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Characterization of MQ-2, MQ-7 and MQ-135 Gas Sensors for Arduino-Based Smoke Detection

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Abstract

Smoke detection in enclosed spaces is important for early fire detection and air-quality monitoring. This paper characterizes and compares the performance of three MQ-series gas sensors (MQ-2, MQ-7 and MQ-135) under an Arduino UNO R3-based system. Three smoke sources (paper combustion, cigarette smoke, and motorcycle exhaust) were evaluated against a commercial CO detector. Parameters assessed include linearity, sensitivity, response time, error, measurement uncertainty (ISO GUM), and output-voltage correction. MQ-2 and MQ-7 exhibit logarithmic voltage–concentration relationships consistent with the power-law model of SnO_2-based metal-oxide-semiconductor sensors, while MQ-135 exhibits a quadratic pattern; all R^2 values exceed 0.98. MQ-7 produced the lowest errors among the three sensors for paper combustion and cigarette smoke, indicating suitability for indicative early-warning detection; however, its best-case relative error of 38% confirms it is unsuitable for precise quantitative CO monitoring without additional calibration. The three sensors exhibited errors exceeding 85% for motorcycle exhaust due to cross-sensitivity resulting from the complex chemical composition of engine exhaust. A voltage-correction analysis showed the errors in Arduino ADC readings were less than 6%, confirming the reliability of the electronic system; this does not mean the accuracy of the gas concentration will be the same, since it depends on the selectivity of the sensors, calibration and environmental conditions.

Keywords: Gas sensor; MQ-series; Smoke detection; Arduino; Sensor characterization

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INTRODUCTION

Smoke is one of the earliest indicators of fire and degraded air quality in enclosed spaces. Most commercially deployed smoke-warning devices are alarm units that detect smoke only in the immediate vicinity of the detector, and installing such systems is relatively costly (Gabriel et al., 2024; Uda et al., 2019). This motivates the development of smoke-warning instrumentation that is easy to install and inexpensive, particularly for residential rooms, boarding houses, and small workspaces where commercial fire-alarm infrastructure is rarely available (Al Ahasan et al., 2018; Mahbub et al., 2021).

Metal-oxide-semiconductor (MOS) gas sensors in the MQ series are widely used as low-cost sensing elements for detecting gases and smoke. Their sensing layer, typically tin dioxide (SnO_2), changes its electrical resistance when reducing gases such as carbon monoxide (CO) adsorb on the heated sensing surface, producing an analog output voltage that can be read directly by a microcontroller (Al-Chalabi et al., 2024; Nagpal et al., 2026). The MQ-2 sensor is marketed for smoke and flammable gases, the MQ-7 for carbon monoxide, and the MQ-135 for general air quality. Although these sensors are inexpensive and easy to integrate with embedded platforms such as the Arduino UNO, their metrological characteristics—sensitivity, linearity, response time, and measurement error—differ between types and are strongly affected by the composition of the target smoke (Jayesh Jain, 2026; Technical Data MQ-135 Gas Sensor, 2019).

Previous studies have examined individual MQ sensors for air-quality monitoring and calibration (Kobbekaduwa et al., 2021a), characterized the sensitivity curves of specific MQ devices (Carrillo-Amado et al., 2020), and developed Arduino-based smoke detectors for indoor use(Al Ahasan et al., 2018). However, systematic side-by-side comparisons of several MQ-series sensors against a common reference instrument and across chemically distinct smoke sources remain limited. Such a comparison is important because a sensor that performs well for one type of smoke may be fundamentally unsuitable for another (Ajiboye A. et al., 2021).

The objective of this work is therefore to characterize and compare the performance of the MQ-2, MQ-7, and MQ-135 sensors in an Arduino Uno R3-based data acquisition system for smoke measurement (Rachmawardani et al., 2024; Adinara et al., 2025). Performance is quantified in terms of (i) linearity of the voltage–concentration relationship (Hossaini et al., 2022), (ii) sensitivity at low, medium, and high gas concentrations (Furuta et al., 2022), (iii) response time (rise time, fall time, and total response time) (Kanaparthi & Singh, 2022), (iv) absolute and relative error with respect to a commercial CO detector (Zimmerman et al., 2018), and (v) measurement uncertainty evaluated according to the ISO GUM framework (Lee, 2009; Pering et al., 2024). Three smoke sources representing common real-world cases are used: paper-combustion smoke, cigarette smoke, and internal-combustion-engine exhaust.

METHOD

Measurement System

The measurement system consists of an Arduino UNO R3 microcontroller connected to three MQ-series gas sensors (MQ-2, MQ-7, and MQ-135), a DS3231SN real-time clock (RTC) module for time-stamping, and a microSD adapter module for data logging (Easterline et al., 2024). The analog outputs (AO) of the MQ-2, MQ-7, and MQ-135 sensors are connected to analog pins A0, A1, and A2, respectively; the RTC communicates through the I²C bus (A4/A5); and the microSD module is connected through the SPI bus (D10–D13). A commercial CO detector with an alarm sensitivity of ppm is placed inside the same chamber and used as the reference instrument. The circuit schematic was designed in Fritzing, the firmware was developed in the Arduino IDE, and the data were processed using Microsoft Excel and Python (Hilary Kelechi et al., 2022; Yasin et al., 2022).

The analog signal of each sensor is digitized by the 10-bit analog-to-digital converter (ADC) of the Arduino UNO and converted into an output voltage (V) and an equivalent gas concentration in parts per million (ppm). Each reading, together with its RTC timestamp, is displayed on the serial monitor and simultaneously stored on the microSD card as a CSV time series.

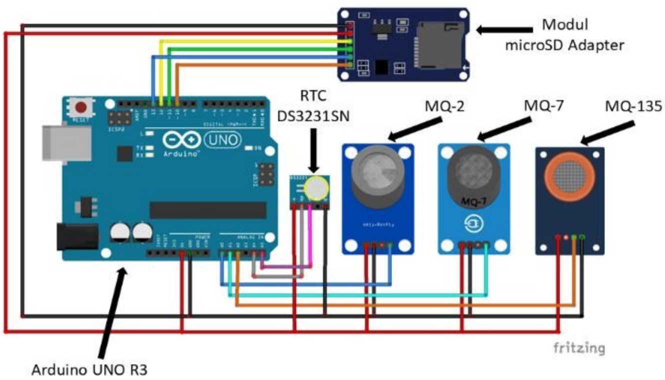

Figure 1. Circuit Schematic of the Test System

Test Chamber and Smoke Sources

All experiments were conducted in a transparent acrylic chamber measuring 26 cm × 15 cm × 36 cm (length × width × height), equipped with an inlet port for smoke injection, allowing visual observation of the measurement process. The ambient temperature inside the chamber during data collection was 30–32°C. Three smoke sources were used as test objects: (1) paper-combustion smoke, (2) cigarette smoke, and (3) exhaust gas from a motorcycle internal-combustion engine.

Before each measurement series, a 60–90 s pre-heating procedure was performed to stabilize the sensing layers of the MQ sensors in ambient air(Reimringer & Bur, 2023). Data collection was repeated 10–12 times for each smoke source, with a 15s interval between repetitions.

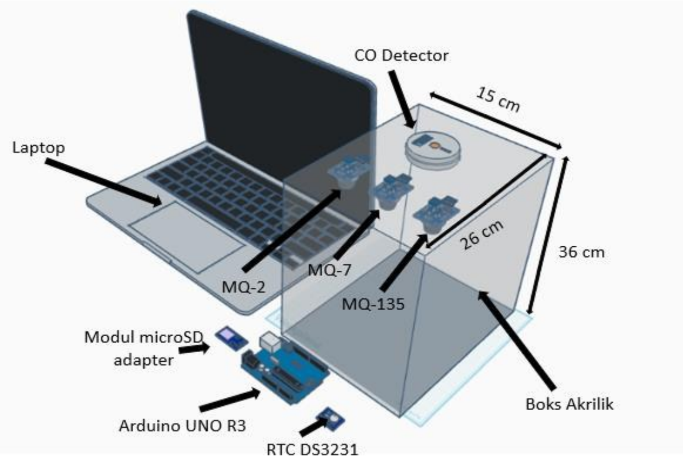

Figure 2. Physical design of the test setup

Data Processing and Performance Metrics

A 60-90-second preheating procedure is performed to stabilize the sensor by conditioning it in ambient air before measuring the target gas. The test circuit starts with the MQ-2, MQ-7, and MQ-135 sensor readings of the surrounding air (Manoj Kumar et al., 2025).

If the air surrounding the sensor contains CO gas, the sensor responds by adjusting its resistance, thereby affecting the output voltage. The voltage is then converted into an input signal for the Arduino UNO R3 microcontroller, which transforms it into an ADC signal representing a quantity of parts per million (ppm). Data collection is conducted by running a test circuit that generates sensor readings of voltage (volts) and gas concentration (ppm), as well as RTC readings for time-series analysis. The data will be displayed on the Arduino IDE's serial monitor and stored on a microSD card. Data are collected 10-12 times, with a time interval of 15 seconds between repetitions. Data processing is performed by accessing the data stored on the microSD module, which is later analyzed with the help of Microsoft Excel and the Python programming language, calculating sensitivity, linearity, and error equations. For the response time, the difference between the time required for the sensor to reach its peak value after gas detection and the time at which the sensor reaches its peak value is calculated. The error calculation uses gas-content data (ppm) from the MQ-2, MQ-7, and MQ-135 sensors and compares it with the CO detector measurement data. Once the sensitivity, linearity, reaction time, and error values of each sensor have been obtained, these data are examined and compared. Then, conclusions can be drawn about the performance of the three sensors in measuring smoke.

RESULTS AND DISCUSSION

This section describes the data-collection process and the results of the sensor performance analysis.

Data Collection Description

The data analyzed are derived from tests conducted in an acrylic chamber at a temperature of 30-32°C. Diverse smoke sources, such as paper smoke, cigarette smoke, and automotive emissions, were employed in the tests, which also included CO detectors and MQ-2, MQ-7, and MQ-135 sensors. This examination encompasses sensitivity, linearity, error, and time response.

Figure 3. Data collection: a) paper smoke, b) cigarettes, and c) motorbikes

Sensor Performance Analysis Results

The data generated during the research were stored in CSV (Comma-Separated Values) files accessed using Microsoft Excel. The CSV files were then processed to extract sensor performance values and visualized using an additional software tool, namely Python.

Linearity

The correlation between voltage and gas concentrations in the MQ-2 and MQ-135 sensor responses is predominantly linear, though not perfectly linear for the paper-smoke source. The MQ-7 has a curved profile, which may affect the sensitivity value at each measurement site. If the correlation between gas levels and voltage is non-linear, the regression is classified as non-linear.

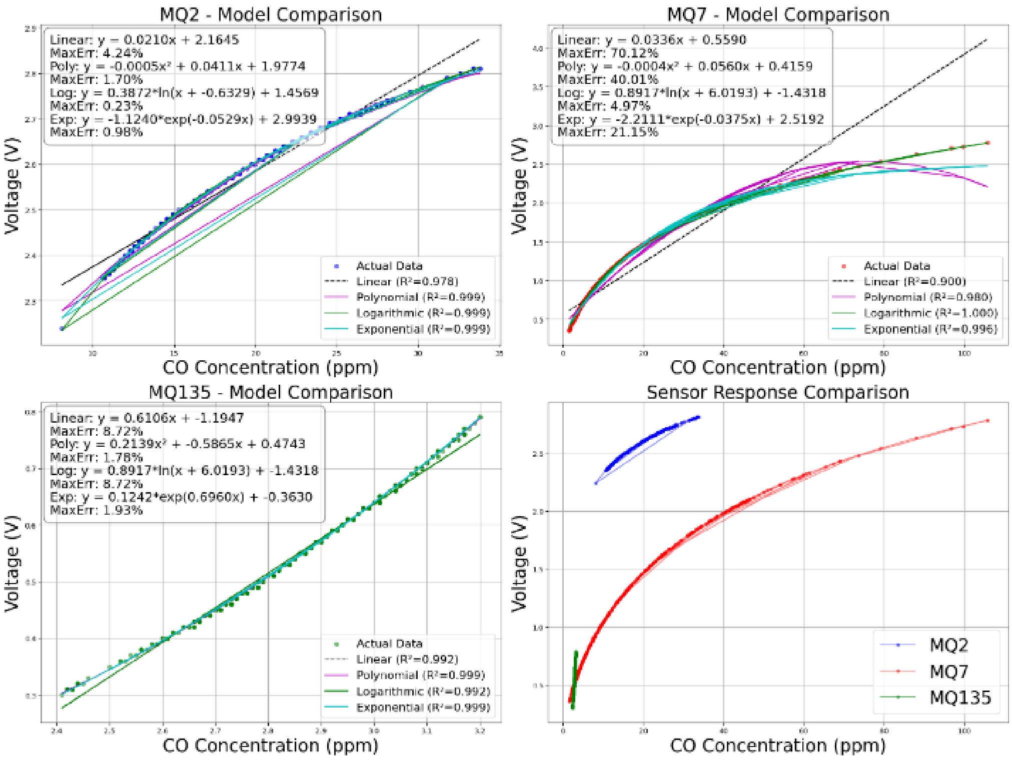

Figure 4. Regression curves matching the pattern of each MQ sensor for the paper-smoke source

A nonlinear regression analysis was conducted to select the appropriate regression model for sensitivity and linearity analysis. The best model was the one with the highest R^2 and the lowest maximum error. For the MQ-2 sensor, the logarithmic model achieved an R^2 of 0.9994 and a maximum error of 0.23%. For the MQ-7 sensor, the logarithmic model achieved an R^2 of 0.9999 and a maximum error of 4.97%. For the MQ-135 sensor, the second-order polynomial model achieved an R^2 of 0.9989 and a maximum error of 1.78%. The results of the regression analysis are presented in the table below.

Table 1. Regression Models for the MQ Sensors for the Paper-Smoke Object

Sensor	Model	R^2	Max	Y
MQ-2	Logarithmic	0.9994	0.23%	$y = 0.3872 \cdot \ln(x - 0.6329) + 1.4569$
MQ-7	Logarithmic	0.9999	4.97%	$y = 0.8917 \cdot \ln(x + 6.0193) - 1.4318$
MQ-135	Quadratic	0.9989	1.78%	$y = 0.2139x^2 - 0.5865x + 0.4743$

Figure 5 presents the regression curves fitted to the voltage–concentration data of each MQ-series sensor for the cigarette-smoke source. For the MQ-2 sensor, the logarithmic model provided the best fit, yielding $R^2 = 0.9973$ and a maximum fitting error of 0.23%. Similarly, the MQ-7 sensor was best represented by a logarithmic model, achieving $R^2 = 1.000$ with a maximum fitting error of 1.96%. In contrast, the MQ-135 sensor was best described by a second-order polynomial (quadratic) model, with $R^2 = 0.997$ and a maximum fitting error of 3.14%.

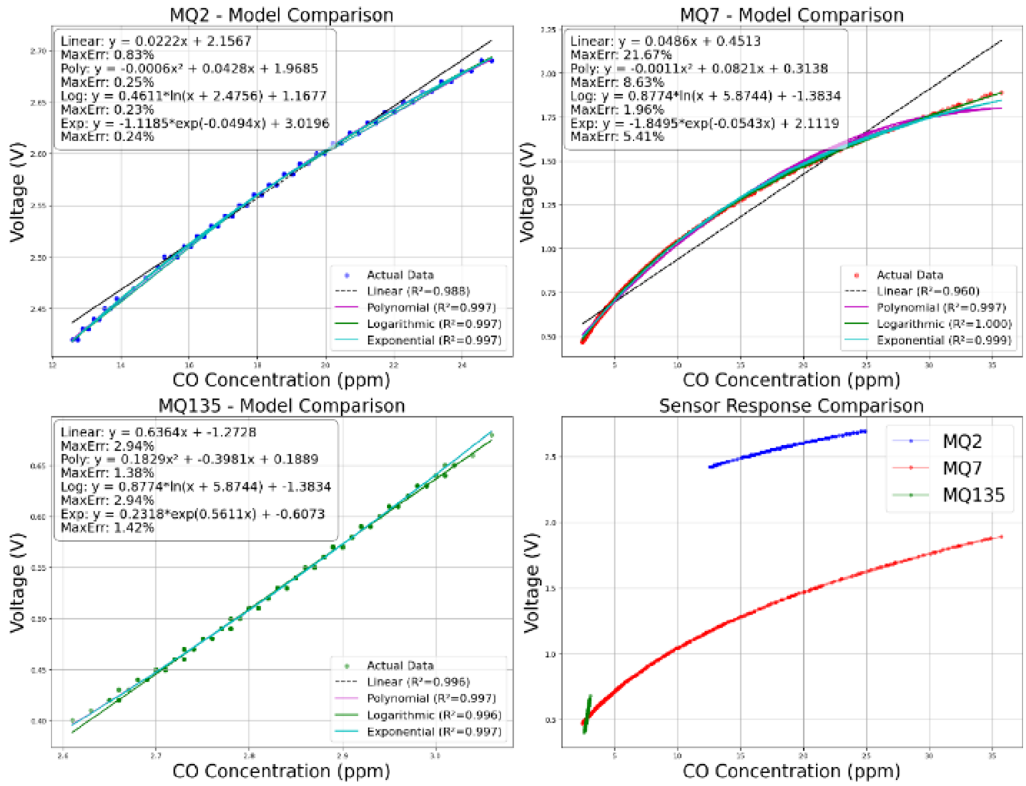

Figure 5. Regression curves matching the pattern of each MQ sensor for the cigarette-smoke source

The complete regression equations and goodness-of-fit statistics for all sensors are summarized in Table 2.

Table 2. Regression Models for the MQ Sensors for the Cigarette-Smoke Object

Sensor	Model	R^2	Max Error	Y
MQ-2	Logarithmic	0.9973	0.23%	$y = 0.4611 \cdot \ln(x + 2.4756) + 1.1677$
MQ-7	Logarithmic	1.000	1.96%	$y = 0.8774 \cdot \ln(x + 5.8774) - 1.3834$
MQ-135	Quadratic	0.997	3.14%	$y = 0.1829x^2 - 0.3981x + 0.1889$

Figure 6 presents the logarithmic model for the MQ-2 sensor, which achieved an R^2 of 0.9819 and a maximum error of 0.19%. For the MQ-7 sensor, the logarithmic model achieved an R^2 of 1.000 and a maximum error of 1.96%. For the MQ-135 sensor, the second-order polynomial model achieved an R^2 of 1.000 and a maximum error of 1.38%. The regression analysis results are shown in the table below.

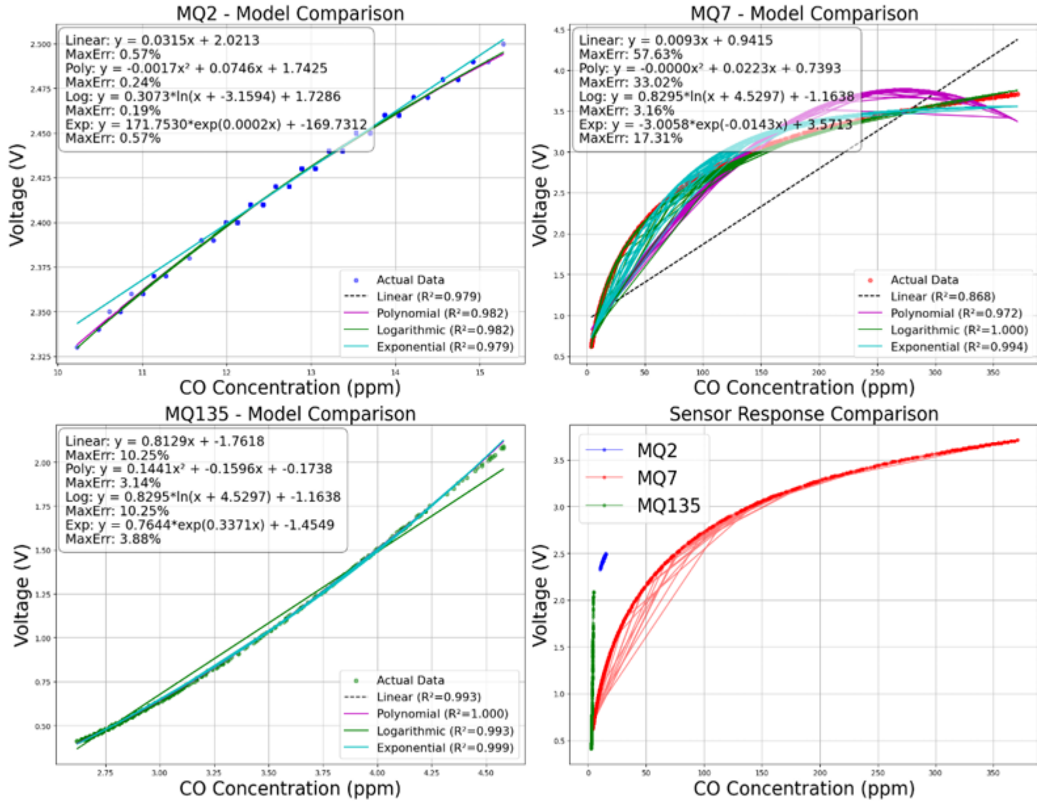

Figure 6. Regression curves matching the pattern of each MQ sensor for the motorcycle-exhaust-smoke source

The outcomes of the regression analysis are presented in Table 3.

Table 3. Regression Models for the MQ Sensors for the Motorcycle-Exhaust-Smoke Object

Sensor	Model	R^2	Max Error	Y
MQ-2	Logarithmic	0.9819	0.19%	$y = 0.3073 \cdot \ln(x + 3.1594) + 1.7286$
MQ-7	Logarithmic	1.0000	1.96%	$y = 0.8295 \cdot \ln(x + 4.5297) - 1.1638$
MQ-135	Quadratic	1.0000	3.14%	$y = 0.1441x^2 - 0.1596x - 0.1738$

The results presented in Tables 1, 2, and 3 reveal distinct voltage–concentration relationships across the three MQ sensors. MQ-2 and MQ-7 both follow a logarithmic model ($R^2 > 0.98$ across all smoke sources), while MQ-135 is best described by a second-order polynomial (quadratic) model. The logarithmic response of MQ-2 and MQ-7 is consistent with the well-established power-law model governing metal-oxide-semiconductor (MOS) sensors based on SnO_2. This power-law, expressed as $Rs/Ro = A \cdot [C]^{-B,}$ where A and B are empirical constants and [C] is gas concentration, combines semiconductor depletion theory with the dynamics of gas adsorption and surface reactions on the SnO_2 sensing layer (Yamazoe & Shimanoe, 2008). The mechanism proceeds as follows: in clean air, atmospheric oxygen adsorbs onto the SnO_2 surface and captures free electrons, forming ionosorbed O^- ions that induce upward band bending and create a high-resistance depletion layer. When reducing gases such as CO are present, they react with these O^- ions, returning electrons to the SnO_2 bulk, reducing band bending, and lowering sensor resistance. Because this surface reaction follows power-law kinetics, the resulting voltage–concentration relationship, when measured using the Arduino voltage divider circuit is logarithmic (Goel et al., 2023).

At higher concentrations, the progressive reduction in available ionosorbed O− sites further diminishes the incremental change in resistance per unit concentration, causing sensitivity roll-off that reinforces the logarithmic curvature (Yamazoe & Shimanoe, 2008). The quadratic pattern of MQ-135, by contrast, is attributable to the fact that CO is not its primary target gas—MQ-135 is designed for NH_3, benzene, and alcohol detection (Easterline et al., 2024)—so its Rs/Ro response to CO does not conform to the standard power-law applicable to sensors optimized for a specific target gas. The second-order polynomial model obtained empirically in this study reflects the complex, non-standard response of MQ-135 to CO within a multi-component smoke matrix. This distinction has important practical implications: the logarithmic response of MQ-2 and MQ-7 is amenable to linearization via a log-transformation of the concentration axis, whereas the quadratic response of MQ-135 requires a polynomial calibration curve, adding complexity for quantitative gas-monitoring applications. The consistently high R^2 values (>0.98) confirm that the selected regression models capture the dominant voltage–concentration trends well, although maximum fitting errors for MQ-7 (up to 4.97%) indicate that careful calibration remains warranted in precision applications.

Sensitivity

Because the regression models for MQ-2 and MQ-7 are logarithmic and MQ-135 is quadratic, the instantaneous sensitivity (dV/d[ppm]) is inherently concentration-dependent and was therefore evaluated at three representative concentration levels: low (minimum), medium (median), and high (maximum).

Table 4. Sensor Sensitivity Analysis

Sensor	Paper Smoke	Cigarette Smoke	Motorcycle Exhaust Smoke
MQ-2	51.78 mV/ppm 16.59 mV/ppm 11.68 mV/ppm	30.63 mV/ppm 23.36 mV/ppm 16.87 mV/ppm	43.46 mV/ppm 30.57 mV/ppm 25.35 mV/ppm
MQ-7	117.19 mV/ppm 75.32 mV/ppm 7.97 mV/ppm	105.53 mV/ppm 84.82 mV/ppm 21.10 mV/ppm	98.87 mV/ppm 66.79 mV/ppm 2.21 mV/ppm
MQ-135	444.38 mV/ppm 636.87 mV/ppm 782.31 mV/ppm	556.63 mV/ppm 637.11 mV/ppm 721.24 mV/ppm	595.42 mV/ppm 635.76 mV/ppm 1160.24 mV/ppm

Table 4 shows that sensitivity decreases with increasing concentration for both MQ-2 and MQ-7, a direct consequence of the power-law response model (Rs/Ro = A·[C]-B). Because the exponent B is positive, the derivative dV/d[C] decreases as [C] increases, meaning sensitivity is inherently higher at low concentrations and lower at high concentrations. Physically, this is reinforced by the progressive depletion of ionosorbed O− ions on the SnO_2 surface at higher gas concentrations. As more O-sites are consumed by reaction with CO, fewer sites remain available for subsequent concentration increments, thereby further reducing the incremental change in resistance per unit concentration (Yamazoe & Shimanoe, 2008; Goel, 2023). This sensitivity roll-off behavior is well documented for MOS sensors in general and for MQ-7 specifically. MQ-7 is designed to operate optimally in the 20–2000 ppm CO range using a two-stage heating cycle mandated by the manufacturer: the heater voltage is set to 1.5 V±0.1 V during the detection phase (CO adsorption) and to 5 V±0.1 V during the recovery phase (surface cleaning of interfering gases), thereby enhancing CO selectivity relative to non-target gases (Hanwei Electronics, 2013; Kobbekaduwa et al., 2021).

In contrast, MQ-135 exhibits increasing sensitivity with concentration (from ~444 to ~782 mV/ppm for paper smoke), which is the expected mathematical behavior of a quadratic regression model whose derivative dV/d[C] = 2a[C] + b increases with concentration. However, this mathematically increasing sensitivity does not translate to high accuracy in CO measurement, because MQ-135 is not designed for CO as its primary target gas. Its SnO_2 sensing layer responds to NH_3, benzene, alcohol, and CO simultaneously, so in the complex smoke matrices tested here, the reported sensitivity values reflect a multi-gas integrated response rather than selective CO detection (Easterline et al., 2024). Therefore, the very high sensitivity of MQ-135 (>700 mV/ppm) should be interpreted with caution: it reflects cumulative response to multiple gases, not CO-specific detection accuracy.

Response Time

Response time is the duration required for a sensor to respond to changes in gas concentration, typically transitioning between a clean-air state and a gas-contaminated state, or vice versa. Two critical elements of response time:

1. Rise Time: The duration required for the sensor to transition from 10% to 90% of the maximum value upon the initial detection of gas.
2. Fall Time/Recovery Time*:* The time required for the sensor to decrease from 90% to 10% of its peak value after the gas is discontinued or reduced.

Repeated response-time data are then averaged. The researcher uses winsorization at the 10th and 90th percentiles to reduce the impact of outliers on the average values.

Table 5. Response Time for Paper-Combustion Smoke

Sensor	Rise Time (s)	Fall Time (s)	Response Time
MQ-2	26.73	27.64	55.27
MQ-7	35.73	21.09	56.36
MQ-135	38.18	40.18	76.55
CO Detector	35.45	28.82	66.00

Table 5 shows that response times differ among sensors for paper-combustion smoke. MQ-2 exhibited the fastest rise time (26.73 s) and overall response time (55.27 s), while MQ-7 had the shortest fall time (21.09 s) and MQ-135 showed the longest overall response (76.55 s). The relatively fast rise of MQ-2 can be attributed to its sensing layer composition, which is optimized for smoke and flammable gas detection and thus responds rapidly when smoke particles and combustion gases contact the heated SnO_2 surface. MQ-135's longer response time is consistent with its broader target gas range and possibly with a thicker or denser sensing layer that requires more time for gas diffusion and surface reaction equilibration. In previous chamber-based studies using similar MOS sensors, rise times in the range of 20–60 s and fall times of 20–80 s have been reported, depending on sensor type, chamber volume, and gas concentration (Reimringer & Bur, 2023), placing the present results within the typical performance range for this class of low-cost sensors.

Table 6. Response Time for Cigarette-Combustion Smoke

Sensor	Rise Time (s)	Fall Time (s)	Response Time (s)
MQ-2	27.4	57.2	87.0
MQ-7	51.0	22.4	75.2
MQ-135	49.0	61.9	113.1
CO Detector	22.6	23.4	44.6

For cigarette smoke (Table 6), the CO detector had the fastest rise time (22.6 s) and total response time (44.6 s), reflecting its purpose-built sensitivity to CO. Among the MQ sensors, MQ-7 showed the fastest fall time (22.4 s) but a prolonged rise time (51.0 s), while MQ-135 had the slowest recovery (fall time 61.9 s). The longer fall times of MQ-2 and MQ-135 for cigarette smoke compared with paper smoke may reflect the higher diversity of chemical compounds in cigarette smoke—including nicotine, acrolein, formaldehyde, and benzene—some of which can adsorb more strongly onto SnO_2 surfaces and require longer desorption times once gas flow ceases (Easterline et al., 2024). The extended recovery time of MQ-135 (61.9 s) is particularly noteworthy, as it implies that in real-world environments with intermittent smoke events, MQ-135 may not return to baseline rapidly enough between events to distinguish successive exposures reliably.

Table 7. Response Time for Motorcycle-Exhaust-Combustion Smoke

Sensor	Rise Time (s)	Fall Time (s)	Response Time (s)
MQ-2	64.33	77.08	152.42
MQ-7	31.25	50.33	82.33
MQ-135	13.42	29.5	46.42
CO Detector	12.00	80.92	92.92

For motorcycle exhaust (Table 7), MQ-135 achieved the fastest fall time (29.5 s) and overall response (46.42 s), while MQ-2 exhibited the longest rise and total response times (64.33 s and 152.42 s, respectively). The very long rise time of MQ-2 in motorcycle exhaust is consistent with the high gas concentration and complex chemical composition of engine exhaust, which can cause sensor overload or diffusion-limited transport of gases to the sensing surface, thereby substantially slowing the rise phase. In contrast, the faster apparent fall of MQ-135 under motorcycle exhaust may paradoxically reflect the sensor's saturation behavior: once the quadratic response reaches a plateau, small changes in concentration near the upper detection limit produce minimal additional voltage change, making the sensor appear to recover quickly while still being exposed to residual exhaust gases. These findings underscore that response-time measurements in complex gas matrices may not fully reflect sensor kinetics and should be interpreted alongside error and accuracy data.

Error

Measurement error was evaluated by comparing sensor readings against the commercial CO detector as the reference instrument. Absolute and relative errors were calculated for each sensor across all three smoke sources, and the results are presented in Figure 8 and Figure 9, respectively.

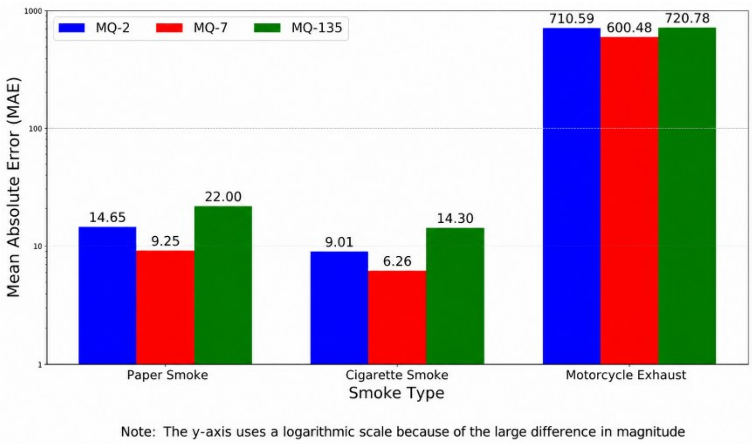

Figure 8. Graph comparing the absolute error values of the three sensors

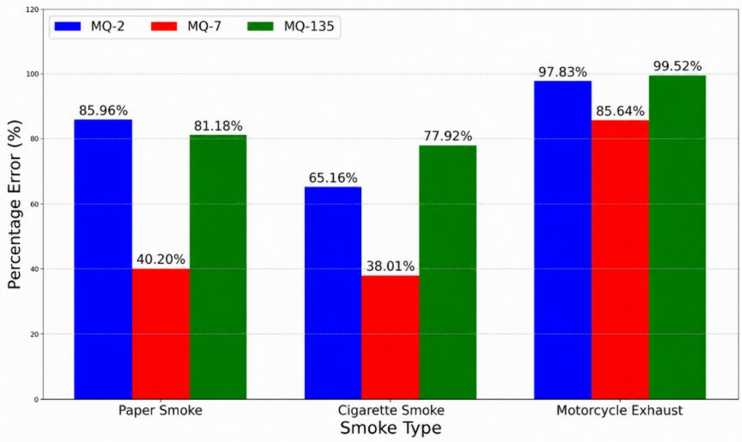

Figure 9. Graph comparing the relative error values of the three sensors

MQ-7 consistently achieved the lowest errors among the three sensors, with relative errors of 40.20% and 38.01% for paper and cigarette smoke, compared with 65–86% for MQ-2 and 77–81% for MQ-135. MQ-7's superior performance is consistent with its design purpose as a CO-specific sensor with a targeted sensing range of 20–2000 ppm CO (Hanwei Electronics, 2013; Kobbekaduwa et al., 2021). Because paper combustion and cigarette smoke both produce CO as a major combustion product, MQ-7's CO-optimized sensing layer provides a better match between the target gas and the reference instrument, resulting in lower systematic error.

MQ-2's relatively higher error (85.96% for paper smoke) likely reflects the broader sensitivity of its SnO_2 layer to flammable gases other than CO (liquefied petroleum gas, propane, methane, hydrogen), causing inflated ppm readings when only CO is measured by the reference instrument. MQ-135's high error (81.18% for paper smoke) despite its very high sensitivity further confirms that high sensitivity alone does not guarantee accuracy: if the sensor output integrates responses to multiple interfering gases, the inferred concentration will be systematically biased (Zimmerman et al., 2018; Carrillo-Amado et al., 2020). For motorcycle exhaust smoke, all sensors exhibited relative errors exceeding 85%, attributable to cross-sensitivity and sensor interference from the chemically complex exhaust mixture (CO, HC, NOx, particulate matter, trace organics), which may also push sensors into saturation beyond their effective detection range (Easterline et al., 2024; Carrillo-Amado et al., 2020; Reimringer & Bur, 2023). It should be noted that even MQ-7's best-case relative error of 38.01% is substantial, meaning MQ-7 is suitable only for indicative early-warning detection, not for precise quantitative CO monitoring without additional calibration and environmental compensation.

Measurement Uncertainty

The ISO Guide to the Expression of Uncertainty in Measurement (GUM) is an international standard published by the International Organization for Standardization (ISO) that guides the determination of measurement uncertainty. The calculated uncertainty comprises the type A and type B components, the combined uncertainty, and the expanded uncertainty. The reported values are based on analyses of 10 peak data points for each sensor and each smoke source. The measurement uncertainty analysis is presented in Table 8.

Table 8. Measurement Uncertainty Analysis

Sensor	Smoke	Mean	U_A	U_B	U_C / U
MQ-2	Paper	23.87	1.986	0.0837	2.007 /
	Cigarette	20.02	0.904	0.0837	0.949 /
	Motor	13.51	0.276	0.0837	0.399 / 0.577
MQ-7	Paper	45.76	7.845	0.1155	7.847 /
	Cigarette	20.56	3.920	0.1155	3.923 /
	Motor	344.8	8.826	0.1155	8.827 /
MQ-135	Paper	3.02	0.034	0.0029	0.148 /
	Cigarette	2.88	0.039	0.0029	0.15 / 0.0783
	Motor	4.02	0.132	0.0029	0.196 /

The MQ-2 sensor exhibits type A uncertainties of 1.986 ppm (paper smoke), 0.904 ppm (cigarette smoke), and 0.276 ppm (motor smoke), along with a type B uncertainty of 0.0837 ppm. The expanded uncertainty (U) of the MQ-2 sensor for each smoke source is ±3.9765 ppm (paper smoke), ±1.8162 ppm (cigarette smoke), and ±0.577 ppm (motor smoke) at the 95% confidence level (k=2).

The MQ-7 sensor has type A uncertainty values of 7.845 ppm (paper smoke), 3.920 ppm (cigarette smoke), and 8.826 ppm (motor smoke), and a type B uncertainty of 0.1155 ppm.

The expanded uncertainty (U) is ±15.6926 ppm for paper smoke, ±7.8441 ppm for cigarette smoke, and ±17.6534 ppm for motor smoke at a 95% confidence level (k=2).

For the MQ-135 sensor, the type A uncertainty values are 3.02 ppm (paper smoke), 2.88 ppm (cigarette smoke), and 4.02 ppm (motor smoke), with a type B uncertainty of 0.0029 ppm. The resulting expanded uncertainty (U) at the 95% confidence level (k=2) is ±0.0682 ppm for paper smoke, ±0.0783 ppm for cigarette smoke, and ±0.2642 ppm for motor smoke.

The large expanded uncertainty of MQ-7 (up to ±17.65 ppm for motorcycle exhaust) relative to the low expanded uncertainty of MQ-135 (≤±0.26 ppm) may at first appear contradictory given MQ-7's superior accuracy. This apparent discrepancy arises because MQ-7 operates at higher ppm output values (mean 45.76 ppm for paper smoke, 344.8 ppm for motor smoke) compared with MQ-135 (mean 3.02–4.02 ppm), and the ISO GUM Type A uncertainty scales with measurement variability in absolute ppm units. Because MQ-135 reports much lower concentration values despite the same smoke inputs, its absolute variability is inherently smaller, yielding a narrow uncertainty band that is nonetheless misleading when the reported ppm values themselves are inaccurate relative to the reference instrument.

In practical applications, a large expanded uncertainty such as that of MQ-7 (±17.65 ppm for motor smoke), implies that the sensor output must be treated cautiously in any scenario requiring precise concentration quantification. For early-warning smoke detection where a threshold exceedance is sufficient (rather than exact concentration), MQ-7 remains the most suitable choice among the sensors tested, since its lower relative error indicates that the central tendency of its readings is closer to the true CO concentration. These findings are consistent with the ISO GUM framework's emphasis that expanded uncertainty characterizes the reliability of a measurement result—sensors with high Type A uncertainty should not be used alone for precision monitoring without additional averaging, calibration, or sensor fusion (Pering et al., 2024).

Output Voltage Correction

The microcontroller receives the result of an analog-to-digital conversion. The Arduino UNO displays the output voltage value on the Arduino IDE serial monitor. The test was conducted 5 times for each of the three sensors. The test results are shown in Table 9.

Table 9. Output Voltage Correction of Arduino versus Multimeter

Sensor	Trial No.	Arduino IDE Output	Multimeter Reading (V)
MQ-2	1	0.48	0.46
	2	0.47	0.47
	3	0.47	0.47
	4	0.48	0.47
	5	0.47	0.47
MQ-7	1	0.26	0.24
	2	0.25	0.25
	3	0.26	0.25
	4	0.25	0.25
	5	0.26	0.25
MQ-135	1	0.19	0.17
	2	0.18	0.19
	3	0.19	0.19
	4	0.18	0.19
	5	0.19	0.19

The voltage-correction analysis showed that all three sensors operated within an acceptable voltage-reading error of less than 6% relative to a calibrated digital multimeter, with

MQ-2 achieving a mean error of 1.7% (CV = 1.0%), MQ-7 at 4.1% (CV = 1.9%), and MQ-135 at 5.4% (CV = 2.5%). Root Mean Square Errors ranged from 0.009 to 0.010 V, indicating negligible systematic bias in the Arduino's 10-bit ADC voltage readout. It is important to note, however, that this voltage-correction result must not be conflated with overall gas-concentration accuracy. The voltage-correction analysis assesses only the fidelity of the electronic voltage-reading chain (sensor analog output → ADC → Arduino serial output vs. multimeter), not the accuracy of the sensor's gas-concentration inference. Gas-concentration accuracy is additionally affected by the sensor's calibration curve, its selectivity to the target gas versus interfering species, ambient temperature and humidity, and the accuracy of the reference instrument.

The high relative errors reported in the previous subsection (38–99% depending on sensor and smoke type) make it clear that even sensors with excellent voltage-reading stability can yield large gas-concentration errors if the sensing element responds non-selectively or if the operational conditions deviate from calibration conditions. This distinction between voltage-reading accuracy and gas-concentration accuracy is consistent with findings from low-cost MOS sensor evaluations in the literature, where electronic stability and gas-measurement validity are treated as separate performance dimensions (Zimmerman et al., 2018; Reimringer & Bur, 2023). In the context of this study, the low voltage errors confirm that the Arduino acquisition hardware is reliable, and that the concentration errors observed in the error analysis section are attributable to the intrinsic limitations of the MQ sensing elements rather than to electronic noise or ADC inaccuracy.

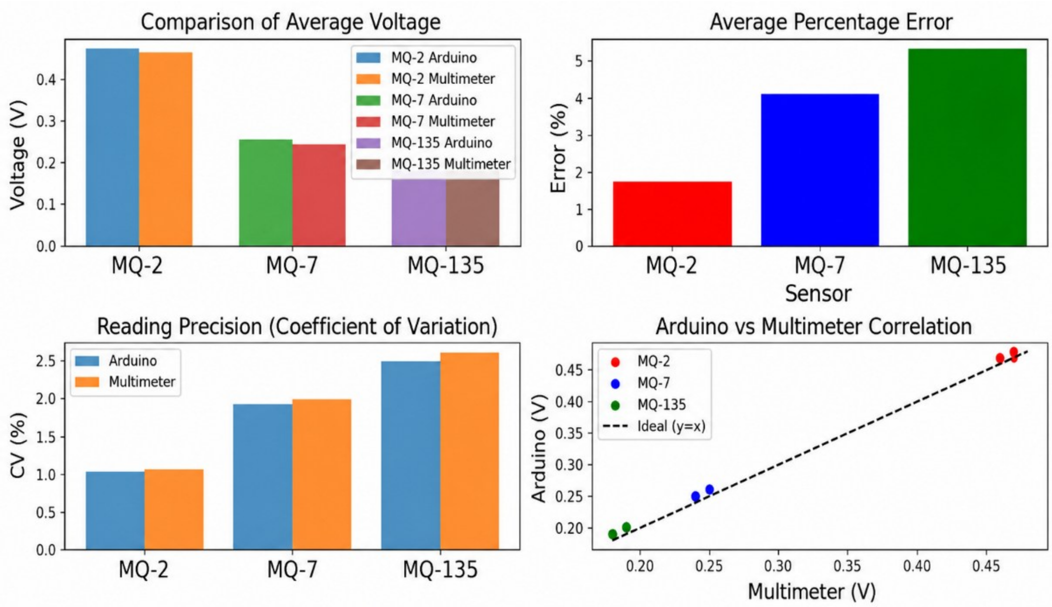

Figure 10. Graphs of the voltage correction between the Arduino and the multimeter

Research Limitations

Several methodological limitations should be acknowledged when interpreting the findings of this study. First, the reference instrument was a commercial CO detector rather than a laboratory-grade gas analyzer or certified reference standard; any systematic bias in the reference instrument will propagate directly into the error and calibration analyses. Second, all experiments were conducted at an ambient temperature of 30–32°C without humidity control. MOS sensor resistance is known to be temperature- and humidity-dependent, and performance at other ambient conditions may differ from the values reported (Reimringer & Bur, 2023; Carrillo-Amado et al., 2020). Third, despite efforts to seal the acrylic chamber, minor smoke leakage or non-uniform smoke distribution within the chamber cannot be entirely excluded, which could introduce spatial variability in the concentration experienced by each sensor relative to the centrally placed CO detector. Fourth, the number of repetitions (10–12 per condition) is sufficient for a preliminary characterization study but is modest for deriving high-confidence calibration curves; a larger repetition set would reduce Type A uncertainty and improve the robustness of the regression models. Fifth, cross-sensitivity was not systematically tested: the smoke matrices used—paper combustion, cigarette smoke, and motorcycle exhaust—all contain multiple chemical species beyond CO, and the extent to which each non-CO constituent contributes to the sensor output could not be isolated in this experimental design. Future work employing gas-mixing rigs with certified concentration standards would enable controlled cross-sensitivity profiling of each sensor.

CONCLUSION

Based on the test results and data analysis in this study, several conclusions can be drawn, among others:

1. For paper and cigarette smoke, MQ-7 is the best-performing sensor among the three evaluated, offering the widest measured concentration range, the highest regression linearity ($R^2 = 1.000$ for cigarette smoke), and the lowest relative error (38.01–40.20%). These characteristics make MQ-7 suitable for simple threshold-based early-warning applications, such as cigarette smoke detection in enclosed rooms. However, because the best-case relative error remains above 38%, MQ-7 should not be used for precise quantitative CO monitoring without additional in situ calibration, environmental compensation for temperature and humidity, and a higher-grade reference instrument.
2. MQ-2 is responsive across medium concentration ranges but shows high relative errors (>65%), attributable to its non-selective sensitivity to multiple flammable gases beyond CO. MQ-135 exhibits the highest sensitivity (>700 mV/ppm) among the sensors tested, but this high sensitivity does not translate into high gas-concentration accuracy; its relative error exceeds 77% for all smoke types because its broadband MOS sensing layer responds to multiple gases simultaneously. This study confirms that sensitivity and accuracy are fundamentally distinct metrics for MOS gas sensors and should not be conflated in performance evaluations.
3. None of the three sensors is recommended for motorcycle exhaust smoke detection under the conditions tested. All sensors produced relative errors exceeding 85%, which is attributable to the chemical complexity of engine exhaust (containing CO, HC, NOx, and particulate matter), cross-sensitivity of MOS sensors to multiple reducing gases, and probable sensor saturation at the high total gas concentrations present in motorcycle exhaust. This finding is consistent with the known limitations of low-cost MOS sensors in mixed-gas environments and reinforces the need for sensor selectivity enhancement (e.g., through operating temperature modulation, filter layers, or machine learning-based calibration) before these devices can be reliably deployed in vehicle-exhaust monitoring contexts.

RECOMMENDATION

Future research should address the limitations identified in this study by conducting gas-interference testing to assess the cross-sensitivity of MQ-series sensors to common interfering gases, including acetone, benzene, formaldehyde, and nitric oxide (NO). The use of higher-grade reference instruments, such as industrial-grade CO detectors or portable gas analyzers, is also recommended to improve the accuracy of measurement validation. Additionally, a more rigorously sealed measurement chamber with silicone rubber gaskets and active temperature and humidity control should be incorporated to enhance the reproducibility and stability of experimental conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

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Annas Dhamar Galuh		✓		✓		✓		✓	✓	✓	✓	✓		
Endang Dwi Wiwin Arinio			✓	✓			✓			✓	✓		✓	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

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