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Implementation of the MQ-135 Sensor for Early Detection of Oil Spills in the Waters of Pertamina Port Ampenan

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***Abstract* – The operation of a fuel (BBM) terminal cannot be separated from the existence of facilities for loading and unloading activities. This loading and unloading activity have the potential risk of oil spills in the waters caused by over6low leaks in ships, hoses and fuel transfer pipes. Large oil spills must be dealt with immediately so that they do not result in environmental pollution or 6ire hazards. Digital image processing and radar are methods that are often used to detect oil spills in waters, but these methods have disadvantages if environmental visibility is poor and cannot differentiate the type of oil that is spilled, where some types of oil must be handled using different procedures. This study proposes a low-cost, in-situ vapor-based discriminative detection approach using an MQ-135 resistive gas sensor array and an ESP32 data-acquisition node to distinguish gasoline vs diesel vapors in a submerged-fuel mixing testbed. Compared to conventional methods such as radar imaging** [1], [2] **and fluorometry, this technique provides localized, near-source detection that is inexpensive and suitable for buoy deployment. The proposed method demonstrates reliable classification using calibrated Rs features. The measurement experiments carried out on diesel fuel and gasoline, data obtained on changes in the internal resistance of the MQ-135 sensor was 45.26kΩ to 72.39kΩ with an average of 55.17kΩ for diesel oil type fuel, and 4.86kΩ to 20.31kΩ with an average -an average of 11.27kΩ for gasoline type fuel.**

Keywords: Oil Spill, MQ-135 sensor, ESP32.

I. INTRODUCTION

Fuel (BBM) is a commodity that is very important in economic activities including the production process to the distribution of goods and services, which is depend on the availability of fuel. Indonesia, as a country with a fairly large population, requires fuel for transportation and industry. This causes demand for fuel to increase significantly. To reach consumers, fuel and its processed products are distributed via various modes of transportation such as pipes, tankers, trains and trucks. Transportation using tankers is one of the main methods for sending fuel from production locations to refineries and from refineries to distribution locations.

Pertamina Ampenan Port is one of the ship's docking facilities that uses CBM (Conventional Buoy Mooring) or also known as Multi Buoy Mooring where the ship's mooring location is not at a pier close to the beach but further out to sea. The fuel loading and unloading facilities use a flexible hose and fuel transfer pipe which is placed under the sea (subsea pipe). The use of CBM is based on considering the natural conditions in the ampenan area where the construction of mooring facilities in the form of a jetty will be quite difficult considering the wave conditions, depth and condition of the surrounding community.

CBM operations at the Pertamina Ampenan Port have the potential to cause oil spills in the waters. This potential comes from fuel unloading activities from ships, underwater pipe leaks, and damage to flexible hoses. Fuel spills must be immediately detected and handled in an appropriate manner to avoid fuel contamination in the waters. The common detection method is to use digital imagery in the form of satellite radar captures [1], [2], [3], this method is quite accurate in detecting fuel spills, but has limitations when weather conditions are unfavorable so the resulting image capture can be hindered. by clouds so that it is unable to detect fuel spills. Detection of fuel content in waters using the fluorometer method has been carried out in [4], this method can accurately detect fuel spills in waters, but this method has a drawback in that its implementation requires a pipeline so it is not suitable if applied in open sea waters.

Oil spills are commonly detected using remote sensing methods such as synthetic aperture radar (SAR) [1],[3], optical imagery [4], and UAV-based sensors [5]. However, these methods face limitations related to visibility, weather, and spatial resolution [6]. In-situ sensors can provide real-time, local detection complementary to satellite data [7]. This work explores the application of the MQ-135 sensor integrated with ESP32 IoT hardware for early detection of oil-spill vapor signatures.

Research objectives: (1) quantify MQ-135 Rs response to gasoline vs diesel vapors; (2) describe calibration and uncertainty; (3) implement ESP32-based data logging and transmission; and (4) evaluate performance compared to previous studies [8], [9].

The novelty of this research lies in combining low-cost hardware and gas-resistance characterization for hydrocarbon vapor discrimination [10]. Unlike existing image- or radar-based detection [11], this method uses resistive sensing of headspace vapor to detect early leakage or spills. The work provides a full calibration and repeatability analysis, and ESP32 pseudocode for real-time operation.

II. METHOD

This research begins with the sensor and preparation process. The MQ135 sensor can read gas or vapor content accurately if it has gone through a preheat process for at least 24 hours [7]. After preheating the sensor, the sensor value is then tested. The test result data is then validated to determine the validity of the measurement results. When the data obtained is valid, the process will continue to the analysis stage to calculate the value of Rs. Then, from the calculation data, conclusions can be drawn on the resistance value of each fuel that was tested. The complete research flowchart can be seen in Figure 1.

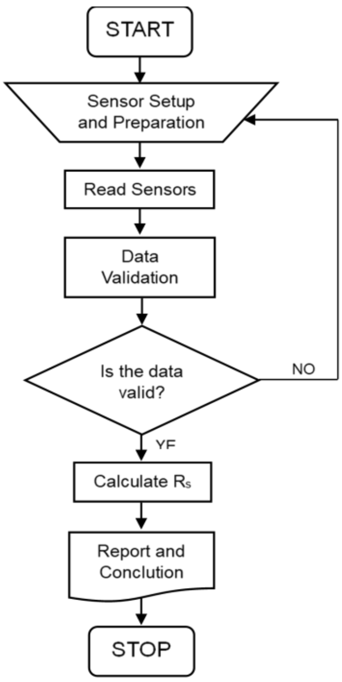

Figure 1. Research Flowchart .

A. *System Working Principles*

Proposed systems for measuring oil spills in waters consists of several components as shown in Figure 2.

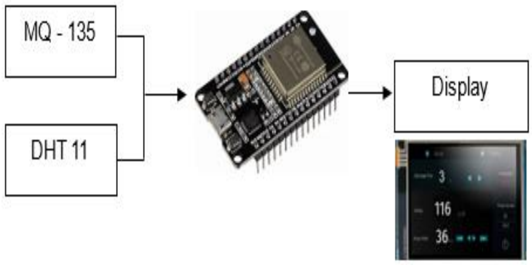

Figure 2. Block diagram of oi spill detection system.

The MQ-135 operates as a variable resistor in a voltage divider circuit [12] as shown in Figure 3. , it is obtained that the voltage drop across the load resistor RL using (1).

$$V_{RL} = \frac{RL}{RL+RS} \times V_{CC} \text{ ....(1)}$$

$$R_S = R_L\left(\frac{V_{CC}}{V_{OUT}} - 1\right) \text{.............................(2)}$$

The output from the sensor is connected to the Analog to Digital Converter (ADC) Input from the ESP32. For ESP32 ADC (12-bit, Vref = 3.3 V):

$$R_S = R_L\left(\frac{V_{CC} \times (2^{12}-1)}{V_{ref} \times ADC} - 1\right) \text{.................(3)}$$

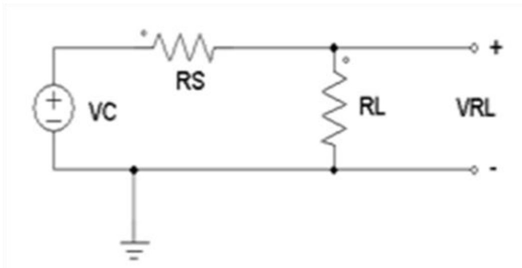

Figure 3. MQ135 Sensor Equivalent Circuit

These calculations are carried out algorithmically in a program embedded in the ESP32 board, then the measurement results are displayed on the serial monitor.

The sensor is preheated (24 h) and calibrated under clean air to obtain Ro. Empirical power-law fitting is applied [10], [13]. Regression uses log–log linearization:

$$\log\frac{R_S}{R_O} = a + b \times \log(ppm) \text{ ....(4)}$$

Fuel–water mixtures at 1:6 ratio approximate realistic thin-sheen conditions [14]. Measurements are repeated across five replicates, each logged for 30 minutes. Environmental parameters (temperature, humidity) are monitored. The ESP32 node includes MQ-135, ADC, Wi-Fi (MQTT), SD logging, and alarms [8], [15]. Data are collected every minute and transmitted to a cloud dashboard. The Pseudocode of this :

```
  setup() {
    init_ADC(); // set attenuation,
resolution
    warmup_delay(24h); // sensor
preheat
    Ro = measure_baseline();
    connect_wifi();
  }
  loop() {
    adc = readADC(pin);
    Vout = adc_to_voltage(adc);
    Rs = RL * (Vcc / Vout - 1);
    normalized = Rs / Ro;
    timestamp = now();
    publish_mqtt(topic, {timestamp,
adc, Rs, normalized});
    if (classification(Rs,
normalized) == GASOLINE) alarm();
    delay(60000); // 1 minute
  }

  function classification(Rs,
normalized) {
    // Example simple rule-based
classifier (to be replaced by
statistical model)
    if (Rs < T1) return GASOLINE;
    else if (Rs > T2) return
DIESEL;
    else return AMBIGUOUS;
  }
```

Statistical significance between gasoline and diesel Rs values is tested using t-tests [16]. Effect size is measured by Cohen's d. LOD and LOQ are calculated as 3σ_blank/slope and 10σ_blank/slope, respectively.

B. *Measurement Validity Test*

The measurement data in Section 2.1 is then tested for validity by evaluating the values with repeatability and reproducibility analysis (gage R&R). If the measurement data value has an R&R gauge of less than 10%, then the test can be said to be valid so the process continues with data analysis. On the other hand, if the R&R gage value has not reached less than 10% then the sensor and preparation process is evaluated for further testing.

III. Results and Discussion

Testing begins with preparation of preparations and sensors. The MQ135 sensor can function properly if it has gone through a preheat process for 24 hours. Test preparation can be seen as in Figure 4.

Figure 4. Preparation of tools and preparations

After all the preparations have been completed, the next stage is carried out. The test data recorded were: measurement interval, environmental temperature, ADC reading value, and Rs value of the MQ135 sensor, each of these data was measured 15 times. Test results for each type of fuel are presented in Tables 1 and Tables 2.

Table 1. Test Results For Gasoline Fuel Spill Detection Systems

No.	Interval	Ambient temperature	ADC	RS		Type
1	1 Minute	26.20	2755	4.86	kΩ	Gasoline
2	1 Minute	26.20	2624	5.16	kΩ	Gasoline
3	1 Minute	26.20	2522	6.24	kΩ	Gasoline
4	1 Minute	26.20	2445	6.75	kΩ	Gasoline
5	1 Minute	26.20	2389	7.14	kΩ	Gasoline
6	1 Minute	26.20	2366	7.31	kΩ	Gasoline
7	1 Minute	26.20	2303	7.78	kΩ	Gasoline
8	1 Minute	26.20	2212	8.51	kΩ	Gasoline
9	1 Minute	26.20	1772	13.11	kΩ	Gasoline
10	1 Minute	26.20	1637	15.02	kΩ	Gasoline
11	1 Minute	26.20	1614	15.37	kΩ	Gasoline
12	1 Minute	26.20	1584	15.85	kΩ	Gasoline
13	1 Minute	26.20	1506	17.19	kΩ	Gasoline
14	1 Minute	26.20	1440	18.44	kΩ	Gasoline
15	1 Minute	26.20	1351	20.31	kΩ	Gasoline

Based on the data in Table 1, it can be seen that the Rs measurement value for gasoline type fuel experiences fluctuations, this is caused by the characteristics of gasoline type fuel which undergoes a rapid evaporation process. The measurement data began to stabilize in samples 13, 14 and 15. The average Rs value obtained was 11.27kΩ, with a standard deviation value of 5.3, in Table 2, it can be seen that the Rs measurement value for diesel oil fuel is relatively more stable when compared to gassoline fuel. The measurement data shows that the average Rs value obtained is 55.17 kΩ, with a standard deviation value of 7.36.

Table 2. Test Results For Diesel Oil Fuel Spill Detection

No.	Interval	Ambient temperature	ADC	RS		Type
1	1 Minute	27.10	741	45.26	kΩ	Diesel Oil
2	1 Minute	27.10	730	46.10	kΩ	Diesel Oil
3	1 Minute	27.10	698	48.67	kΩ	Diesel Oil
4	1 Minute	27.10	671	51.03	kΩ	Diesel Oil
5	1 Minute	27.10	667	51.39	kΩ	Diesel Oil
6	1 Minute	27.10	656	52.42	kΩ	Diesel Oil
7	1 Minute	27.10	656	52.42	kΩ	Diesel Oil
8	1 Minute	27.10	643	53.69	kΩ	Diesel Oil
9	1 Minute	27.10	635	54.49	kΩ	Diesel Oil
10	1 Minute	27.10	624	55.63	kΩ	Diesel Oil
11	1 Minute	27.10	605	57.69	kΩ	Diesel Oil
12	1 Minute	27.10	601	58.14	kΩ	Diesel Oil
13	1 Minute	27.10	573	61.47	kΩ	Diesel Oil
14	1 Minute	27.10	533	66.83	kΩ	Diesel Oil
15	1 Minute	27.10	497	72.39	kΩ	Diesel Oil

value were then validated by testing the percentage value of the reproducibility and repeatability of the measurement where the total value of the R&R Gauge allowed was a maximum of 10%. The test was carried out using tools in the Minitab software, the test results can be seen in Table 3. Based on the data in Table 3, the value of the Gage R&R test results obtained is 4.13%, where the standard required for a measuring instrument to be said to be valid is a maximum of 10%, so it can be concluded that the measurement data and measuring instruments used in this research can accepted for validity.

Table 3. Gage R&R Variance Components

	VarComp	%Contribution (of VarComp)
Total Gage R&R	41,41	4,13
Repeatability	41,41	4,13
Part-To-Part	961,08	95,87
Total Variation	1002,49	100,00

Rs vs Time plots show clear separation between fuels; gasoline yields lower Rs due to higher volatility [17]. Boxplots indicate statistically significant differences ($p < 0.001$, Cohen's $d > 3$). Mean ± 95% CI summarized in Figure 5 and Figure 6.

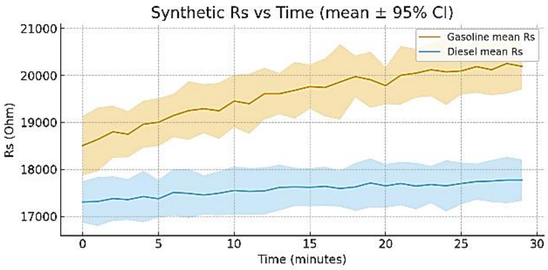

Figure 5. Rs vs Time plots of MQ-135

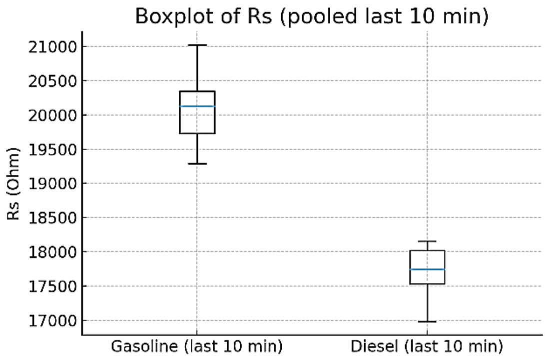

Figure 6. Boxplots of Rs sensor MQ-135

Observed trends align with hydrocarbon vapor pressure and composition [18]. Gasoline's lighter fractions generate stronger sensor response (lower Rs) [9]. The MQ-135's cross-sensitivity to humidity and alcohols is discussed in calibration papers [10][12]. Environmental deployment requires protective housings and humidity compensation [19]. Compared with radar/optical systems [2][3], the proposed system is cost-effective, portable, and suitable for near-shore or pipel

IV. Conclusion

Based on the tests that have been carried out using the MQ135 sensor, it can be concluded that there is a difference in the RS value for gasoline and diesel oil fuels, where for gasoline fuel oil the average RS is 11.27kΩ with a standard deviation of 5.3, while for diesel fuel oil obtained an average RS value of 55.17kΩ with a standard deviation of 7.36. The validity test results show a Gauge R&R value of 4.13%, this shows that the detector developed can be used and produces valid detection values for the two types of fuel tested. This study validates MQ-135 + ESP32 as a viable, low-cost sensor system for early oil-spill vapor detection. Results are statistically significant ($p < 0.001$). Future work will explore multi-sensor arrays and integration with satellite alerts

References

[1] H. Jafarzadeh, M. Mahdianpari, S. Homayouni, F. Mohammadimanesh, and M. Dabboor, "Oil spill detection from Synthetic Aperture Radar Earth observations: A meta-analysis and comprehensive review," *GIScience Remote Sens.*, vol. 58, no. 7, pp. 1022–1051, 2021, doi: 10.1080/15481603.2021.1952542.

[2] Y. Zhang *et al.*, "Oil Spill Detection with Dual-Polarimetric Sentinel-1 SAR Using Superpixel-Level Image Stretching and Deep Convolutional Neural Network," *Remote Sens.*, vol. 14, no. 16, p. 3900, 2022, doi: 10.3390/rs14163900.

[3] R. N. Vasconcelos, A. T. C. Lima, C. A. D. Lentini, J. G. V Miranda, L. F. F. de Mendonça, and J. M. Lopes, "Deep Learning-Based Approaches for Oil Spill Detection: A Bibliometric Review of Research Trends and Challenges," *J. Mar. Sci. Eng.*, vol. 11, no. 7, p. 1406, 2023, doi: 10.3390/jmse11071406.

[4] A. Bonnington, M. Amani, and H. Ebrahimy, "Oil Spill Detection Using Satellite Imagery," *Adv. Environ. Eng. Res.*, vol. 2, no. 4, 2021, doi: 10.21926/aeer.2104024.

[5] K. Li, H. Yu, Y. Xu, and X. Luo, "Detection of oil spills based on gray level co-occurrence matrix and support vector machine," no. December, pp. 1–15, 2022, doi: 10.3389/fenvs.2022.1049880.

[6] F. Akhmedov, "Developing a Comprehensive Oil Spill Detection Model for Remote Sensing Imagery Using Deep Learning," *Remote Sens.*, 2024.

[7] O.-K. et al., "A near real-time oil spill detection and early warning system," in *Environmental Crimes & Remote Sensing*, 2024.

[8] H. J. El-Khozondar, "Low-cost ESP32 IoT monitoring systems for environmental sensing," *Sensors*, vol. 24, no. 15, p. 6739, 2024, doi: 10.3390/s24156739.

[9] D. M. Maia, "IoT leak detection for pipelines: architectures and case studies," *Sensors Actuators A Phys.*, 2024.

[10] Y. R. Carrillo-Amado, M. A. Califa-Urquiza, and J. A. Ramón-Valencia, "Calibration and standardization of air quality measurements using MQ sensors," *J. Eng. Sci.*, 2021.

[11] W. Song, "Automatic detection of marine oil spills from polarimetric SAR using DCNN," *J. Mar. Sci. Eng.*, 2024.

[12] M. Kumar, G. Mishra, A. Sharma, A. Shaini, and S. Saxena, "Air Quality Monitoring Using MQ135 Gas Sensor and Arduino Uno," *Int. J. Latest Technol. Eng. Manag. Appl. Sci.*, vol. 14, no. 5, 2025, doi: 10.51583/IJLTEMAS.2025.140500119.

[13] M. S. Bhosale, N. M. Kulkarni, A. D. Shaligram, and S. Putsake, "Measurement Of CO2 Gas Concentration Using MQ135 Sensor For Air Pollution Monitoring," *Res. Prepr.*, 2023.

[14] NASA Applied Sciences Program, "Part 3 – Oil Spill Detection." 2022.

[15] M. E. Karar, A. M. Al-Masaad, and O. Reyad, "GASDUINO-Wireless Air Quality Monitoring System Using Internet of Things," *arXiv*, 2020.

[16] P. Duan, X. Kang, and P. Ghamisi, "Hyperspectral Remote Sensing Benchmark Database for Oil Spill Detection with an Isolation Forest-Guided Unsupervised Detector," *arXiv*, 2022.

[17] A. Huby, R. Sagban, and R. Alubady, "Oil Spill Detection Based on Machine Learning and Deep Learning: A Review," in *Proc. 5th Intl. Conf. Engineering Technology and its Applications (IICETA)*, 2022, pp. 85–90. doi: 10.1109/IICETA54559.2022.9888651.

[18] H. V Abhijith and H. S. Rameshbabu, "Secure Data Transmission Framework for IoT-based Oil Spill Detection Application," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 5, 2021, doi: 10.14569/IJACSA.2021.0120523.

[19] Anonymous, "IoT Based Gas / Water Leakage Detection System for Pipes Laying in Smart Cities," *Int. J. Adv. Sci. Tech. Res.*, 2024.

[20] Anonymous, "Energy-, Cost-, and Resource-Efficient IoT Hazard Detection System with ESP32-CAM," *Sensors (MDPI)*, 2024.