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Embedded System of LPG Leakage Detection Using Arduino Microcontroller and Kalman Filter Algorithm

Rakha Hafizh Pramana
Departement of Electrical Engineering, Faculty of Engineering, Universitas Negeri Semarang
rakhahp1@students.unnes.ac.id

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ABSTRACT

Liquefied Petroleum Gas (LPG) leakage is a significant safety concern that commonly occurs in household kitchens, especially when LPG serves as the primary fuel for cooking. This is a serious issue that can lead to risks of fire or explosion. To address this problem, a study was conducted to develop an LPG leakage detection system based on Arduino, equipped with an MQ-2 sensor, Kalman filter, and exhaust fan. The MQ-2 sensor is used to detect LPG leaks in the air, while the Kalman filter reduces noise and improves the accuracy of sensor measurements, allowing the system to operate more reliably and stably. The system is designed to provide a quick and accurate response in detecting gas leaks, delivering early warnings and automatically taking preventive actions. The test results show that the Kalman filter, with constants R=10 and Q=0.01, produces smoother and more stable sensor readings compared to the absence of a filter. Additionally, sensor placement distance is a crucial aspect in optimizing system performance. Therefore, this system is expected to be an effective solution to enhance safety in small commercial areas and provide better protection for users against the risks of LPG leaks.

Corresponding Author:

Corresponding Author
Departement of Electrical Engineering, Faculty of Engineering
Universitas Negeri Semarang
Semarang, Jawa Tengah, Indonesia
Email: rakhahp1@students.unnes.ac.id

1. INTRODUCTION

The increasing human population has led to a higher demand for resources, particularly in fuel consumption for cooking purposes. The transition from kerosene to Liquefied Petroleum Gas (LPG) is driven by its economic advantages and relative affordability in Indonesia. LPG has become the primary choice for daily cooking activities in almost every household in Indonesia due to its versatility as an energy source, clean combustion, and efficiency [1]. However, despite being more economical than kerosene, LPG poses significant risks, especially in the event of gas leaks. LPG leaks can occur in either liquid or gaseous form [2]. When an LPG tank is damaged, the gas will leak and expand up to hundreds of times its liquid volume. This gas can immediately mix with air and form vapor [3]. A large accumulation of leaked LPG gas can become highly flammable, leading to explosions and fires. The explosion limit of LPG at normal temperature and pressure is between 4.3% and 11.9%. This means that if the concentration of LPG vapor in the air falls within this range, the vapor will explode when it comes into contact with an ignition source [4]. LPG gas leaks can be caused by various factors, such as an unsecured hose connection, poor hose quality, or improper valve installation. These incidents pose a high risk as the gas may continue to flow undetected, increasing the potential for fire and explosion hazards, especially in household environments like kitchens. Therefore, early detection and preventive measures are essential to avoid dangerous incidents [5]. If not properly managed, these hazards can result in significant physical and material losses, including major accidents like fires and explosions caused by flammable gas leaks, leading to property damage[6].

Cooking is generally done daily according to the family's needs, requiring the repeated use of LPG in daily cooking activities. This ensures the freshness of the food served, but also increases the frequency of LPG use at home. However, gas leak monitoring is often inadequate due to various limitations. Several measures can be taken to prevent or manage LPG leaks, such as public awareness campaigns on proper LPG usage and gas leak prevention. Additionally, technological advancements can be leveraged to develop a safety system. This study proposes the development of an Arduino-based LPG leakage detection system equipped with an automatic exhaust fan control mechanism as a preventive measure when a gas leak is detected by an MQ-2 sensor. To prevent accidents caused by gas leaks, this study proposes the use of an intelligent embedded system [7]. This system is designed to reduce excessive gas and smoke concentrations, using the MQ-2 sensor, which can detect alcohol, LPG, carbon monoxide (CO), hydrogen (H2), methane (CH4), propane, and smoke [2][8]. To address sensor instability and noise in readings, a Kalman filter is implemented to enhance data accuracy, ensuring the sensor operates efficiently. Previous research in [9] demonstrated that Kalman filtering effectively reduces drift. Random errors can be classified into two types based on their frequency: noise and drift. Noise consists of high-frequency random fluctuations over short durations, whereas drift appears as a slow-moving, low-frequency change over time [10].

The integration of the Kalman filter as an algorithm in this system is expected to significantly minimize fluctuations in sensor readings, making gas detection more consistent compared to systems without filtering [11]. This study aims to answer the central question: Can an Arduino-based system equipped with a Kalman filter detect LPG leaks more stably and accurately than a system without a filter? The proposed system is designed as a reliable and precise solution for detecting LPG leaks, with the goal of enhancing user safety and preventing financial losses caused by potential fires or explosions resulting from gas leaks.

2. RESEARCH METHOD

This study develops and tests an Arduino-based LPG leakage detection system equipped with an MQ-2 sensor, a Kalman filter, and an automatic exhaust fan. The research method is carried out through several key stages as follows:

2.1. System Design

In this study, the block diagram of the system consists of several main components, including an Arduino Uno, an MQ-2 sensor, a 5V relay, a buzzer, an I2C LCD, and a 12V DC fan. The system is designed using Arduino as the main controller and an MQ-2 sensor to detect LPG gas in the event of a leak [12]. Kalman filter to enhance the accuracy of sensor readings, and an exhaust fan to expel the detected gas. The hardware is assembled with other essential components, such as a relay module to control the exhaust fan, a buzzer for warning alarms, and an LCD module to display system status information.

Tabel 1. Pin I/O

NO	ARDUINO	MQ-2	RELAY 5V	LCD	FAN	PS
1	PIN 2	-	S	-	-	-
2	PIN A0	A0	-	-	-	-
3	PIN A4	-	-	SDA	-	-

4	PIN A5	-	-	SCL	-	-
5	-	-	NO	-	(+)	-
6	-	-	-	-	(-)	-V
7	-	-	COM	-	-	+V
8	5V	VCC	(+)	VCC	-	-
9	GND	GND	(-)	GND	-	-

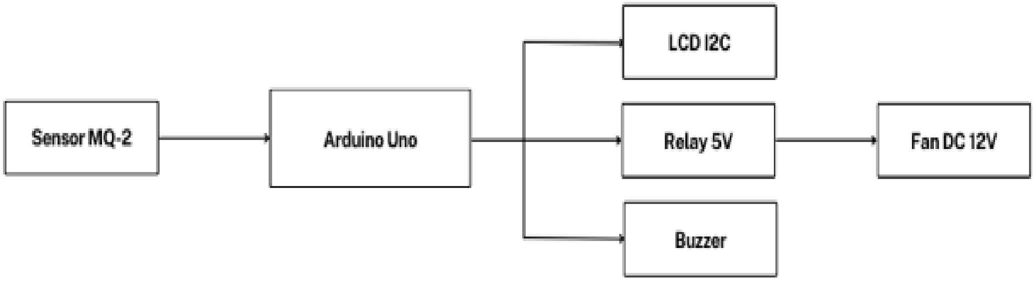

Figure 1. System Block Diagram

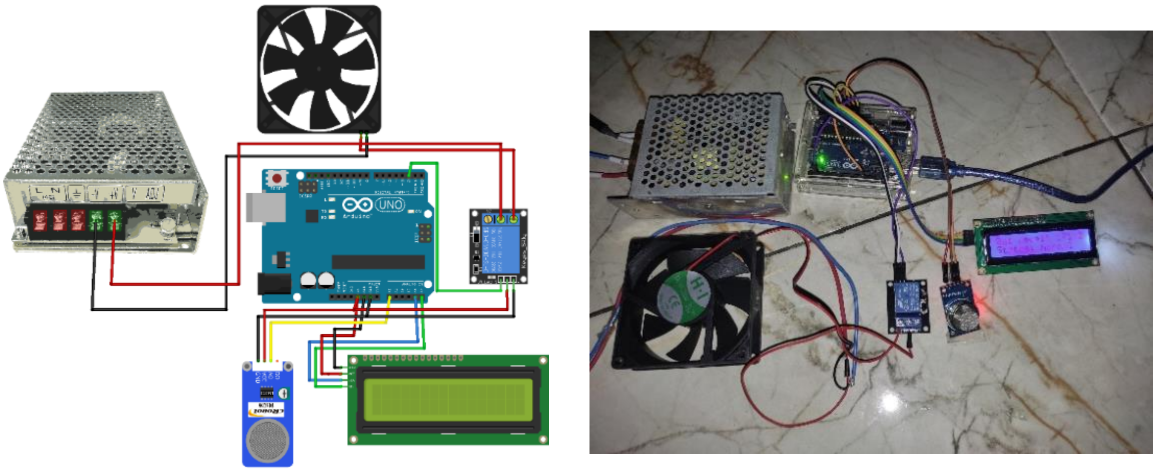

Figure 2. (a) Wiring System (b) Hardware Design

2.2. Kalman Filter

The Kalman Filter (KF) algorithm has been widely used in sensor readings to address noise in the model and measurements, with the goal of improving the accuracy of the data obtained from the sensor [13]. The primary objective of the Kalman filter is not to filter or attenuate the received signal but to estimate values based on incoming data [14]. Due to its advantages in real-time processing, speed, efficiency, and robustness against disturbances, the Kalman filter has been widely applied in various fields, including navigation, control systems, and signal processing [15]. There are several types of Kalman filters, including the Standard Kalman Filter [16], Extended Kalman Filter [17], Unscented Kalman Filter [18], and Ensemble Kalman Filter [19]. Based on the study [20], the Kalman Filter was chosen due to its better ability to maintain the average velocity value compared to the autoregressive moving average (ARMA) filter model. In the comparison, the Kalman Filter proved to be more effective in reducing noise without compromising the accuracy of the average value estimation. Therefore, the Kalman Filter is applied in this system to reduce disturbances in the MQ-2 sensor readings, as it outperforms the moving average filter, which tends to introduce lag in the estimates and is less responsive to rapid changes in the data. Among many filtering algorithms, the Kalman filter algorithm structure is relatively simple and easy to implement. Most importantly, its operation is fast, which is crucial for real-time monitoring systems [21]. Key parameters in the Kalman filter include the measurement noise (R) and process noise (Q), which are optimized through experimentation to achieve the most accurate results.

In this study, the Kalman filter is modified to suit the requirements of the MQ-2 sensor, consisting of two main stages: prediction and update. The prediction step is the initial phase of the Kalman filter, where the predicted state is calculated while ignoring dynamic noise [22]. The mathematical equations used in this study are derived from previous research, as follows [11].

Prediciton:

$$x_{t|t-1} = x_{t-1|t-1} \tag{1}$$

$$p_{t|t-1} = x_{t-1|t-1} + Q \tag{2}$$

Update:

$$x_{t|t} = x_{t-1} + k_t(y_t - x_{t|t-1}) \tag{3}$$

$$k_t = p_{t|t-1} + R)^{-1} \tag{4}$$

$$p_{t|t} = (1 - k_t)p_{t|t-1} \tag{5}$$

Equations (1)–(5) represent the mathematical formulation of the Kalman filter. In the initial stage, the state prediction is described by Equation (1). This equation indicates that the predicted state value at time t is directly taken from the previous update at $t-1|t-1$, since the system has no dynamics or external input. Next, the prediction of the error covariance is expressed in Equation (2), where P represents the error covariance and Q_t denotes the process noise covariance. This illustrates that the uncertainty in the current prediction results from the accumulation of the previous uncertainty and the internal process noise.

After the prediction step, the next stage is to update the state estimate based on sensor data using Equation (3), by adjusting the difference between the actual sensor measurement y_t and the previous predicted value. The magnitude of the correction is determined by the Kalman gain K_t, which is calculated using Equation (4), where R represents the covariance of the sensor noise. The smaller the value of R, the more accurate the sensor is considered to be, leading to a larger K_t and a greater weighting of the correction applied to the prediction. Finally, the error covariance is updated to reflect the level of uncertainty after the correction, as described in Equation (5).

These equations are converted into an Arduino IDE program to filter sensor readings. As shown in the flowchart, the process begins with initializing the parameter values in the Kalman filter, where the parameters R and Q determine the quality of the filtering results. The next stage (SensorData) involves raw readings from the MQ-2 sensor, which have not yet been processed. These readings are then processed using the prediction calculations (Xt_predict) as the predicted state variable and (Pt_predict) as the variance variable. Subsequently, in the update phase, the Kalman gain (Kt) is calculated, followed by updating the estimation variable (Xt) and the variance variable (Pt). The output of the Kalman filter algorithm is the latest estimated predicted state (Xt). The final estimated state value and variance are also stored as initial data for the next iteration. This process continuously repeats as long as the system is running. The testing was carried out to determine the parameters RRR and QQQ by assigning several values and then analyzing them to find which values are the most optimal in order to obtain the best filtering result.

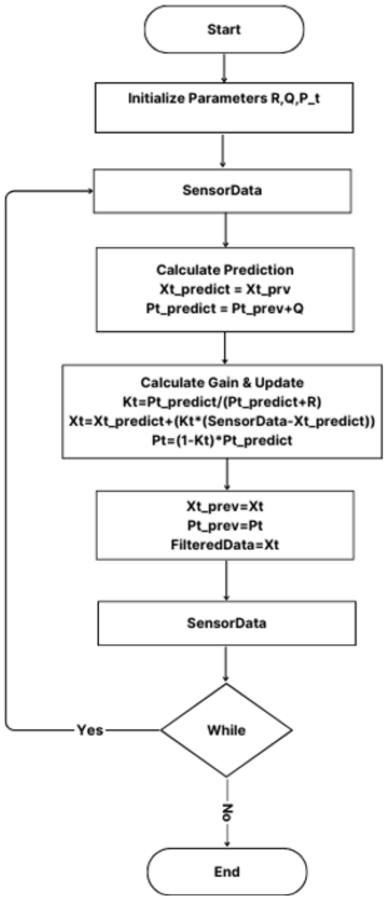

Figure 3. Kalman Filter Flow Chart

3. RESULTS AND ANALYSIS

The testing process consists of three stages. First, an accuracy test is conducted on the MQ-2 sensor readings to evaluate the effect of constants on the implementation of the Kalman filter algorithm. Second, the system's response in detecting LPG leaks is tested by activating the automatic mitigation mechanisms, such as the buzzer and exhaust fan. Third, the performance of the exhaust fan is tested to assess its effectiveness in reducing the concentration of leaked gas in the air after a leak is detected. These tests are conducted to evaluate the overall performance of the system and ensure it functions as expected.

3.1 Performance Evaluation Based on Kalman Filter Parameters

The system is tested with LPG gas concentrations to evaluate the accuracy of the MQ-2 sensor readings before and after applying the Kalman filter. The results obtained from this test involve variations in the R and Q constants, allowing an analysis of the filter's performance in improving the MQ-2 sensor readings.

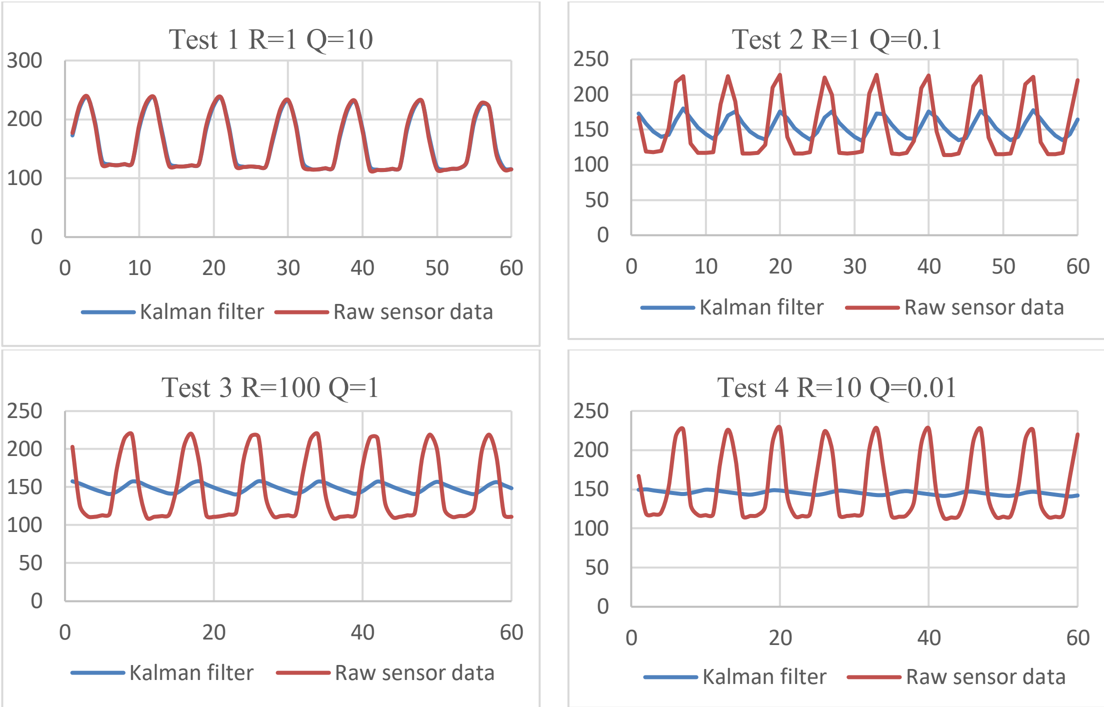

Figure 4. Performance Evaluation Based on Kalman Filter Parameters

Based on the Kalman filter parameters, it can be observed that the constants R and Q significantly affect the filter's performance. In Figure 4, when R = 1 and Q = 10, the filter's performance is not significant and does not have any noticeable impact on the sensor readings. The best Kalman filter performance, according to the conducted tests, is shown in Figure 6 and Figure 7. Based on the constants R and Q in these tests, it was found that R should always be greater than Q to achieve optimal filter performance. After filtering, the sensor readings become smoother and more stable. From the test results, Figure 7, where R = 10 and Q = 0.01, provides the best filter performance with minimal fluctuations and a smoother output.

From Test 1 to Test 4, the filter's performance was evaluated by comparing the filtered results with the actual values. The difference was calculated using the Mean Absolute Error (MAE), which is expressed by the following equation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Yi - \hat{Y}| \tag{6}$$

The calculation results of Mean Absolute Error (MAE) in Table 2 show that the larger the difference between Y and Ŷ, the smaller the MAE value. Based on Table 2, it is observed that Test 4 has the highest MAE value, with smoother sensor readings. The test results show that the effectiveness of noise reduction in the Kalman Filter is strongly influenced by the ratio between the R and Q parameters. The larger the ratio, the stronger the damping effect produced, but it may result in the loss of original information from the data. Conversely, a smaller ratio yields lighter damping, thus better preserving the original signal shape. The ratio value between R (measurement error) and Q (process error) in the Kalman filter indicates the extent to which the filter relies on sensor measurements versus the prediction model. A higher ratio suggests greater confidence in the model prediction, whereas a lower ratio implies increased reliance on sensor data.

Tabel 2. Mean Absolute Error & Ratio Value

Testing	Kalman Filter Parameter		R&Q Rasio	MAE
	R	Q		
1	1	10	10	2.44
2	1	0.1	10	31.87
3	100	1	100	38.16
4	10	0.01	1000	40.22

3.2 Experimental Results of the System

Based on the table, testing is conducted to evaluate the system's response to LPG leaks at various distances between the sensor and the gas concentration source. This test includes several key parameters: measurement distance, detection time of the gas concentration threshold, activation time of the exhaust fan until the gas concentration drops below the threshold, and evaluation of the system's response. Based on the test results regarding the system's response, the measurement distance of the sensor significantly affects system performance. As shown in Figures 4 and 5, the sensor responds quickly to gas, detecting it within 5 seconds, while the exhaust fan operates for approximately 12-13 seconds to reduce gas concentration in the air. However, at a measurement distance of 15 cm, the sensor becomes less responsive, requiring a longer detection time of 26 seconds.

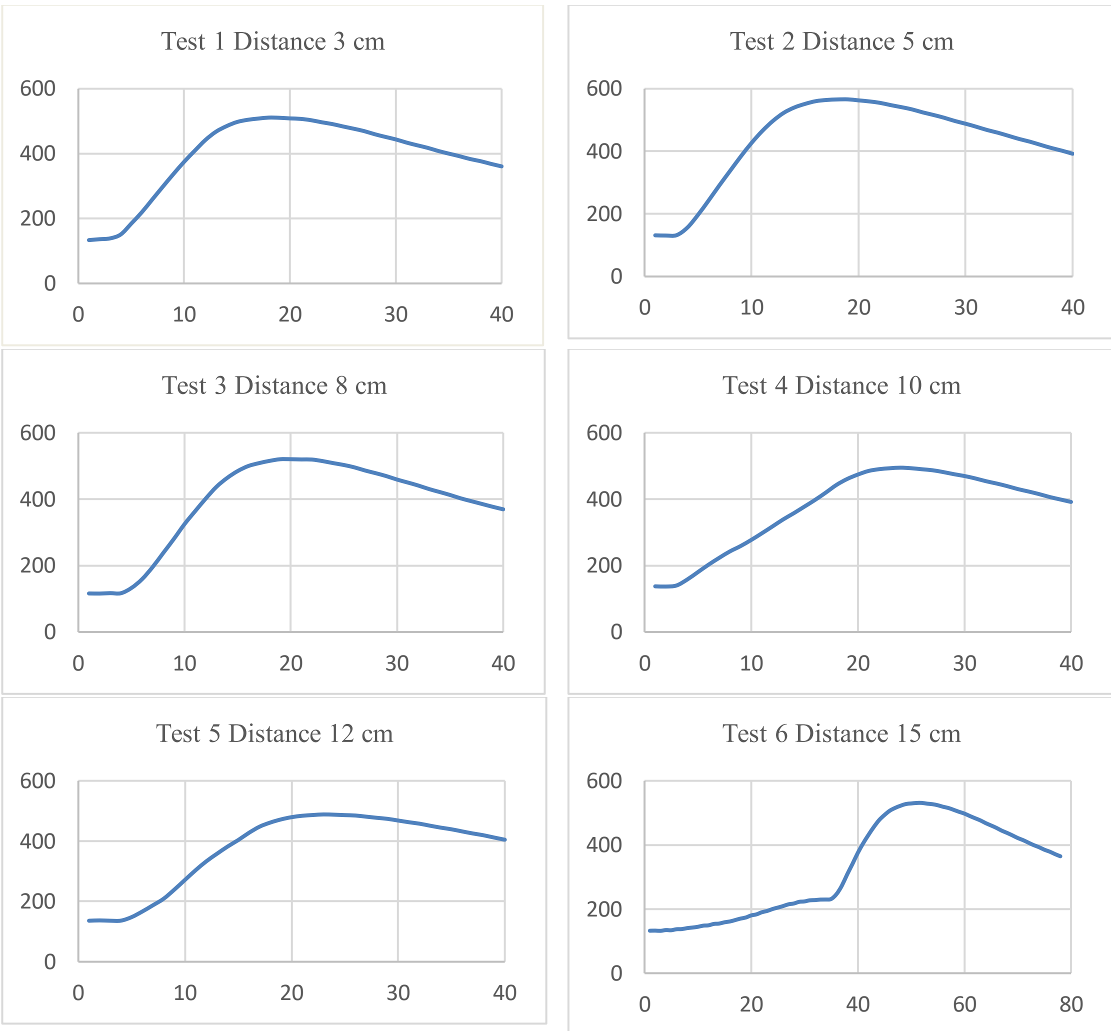

Figure 5. Experimental Results of the System

Based on the test results regarding the system response, it is shown that the measurement distance of the sensor affects system performance. In Figure 4 and Figure 5, the sensor responds to gas quickly, with a detection time of 5 seconds, and the fan operates for approximately 12-13 seconds to reduce the gas concentration in the air. However, when the measurement distance is increased to 15 cm, the sensor becomes less responsive, requiring a longer detection time of 26 seconds.

Table 3. Experimental Results of the System

No	Measurement Distance	Detection Time	Fan ON Time	System Response
1	3 cm	5 seconds	12 seconds	Fast
2	5 cm	5 seconds	13 seconds	Fast
3	8 cm	5 seconds	14 seconds	Fast
4	10 cm	7 seconds	14 seconds	Fast
5	12 cm	10 seconds	15 seconds	Slow
6	15 cm	26 seconds	18 seconds	Slow

In the LPG leak detection system, the exhaust fan plays a crucial role as a mitigation solution to reduce the gas concentration detected in the air. When the sensor detects a gas leak, the fan is activated to expel air and accelerate the process of lowering the gas concentration, which can help reduce the potential danger from gas accumulation. According to the test results, the exhaust fan can operate within about 12-13 seconds after detecting the gas, thus helping to bring the gas concentration below the hazardous threshold. However, the effectiveness of the exhaust fan heavily depends on the measurement distance of the sensor from the gas leak source. At a closer distance (such as 5 cm), the sensor can quickly detect the gas, and the fan can be activated immediately to begin the mitigation process. On the other hand, at a greater measurement distance, such as 15 cm, the sensor takes longer to detect the gas leak, resulting in a delay in activating the fan and prolonging the time required to reduce the gas concentration. This indicates that although the exhaust fan is effective in reducing gas concentration, the overall system response—especially the gas detection time by the sensor—can impact how quickly the fan can operate to mitigate the leak risks. Therefore, it is essential to consider the sensor measurement distance and the sensor's characteristics in designing a more efficient gas leak detection system.

4. CONCLUSION

Based on the tests conducted on the LPG gas leakage detection system, the following conclusions were obtained:

1. The application of the Kalman Filter in MQ-2 sensor readings for noise reduction is highly dependent on the ratio between the *R* and *Q* parameters. A higher ratio results in stronger noise suppression but carries the risk of losing important information from the original signal. Conversely, a lower ratio provides milder filtering, better preserving the original characteristics of the signal. Therefore, selecting an appropriate *R/Q* ratio is crucial to balancing sensor reading stability and the preservation of accurate information from raw data. The optimal parameter combination was found at $R = 10$ and $Q = 0.01$, which effectively reduced sensor reading fluctuations and provided more reliable data.
2. System response testing shows that the distance between the sensor and the gas source significantly affects detection speed and fan activation time. Shorter distances enable faster detection, while longer distances delay the response, highlighting the importance of optimal sensor placement for effective system performance.

Overall, the developed system successfully addresses the research question and demonstrates potential as a reliable solution for detecting LPG gas leaks with improved accuracy and stability. However, several challenges remain in real-world implementation, such as sensor performance degradation over time, environmental influences (e.g., temperature and humidity), and variability in gas source characteristics.

For future development, it is recommended that the system be tested continuously under real-world scenarios. In addition, integrating the system with Internet of Things (IoT) technologies and cloud-based monitoring is essential to enable remote and real-time gas leak detection, which is highly relevant for enhancing safety in both domestic and industrial environments.

Furthermore, considering the system's sensitivity to the selection of R and Q values, the development of adaptive Kalman filter algorithms is a promising research direction. This approach allows R and Q parameters to be dynamically adjusted based on environmental conditions or real-time sensor reading patterns, thereby improving the system’s flexibility and accuracy when operating under varying field conditions.

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