intensity decreases as well as for the levels of combustible gases and the oxidation of residual char results in smouldering combustion. This form of combustion is slow, occurs at lower temperatures, and is the most persistent type of combustion. As an incomplete combustion reaction, it releases pollutants in greater quantities than flaming combustion [13]. They are characterised by the production of early gas emissions that can include high levels of CO, Volatile Organic Compounds (VOCs) and particulate matter (PM) due to the presence of pyrolysate, which does not burn in the absence of a flame [11, 14]. Since smouldering fires are cold fires (compared to flaming fires) the smoke disperses slowly throughout the volume of the room, rather than rising straight to the ceiling, where the conventional smoke detectors are located, resulting in long warning times [6].

Flaming and Smouldering combustion are closely related, and one can lead to the other. A smouldering fuel reacts to an increased supply of oxygen (e.g. wind) by becoming faster and hotter, until flames might eventually appear. The transition from smouldering to flaming is a severe threat in residential fires, and together with the slow buildup of CO and other toxic substances, they pose the largest life hazards [11]. It is therefore essential to detect these emissions during these combustion phases at early stage, using early warning systems such as gas detectors that can detect the compounds emitted before the fire spreads.

A wide variety of materials are found nowadays inside occupied buildings. During the open burning of household solid waste, which often includes plastics, the emissions can vary significantly as the combustion releases different combustion products, namely aerosols and gases. Studies have shown that the gases from burning plastics can include common pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x), Sulfur dioxide (SO₂) and high concentrations of particulate matter (PM_{2.5} and PM₁₀) [7, 8]. Additionally, products not actually burning may reach temperatures high enough to suffer from thermal decomposition and pyrolysis, producing thereby additional emission of gases, volatile and smoke. Smoke is defined as “the airborne solid and liquid particulates and gases evolved when a material undergoes pyrolysis or combustion” [6].

As previously mentioned, fires can release various of gases and volatile. However, certain gases particularly relevant due to either their volume significant volume or their toxicity, are reviewed by *Fonollosa and al., 2018* [6]. For instance CO, which is the most important toxic emission from fires and is particularly present during smouldering fires and if there is enough oxygen, is oxidised to CO₂. However, in the absence of sufficient ventilation, this oxidation step is not efficient and larger concentrations of CO are found. NO_x that appear mostly in the form of nitric oxide (NO) and nitrogen dioxide (NO₂).

Additional emissions generated during combustion processes are Volatile Organic Compounds (VOCs). They are organic chemical compounds with potential to evaporate under normal indoor atmospheric conditions of temperature and pressure (Indoor Air Quality (IAQ), US EPA) [15]. Many organic compounds in the air do not appear naturally, as they are instead human-made, formed during industrial processes or combustion, such as burning fuel like gasoline, wood, coal, natural gas and other products used at home or work [16].

Other emissions produced during a fire include particulate matter (PM), which consists of microscopic, inhalable particles. Ambient particulate matter is composed of a mixture of solid and liquid particles suspended in the air, such as dust, soot, smoke, and liquid droplets [17]. During fire, particulate matter is emitted in large quantities, especially from sources like wood and coal burning. If ventilation is insufficient, these particles can become trapped indoors, posing a direct threat to air quality within residences. [18]. The particles may vary in size and composition. The two subcategories commonly heard of are PM₁₀ and PM_{2.5}. PM₁₀ refers to particles with an aerodynamic diameter smaller than 10 µm, while PM_{2.5}, also called fines particles, refers to particles with an aerodynamic diameter smaller than 2.5 µm. Additionally, PM_{1.0} and PM_{4.0} exist, characterised by aerodynamic diameters smaller 1 µm and 4 µm, respectively.

1.2 Fire detection using Multi-sensors

Conventional smoke detectors refer exclusively to the detection of fire particulates, not including gas detection. Photoelectric detectors, which use light scattering, and ionisation detectors are the two methods conventionally used for fire detection. Light scattering and ionisation detectors lack sensitivity to toxic emissions, potentially failing to provide adequate protection during smouldering fires and may have a delayed response time, allowing dangerous concentrations of toxic gases to accumulate and reach life-threatening levels before the alarm is triggered [6].

Photoelectric detectors, which are used later in this work, include a light emitter and a photocell to detect airborne particles. When a smoke particle enters the sensor chamber, this particle obstructs the light source and scatters light onto the photocell. The incident light on the photocell causes it to generate a current. Soot particles with large diameter are more influential in scattering light than the small soot particles generated during flaming fires. Due to the prevalence of large particles in smouldering fires, photoelectric alarms tend to show faster response and higher sensitivity than ionisation detectors in smouldering fires. [6, 19]. Studies have observed that in general, ionisation smoke alarms sense flaming fires sooner than photoelectric smoke alarms, while photoelectric smoke alarms sense smouldering fires typically much sooner than ionisation alarms [20].

Nowadays, conventional smoke detectors are standard in fire alarm systems even though they have practical limitations, particularly in detecting early gas emissions [19, 14]. The main advantages of multi-sensor approaches to early fire detection over traditional single smoke detector have been reviewed in the literature [6, 3, 21]. They are a shorter detection time, an improved sensitivity to real fires and a reduction to false alarms.

Previous researches have used various combinations of multi-sensor measurements for early fire detection. *Milke et al., 1999* [22] explored the use of multi-sensor detection systems as a means of improving fire detection by distinguishing between real fire events and nuisance sources. The focus was on analysing fire signatures from various fire types (flaming and non-flaming), utilising measurements including temperature, light obscuration, CO, CO₂, and O₂ concentrations. Flaming fires were identified by high CO₂ concentrations or rate-of-rise, while non-flaming fires were identified by the rate-of-rise of CO concentration.

Krüger et al., 2017 [23] discovered that the smouldering process of various polymeric materials (such as wood, foam, and PE) present in households releases significant amounts of H₂ in the early stages of a fire, preceding detectable levels of CO and smoke. They suggested that incorporating H₂ sensors alongside other sensors (e.g., smoke detectors) could enhance early fire detection.

Fonolosa et al., 2018 [6] reviewed chemical sensor systems for fire detection and explored various studies. Among these is a study carried out by the SP Fire Research in Norway that conducted experiments on smouldering fires to evaluate if smoke detectors with CO sensors could alert occupants earlier than photoelectric smoke detectors. The study concluded that smoke detectors combined with CO sensors activated much faster than photoelectric detectors, with photoelectric detectors failing to trigger alarms in three experiments. The research highlighted the effectiveness of chemical sensors in enhancing safety for some fire scenarios (smouldering fires). Moreover, it also pointed out that commercial and standardised fire detectors typically only detect smoke or CO, despite the presence of other toxicants, failing to provide adequate protection against these others toxic substances.

Solórzano et al., 2022 [14] employed a multi-sensor array to detect hydrogen (H₂), methane (CH₄), nitrogen oxides (NO_x), and volatile organic compounds (VOCs). They explored the performance of a gas sensor array in detecting smouldering and plastic fires while minimising false alarms from various nuisances. Their experiments, conducted in a validated standard fire room, demonstrated that gas sensor array systems offer a faster fire alarm response compared to traditional smoke-based fire alarms. The authors highlighted the significance of CO and VOCs as early fire indicators due to their significant emissions during smouldering fire scenarios. They emphasised the importance of incorporating VOC measurements within a multi-sensor system approach for the early detection of fires.

Vorwerk et al., 2023 [24] conducted a comprehensive study on the behaviour of various sensor measurements, including PM, VOC, CO, CO₂, H₂, UV, air temperature, and humidity, to evaluate their effectiveness as early fire indicators. They focused on the dispersion characteristics and the time it takes for these measurements to become relevant in different incipient fire scenarios. By varying the distance between the sensor node and the fire source in a standard EN 54 test room, they identified five key early fire indicators: H₂, CO, PM0.5, PM1.0, and VOC. Their findings highlight the importance of understanding sensor measurement interactions and their robustness for achieving the earliest possible fire detection. Additionally, they proposed the term "early fire indicators" for direct sensor measurements and emphasised the need for further research on model-based indicators to enhance early fire detection systems.

In this master's thesis, the same terminology of "indicators" is adopted from their work to refer to fire emissions studied.

Chapter 2

Fire Detection Sensor Node Prototype

This chapter introduces the prototype upon which the continuation of the work is based. Section 2.1 outlines the specifications and technologies of the selected sensors, while Section 2.2 details the proposed prototype that will be used in the subsequent experiments conducted in Chapters 3 and 5.

2.1 Sensors Selection

The sensor selection aims to target some of the main combustion products reviewed in Chapter 1. A combination of two sensors was chosen: SCD30, a CO₂ sensor based on non-dispersive infrared absorption (NDIR) principle, and SEN55, a compact environmental sensor node collecting VOC, PM and NO_x. Both sensors also integrate temperature and humidity measurement capabilities. Figure 2.1 present the sensors used in this work.

SCD30 This sensor utilises Non-Dispersive Infrared (NDIR) technology to measure CO₂ concentration. In addition to CO₂ detection, the sensor module integrates humidity and temperature measurements, with the SHT30 included [25]. The module has a supply voltage of 3.3 – 5.5 V and consumes 19 mA for a measurement every 2 seconds.

SEN55 The SEN55 is a compact, all-in-one environmental node sensor designed for measurement of environmental parameters, such as PM, VOCs and nitrogen oxide compounds (NO_x) [26, 27]. This module is equipped with a SHT4x sensor [28] for relative humidity and temperature, a particulate matter sensing technology for PM, a SGP41 sensor for VOC and NO_x, and a microcontroller featuring VOC and NO_x Index, relative humidity and temperature outputs via I²C interface. It integrates proprietary algorithms for temperature and humidity compensation and

VOC/NOx Index calculation. The module has a supply voltage of 4.5 – 5.5 V. The average supply current in measurement-mode is 63 mA.

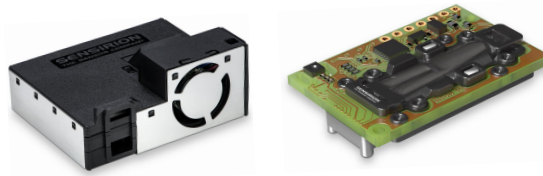


Figure 2.1: Sensors selection : SEN55 (left) and SCD30 (right)

Particulate matter sensing technology

The particulate matter sensing operates on the principle of laser scattering [29]. A fan generates a controlled airflow within the sensor, which is stabilised by an internal feedback loop between the microprocessor and the fan. Environmental PM enters the sensor through the inlet and exits through the outlet, carried by the airflow (black dots in Figure 2.2). As particles in the airstream pass through a focused laser beam near the photodiode, they scatter light. This scattered light is detected by the photodiode and is processed into a mass/number concentration output using Sensirion's proprietary algorithms running on internal microcontroller.

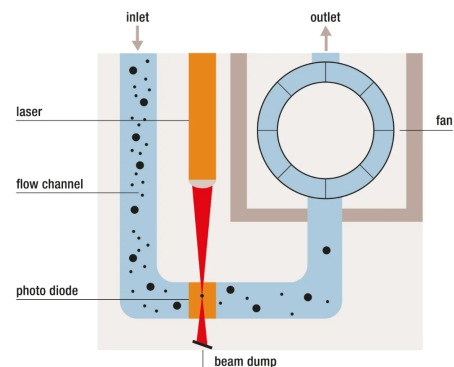


Figure 2.2: Working principle of the PM sensing technology based on laser scattering (Source: Sensirion)

VOC and NOx indexes

The SGP41 is a MOX-based gas sensor designed to detect VOC and NOx compounds [30, 31]. The raw signals from the sensor are processed using Sensirion's Gas Index Algorithm, which generates VOC and NOx Indices. This algorithm automatically adapts its outputs to any indoor environment and maps all VOC and NOx events to a VOC and NOx Index scale from 1 to 500 index points. On the VOC Index scale a value of 100 refers to the average indoor gas composition over the past 24 h. A VOC Index above 100 means that there are more VOCs compared to the average while a VOC Index below 100 means that there are fewer VOCs compared to the average [32]. For the NOx Index, the average condition is mapped to a value of 1 and therefore, the NOx Index displays values between 2 and 500 when NOx events are present [33].

Table 2.1 summarises the specifications of the sensors used in this work.

	SDC30, <i>Sensirion</i> and SHT30	SEN55 PM	SEN55, <i>Sensirion</i> SGP41	SEN55 SHT4x
Sensor type	NDIR	PM sensing technology	MOX	Temperature and humidity
Measured parameters	CO ₂ , T and H	PM	VOC and NOx	T and H
Measurement Range	CO ₂ : 400 - 10000 ppm T : -40 to 125°C H : 0 to 100%RH	0 - 1'000 µg m ⁻³	VOC/NOx : 1 - 500 Index points	T : -10 to 60°C H : 0 to 95%RH
Size range	— — — —	PM1.0 : 0.3 – 1.0 µm PM2.5 : 0.3 – 2.5 µm PM4.0 : 0.3 – 4.0 µm PM10 : 0.3 – 10.0 µm	— — — —	— — — —
Accuracy	±(30 ppm + 3% mv) ±0.2 °C and ±2 %RH	±5 µg m ⁻³ and 5% m.v	<±15 VOC Index points <±50 NOx Index points	±0.45 °C and ±4.5 %RH
Response time	CO ₂ : 20s T : >2s and H : 8s	—	VOC : <10s and NOx : <250s	T : < 60s and H : < 20s

Table 2.1: List and specifications of the sensors included in the system

2.2 Sensor Node

The experimental fire detection prototype is based on a Arduino Nano ESP32 board for control and acquisition, and on the two sensor platforms SEN55 and SCD30, operating and communicating through the I²C Interface. This prototype system is referred as sensor node in the following work and is shown in Figure 2.3.

Arduino Nano ESP32

The Arduino Nano ESP32 [34] features the ESP32-S3 system on a chip (SoC) from Espressif, which is embedded in the NORA-W106 module. The operating voltage of this SoC is 3.3 V. The ESP32-S3 has a dual-core microprocessor Xtensa 32-bit LX7, supporting clock frequencies at up to 240 MHz. It has support for the 2.4 GHz Wi-Fi band as well as Bluetooth Bluetooth Low Energy (LE). The NORA-W106 also embeds an antenna for Bluetooth and Wi-Fi connectivity. The Nano ESP32 has one USB-C port, used to power and program the board as well as sending and receiving serial communication.

The Arduino Nano ESP32 is selected for this project due to its integrated Wi-Fi connectivity and support for MicroPython.

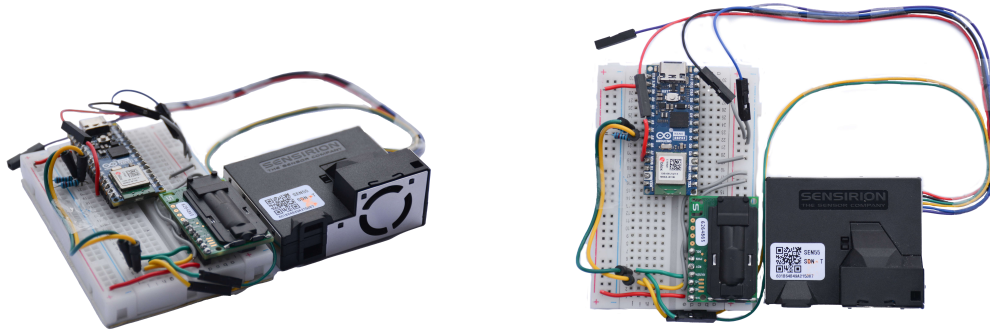


Figure 2.3: Sensor node including two sensors measuring 9 different parameters (CO₂, PM1, PM2.5, PM4, PM10, VOC index, NO_x index, Temperature and Humidity). The signal acquisition platform is based on an Arduino Nano ESP32.

The serial protocol used to communicate between the sensors and the microcontroller is I²C. Each of the sensor having a unique address, they are connected to the Arduino via the same serial data line (SDA) and serial clock line (SCL). SDA and SCL lines correspond to Pin A4 and A5, respectively, on the Nano ESP32. Two external pull-up resistors, of value $R_p = 10\text{ k}\Omega$ as advised in the datasheet, are connected to both SCL and SDA lines that are open drain I/Os.

The system is powered via USB-c cable supplied by either a computer source, for the first experience in Chapter 3, or by an external battery, for the second experience in 5.

The block diagram of the SEN55 is shown in Figure 2.4.

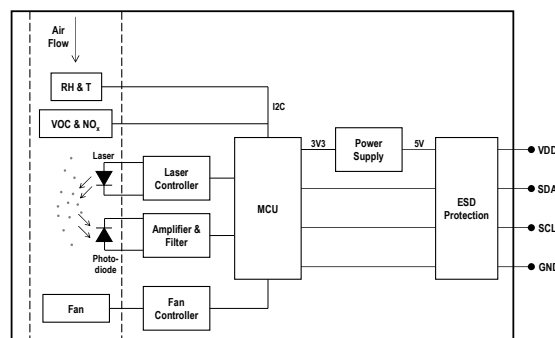


Figure 2.4: SEN55 Block diagram. Source : Sensirion [27]

Micropython Driver

To receive data from the sensors that communicate over I₂C, libraries for the SEN5x sensors are used. These libraries are based on an open source Micropython driver for Sensirion SEN5x sensors [35]. The code, dataset and videos used in this thesis can be found at the following GitLab repository: <https://gitlab.flavio.be/flavio/mt-aurore-magnan>

Chapter 3

A controlled burn experiment : Analysing early fire Indicators

In this chapter, a set of experiments is conducted and aims to observe the behaviour of emissions during fire events over time for different distances and heights. Various fires, involving common building materials, are analysed to determine when key indicators appear during combustion and to assess their potential for early fire detection. The experimental procedure is explained, followed by the observations of fire characteristics during the experiments and finally the results are presented and discussed.

3.1 Proposed methodology

The experience consists in (1) measuring the emissions of CO₂, PM, VOC, NO_x, temperature, and humidity, from different burning materials and observe the variations in their gas signatures once ignited. (2) In addition, the objective is to estimate the time needed for sensor nodes to detect fire events and determine the corresponding fire stage. (3) Additionally, it will establish the optimal height at which the sensor nodes can detect gas anomalies most rapidly.

3.2 Experimental Setup

In order to observe the behaviour of the emissions at different height from the ground, two sensor nodes are strategically placed at varying heights from the fire source : 1m and 2m. Communication with the sensor nodes is facilitated via a USB cable directly connected to a computer for data storage. The experimental environment is established inside of a warehouse, an enclosed space of dimensions

6m x 4m x 2.5m. To ensure quick aeration between measurements, the sensors were positioned near the overhead door of the warehouse. For safety reasons the fires are ignited on a metal board. The experimental set up is shown in Figures 3.1 and 3.2.

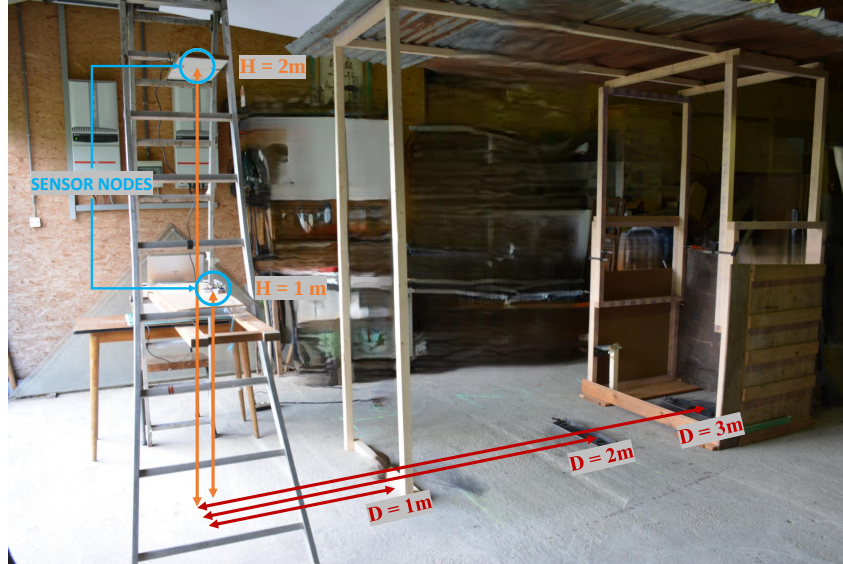


Figure 3.1: Experimental set up, where D : Distance from the sensor nodes to the fire source, H : Height at which the sensor node is positioned



Figure 3.2: Experimental set up

3.2.1 Procedure

In this initial data collection experience, small fires were ignited. In total, four experiments were conducted, each associated with a specific type of fuel commonly found in warehouses, workshops, houses and garages: rubber, plastic, wood chips, and paper. For each fuels, three fires were ignited at three different distances from the sensor nodes: 3m, 2m, and 1m, in that order. The sensor nodes were

fixed at different heights: 1m and 2m. These nodes read 1 sample every 3 seconds. To ensure proper normalisation and comparison of data, a weight of 30 grams of fuel was burned for each fire. This setup effectively captured the signature and behaviour of gases released during combustion and allowed the testing of fire detection by the sensors.

One experiment lasts 55 minutes and corresponds to the burning of 3 x 30grams of the same material, at the 3 defined distances. The first 5 minutes are used to stabilise the sensor nodes, in order to reach a VOC index of 100 (offset average mapped to the value of 100 [32]). The first fire is then started at a distance of 3 meters, and lasts 13 minutes to allow all the fuel to burn off and the smoke in the air to almost vanish. This is followed by a 3-minute aeration phase, when the garage door next to the nodes is opened. This aeration renews the ambient air in the garage, and the sensor readings return to a steady state. The garage door is closed for 2 minutes before starting the next fire. For simplicity, the ventilation phase is considered to be 5 minutes (3 minutes with outside air + 2 minutes in the garage ambient air). All fires were ignited using 2 or 3 matches.

The second fire was ignited at a distance of 2 meters from the sensors and also lasted 13 minutes before being extinguished. This was followed by another 5-minute ventilation phase. The third fire was finally started at a distance of 1 meter from the sensor nodes. After 13 minutes of combustion, the garage door was reopened, and the sensor measurements were stopped 1 minute after ventilation.

In total, 4 experiments were conducted for the 4 different fuels. Between each experiment, a 45-minute delay was waited to allow complete ventilation of the warehouse as well as the re-calibration of the CO₂ sensors. The order of burned materials was defined according to their burning speed. The first experiment applied to rubber, which takes the longest time to burn, followed by plastic, wood chips and paper.

The selected fuels are listed in Table 3.1 and are shown in Figure 3.3.

Fuels	Combustion material	Weight
Rubber	Rubber tube cut into pieces	3x30grams
Plastic LDPE	Low-Density Polyethylene	3x30grams
Wood chips	Oak wood	3x30grams
Paper	Inkless white printing paper	3x30grams

Table 3.1: Selection of fuels



Figure 3.3: Fuels selection from left to right : Rubber tube, LDPE plastic, Wood chips and Paper. The above image shows 30 grams of each fuel untouched. The second image below corresponds to the fuels harvested after combustion.

3.2.2 Dataset logging

Throughout the fire experiments, data logging was carried out to capture the emissions released during the combustion of the four fuels. This set of experiments was conducted three times, producing three distinct datasets. Due to some challenges encountered in the first two datasets, this study focuses on the analysis of the third dataset.

The first dataset was collected using only the SEN55, which lacked CO₂ sensors. Monitoring PM, VOC and NO_x levels alone proved inadequate, leading to potential false alarms due to the absence of CO₂ data. This limitation necessitated the collection of another dataset.

In the second dataset, CO₂ sensors were included; however they were not properly calibrated. Additionally, the original warehouse roof slope was not suitable for this experiment, as it caused smoke to rise straight up and to accumulate at the highest point of the roof (6 m), resulting in measurement spikes that made the data difficult to interpret. This prevented from accurately linking gas increases to fire ignition or ventilation. To address this problem, a flat metal sheets ceiling was installed as seen in Figure 3.1, allowing smoke to reach the sensors more effectively.

The third dataset, which is used for observations (Section 3.3) and analyses (Section 3.4) in this chapter, reflects the improvements made. The CO₂ sensors underwent re-calibration to ensure they both operated at the same level, for a relevant comparison. Since SCD30 are NDIR based, CO₂ sensors, they are delicate optical systems. Mechanical stresses on the optical cavity can change physical properties of the sensor affecting the calibration, resulting in reduced accuracy. As proposed in the document [36], full accuracy of the SCD30 has been restored using the field forced re-calibration (FRC) algorithm.

All datasets can be found on the repository of the thesis. The videos recorded during the experiments of the third dataset are available as well.

3.3 Fire Characteristics and Observations

Observations related to the characteristics of the burning materials during the experiments are reported in Table 3.2. These features will provide a detailed and comprehensive description of each fire, assisting in the analyses and comparison of the different materials.

Figure 3.4 shows the combustion of the 4 fuels. The residues harvested from the burnt fuels are shown in Figure 3.3.



Figure 3.4: Flaming materials

Characteristics	Rubber	Plastic	Wood	Paper
Flame Colour	Bright orange	Orange and blue	Orange pink	Yellowish
Flame height	30 - 50 cm	± 7 cm	± 15 cm	± 10 cm
Smoke Colour	Black	White	White/grey	White/grey
Smoke Appearance	Immediate	Rapid	Very rapid	Immediate
Total Burn Duration	9 min	8 min	7 min	8 min
Residues	Carbonised	Melted	Wood charcoals	Ashes

Table 3.2: Characteristics of fires for different materials

Rubber ignited quickly, producing intense flames accompanied by thick, dark smoke, with flames reaching heights of around 50 cm. In contrast, plastic also caught fire rapidly but had a more smouldering combustion than flaming, emitting white smoke and tending to melt rather than fully combust like rubber. Wood initially flamed but required stirring to prevent the surface from charring; it produced grey smoke and some charred wood chips and ash harvested. Paper ignited instantly, with flames extinguishing quickly, leaving smoke and ash in the air.

3.4 Results

The results of the sensor readings during the four 55-minutes experiments are given in this section. The time period corresponding to each of the three combustion phases are : from 5 to 18 minutes at 3 m, from 23 to 36 minutes at 2 m and from 41 to 54 minutes at 1 m. For ease of understanding, these burning periods, between the fire source and sensor nodes, at distances of 3 m, 2 m and 1 m are called **D3**, **D2** and **D1**, respectively.

For a better visualisation, three colours are used to distinguish the different events occurring during the 55-minutes experiments. This legend is presented in Figure 3.5 and applies to all graphs in this work. In addition, all the graphs show four curves, each corresponding to the combustion of 3x30grams of a fuel during a 55-minute experiment: rubber in blue, plastic in orange, wood in green and paper in red. The dotted markers on each curve represent the transition between the dominant flaming and the dominant smouldering phases of fire. These markers indicate that the flaming fire has ended and only smoke is visible. Their positions were determined based on video footage from the experiments.

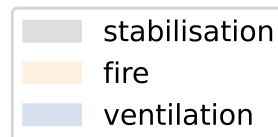


Figure 3.5: Graph's Legend of the coloured windows : Stabilisation of the sensors during 5 minutes (silver), Fire window during 13 minutes (light orange), Ventilation window during 5 minutes (light blue)

Furthermore, in order to reduce noise and get rid of data spikes, all captured signals were processed using a Butterworth filter (order 5, cutoff frequency of 0.3).

3.4.1 Time Analysis

The data collected by the sensor nodes for different types of fires (e.g., rubber fire, plastic fire, paper fire and wood fire), corresponding to emissions of CO₂, PM and VOC, are presented below in Figures 3.6, 3.7 and 3.8. Each of these figures show two graphs, for 1m and 2m of height respectively, presenting compound variation over time during three combustion periods, with ventilation and stabilisation periods in between. In order to analyse the data for early fire detection, the focus is set on several aspects. First by identifying if there are specific patterns or trends in gas emissions (CO₂, PM, VOC index) that occur at the early stages of a fire. Then by analysing the average values and variations in gas readings at the early stages.

1. CO₂ concentration over time

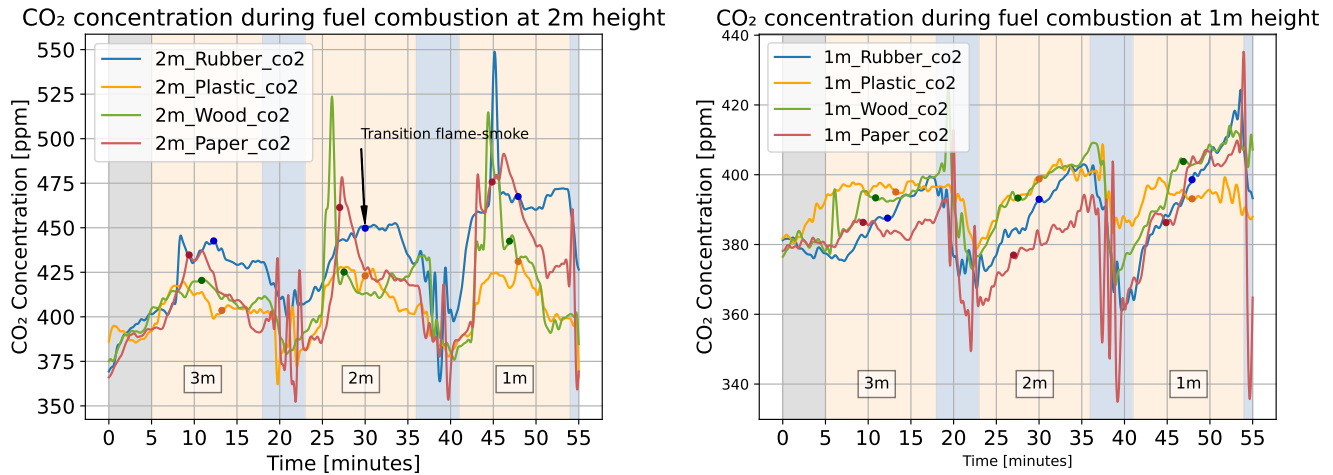


Figure 3.6: CO₂ concentration measured by sensor nodes during fuel combustion of Rubber, Plastic, Wood and Paper at 2m height (left) and 1m height(right).

General trend First of all a general trend is noticeable in the curves of Figure 3.6, for all type of fuels, whether during D3, D2 or D1 at 1m or 2m height, an increase in CO₂ concentration is noticed when fires are ignited, as well as a significant decrease during the aeration phases. CO₂ levels under normal conditions are stabilised to ± 380 ppm. Overall rubber is emitting more CO₂ than the other fuels, followed by paper and wood and finally plastic that stabilises fast and decreases gradually. CO₂ concentrations are generally higher at the 2m height compared to 1m height, suggesting that this gas accumulate upwards during combustion. In addition, peaks concentrations are higher and raise sharper during D1 compared to D3. The proximity to the fire source significantly impacts the CO₂ concentration, with closer distance resulting in higher concentration for 1m and 2m height. During ventilation phases, spikes are observed, indicating rapid fluctuations as the air is refreshed.

Observation at 2m At a height of 2 meters, the concentration increase more quickly and the rise is significantly sharper, approximately 2-3 minutes after the fire starts, then stabilises. For paper and rubber, there is a sharp raise with peaks reaching ± 525 -550 ppm, followed by stabilisation and a subsequent decrease after several minutes. For plastic, the concentration also increases, but with less intensity, and then gradually decreases. For wood, on the other hand, the concentration increases after 3-4 minutes from the start of the fire, during D2 and D1, before

decreasing.

Observation at 1m At a height of 1 meter, the fuel concentrations continue to rise gradually throughout the entire duration of the fire test, without reaching a peak by the end. Using this signature could be a good way to recognise a fire but over a very long time range (13 minutes), meaning the fire can already propagate through the combustible around.

Transition from dominant flame to dominant smouldering fire (dotted marker) At 2 meters height, CO₂ levels have stabilised after 7-8 minutes, indicating the absence of active flaming combustion. The stabilisation followed by a decrease in CO₂ concentration marks the transition to the smouldering phase, during which less CO₂ is produced compared to the flaming phase. During the transition from flaming to smouldering, the sensor at 1 meter still detects certain values. This indicates that CO₂, which was produced during the flaming phase, is now moving downwards and reaching the sensor positioned at this height.

It suggests that the behaviour of CO₂, emitted during the flaming phase and initially rising due to the thermal buoyancy of the flames, eventually descends as the flames subside. This downward movement of CO₂ is detected by the sensor at 1 meter, suggesting that the combustion gases are cooling and settling closer to the ground level as the fire transitions to the smouldering phase. This phenomenon is a key for understanding the dispersion and behaviour of CO₂ in different phases of a fire.

2. PM mass concentration over time

Surprising results were obtained for particulate matter, as the same data were measured for particles of different aerodynamic diameters (PM1, PM2.5, PM4 and PM10) throughout the entire duration of the experiments. A single graph is therefore presented for these measurements in figure 3.7.

As this result was obtained for four sensors tested under the same conditions, one might think that the error stems from the way the raw signals are processed in the sensor node prototype. However, the SEK-SensorBridge, an evaluation tool supplied by Sensirion, was used as a second step to determine whether the way of processing the data might be erroneous. The results (see A.3) for a paper fire emitting ash and black smoke were the same as those obtained in the experiments, confirming that data processing is therefore not at issue.

This could suggest that in these fire tests, the particles were mostly small, 0.3 — 1 μm , which would still be surprising since almost the same measurements are obtained. Another investigation for future works would be to measure these particles with sensors from other suppliers, to obtain a better view of particle

matter as early indicators of fire. For the purposes of this work, no more distinction will be made between the different size range of particles, and they will be referred to solely as PM.

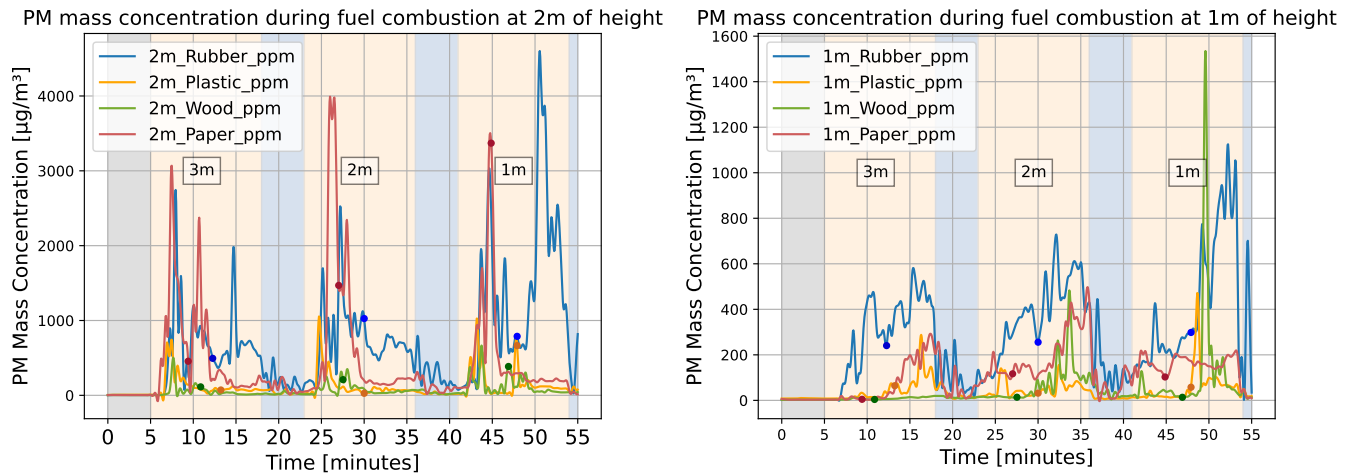


Figure 3.7: PM mass concentration measured by sensor nodes during fuel combustion of Rubber, Plastic, Wood and Paper at 2m height (left) and 1m height(right).

General trend As expected, particulate matter emissions are observed during the fire events across all fuel types, regardless of whether the measurements were taken at 1m or 2m heights during D3, D2, or D1. Under normal condition in the warehouse, PM levels are close to 0-10 $\mu\text{g}/\text{m}^3$. PM mass concentrations are generally higher at the 2m height compared to 1m. Notably, at 2m, there is a sharp and immediate increase in PM concentration as the fire starts for all fuels, whereas at 1m, the increase in mass concentration occurs a few minutes later, except for rubber, which is detected earlier.

At 1m, the rise in PM concentration occurs later, while at 2m, it occurs much earlier for all fuels. Significantly more PM is detected at 2m compared to 1m, with peaks for rubber and paper exceeding 3000 $\mu\text{g}/\text{m}^3$, whereas the maximum concentration at 1m does not exceed 1600 $\mu\text{g}/\text{m}^3$.

Observation at 2m height At a height of 2m, the proximity to the fire source does not have a significant impact as it was the case for CO_2 concentration. PM emissions are detected within a similar range for D1, D2, and D3 across all materials. The increase in PM concentration is sharp and occurs very quickly, typically within 1 to 2 minutes after the fire starts.

Paper and rubber produce substantially larger quantities of PM at the early stages of combustion, with a rapid and pronounced peak occurring just 1 to 2 minutes after ignition. For instance, PM levels for rubber and paper quickly reach peaks around $3000 \mu\text{g m}^{-3}$, even for D3, indicating that large amounts of PM are emitted almost immediately after the fire begins. In contrast, plastic and wood produce lower quantities of PM compared to paper and rubber. Although PM emissions for plastic and wood also occur rapidly within 1-2 minutes of ignition, the peaks are lower, around $500\text{-}600 \mu\text{g m}^{-3}$. In addition distance has little effect on the measurement of PM for plastic or wood at 2 m, as their emissions remain relatively constant.

These PM peaks decrease just as quickly as they rise, with emissions gradually declining after 5-6 minutes. Despite this decrease, PM levels remain elevated compared to normal conditions, where concentrations range between $0\text{-}10 \mu\text{g m}^{-3}$.

Observation at 1m height

Detection of emissions occurs later at 1m, particularly for D3, where PM levels are detected around 8-9 minutes after the fire starts for all fuels, except for rubber, which is detected earlier. Distance has an influence in this case, as an increase in PM mass concentration from D3 to D1 is observed at 1m height, with significant peaks becoming higher as the fire approaches the sensor. A significant decrease in PM levels is also noted during the aeration phases.

The peaks at 1m height are significantly lower than those at 2m, with rubber reaching $600\text{-}1000 \mu\text{g m}^{-3}$ and paper and plastic ranging between $200\text{-}400 \mu\text{g m}^{-3}$. Wood does not show significant PM concentration peaks at 1m compared to 2m. The peak observed for wood in D1 is primarily due to the fire being directly beneath the sensor. Additionally, during the wood experiments, it was necessary to stir the wood chips to prevent surface-only carbonation, which sometimes led to forced combustion and the release of excessive smoke.

Transition from dominant flame to dominant smouldering fire (dotted marker) Initially, the particles rise upward before descending. During the transition from flame to smouldering fire, there is an increase in PM levels at 1m height, confirming that smoke contains a significant amount of particulate matter. This indicates that whether the fire is smouldering or flaming, it has a substantial impact on the behaviour of PM and the type of material being burned. PM remains suspended in the air for a long time, as evidenced by the high PM concentrations at 2m when the fire starts, and then gradually descend and reach the sensor node at 1m.

3. VOC index variation over time

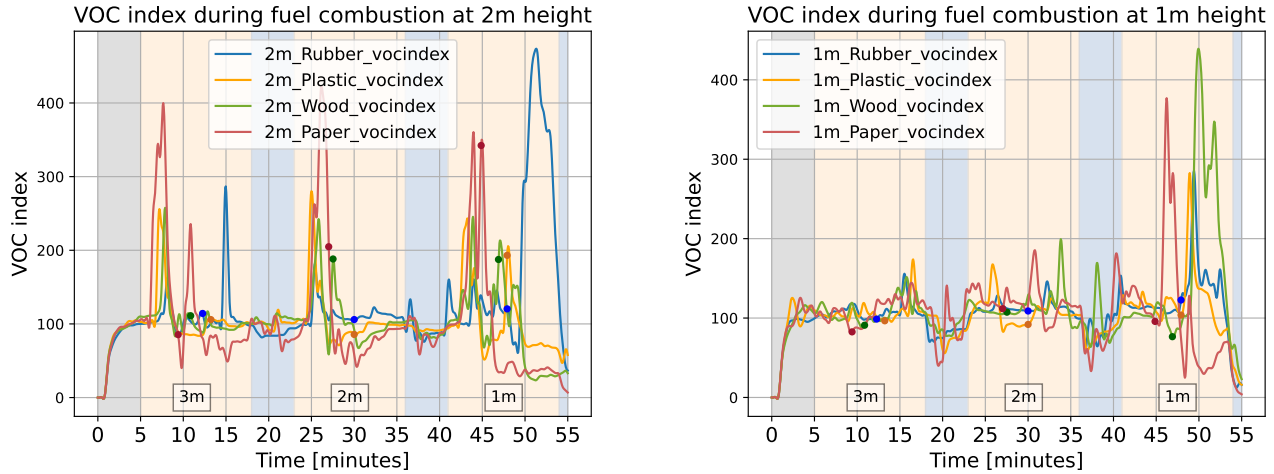


Figure 3.8: VOC index measured by sensor nodes during fuel combustion of Rubber, Plastic, Wood and Paper at 2m height (left) and 1m height(right).

General trend As observed in Figure 3.8, VOC levels are detected significantly higher at a height of 2m compared to 1m, except when the fire source is close to sensor nodes (D1). For all fuels, the rise in the VOC index indicates significant VOCs emissions during their combustion. Before the fire tests began, the VOC index stabilised at 100, indicating a normal average indoor gas composition, as mentioned in 2.1.

Observation at 2m When the fire starts, the sensor placed at 2m detects emissions almost immediately, within 1 to 2 minutes, with a distinct deviation from normal levels. Paper and rubber show higher VOC emissions compared to plastic and wood, with peaks reaching a VOC index of 400 for paper, 300-400 for rubber, and above 200 for both plastic and wood.

Observation at 1m At 1 meter, similarly to PM, the VOC index shows significant changes only after about 8 minutes. During D3 and D2, the VOC index remains below 200 for all fuels. During D1 the peaks are around 375 for paper and below 300 for plastic and rubber. For wood, however, there is a higher peak above 400, likely for the same reason observed with PM, i.e. when the wood chips were stirred,

leading to increased emissions.

Transition from dominant flame to dominant smouldering fire (dotted marker) At 2m, during the flaming phase, VOC levels initially rise and then decrease until the fire changes into a smouldering state, at which point VOC concentrations in the air increase again. This can be observed by the dotted points on the graphs, where VOC levels begin to rise after the transition to smouldering. However, at 1m, the behaviour is different. After the transition marked by the dotted point, VOC levels seem to increase, indicating that VOCs are moving downward rather than staying elevated.

4. Comparison between PM, CO₂ and VOC

The objective of this thesis is to determine whether early fire detection is possible using these fire emissions . As seen in Chapters 1, smoke and flames release significant amounts of PM, VOCs, and CO₂. This experiment showed that, when measurement is made at 2m height, there is a noticeable increase in fluctuations at the start of a fire for these three indicators. Time analysis showed that after 2 - 3 minutes, there is a clear rise in concentration levels for CO₂ as well as a rise in PM emissions in the first minute, and a significant increase in the VOC index in the 1 - 2 minutes interval. Additionally, as the fire source moved closer to sensor nodes, the peaks were higher and the values increased more rapidly and sharply.

5. NO_x, Temperature and Humidity variation over time

Nitrogen oxides

This experiment shows that it is difficult to obtain results for NO_x through combustion. The data graph for NO_x can be found in Appendix A in Figure A.1. Results are encountered however when the sensor is operating under a closed environment, as a glass bell. A demonstration presented as well in Appendix A, shows results when igniting a flame using such a confined environment.

Temperature and Humidity

The temperature and humidity readings are not subject to major variation. The experiments were conducted from 8am to 3pm. The temperature outside raised, slowly affecting the sensor readings. Temperature fluctuated between 20°C and 22.5°C, whether the sensor node was placed at a height of 1m or 2m. Humidity varied between 70%RH and 80%RH during the entire experience. The related graphs are presented in Appendix A.2.

These parameters measured with SEN55 will not be considered in the continuation of this work, since they do not vary according to fire tests, but according to the

atmosphere outside.

However the sensor SHT30, included in Sensirion SCD30 module along with the CO₂ sensor, shows measures of temperature with more accuracy and has a lower response time than the SHT4x included in SEN55 (Refereed in Table 2.1). During the data logging, because of memory issues on the boards, temperature and humidity were exclusively measured with SEN55 at 1m and 2m. These parameters, measure with SHT30, will be considered in the second part of this work in Chapter 5

3.4.2 Optimal Sensor Height

The results highlight the critical importance of sensor node positioning for the rapid detection of gas anomalies. The sensor node placed at 2 meters detected fire activity faster and with higher levels compared to the one at 1 meter. This is because the smoke tends to rise and accumulates upwards to reach the upper sensors more effectively. Time analyses of the data revealed that emissions reach the sensor nodes faster at 2 meters than at 1 meter. Additionally, concentrations accumulate more at higher levels, resulting in the sensor at 2 meters detecting significant changes in concentration sooner than the sensor at 1 meter. While the sensor at 2 meters has already registered a substantial change, the sensor at 1 meter is still gradually increasing, requiring more time to detect the fire event. At 1 meter, measurements of CO₂, PM, and VOCs are generally lower and arrive slower compared to those at 2 meters, across all distances (D3, D2, D1).

The main objective is early fire detection, which leads to choose a higher sensor placement for all the reasons discussed before. However, if the aim is to localise the fire source, it could be advantageous to position the sensors at different heights during real-time monitoring.

Furthermore, during ventilation phases, more peaks in VOC index are observed at a height of 1 meter compared to 2 meters. This indicates that the sensor at 1 meter height is more responsive to the mixing of ambient air from the warehouse with outside air, while the sensor at 2 meters does not show significant peaks. This provides additional support in favour of placing sensor nodes at a height of 2 meters.

Another discovery during the testing phases was the impact of ceiling presence. Tests with and without a ceiling showed that detection is better when a ceiling is present. The most effective configuration was with a ceiling and the sensor placed at the same height as the ceiling. This indicates that the closer the sensor is to the ceiling, the more efficiently it can detect fire. A limitation of this system is that if the roof is high and pointed, the smoke rises and does not easily reach the sensors if they are not placed at roof height. This was evident during the first and second

data logging of the controlled combustion experiments 3.2.2.

For safety and space reasons, this system has not been tested for sensor nodes placed more than 2 meters above ground level. It is suggested that the system would also work at higher heights, provided the sensor is placed at ceiling height.

Consequently, in the continuation of this work, the sensor nodes will be positioned at 2m from the ground.

3.5 Further analyses for Early fire detection

Further analyses are conducted in this section to better understand the behaviours and fluctuations in emissions during fires. This includes a comparison of emission distributions across different materials and a dynamic analysis of the rate of change in PM, VOC, and CO₂ for each material. Additionally, correlations between different gas readings are analysed to identify any combinations that may signal early fire stages. Since a height of 2 meters has proven to be the most effective for faster event detection, all subsequent analyses will focus on sensors positioned at this height from now. This decision is mainly based on time analysis and other results discussed below. However, the further analyses corresponding to 1-meter height are provided in Appendix B.

3.5.1 Distribution Analysis

Another observation during the burning experiments is that emissions levels vary significantly depending on the material. As discussed in the time analysis, rubber, paper, plastic and wood release varying amounts of CO₂, particulates, and VOCs. This variability makes detection more challenging when multiple materials are involved. Figures 3.9 and 3.10 show distributions of CO₂, PM and VOC emissions during fire events across the four materials.

For this analysis of emissions distribution during fire tests, the focus should primarily be on the upper whiskers and outliers in the box plots, as these represent the most significant emissions during combustion. The lower whiskers and lower outliers, on the other hand, indicate the ventilation phases between fire tests.

CO₂ box plots

Rubber generally emits more CO₂ than the other materials, with the highest median of 430ppm. It shows a wide range of emissions, including several outliers, indicating significant peaks during rubber combustion tests. Wood, exhibits the most outliers among the materials, suggesting that it produces high spikes in CO₂ emissions. In contrast, plastic shows the lowest median of CO₂ concentration, indicating that it emits less CO₂ compared to the other materials. Additionally, plastic has no outliers, and its upper whisker is relatively short, suggesting minimal spikes and a narrow range of CO₂ concentrations during the fire. Paper, on the other hand, has long upper whiskers corresponding to the flaming fire phase, during which its CO₂ emissions reach their peaks. The lower whiskers correspond to the decreasing periods during ventilation.

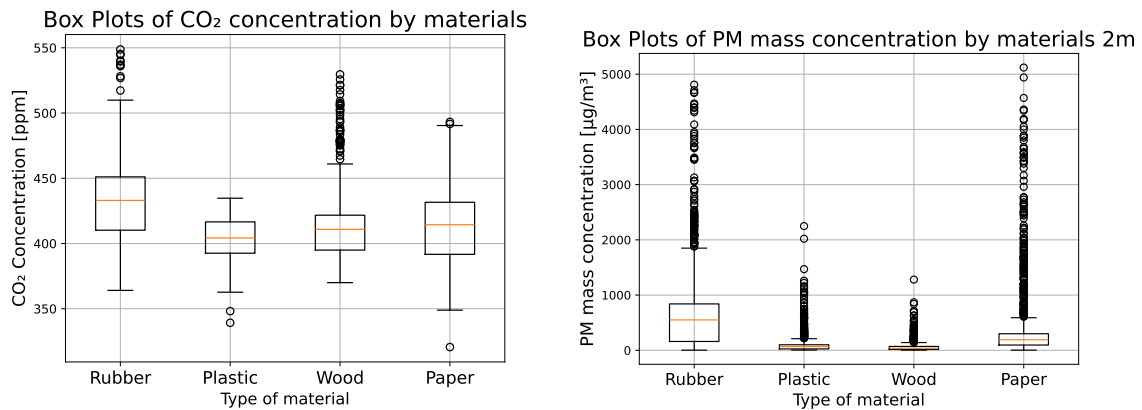


Figure 3.9: Box Plots of CO₂ concentration (left) and PM mass concentration (right), by materials at 2m Height.

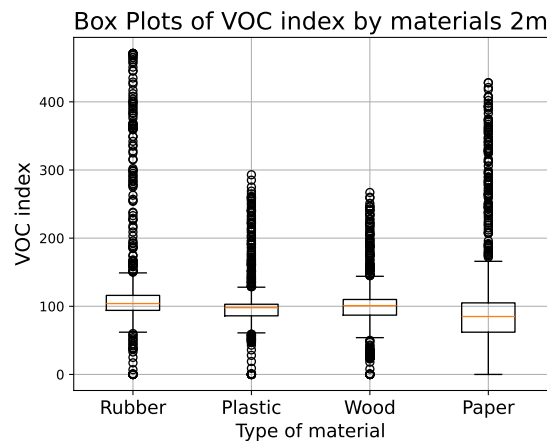


Figure 3.10: Box Plots of VOC index concentration and PM mass concentration, by materials at 2m Height.

PM box plots

Rubber shows the highest median PM level, indicating it generally emits more PM than the other materials. However, paper show the most outliers, suggesting it burns more irregularly, with occasional high spikes in emissions. Plastic and wood exhibit lowest median PM levels, indicating they generally emit less PM than the others. Despite this, wood and plastic still have outliers that exceed the typical PM range, indicating occasional spikes in their emissions.

Rubber has the longest whiskers, indicating a greater range of PM levels, followed by paper. In contrast, plastic and wood have shorter whiskers, suggesting more

consistent PM emissions. All materials have several outliers with PM levels significantly higher than the upper whisker, indicating occasional large spikes in emissions. Rubber and paper's outliers are particularly extreme, far exceeding the typical PM range, indicating peaks in combustion events that lead to high emissions.

Specifically, rubber has a median PM level around $600 \mu\text{g m}^{-3}$, with outliers corresponding to high peaks of PM emissions above 2000. Paper, after rubber, shows the most PM emissions, with a median around 200 during all three periods of combustion and outliers above 1000, corresponding to peak emissions during the fire. Plastic shows less PM emissions overall but still has outliers ranging between 200 and 1000. Wood emits the least PM during combustion, with outliers ranging between 100 and just under 1000.

An important observation to bear in mind is that PM emissions consistently exceed $900 \mu\text{g m}^{-3}$ for all fuels at one moment of the fire.

VOC index box plots

These box plots illustrate the distribution of the VOC index during the combustion of materials. The median for all fuels is around 100 (except for plastic, which has a slightly lower median), indicating baseline conditions without fire. The upper whiskers and outliers represent VOC levels during fire events, while the lower whiskers and outliers reflect the noticeable decrease in VOC index, under 100, following the peaks during combustion.

All materials show several outliers with VOC levels significantly above the upper whisker, indicating occasional large spikes in emissions. Rubber and paper have particularly extreme outliers, far exceeding the typical VOC range, indicating that their combustion leads to more significant and irregular emissions compared to other materials. Paper has a maximum whisker and numerous outliers reaching up to 400, suggesting that the VOC index fluctuates widely during combustion, with substantial peaks at certain points. Plastic and wood present relatively similar distributions, with slightly fewer outliers for plastic than wood. However, both materials still show significant VOC emissions during burning peaks.

An important observation to bear in mind is that VOC emissions exceed an index of 200 for all fuels during the fire.

3.5.2 Rate of change analysis

By analysing the rate of change in concentration rather than absolute concentrations, it is possible to detect early signs of fire regardless of the material being burned, even if the absolute levels are low due to the type of material. Small, rapid changes in CO₂, VOCs, or PM levels can trigger alerts earlier than waiting for concentrations to reach a certain threshold. This is particularly useful in environments with varying baseline levels of these gases or particulates, where absolute concentration thresholds might be less effective. Gaining a dynamic understanding of how quickly emissions are released can be highly valuable for studying early fire emissions and it is suited for real-time monitoring, allowing for continuous assessment of fire risk.

In the context of this work, the rate of change per unit time refers to the difference between the current concentration emission level and the preceding one. This rate is measured either per time sampling interval (**Ts**) which in the experiments is 3 seconds, or per 3 minutes or 1 minute. Figures 3.11, 3.12 and 3.13 show the rate of change in CO₂ concentration, PM mass concentration, and VOC index, respectively. Each Figure is associated to a specific indicator — CO₂, PM or VOCs — and include eight graphs, with two graphs by materials. For each material, the top graph displays the indicator's emission levels over time, while the below graph illustrates the rate of change in emission levels per unit of time.

Since different values are obtained for the different combustion periods (D3, D2, and D1), to simplify and clarify the analysis, only one value per time unit will be provided in the analyses, for each material. It will correspond to the minimum peak observed across all combustion periods, during the early stage of fire, specifically within the first minutes after the fire starts.

Rate of change in CO₂ concentration As observed in Figure 3.11, CO₂ takes some time to show a noticeable change in concentration due to fire. Since no significant rate of change per sampling interval (**Ts**) is observed (bright blue curves), considering the rate of change per minute (red curves) or per 3 minutes (violet curves) is more relevant. Comparing the current concentration to the concentration one minute earlier already provides more meaningful results than per **Ts**, making it effective for detecting changes in concentration for early fire detection. Comparing the current concentration to the concentration from 3 minutes earlier shows even greater differences.

As mentioned, the analysis focuses on rate of changes corresponding to the peaks at early stage. For rubber and paper, the change in concentration when fire starts is around 20 ppm per minute, while it increases to approximately 40 ppm per 3 minutes. For wood, the change in concentration is about 80 ppm per minute and

exceeds 100 ppm per 3 minutes. For plastic, the 3-minute difference shows the most significant changes in concentration, with 30 ppm per 3 minutes, compared to only 10 ppm per minute.

For all materials, the rate of change in CO₂ concentration yields acceptable results, making this approach relevant for early fire detection. Therefore, this dynamic approach is more appropriate for this gas than relying on absolute thresholds.

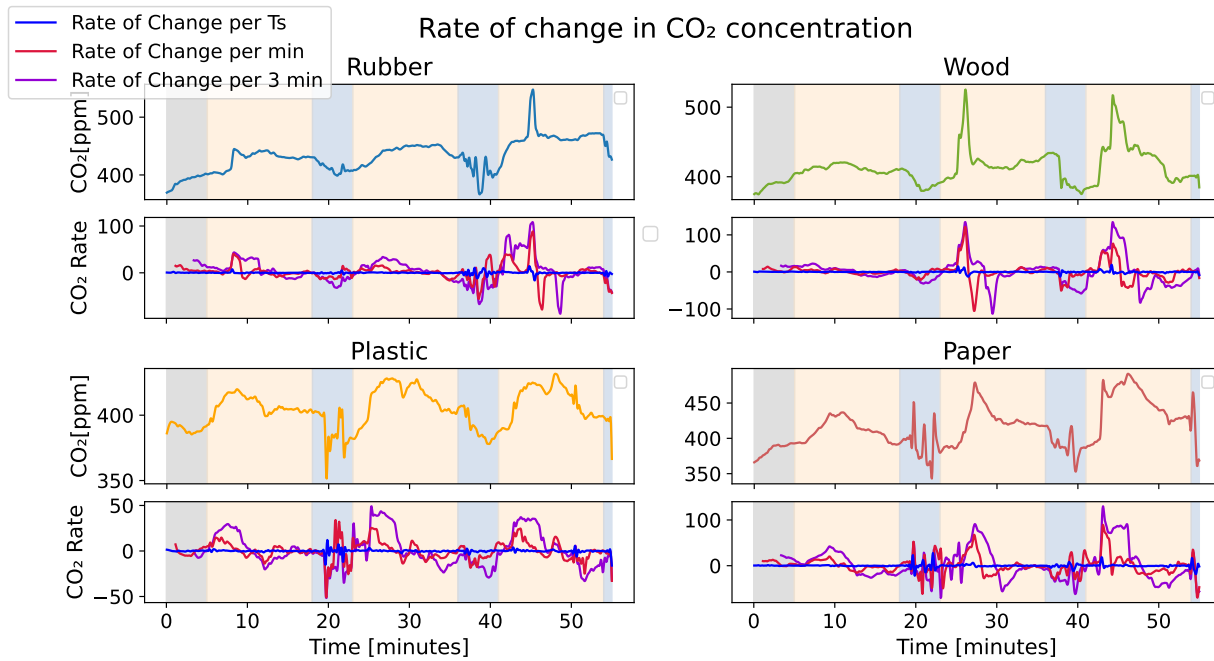


Figure 3.11: Rate of change in CO₂ concentration by materials at 2m Height. Ts stands for Time sampling (3,15 seconds during experiments)

Rate of change in PM mass concentration Figure 3.12 shows the change in PM mass concentration per time sampling interval. The general trend indicates that PM mass concentration not only changes significantly faster than CO₂ concentration but also reaches substantial levels, for all materials.

This observation further confirms that PM is a robust indicator for early fire detection, as it is detected almost immediately when a fire starts,

Rate of change of VOC index VOC index being already an indicator of quality air, it is still interesting to observe how fast this indicator is varying when being subject to fire events. When looking at Figure 3.13, the rate of change per Ts does not lead to significant results. However, when comparing the current VOC index

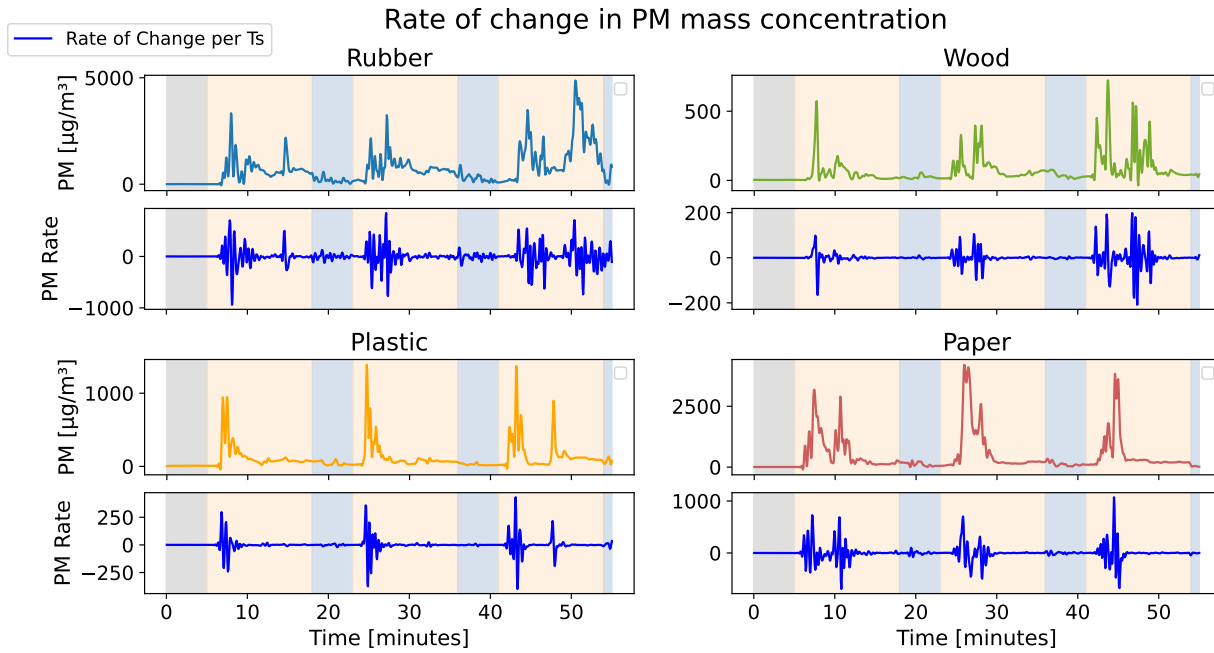


Figure 3.12: Rate of change in PM mass concentration by materials at 2m Height.

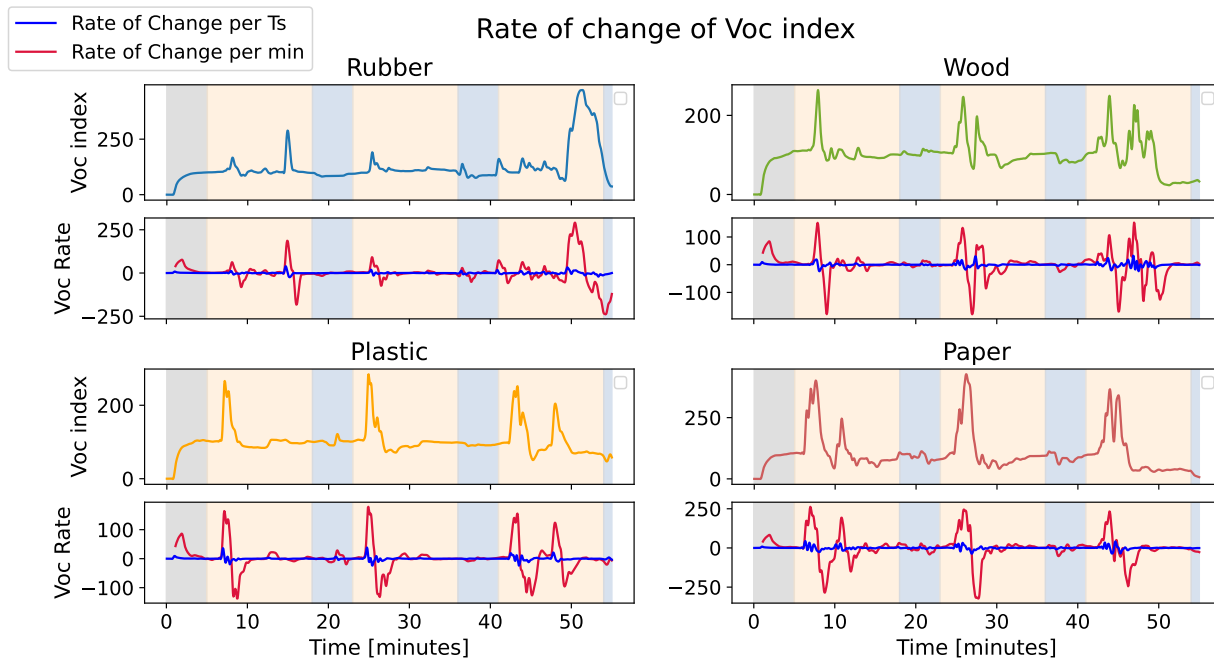


Figure 3.13: Rate of change of VOC index by materials at 2m Height.

to the value from one minute earlier, more substantial changes in the index are detected.

Focusing on the rate of change corresponding to the peaks during the early stages of the fire, the VOC index rate of change per minute is above 100 for plastic and wood, while for paper, this rate is slightly lower than 250. For rubber, the rate of change per minute at early stage is around 60.

3.5.3 Correlation Analysis

Correlations between the different readings is investigated to identify any combination of gases that together indicate early fire stages. Tables 3.3, 3.5, 3.4 and 3.6 present the correlation matrices between CO₂, PM and VOC for Rubber, Plastic, Wood and Paper, respectively.

	PM	CO ₂	VOC
PM	1.000000	0.544879	0.703715
CO ₂	0.544879	1.000000	0.457383
VOC	0.703715	0.457383	1.000000

Table 3.3: **Rubber** Correlation Matrix between PM, CO₂, and VOC

	PM	CO ₂	VOC
PM	1.000000	0.283869	0.445278
CO ₂	0.283869	1.000000	0.456067
VOC	0.445278	0.456067	1.000000

Table 3.4: **Wood** Correlation Matrix between PM, CO₂, and VOC

	PM	CO ₂	VOC
PM	1.000000	0.235554	0.601972
CO ₂	0.235554	1.000000	0.179713
VOC	0.601972	0.179713	1.000000

Table 3.5: **Plastic** Correlation Matrix between PM, CO₂, and VOC

	PM	CO ₂	VOC
PM	1.000000	0.351022	0.722521
CO ₂	0.351022	1.000000	0.114718
VOC	0.722521	0.114718	1.000000

Table 3.6: **Paper** Correlation Matrix between PM, CO₂, and VOC

When comparing the correlation matrices between different fuels, it appears that the correlations between PM, CO₂, and VOCs vary depending on the material. PM and CO₂ show little to no correlation, with only a slight correlation observed for rubber. This suggests that these indicators do not have a strong relationship and do not tend to increase together during combustion. In contrast, PM and VOCs are more correlated for most fuels, except for wood. Correlation coefficients are 0.7 for rubber, 0.72 for paper, and 0.6 for plastic, indicating a moderate relationship

where emissions tend to increase together during combustion, as observed in time analysis. On the other hand, VOCs and CO₂ show no correlation for plastic and paper. Even though there is a slightly higher correlation for rubber and wood, with coefficients around 0.45, this still does not indicate a strong positive relationship. Overall, these findings suggest that the relationships between these indicators are generally weak, and their emissions do not consistently increase together during combustion, except for PM and VOCs, which show a moderate positive correlation for three of the four materials.

3.5.4 Conclusion

The comparative analysis of the distribution of emission levels for PM, CO₂, and VOCs revealed significant variations in emissions across different materials.

The rate of change analysis indicates that, for each material, the change in PM concentration occurs significantly faster, within the time sampling interval, compared to VOC levels and CO₂ concentration, which take approximately 1 minute and 3 minutes, respectively, to be properly detected.

These results align with findings from the literature, demonstrating the effectiveness of monitoring VOCs, PM, and CO₂ for early-stage fire detection, as relatively fast emissions of these indicators were observed during testing. However, it is essential to consider various materials during studies, as they release different quantities of emissions.

The correlation analysis showed that the relationships between these indicators vary depending on material. However PM and VOCs show a moderated correlation between rubber, plastic and paper, which indicates that emissions tend to increase together during combustion, as observed in time analysis. Despite that, nothing definitive can be drawn regarding the correlation between these indicators and more data collection during fire combustion is needed to arrive to robust conclusion.

These analyses are essential for identifying anomalies caused by fire, as they identified patterns and behaviours of CO₂, PM and VOCs emissions, at early fire stages. They will serve as a foundational basis for the subsequent chapters. It is now necessary to establish baseline emission levels under normal environmental conditions, without any fire event. Additionally, to test whether this multi-sensor system can enhance the detection of fire at its early stage, a real-time monitoring system is developed in Chapter 5.

Chapter 4

Fundamentals for the real-time monitoring system

Another aspect of this work involves using real-time monitoring for early fire detection. Chapters 4 and 5 are devoted to assessing the effectiveness of the multi-sensor system in enhancing early fire detection through real-time monitoring. For ease of monitoring, a real-time monitoring system based on the MQTT protocol is developed in Chapter 5. This communication protocol is detailed in 4.1. The flow-based programming tool Node-RED, also used for the implementation of the system, is explained in 4.2.

4.1 MQTT communication protocol

Message Queuing Telemetry Transport (MQTT) [37, 38, 39, 40] is a lightweight publisher/subscriber application-layer protocol used in the scope of the Internet-of-Things (IoT) and suitable for resource-constrained embedded systems. The protocol design principles are to minimise network bandwidths and device resource requirements while also attempting to ensure reliability and some degree of assurance of delivery. MQTT operates at the application layer of the Transmission Control Protocol/Internet Protocol (TCP/IP) model and uses port 1883.

MQTT defines the messaging format and rules for communication, while TCP/IP provides the underlying framework for routing and delivering MQTT messages between devices connected to the network. In this work, the underlying network over which MQTT will operate is Wi-Fi (IEEE 802.11 Standard). The Wi-Fi network provides available means of connecting devices to the internet and facilitates the transmission of messages between devices and the broker, enabling real-time data exchange. Figure 4.1 shows the layers of the TCP/IP model related to the IoT system standards.

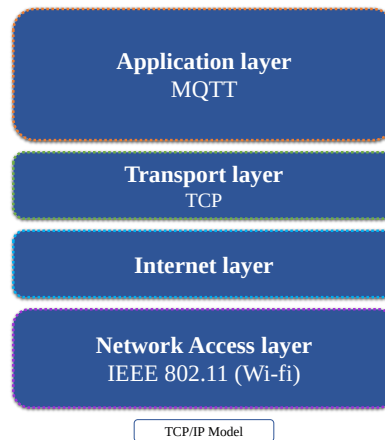


Figure 4.1: TCP/IP Model.

The MQTT architecture comprises a broker and end nodes designated as clients connected to the broker. Clients can be data sources (publishers), data consumers (subscribers), or both. Publishers publish certain data as a message under a specific topic. Any client interested in receiving updates on a given topic have to first register as subscriber of such a topic. All the data transfer and communication is performed through the broker, so that clients interact only with the broker. When a client publishes a message, the broker receives it, identifies the corresponding topic and the list of subscribers to finally forward the publisher message to each one of them. Hence data addressing is performed via the concept of topics. Topics are coded in MQTT messages and are structured hierarchically, in a way that resembles folders and files in a file system (e.g: sensors/ArduinoNano1/temperature) [38].

Many MQTT local or public brokers exist. The presented system in this work will use Eclipse Mosquitto™ [41], an open source MQTT message broker that implements the MQTT protocol. Mosquitto is lightweight and is suitable for use on all devices from low power single board computers to full servers.

MQTT provides three Quality of Service (QoS) levels to ensure reliable message delivery between publishers and subscribers:

QoS 0 (deliver at most once): Messages are sent once without acknowledgement, so delivery is not guaranteed, and message loss is possible.

QoS 1 (deliver at least once): Ensures that a message is delivered at least once to its receiver, but duplicates can occur due to retransmissions, avoiding message loss.

QoS 2 (deliver exactly once): Guarantees that each message is received exactly

once, with no loss or duplicates, making it the most reliable but also the most resource-intensive and the slowest.

The complexity and latency increase from QoS 0 to QoS 2. The QoS level of each link (publisher-broker and broker-subscriber) is set independently.

Another feature is the Keepalive parameter. Once the connection is established, if the broker does not receive any packets from the client within 1.5 times the Keepalive time, it assumes there is an issue with the connection and will disconnect from the client.

4.2 Node-RED

Node-RED is a flow-based programming tool [42]. Once developed by IBM's Emerging Technology Services team, it is now a part of the OpenJS Foundation. This tool provides a browser-based flow editor, which is used to create JavaScript functions. This tool makes it easy to wire together flows using the wide range of nodes in the provided palette. Node-RED consists of a Node.js based runtime at which a web browser points to access the flow editor. The application is then deployed back to the runtime where it is run. The platform offers many programmed capabilities, including MQTT functionalities.

In this work, the platform is used to connect MQTT subscriber clients to the broker as seen in the Chapter 5.

Chapter 5

Validation of early fire indicators through real-time monitoring

In this chapter, a second experience is carried out to evaluate whether the studied indicators can enhance early fire detection through real-time monitoring. The goal is to determine if the multi-sensor system is effective under real-life conditions in a warehouse setting. The experience involves (1) determining the typical baseline readings of CO₂, PM and VOCs under normal environmental conditions, in Section 5.2. (2) In Section 5.3, the response of the system to a series of fires involving different materials is tested and compared to the response of conventional smoke detectors, using simple fire detection rules based on the analyses of Chapter 3.

5.1 Proposed methodology

The proposed fire detection system consists in a real time monitoring system, using the same sensor nodes as in the first experience. In order to transmit data to the server, the fire alert system integrates the MQTT publisher-subscriber push architecture (see 4.1). In this work *Eclipse Mosquitto* is the chosen broker using MQTT protocol, installed on a Raspberry Pi 4. The sensor nodes act as publisher clients and publish messages, containing measured data, periodically via topics. The subscriber clients are implemented as "MQTT Input Nodes" within Node-RED, an IoT integration platform that is installed on a computer (see 4.2). The MQTT Input Nodes connect to the broker and subscribe to the matching topics, in order to receive messages published from the sensor nodes. Once being powered by a power bank, the sensor nodes establish a connection to Wi-Fi and the broker. Once connected, they begin reading and transmitting their data every 3 seconds. The configuration chain is illustrated in Figure 5.1.

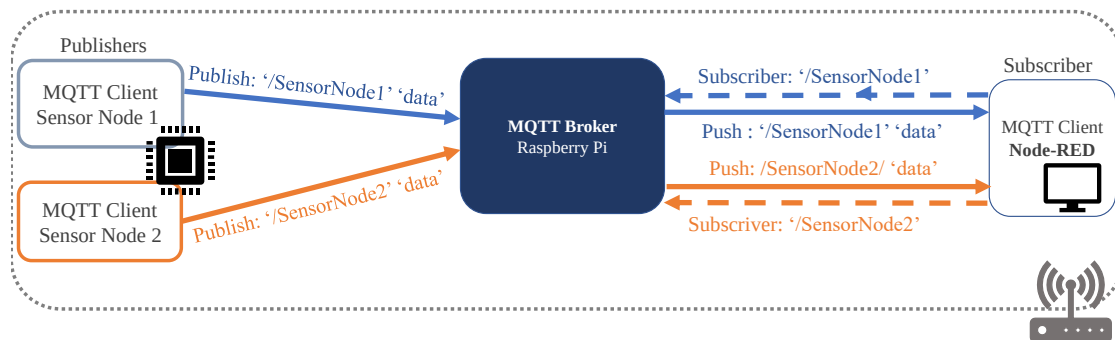


Figure 5.1: MQTT-based RT system working chain

5.2 Baseline emission levels under environmental conditions

The first step to enable fire detection is understanding the environment and identify the typical baseline levels of CO₂, VOC, PM in the environment under normal conditions, i.e. without fire. The environmental variability has to be considered by observing how these baseline levels fluctuate naturally due to factors like ventilation, human activity, or external weather conditions. To this end, data were gathered from the environment where the sensors are deployed for experiments, using the MQTT-based RT system.

5.2.1 Experimental Set up

The same experimental room was used, with some adjustments by setting up the two sensors nodes at 2m height from the ground, facing each other and distanced from 3 meters. These data were gathered by the two sensors during 10 hours, from 1pm to 11pm. The overhead door of the warehouse was closed during the measurements to avoid any disturbance coming from outside. During the data collection, there was human traffic in the room and little ventilation through the roof. This data collection was carried out on a warm day, with an average temperature of 26.7°C and an average relative humidity of 59% (see Table 5.1). Figure 5.2 shows the distribution of CO₂, PM, VOCs, temperature and humidity, over 10 hours. The Node-Red flow is configured to receive messages containing data from sensor nodes through MQTT. These data are displayed on the dashboard of Node-Red and stored in local files.

5.2.2 Results

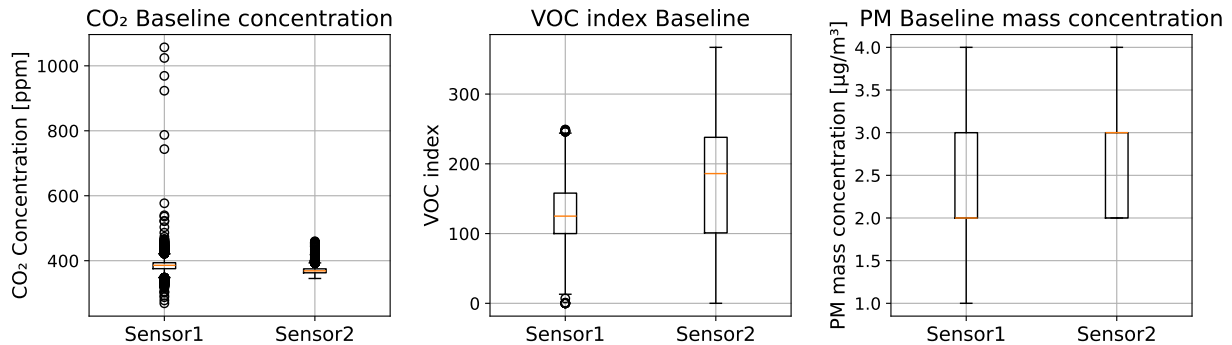


Figure 5.2: Baseline levels distribution of CO₂ concentration, PM mass concentration and VOC index, over 10 hours, for Sensor nodes 1 and 2.

The typical CO₂ concentration in the warehouse is a little bit under 400 ppm, with Sensor node 1 showing a little more variability in readings than Sensor node 2. Even though they were placed under the same conditions, the two VOC sensors show differences in their readings, with a VOC index median around 130 for Sensor 1 and 180 for sensor 2. Even in the same room and placed 3 meter from each other, small environmental differences, such as air flow, slight differences in humidity or temperature gradients can affect sensors differently. As a result, one sensor may have been exposed to slightly different conditions, with VOC source or airflow, and recorded higher levels than the other.

Typical levels for PM are around 2 and 3 $\mu\text{g m}^{-3}$, indicating low levels of airborne particles under normal conditions.

Table 5.1 summarises the statistics based on the combined data from the two sensors gathered.

Statistic	CO ₂ [ppm]	VOC index	PM [$\mu\text{g m}^{-3}$]	T [°C]	RH [%]
Mean	378.43	150.43	2.44	26.73	59.06
Median	375.17	138.00	2.00	27.04	58.99
Std	20.60	68.47	0.51	1.16	5.05
Min	268.80	0.00	1.00	23.33	51.01
Max	1056.89	367.00	4.00	28.40	69.70

Table 5.1: Summary statistics of baseline emissions for both sensor nodes 1 and 2.

5.3 Multi-sensors based fire detection

Based on the results of fire behaviours and anomalies identified during fire tests in the first experiment (Chapter 3), along with the baseline emission levels under normal conditions (Section 5.2), a prototype for early fire detection can be tested. The aim is not to develop a flawless detection rule, but to explore the enhancement of early fire detection through real-time monitoring and multi-sensor integration. In this final experiment, the focus is on validating whether the multi-sensor system can improve fire detection compared to traditional smoke detectors and assessing the ability of this sensor array to detect fires at an early stage. The system's response to a series of fires involving different materials is tested and compared to the response of conventional smoke detectors, using a straightforward fire detection rule.

5.3.1 Experimental Set up

Two sensor nodes were disposed in the experimental room at 2m height from the ground, positioned 4 meters apart and facing each other. One node was installed near the overhead door of the warehouse, while the other was placed directly opposite the first, at a distance of 4 meters. The experiments consist of 4 fires controlled by the two sensor nodes. Fuels (rubber, plastic, wood and paper) were burned at a distance of 2.5 meters from the first node and 1.5 meters from the second. The entire experience spanned approximately 80 minutes, starting with a 14 minutes stabilisation period. Each of the combustion lasted 10 minutes, followed by a 6-minute ventilation phase. The procedure related to the burning and ventilation processes are provided in the first experience, found in subsection 3.2.1.

This time two traditional photoelectric detectors were used to compare their response times with those of the multi-sensor system. The smoke detectors selected are standard models commonly found in stores : Alecto SA-29/5 and brennenstuhl RM C 9010. They were placed on the same plate as the sensor nodes. The experience is illustrated in Figure 5.3.

The Node-Red flow is configured to receive data from sensor nodes through MQTT. Once the data is received, it enters a function node that checks the predefined rules, detailed in subsection 5.3. If all condition of the rule are satisfied, a message is displayed on the dashboard and the alarm's timestamp, along with the fire indicators values are stored in local files. The flexibility of Node-Red is that multiple nodes can be connected, making it easy to implement and set up rules in the flow.

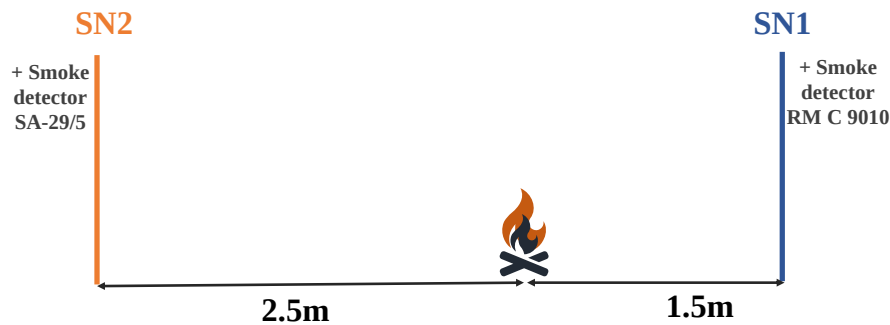


Figure 5.3: Experimental Set up: sensor nodes SN1 and SN2 placed at 1.5m and 2.5m, respectively, from the fire source.

5.3.2 Multi-sensors fusion thresholds

The analyses from Section 3.5 assist in establishing threshold rules for configuring the fire alarm system. These data are used to examine how gas levels fluctuate during a fire compared to normal conditions.

In the early stages of a fire, the CO_2 concentration tends to rise gradually, and for some materials, like wood and plastic, the increase is less significant compared to the others. Therefore, instead of using an absolute threshold, the dynamic approach based on CO_2 concentration changes is used. Comparing current concentrations with the one from 3 minutes earlier allows to set an upper rate limit. However, a lot can happen within 3 minutes, such as and airflow changes; interfering and making the concentration rise. Hence in order to reduce the time gap between the values being compared, a 1-minute comparison is also integrated in the Node-Red flow, even though it may not provide as much insight into rate analysis. A limit of 50 ppm was chosen for the 3-minute rule, while a limit of 20 ppm was set for the 1-minute rule.

For particulate matter, with baselines typically ranging between $2\text{--}3\text{ }\mu\text{g m}^{-3}$, rate analysis revealed that PM levels increase and fluctuate very rapidly. Time and distribution analyses showed that PM levels experience significant spikes within very short intervals but remain airborne for extended periods with substantial mass concentration. Therefore, a simple absolute threshold for PM may be sufficient for the experimental early fire detection rules. Rather than focusing on peaks, which occur faster than those of VOC and CO_2 and vary in intensity depending on the material, the threshold is based on distribution analysis. For all fuel types, many outliers corresponding to PM emissions during the early stages of a fire were above $1000\text{ }\mu\text{g m}^{-3}$, except in the case of wood. To ensure robust detection, an absolute threshold of $1100\text{ }\mu\text{g m}^{-3}$ has been set, including an additional 10% margin for

safety.

For volatile organic compounds, the VOC index is already an air quality indicator, with a baseline of 100 as defined by the supplier, but in the warehouse, it can naturally vary around 100-150. During time and distribution analysis, it was observed that in the early stages of a fire (within 1-2 minutes) and at every distance from the fire source (D3, D2 and D1), the sensor nodes recorded VOC index readings above 200 for all materials. To ensure robust detection and avoid interference from typical VOC levels in the warehouse, a threshold of 220 has been set.

Relying solely on the rate of change for PM, VOC, and CO₂ would not be appropriate because the increases of these indicators are not synchronised. When CO₂ levels are beginning to rise significantly, PM levels are already decreasing, although PM remains in the air for an extended period with concentrations still far above baseline levels. VOC levels increase more slowly than PM but faster than CO₂. By the time VOC levels reach their peak and start to decline, CO₂ levels only begin to rise.

The fire detection system prototype employs two specific rules, outlines below, to assess whether the studied indicators, support by real-time monitoring, can enhance early fire detection. Both rules share the same thresholds for PM and VOCs, i.e. an absolute threshold where PM exceeds 1100 and an absolute threshold where the VOC index exceeds 220. The distinction lies when considering of CO₂ concentration. The first rule evaluates the rate of change per minute, while the second considers the change in concentration over a 3-minutes interval. These two rules are referred to as **Rule 1min** and **Rule 3min**. An outline of the function logic is given in the following box.

Experimental Rules for R-T Fire Detection System : Pseudocode

Rule 1min : Comparison of CO₂ concentrations per minute

```
1 if (VOCindex > 220 && PM > 1100 && CO2Increase > 20) {  
2     'Pass alert message if the rule is met'}
```

Rule 3min : Comparison of CO₂ concentrations per 3 minutes

```
1 if (VOCindex > 220 && PM > 1100 && CO2Increase > 50) {  
2     'Pass alert message if the rule is met'}
```

5.3.3 Results

The results of the second experiment are presented as follows: first, the key indicators that have been studied since the beginning of this work are reviewed once more, providing a final comparison between the results obtained in this experiment and those from the first. Next, the response time of the experimental alarm system

rules are compared. Finally, the variations in temperature and humidity observed during fire events are discussed.

CO₂, PM and VOCs over time

In Figure 5.4, the sensor nodes are referred to as SN1 (in blue) and SN2 (in orange). SN1 was positioned at 1.5 meters from the fire source and SN2 at 2.5 meters. This Figure enables a clear observation of the emissions of the fuel combustion of different materials (starting with rubber, then plastic, wood, and finally paper).

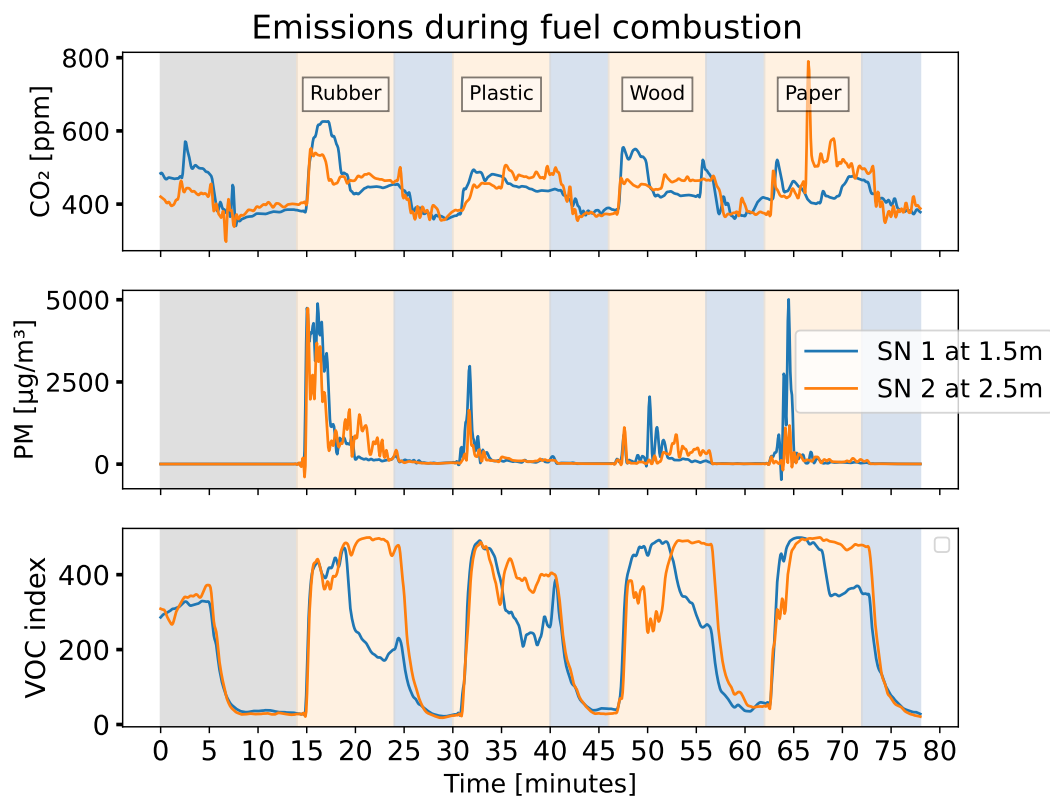


Figure 5.4: CO₂ and PM concentrations, along with VOC index variation during the second experiment, which involved the combustion of four fuels: rubber, plastic, wood, and paper. The readings were taken from two sensor nodes, SN1 and SN2, positioned at 1.5m and 2.5m from the fire source, respectively.

During the first few minutes of fuel combustion, similar trends to the one in the first experience are observed. For CO₂ it appears that at both 2.5m and 2.5m distances from the fire source, emissions reach the sensor nodes rapidly. This validates the choice of placing the sensors at a height of 2m. The concentration levels do not drop immediately; instead, they remain relatively constant throughout the combustion

process for all types of fuel. Once the garage door is opened, the concentration returns to normal levels, around 400ppm.

During the initial combustion, rubber shows a sharp and significant spike in CO₂ levels within the first few minutes, indicating a rapid release as the fire consumes the material. Similarly, plastic and wood combustion also causes a sharp increase in CO₂ concentration, though the peaks are less significant than for rubber, suggesting that these fuels ignite quickly, but with lower CO₂ output. Plastic combustion stabilises more quickly compared to rubber.

In the early minutes, rubber combustion produces significant spike in PM concentration. Plastic follows with a less extreme rise in PM concentration in the early stages. It indicates that plastic, like rubber, burns quickly and releases a large amount of particulates early on, but with less intensity. Wood combustion has the smaller increase in PM levels in the first few minutes. Notably, for SN1, significant PM levels arrive after 5 minutes, which is delayed compared to other fuel types and what was observed in the first experience.

For the VOCs, the pattern observed at a distance of 1.5m is consistent across all four combustion events. The same consistency is also observed with the sensor node positioned at a distance of 2.5m. The VOC index for all fuels shows a sharp increase immediately after ignition, reflecting the rapid release of volatile organic compounds as they burn very early in the fire. These VOC stay in the air during a long time as they are still being capture by the SN2, placed further. It may also be due to the smoke propagating through the open space of the warehouse, since SN1 is situated just near the overhead door, closed during the tests. VOC are reaching, both for SN1 and SN2, the maximal value VOC index of 500, signifying that these volatile are present during every combustion of the synthetic and natural fuels, and at a very high emission level. It is different from the first results where plastic and wood where showing less higher levels in VOC emissions.

The VOC index for all fuel types shows a sharp spike soon after ignition, indicating the rapid release of volatile organic compounds early in the fire. These VOCs persist in the air for a certain period, as they continue to be detected by SN2, which is placed further away. The continued detection of PM after 13 minutes by SN2 may be influence by the smoke dispersing through the open space of the warehouse, given that SN1 is located near the overhead door, which remained closed during the tests. Both SN1 and SN2 reach the maximum VOC index value of 500, indicating that these volatile compounds are present at very high levels during the combustion of both synthetic and natural fuels. This contrasts with previous results, where plastic and wood showed comparatively lower VOC emissions than the other fuels.

Time comparison between the RT system and the photoelectric detectors

The bar diagram in Figure 5.5 shows the alert system's response time when a fire is ignited. The conventional smoke detectors did not triggered for any of the four fires, they are therefore not included in this diagram. For each type of fuel, four bars are displayed : the two bars on the left represent the response times of SN1 and SN2 for **Rule 1min**, while the two hatched bars on the right correspond to the response times of SN1 and SN2 for **Rule 3min**.

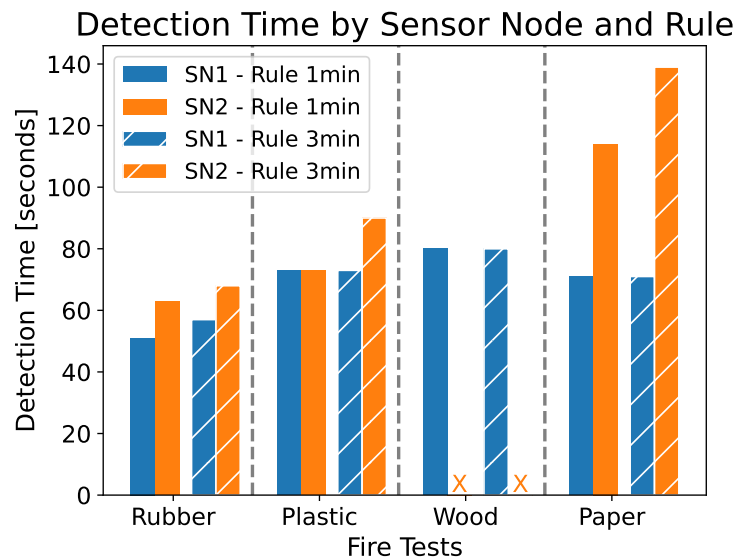


Figure 5.5: The comparison of time, in seconds, to alarm in Experience 2 between Sensor Node 1 (SN1) at 2.5m and Sensor Node 2 (SN2) at 1.5m, for the considered rules based on the CO₂ rate of change per minute and 3 minutes.

Both experimental rules yielded to positive results, since both SN1 and SN2 detected all fire events, with the exception of SN2, which did not detect wood emissions. As expected, SN1 show faster response than SN2, since being closer to the fire source. The response time of the alert system ranged between ± 50 and 140 seconds. Both rules showed promising results, with the **Rule 1min** generating faster alerts due to the CO₂ rate of change being set to 20ppm. In the case of wood, as seen in Figure 5.4, the PM peak for SN1 occurs later than the peak of CO₂, which already begun to decrease when PM where only starting to rise. For SN2, the highest PM mass concentration barely reached 1000 $\mu\text{g m}^{-3}$. This shows the limitations of a system based mainly on absolute thresholds. A model can not rely only on the observation of gases, as gases can show unexpected behaviours. Moreover, detection systems must be calibrated to identified both high-intensity fires (like rubber), and slower,

smouldering fires (like plastic and wood), which may produce less pronounced initial spikes.

As the smoke detector never triggered during the experiment, this highlights the need for more robust and efficient detection systems. The multi-sensor system demonstrated promising results, showing that the combination of CO₂, PM, and VOCs can significantly improve early-stage fire detection.

Temperature and Humidity over time

The sensor SHT30, integrated in the SCD30 module, was used to monitor the temperature and humidity during the experiments. As expected, this sensor showed higher accuracy compared to the SHT4x used in the first experience. Fire events are clearly identifiable in the curves shown in Figure 5.6.

A clear correlation can be observed between temperature and humidity during the burning tests. The graphs clearly show the temperature increase when a fire happened. Both temperature and humidity appear to change gradually over time during fire events. The consistent behaviour of both parameters suggests that the fire combustion had a continuous effect on these parameters.

CO₂, PM and VOC sensors show a faster response compared to the gradual response of temperature and humidity. However, by leveraging the small and consistent variations in these temperature and humidity indicators, the multi-sensor approach can be enhance. Unlike volatile compounds, particle or gases, which can spread unpredictably, temperature is a stable parameter that adds more robustness to the model and is important to considered in the fire detection system.

Correlation between indicators

	PM	CO ₂	VOC	T	RH
PM	1.000000	0.437024	0.315336	0.187859	-0.122234
CO ₂	0.437024	1.000000	0.764089	0.259017	-0.128798
VOC	0.315336	0.764089	1.000000	0.177144	-0.023472
T	0.187859	0.259017	0.177144	1.000000	-0.973222
RH	-0.122234	-0.128798	-0.023472	-0.973222	1.000000

Table 5.2: Correlation matrix of PM, CO₂, VOC index, Temperature and Humidity measurements from both sensor nodes SN1 and SN2.

The correlation matrix, given in 5.2, provides insights on the relationships between PM, CO₂, VOC index, temperature (T), and relative humidity (RH) during the

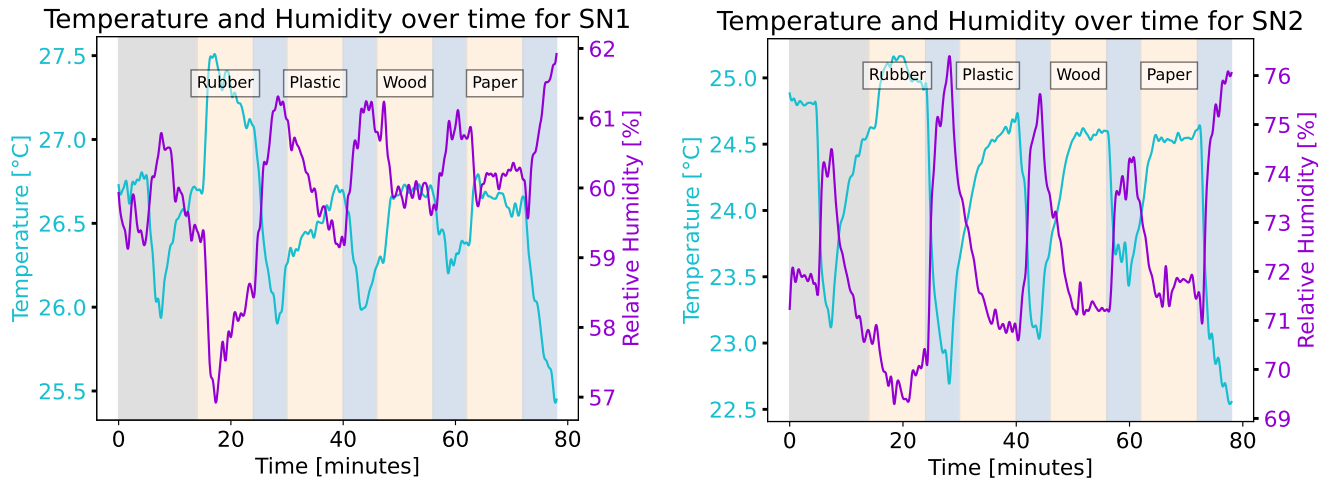


Figure 5.6: Temperature and humidity measurements during fuel combustion for the sensor nodes SN1 (left graph) and SN2 (right graph) distanced from the fire source of 1.5m and 2.5m, respectively.

fire experiments. The correlations are made with the combined datasets recorded by SN1 and SN2, i.e. for all materials taken together.

There is a moderate positive correlation (0.437) between PM and CO_2 , suggesting that as particulate matter increases, CO_2 levels also tend to increase during fire events. The strongest positive correlation is observed between CO_2 and VOC (0.764), indicating that these two indicators often rise together. In contrast to what was observe during the first experience, a moderate positive correlation (0.315) exists between PM and VOC. There is a strong negative correlation (-0.973) between temperature and relative humidity. This is expected, as temperature increases during fire events typically result in decreased humidity. Temperature and humidity do not show strong correlations with the other indicators.

Caution is needed, as different results were obtained in the first experiment. When analysing materials individually, the correlation matrices varied significantly. In this case, CO_2 and VOC appear to be more related, whereas in the first experiment, PM and VOC were more closely linked for certain materials. Therefore, no definitive conclusions can be drawn regarding the correlations between these indicators based solely on this data.

5.4 Discussion

This experiment demonstrated that the multi-sensor system, under real-life conditions in a warehouse setting, effectively detects fires at an early stage by identifying changes in CO₂, VOCs and PM emissions levels during fire events involving different fuels. Integrating these sensors creates a robust multi-parameter fire detection system, as these three indicators show significant levels within the first 1-2 minutes of combustion. Additionally, the analysis of temperature and humidity behaviours suggests that incorporating these parameters can further enhance the detection systems robustness and reliability.

The experimental fire alarm system was based on simple detection rules, designed to evaluate the indicators time response abilities. However, these rules were limited to four specific materials. In real-world scenarios, a wide variety of materials exist, making it impractical to set fixed rules for all potential materials. Therefore, other models are necessary to adapt to rapid changes and detect small emissions quickly over greater distances. Besides, these rules did not considered nuisances (dust, cooking emissions, vapour) that could be subject to false alarms. Studying nuisances emissions in parallel is essential and could be explored in future works, to combine mutli-sensor and machine learning.

The analysis of emissions over time revealed important differences in emission profiles across different materials, especially in the early stages of combustion. For instance, synthetic materials like rubber generate higher emissions much faster than natural materials like wood and paper in the early minutes of combustion. This outlines the importance of understanding material-specific burning characteristics for fire alert systems.

Another notable observation lies in the stabilisation phase seen in the graphs of Figure 5.4. Before starting the fire tests, the sensors were powered up for several hours with the door closed, and then the door was reopened to refresh the air for the experiments. The decrease in CO₂ concentration as well as in the VOC index correspond to this ventilation. Interestingly, the PM do not undergo any changes during this event, demonstrating their stability under normal conditions and making them a reliable indicator to include in a multi-sensor fire alarm system. However, since nuisance scenarios were not included in these tests, it is suggested to analyse how these indicators react during everyday activities, such as cooking or vaporous emissions.

Chapter 6

Work extension

6.1 Limitations and Improvements

For safety and space reasons, this system has not been tested for sensor nodes placed more than 2 meters above ground level. It is suggested that it also works at a higher height, provided the sensor is placed at ceiling height. An interesting issue that was encountered during the first and second data logging of the controlled combustion experiment is that in cases where the ceiling is high and sloped, smoke may rise and fail to reach the sensors effectively if they are not positioned at roof height. It was the case during the first and second data logging of the controlled combustion experiments. Therefore, this system is best suited for rooms with flat ceilings. Additionally, for optimal performance, sensors should be placed at ceiling height. Further testing is needed for larger spaces. In such cases, multiple sensors may be required for adequate coverage.

The maximum tested distance between the fire source and the sensor nodes was 3 meters. At this distance, with 30 grams of fuel burned, emission levels from some materials were less significant than at closer distances, making detection challenging. Additionally, the behaviour of gases and volatile compounds proved to be highly variable and analysis revealed that the four burning materials each have distinct behaviours and signatures, making detection based on a straightforward threshold rule challenging. This highlights the need for a more accurate model to improve detection capabilities.

Another limitation of this real-time monitoring system is its operation on Wi-Fi, which makes it unsuitable for environments without a stable Wi-Fi connection or access points. This can be problematic in industrial settings or buildings without widespread internet coverage, especially when trying to extend connectivity to uncovered areas such as remote sites. However alternative communication protocols specific to IoT could be explored as replacements for the Wi-Fi standard, such as

IEEE802.15.4 combined with Zigbee, or LoRaWAN.

The system is currently in a prototype state energetically speaking, due to its reliance on batteries, and data transmission every three seconds. This approach is not practical and is overkill for an IoT system. In this project, the goal was limited to develop an experimental prototype to study the behaviour of gases, so power consumption was not a primary concern. However, to implement such an IoT system in a real-world scenario using the same sensor node and Micropython, it is possible to reduce power consumption by taking advantage of specific MicroPython functions. It is worth noting that the MicroPython library "Machine" includes power-saving functions, such as lightsleep and deepsleep modes, which can significantly reduce power consumption [43].

6.2 Future works

Future researches could focus on investigating the chemical signatures of many different burning fuels. Differentiating between pyrolysis and oxidation processes during fire tests by analysing the emitted gases may also provide a more detailed understanding of fire at early stages. Additionally, incorporating other gas sensors, such as CO or H₂ as reviewed in the literature, can improve early detection. Studying PM with other sensors may reveal additional insights regarding PM with different aerodynamic sizes.

Combining multi-sensors with machine learning can enhance the accuracy of fire detection to distinguish between fire and non-fire situations based on sensor data, as reviewed in [14]. To this end, additional datasets of various fuel combustion's under different conditions will need to be recorded. Classification models could also be explored with the idea of identifying specific patterns and signatures unique to each material, enabling the identification of the fuel burning source based on its signature. When developing a more robust detection model, attention should be paid to nuisances, causes of false alarms. It involves studying the emissions detected by sensor nodes during nuisances tests (cooking emissions, dust, cigarette) to ensure the robust operation for a system fighting false alarms.

After developing a robust model, another study is to determine the appropriate number of sensor nodes needed to effectively monitor spaces such as warehouses, industrial area, or similar environments.

Conclusion

The motivation for this research stems from the need to further explore the behaviour of emissions during the early stages of a fire, particularly when different materials with varying chemical compositions are involved. Through controlled experiments, this research aims to evaluate whether a multi-sensor system can improve early fire detection by offering a more comprehensive understanding of how emissions from various types of fuels behave during combustion. By analysing early fire indicators, including CO₂, VOCs, particulate matter, NO_x, temperature, and humidity, in real-life indoor environments, this study examines how factors such as fuel type, distance, and sensor placement influence the effectiveness of fire detection.

The analyses of the results from the experiments led to interesting findings. Emission levels vary significantly by material, with rubber, paper, plastic, and wood each producing different ranges of CO₂, particulate matter, and VOCs. For instance, synthetic materials like rubber generate higher emissions much more quickly than natural materials such as wood and paper during the early stages of combustion. This highlights the importance of understanding material-specific burning characteristics for fire alert systems.

Time analysis revealed a clear rise in CO₂ concentration levels after 2-3 minutes and a significant increase in the VOC index within 1-2 minutes. Particulate matter was detected within the first minute of fire ignition, with immediate and substantial emission peaks released into the air. The rate of change analysis indicates that PM concentrations for each material change significantly faster within the sampling interval compared to VOC and CO₂ levels. CO₂ detection becomes more effective when focusing on the rate of concentration change over a period of one to three minutes. Correlation analysis further revealed that the relationships between these indicators vary based on the material, highlighting the challenges of achieving consistent fire detection across different types of materials.

In addition, the experiments showed that while NO_x readings were obtained in a closed environment, no conclusive data could be obtained during the combustion tests in the warehouse, as no readings appeared. This suggests that NO_x may dissipate rapidly in open air, and materials like paper, plastic, or wood might

release NOx in short bursts.

The height at which the sensor is positioned significantly impacts fire detection time. At the start of a fire, the highest emission levels, along with fastest rates of increase, are observed with the sensor placed at 2 meters, while the sensor at 1 meter shows a slower increase, detecting significant emissions only after several minutes, as the smoke cools and descends. Interestingly, the sensor at 1 meter exhibited emission patterns that, when combined with the data from the 2-meter sensor, could prove useful in future research focusing on optimising sensor distribution to locate the source of a fire. The findings of these experiments suggest that the closer the sensor is placed to ceiling height, the faster emissions are detected.

The second experiment demonstrated that the combination of CO₂, VOCs, and particulate matter is effective in detecting fire events, as these three indicators reached significant levels within the first 1-2 minutes of combustion, triggering the alarm in the MQTT-based real-time monitoring system. The fire alert system is based on experimental, straightforward rules derived from the analysis of the first experiment and the study of baseline levels in the warehouse. The multi-sensor system effectively detected anomalies in gas signatures during fire events, whereas traditional smoke detectors failed to trigger throughout the experiment.

Some limitations are inherent to the design of the experiment. The fire alarm system relied on simple detection rules tailored to four specific materials, which may not reflect the diversity of materials encountered in real-world scenarios. Setting fixed rules for all possible materials would be impractical. Additionally, these rules did not consider nuisances such as dust, cooking emissions, or vapours, that could be subject to false alarms. Exploring nuisance emissions in parallel is essential and could be a focus of future research. Furthermore, the maximum tested distance between the fire source and the sensor nodes was 3 meters. At this distance, with 30 grams of fuel burned, emission levels from certain materials were less pronounced than at closer distance, making detection challenging. The experiments also revealed that emission behaviours vary significantly across different materials, making detection based on straightforward rules challenging. This highlights the need for a more robust model to enhance detection accuracy, by combining multi-sensors with machine learning.

These results emphasise the need for continued research of more sophisticated systems to better capture the fire emissions at early stages. As the smoke detector never triggered during the experiment, this highlights the need for more robust and efficient detection systems to enhance indoor fire safety. The multi-sensor system demonstrated promising results, showing that the combination of CO₂, PM, and VOCs can significantly improve early-stage fire detection.

Appendix A

Readings with SEN55

A.1 NOx readings

The results obtained during the experiments in Chapter 3 are shown in the graph below (Figure A.1). The same measurement were obtained at 1m and 2m heights.

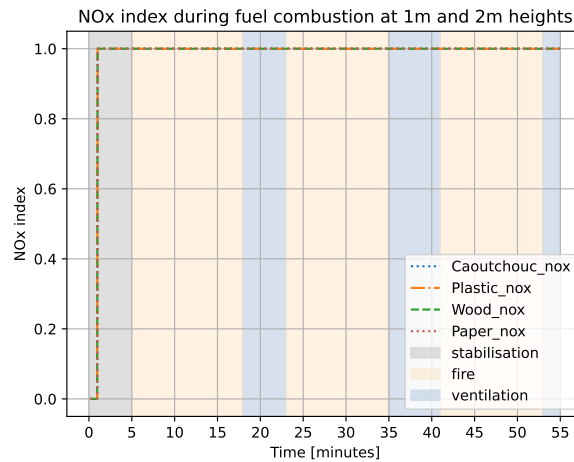
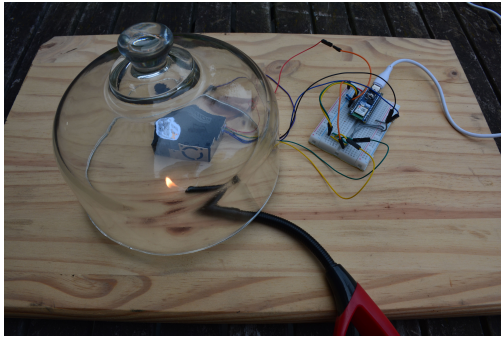


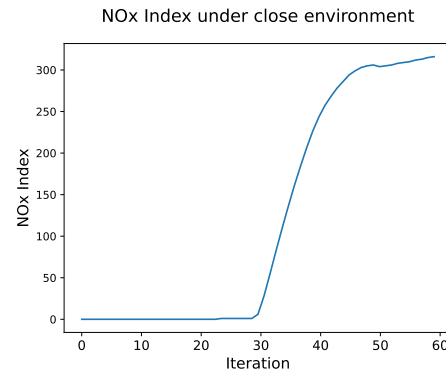
Figure A.1: NOx index during fuel combustion at 1m and 2m heights

During the fuel combustion experiment, the NOx sensor showed no readings : NOx indice of 0 or 1 means that there are (nearly) no NOx gases present [33]. To try to encounter the matter experienced with the SEN55 sensors where no proper NOx readings are obtained, an experiment in controlled environments with limited ventilation to increase NOx concentration levels for detection has been conducted. Figure A.2 shows the set up the results.

An increase of the NOx index is observed when the lighter is turned on. This



SEN55 module operating under close environment



NOx readings

Figure A.2: NOx index measured by SEN55 module when igniting a lighter under a glass bell.

concludes that the NOx are release and can measure by the sensors, in close environment. Significant results are being observed when the SEN55 sensors are being submitted to tests under close environment. Therefore the issue experienced when burning various materials in the warehouse, could be influenced by several factors.

NOx gases can decompose rapidly, especially in ventilated indoor spaces. This leads to lower concentration that are harder for the sensor to detect ¹.

Burning materials like paper, plastic, or wood might release NOx in short bursts, which can be challenging for sensors to detect if the emission duration is brief and the sensor is distanced from the burning source. This NOx parameter could be relevant for fire tests of larger scale.

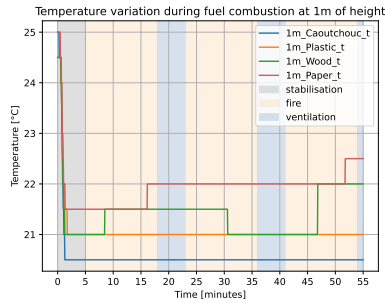
The sensor sensitivity and detection thresholds for NOx might require higher concentrations or longer exposure times to register readings accurately.

The SEN55 has a learning window for VOC and NOx signals. This learning period allows the sensor to calibrate and provide accurate readings. The readings must stabilise for some time.

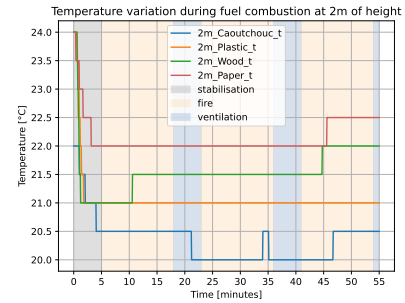
SEN5x integrates SGP41 to senses VOC and NOx. SGP41 sensor's technology is based on a metal oxide (MOX) sensor. Consideration have to be taken on the limitations of a MOX based NOx sensor. As referred in the document [44] from Sensirion.

¹Specific guidance tailored by consult with Sensirion Support.

A.2 Temperature and Humidity readings



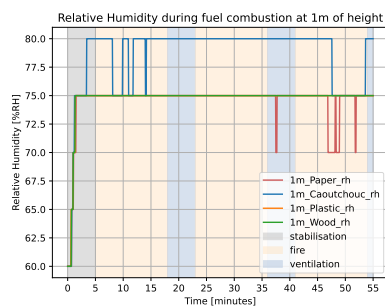
Sensor node placed at 1m Height



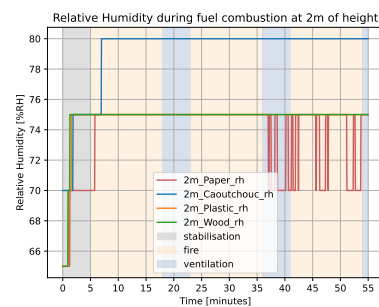
Sensor node placed at 2m Height

Figure A.3: Temperature variation during fuel combustion.

The temperature and humidity data logged during the experience in Chapter 3 are shown in Figures A.3 and A.4. The gradual increase in temperature follows the same order in which the materials were burned: rubber was the first to be burned, followed by plastic, wood and finally paper. As the experiment lasted 7 hours, temperature changes outside influenced the measurements, as can be seen on the graphs.



Sensor node placed at 1m Height



Sensor node placed at 2m Height

Figure A.4: Humidity variation during fuel combustion.

A.3 Particulate matter readings with SensorBridge

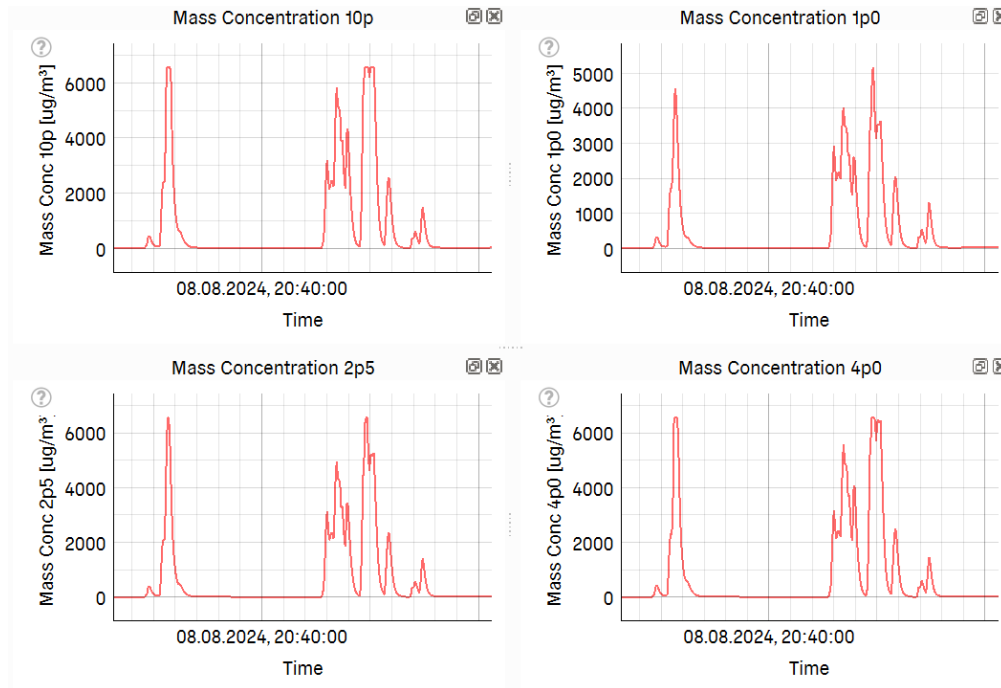


Figure A.5: PM1, PM2.5, PM4 and PM10 mass concentration using SEK-SensirionBridge and plotted with Control Center application

Appendix B

Results for 1-meter Height

B.1 Distribution analysis

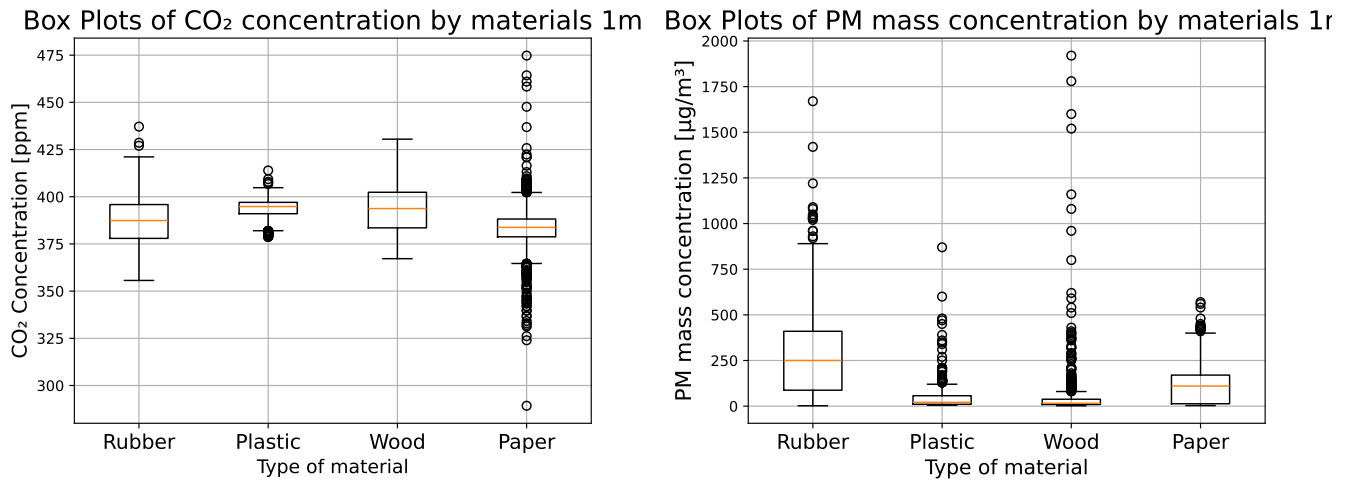


Figure B.1: Box Plots of CO₂ concentration and PM mass concentration, by materials at 1m Height.

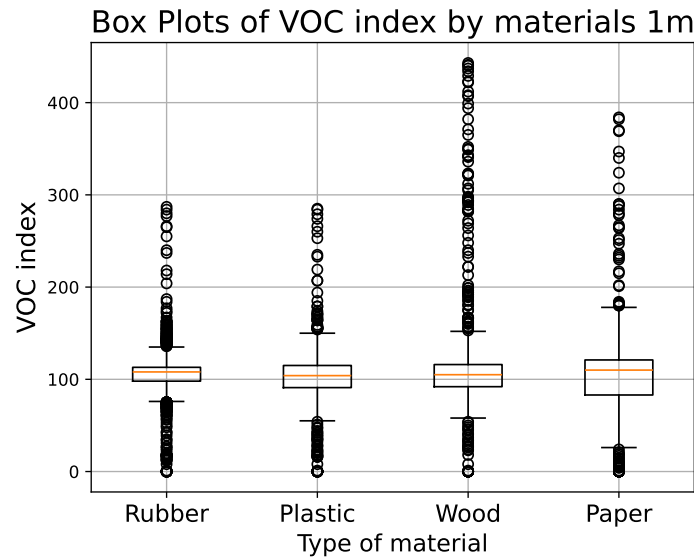


Figure B.2: Box Plots of VOC index concentration and PM mass concentration, by materials at 1m Height.

B.2 Rate analysis

This section referred to Section 3.5.2. The following graphs show the rate analysis when sensors are positioned at 1m height. Readings comes later when particles and gases go down. While rate analysis at 1-meter height is still giving correct results for detecting fire activity, as already mentioned, the indicators show response later than at 2-meters height. Figures B.3, B.4 and B.5 show the rate of change in CO_2 concentration, PM mass concentration and of the VOC index, respectively.

B.3 Correlation analysis

Here for rubber correlated with PM ==> because when seeing time analysis, they increase at same time but late in the process. So together not indicator of "early" fire (8 minutes). Tables B.1, B.3, B.2 and B.4 are the correlation matrices between CO_2 , PM and VOC for Rubber, Plastic, Wood and Paper, respectively.

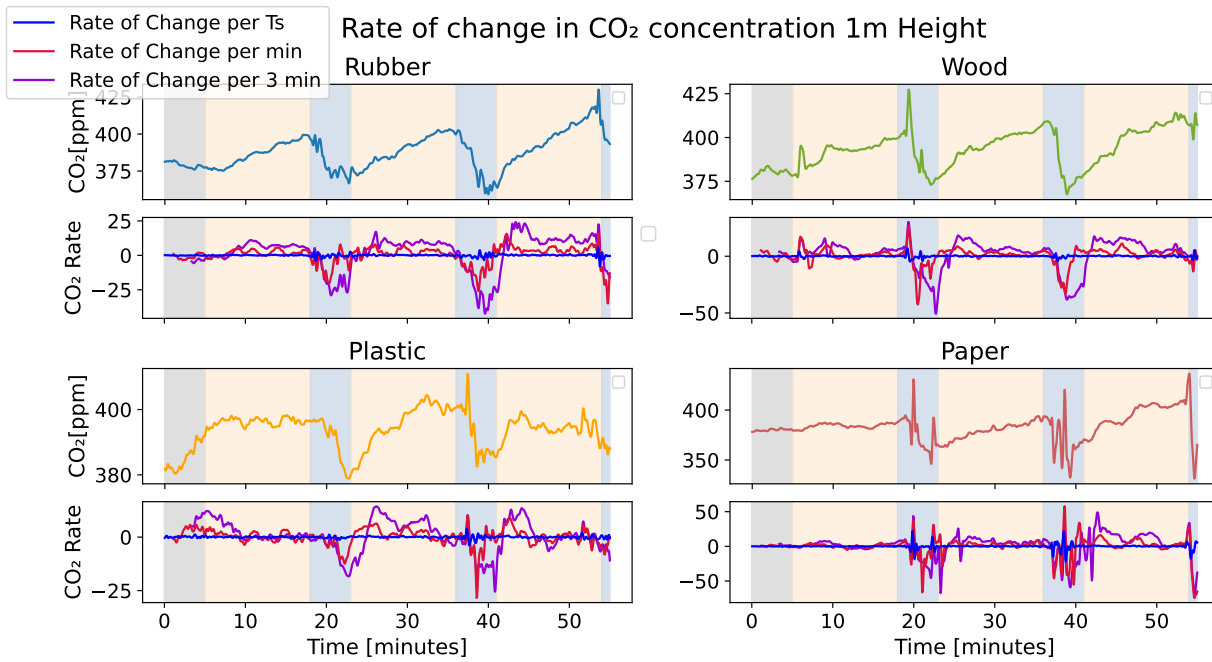


Figure B.3: Rate of change in CO₂ concentration by materials at 1m Height.

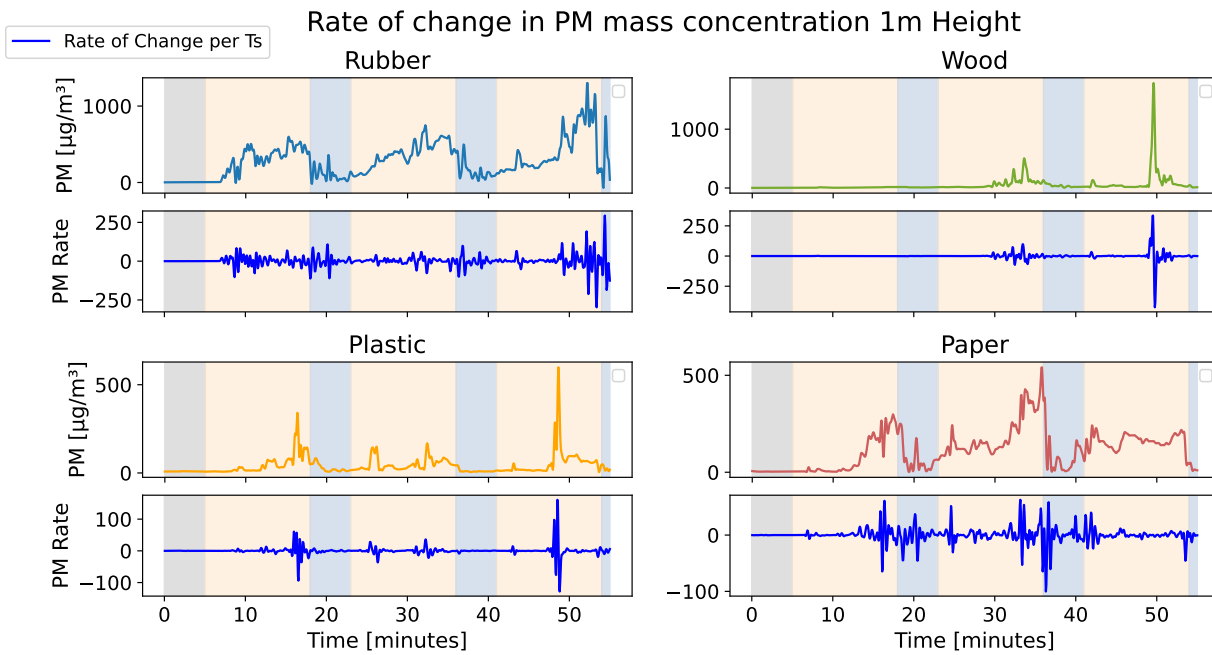


Figure B.4: Rate of change in PM mass concentration by materials at 1m Height.

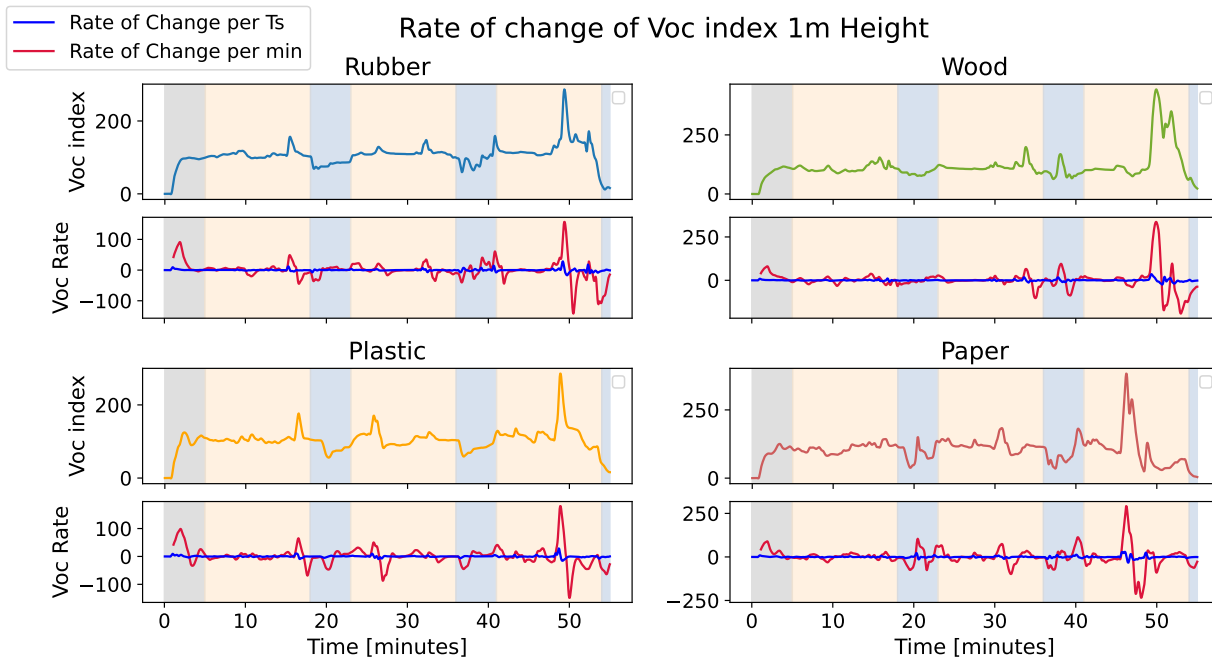


Figure B.5: Rate of change of VOC index by materials at 2m Height.

	PM	CO2	VOC
PM	1.000000	0.730142	0.479887
CO2	0.730142	1.000000	0.221496
VOC	0.479887	0.221496	1.000000

Table B.1: **Rubber** Correlation Matrix between PM, CO2, and VOC, at 1m.

	PM	CO2	VOC
PM	1.000000	0.210479	0.455821
CO2	0.210479	1.000000	0.254114
VOC	0.455821	0.254114	1.000000

Table B.3: **Plastic** Correlation Matrix between PM, CO2, and VOC, at 1m.

	PM	CO2	VOC
PM	1.000000	0.275304	0.551991
CO2	0.275304	1.000000	0.358236
VOC	0.551991	0.358236	1.000000

Table B.2: **Wood** Correlation Matrix between PM, CO2, and VOC, at 1m.

	PM	CO2	VOC
PM	1.000000	0.277364	0.285265
CO2	0.277364	1.000000	-0.096874
VOC	0.285265	-0.096874	1.000000

Table B.4: **Paper** Correlation Matrix between PM, CO2, and VOC, at 1m.

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Declaration of the generative AI in the writing process

During the writing process of the work, *DeepL* and *ChatGPT* were used to ensure correct grammar and spelling errors. In addition to the use of these tools, the work was corrected by English readers and thoughtfully reviewed by the author, assuming full responsibility for the final content.

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