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Design and Implementation of an IoT-Based Indoor Air Quality Monitor with Ensemble and Unscented Kalman Filter Forecasting

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Abstract The increase in air pollution resulting from intensified human activity in urban areas poses a serious threat to public health and environmental sustainability. In the long term, this situation also has the potential to reduce productivity, as evidenced by the spread of respiratory diseases affecting humans. Exposure to air pollution occurs not only outdoors but also indoors. This can happened due to ignorance of hygiene or exposure to outdoor air. To address this issue, a device is required that can accurately and affordably detect changes in indoor air quality. This research developed an affordable Internet of Things (IoT) based monitoring system to address these issues. By utilizing the ESP32 microcontroller along with DHT11 and MQ135 sensors, this device is capable of measuring ambient temperature, humidity, and carbon monoxide (CO) levels. The measurement results obtained by the device are then visualized using the real-time application ThingSpeak to identify changes in air quality over time. In addition, this research also employs analytical and forecasting approaches to the air quality measurement data utilizing the Ensemble Kalman Filter (EnKF) and Unscented Kalman Filter (UKF) methods. In addition, this research also applied analytical and short-term forecasting approaches to the concentration of CO, which is considered one of the air pollutants, using the Ensemble Kalman Filter (EnKF) and Unscented Kalman Filter (UKF) methods. The simulation results indicate that the EnKF method achieved the best forecasting error (RMSE) value of 0.19.

Keywords Air Quality Monitoring; Healthy Lives; Internet of Things; Machine Learning; Pollution

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1. Introduction

Air pollution is a real condition that cannot be avoided in human life today due to the increase in population and human activities [1]. The factors of population and human activities, which increase every year, also contribute to the increase in pollutant concentrations in the air. These air pollutants are the result of the use of various tools that support human activities, such as machines and vehicles [2]. Various types of pollutants are produced, including Nitrogen Dioxide (NO2), Carbon Monoxide (CO), Ozone (O3), Sulfur Dioxide (SO2), and several other particles such as PM2.5 and PM10, where high concentrations of these pollutants can have a direct impact on human health and the environment [3, 4]. Examples of health impacts that can be felt directly by humans include the emergence of diseases that attack the respiratory system and, in the environment, an increase in global warming as a result of the greenhouse effect [5].

In response to this phenomenon, various air quality monitoring devices have been developed in major cities to provide real-time data. The emergence of air monitoring tools today is a breakthrough that deserves appreciation.

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By utilizing advances in Internet of Things (IoT) technology, the construction and development of these air monitoring tools have been equipped with sensors that can connect directly via the internet and are equipped with cloud storage system [6]. The key advantage of developing this air monitoring device is its ability to generate data quickly and accurately, as well as to improve efficiency by reducing operating costs, since the device is fully computerized [7].

Based on the above explanation, this research developed a simple IoT-based indoor air monitoring device using DHT11 and MQ135 sensors to measure temperature, humidity levels and carbon monoxide (CO) concentrations. The overall performance of these sensors is controlled using a microcontroller named ESP32. Some of the advantages of implementing this IoT technology include cost efficiency, data accuracy, and support for decision-making processes [8]. The data collected from the sensor measurements will be visualized using the Thingspeak official website and further analyzed and predicted using machine learning technology. Machine learning technology is a branch of Artificial Intelligence (AI) that can perform computations automatically using advanced methods or algorithms.

Considering the objective of this research, which is to design and develop a simple IoT-based indoor air quality monitoring device and also to forecast air quality values in the short term based on CO concentration, as one of the indicator. The forecasting method used in this research is the Ensemble Kalman Filter (EnKF) and Unscented Kalman Filter (UKF) methods. The EnKF method is an enhanced version of the Kalman Filter (KF) first proposed by Evensen in 1994 [9]. While UKF is another development method from Kalman Filter (KF) that deals with more complexity but with higher accuracy [10]. The complexity of UKF raised from calculation of sigma points that carried out by Cholesky factorization [11]. Both methods were implemented due to the need to capture data patterns generated by sensors on devices that tend to be non-linear. Non-linear data patterns require a robust and stable method because they will affect the resulting forecasting output.

1.1. Focus of the Research

This research focuses on the design and development of an IoT-based air quality monitoring device, as well as the implementation of the EnKF and UKF methods for short-term forecasting of CO concentrations based on the measurement results from the device.

1.2. Contributions

The contributions of this research include, as follows:

1. To produce practical results regarding the design, development, testing, and evaluation of a low-cost, IoT-based indoor air quality monitor using the ESP32 as the microcontroller and integrating the DHT11 and MQ135 sensors.
2. Analysis and implementation of air quality measurement results based on indicators for each pollutant, as well as short-term forecasting to determine indoor CO concentration levels using the EnKF and UKF methods.

1.3. Limitations

Several limitations of this research can be identified as follows:

1. The design of the air quality monitoring device employed in this research is limited to two sensors—namely, the DHT11 and the MQ135. Furthermore, the Thing Speak website application was leveraged to visualize the results in real time.
2. The dataset used includes data collected on September 17, 2025 consisting of 335 rows and 6 columns.
3. The short-term forecasting methods applied in this research are EnKF and UKF.

2. Related Works

Several previous research have discussed the design of low-cost IoT-based indoor air monitoring devices. The details of the discussion regarding the design of this device are very dynamic, covering the components involved and a variety of testing locations. In 2022, [12] designed a low-cost air quality monitor. The device uses the BMD-280, Sensirion SPS30, MiCS-4514, and MQ131 sensors. These components are connected to an Android device via Bluetooth LE. A total of 40 of these devices were manufactured and distributed to volunteers to measure air temperature and humidity in the Pakila, Finland. The results showed that the average temperature in outdoor areas ranged from 4 to 16 degrees, while in indoor areas it ranged from 28 to 37 degrees. A research conducted by [13] predicted PM2.5 concentration levels using wavelet transformation, fuzzification, Particle Swarm Optimization (PSO), and Neural Network (NN) algorithms based on data from the Central Pollution Control Board (CPCB) in Delhi, India. This research did not develop IoT-based air quality monitoring devices. This research did not develop an IoT-based air quality monitoring device, but only predicted PM2.5 levels in the area. The results of the forecasting indicate that the R^2 values range from 0.96 to 0.98.

In 2021, [14] conducted research on the design of an indoor air quality monitor using a BMP680 sensor, ESP32 microcontroller, Raspberry Pi server, and web server. The device was tested in two locations: the kitchen and the study room. In addition, the testing was conducted during two different seasons: summer and autumn. The results of this study show that the average concentration of gas particles in the kitchen ranges from 454.63 in the summer to 438.77 in the autumn. The results of these gas particle measurements are also displayed through a web application built using PHP. The research related to developing IoT-based device integrated with forecasting technique conducted by [15]. In the research that has been conducted, it was found that there are three sensor detectors connected to the Arduino Uno – the MQ7, MQ135, and MQ131. Furthermore, there are four forecasting methods applied to determine the values of CO and NH_3: AR, ARMA, ARIMA, and Naive Bayes (NB). The forecasting results indicate that the ARIMA method yielded the lowest error values of 1.67 and 1.79, respectively, for forecasting CO and NH_3 levels. From several previous studies, it is evident that there has been limited discussion regarding the integration of IoT and ML technologies. Therefore, this research aims to fill that gap by employing EnKF and UKF forecasting methods.

3. Methods

3.1. Design Concept for Device and Work System

Table 1. The Device Design Components

Type of Component	Name of Component	Function of Component
Hardware	Expansion Board	As a medium for installing IoT components.
	ESP32 (microcontroller)	As the brain that controls the performance of all IoT components.
	DHT11 (sensor) with error tolerance 2-5%	The type of sensor that measures temperature and humidity.
	MQ135 (sensor) with error tolerance 2-5%	This sensor measures other particles in the air, such as carbon monoxide (CO), smoke, and ammonia (NH3).
	Connector Cable	This component is used to connect the sensor pins to the base board.
	USB Cable	This component is used to connect the IoT device to the laptop/PC.
Software	Arduino IDE	This app is used to program IoT device components.
	ThingSpeak Web Application	This app is used to visualize real-time air quality measurement results.

The design concept for the indoor air quality monitor implemented in this research employs three main components: the ESP32 as the microcontroller and two sensors—the DHT11 and MQ135—used to detect air pollutants. The measurement results are then displayed using the web-based Thing Speak application. The programming and testing of this air quality monitor were conducted using the Arduino IDE. Details of the components and supporting software required for the design of this device are summarized in Table 1. Furthermore, in Table 2 are lists the specifications of the computer equipment utilized in this research.

Table 2. Computer Device Specifications

Specification	**Type**
Processor	Intel Core i5-8250u
Hard Disk Drive (HDD)	1Tb
Memory (RAM)	8Gb
Operating System (OS)	Windows 10 Pro

3.2. Research Methodology

The research method applied in this study integrates the design and development of an indoor air quality monitoring device with an analytical and forecasting approach using the EnKF and UKF methods. The development process for an indoor air quality monitor starts with the initial identification of the problem and continues through to the stage of testing the device at a designated location. The measurement results obtained by the device are then analyzed and forecasted in the short term using the EnKF and UKF methods. The Fig. 1 illustrates the details of the research methodology applied.

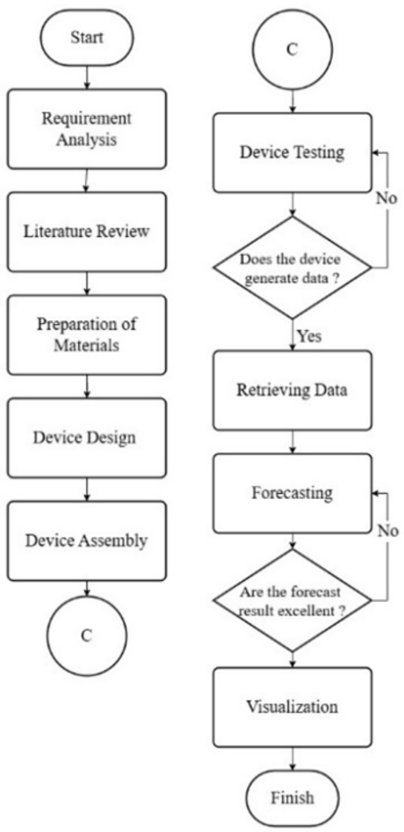

Figure 1. Flowchart of Research Methodology

In Fig. 1, it can be observed that the process of this research begins with analyzing requirement that related to the case study and followed by literature review that required as references and preparing several components. It should be noted that in the process of developing a low-cost IoT-based indoor air quality monitoring device, there are several issues that require attention during testing, namely the potential for sudden loss of connection while the process is underway. Under normal and stable conditions, the monitoring device—which has been connected and programmed using the Arduino IDE—will send data that can be viewed on the terminal panel. The data displayed in the Arduino IDE terminal is then visualized using the publicly available ThingSpeak web application, which supports integration with IoT-based devices. When communicating with this application, the ESP32 microcontroller utilizes the HTTP protocol. The ThingSpeak application was selected for use in this research because it is effective in storing large amounts of historical data [16].

Furthermore, historical data stored in the ThingSpeak application was retrieved for analysis and forecasting using the proposed methods in order to determine the error values produced by each method. Furthermore, historical data stored in the ThingSpeak application was retrieved for analysis and forecasting using the proposed methods in order to determine the error values produced by each method. The results of this analysis and forecasting are useful in the decision-making process regarding future technology development.

3.3. Statistical Analysis

In the process of analyzing the measurement data, three statistical tests were conducted: the normality test, the stationarity test, and the correlation test. Eq. 1–3 below represent the functions for each of these test methods.

$$SW = \frac{\sum_{i=1}^{n} a_i x_{(i)}}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

$$ADF = (\rho - 1)Y_{t-1} + \varepsilon_t \tag{2}$$

$$Corr = \frac{\sum_{i=1}^{n} w_i(X_i - \bar{X}_w)(Y_i - \bar{Y}_w)}{\sqrt{\sum_{i=1}^{n} w_i(X_i - \bar{X}_w)^2}\sqrt{\sum_{i=1}^{n} w_i(Y_i - \bar{Y}_w)^2}} \tag{3}$$

3.4. Forecasting Methods and Evaluation Metrics

EnKF and UKF, both methods known as development of KF. EnKF is an algorithm which applied to address for sequential data assimilation problems. This algorithm employed state ensemble to approximate statistical information of the forecasted state, including model covariance matrix [17], while UKF employs Unscented Transformation (UT) [18]. In addition to the two methods mentioned earlier, this research also applies the ARIMA method, which is used as the baseline method. The ARIMA model is one of the most commonly employed methods in time series analysis and forecasting proposed by Box and Jenkins in the early 1970s and used to model non-stationary time series [18]. Eq. 4–6 below represent a functions of the ARIMA method.

$$p = \alpha + \sum_{i=1}^{p} \beta Y_{t-i} + E_t \tag{4}$$

$$d = \alpha + \beta E_t + \sum_{i=1}^{q} \gamma E_{t-i} \tag{5}$$

$$q = \alpha + \sum_{i=1}^{p} \beta Y_{t-i} + \sum_{i=1}^{q} \gamma E_{t-j} + E_t \tag{6}$$

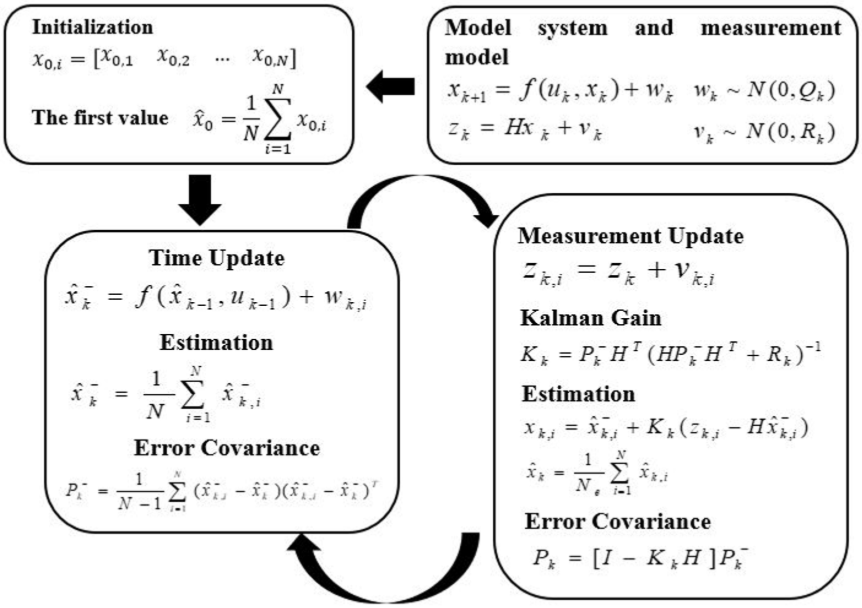

Figure 2. Flow of EnKF

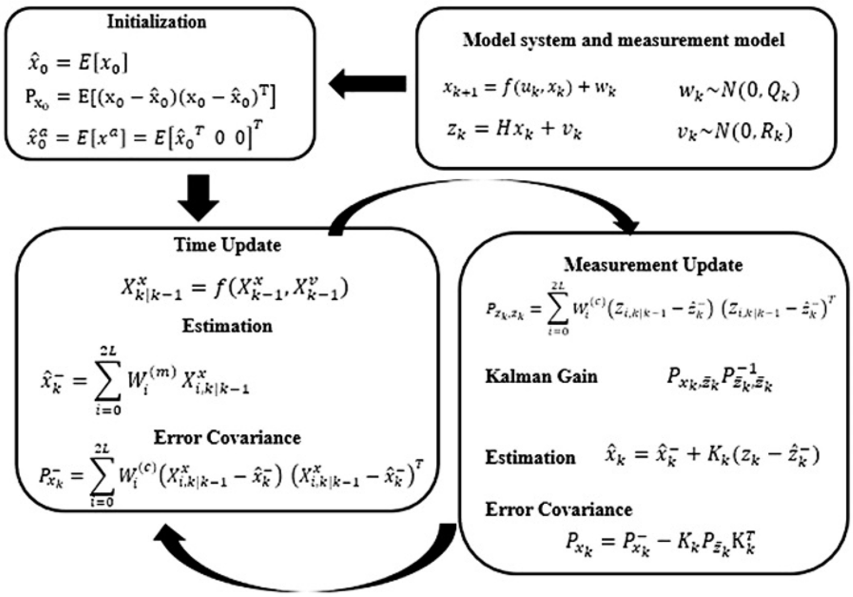

Figure 3. Flow of UKF

In the Fig. 2 and Fig. 3 above represent the working flow of the EnKF and UKF methods, respectively. In this research, three state conditions (referred to as states) were utilized, namely CO concentration, gas source flow rate, and sensor baseline shift. As for the EnKF method, there are several important parameters that influence the forecasting result, namely number of ensembles (N), the process noise matrix (Q), and the measurement noise matrix (R). There are also some adjustment that require to be carried out when implementing this method. Regarding the number of ensembles, initializing a large number of them will yield better results. However, this can increase computation time. Additionally, the Q parameter determines the magnitude of the random noise added during forecasting. If Q is large, it suggest that the state can change rapidly, but if it small, the model is considered accurate.

Furthermore, the UKF method also involves several important parameters including the alpha (α), beta (β), and gamma (γ) parameters, which are used to determine the position and weight of the sigma value. The Q and R parameters are the same as those in the EnKF method, and the initial covariance (P) represents the initial state uncertainty, which affect the convergence rate.

To evaluate the forecasting results, several metrics are applied as presented in Eq. 7–8 below.

$$MSE = \frac{\sum_{i=1}^{n}(X_i - F_i)^2}{n} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - F_i)^2}{n}} \tag{8}$$

4. Results and Discussion

4.1. Results of the Development of Indoor Air Quality Monitoring Device

Based on the design and development of an IoT-based indoor air quality monitor, the final product is depicted in Fig. 4 below.

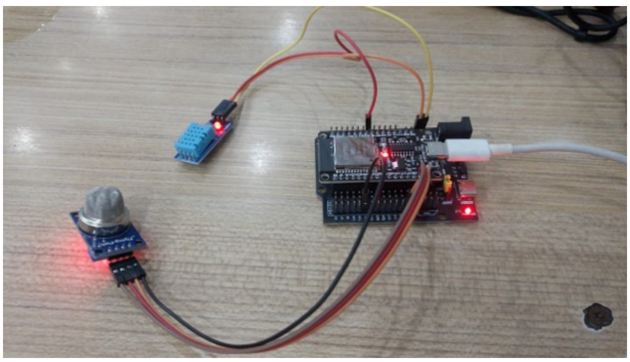

Figure 4. The Air Quality Monitoring Device

Figure 5. The IoT Device Connection Scan using Arduino IDE

Fig. 4 illustrates that the indoor air quality monitor is ready for use and has been connected to the laptop through USB cable. The figure also shows that both sensors (DHT11 and MQ135) are properly connected to the expansion board and that the indicator lights are on simultaneously. Furthermore, the device connected to the PC or laptop is executed using the Arduino IDE to take measurements, which are then transmitted to the ThingSpeak application to generate a visualization. The measurement results are displayed in both applications. In the Arduino IDE, the results appear in the program terminal, while in ThingSpeak, the results are displayed as a diagram. For the information, as a cloud-based application, ThingSpeak also provides APIs and channel IDs to enable communication between devices and the application. Then, all visualization results and measurement data are saved in a downloadable CSV file for further analysis and forecasting. Fig. 5 below shows an example of the scanning process for a wireless internet connection and an IoT device to the Arduino IDE application. Meanwhile, in Table 3 presents the measurement data from the air quality monitoring device.

Table 3. Measurement Data

Created at	Index	Temperature	Humidity	CO Level	Air Quality
16/11/2025	1	31.8	75	0	100
16/11/2025	2	31.8	75	0	100
16/11/2025	3	31.8	75	0	100
16/11/2025	4	31.1	75	0	100
16/11/2025	5	31.2	74	125	89
16/11/2025	6	31.8	75	74	93
16/11/2025	7	31.3	75	50	95
16/11/2025	8	31.4	74	42	96
...	...	...	...	...	...
16/11/2025	335	30.1	76	9	99

4.2. Results of Analysis

Based on the data obtained from real-time measurements over a period of approximately two hours, as presented in Table 3 above, the next step is to conduct an analysis. It is observed that the overall condition of all features recorded during the measurement process is depicted in Fig. 6 below.

From Fig. 6, several key points can be identified indicating that all four features experience sharp fluctuations (increases and decreases) at particular times. This situation may occur due to increased activity in that room. Furthermore, based on the above plot, it is evident that this increase triggered a spike in pollutants, particularly CO concentrations. Table 4 –Table 5 below present the results of further analysis in the form of predetermined statistical tests.

Table 4. The Result of Normality Test

Feature	Obtained Value	Conclusion
Temperature	p-value : 0.00	Non-normal distribution
Humidity	p-value : 0.00	Non-normal distribution
CO Level	p-value : 0.00	Non-normal distribution
Air Quality	p-value : 0.00	Non-normal distribution

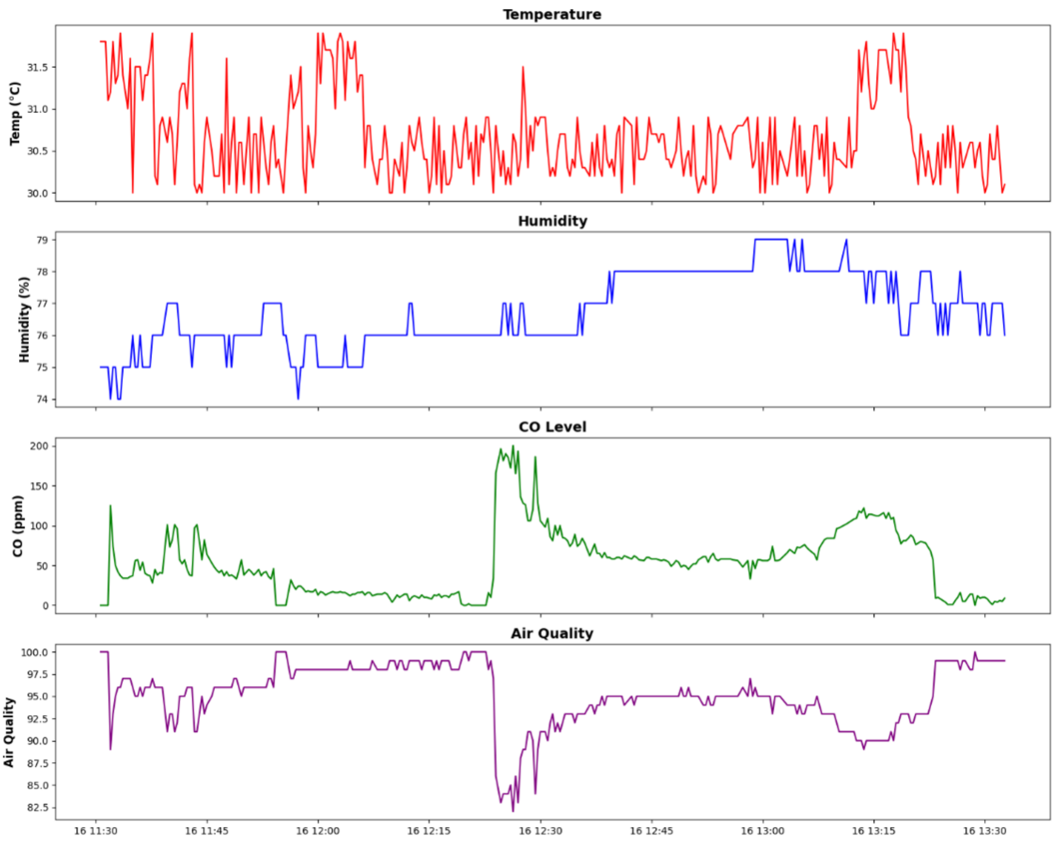

Figure 6. The Plot of Measurement Results

Table 5. The Result of Stationarity Test

Feature	Obtained Value	Conclusion
Temperature	ADF : -5.21, p-value : 0.00	Stationary
Humidity	ADF : -2.71, p-value : 0.07	Non-stationary
CO Level	ADF : -3.58, p-value : 0.006	Stationary
Air Quality	ADF : -3.82, p-value : 0.003	Stationary

Based on Tables 4 and 5 above, it can be observed that none of the features are normally distributed, and only the "Humidity" feature is non-stationary. Furthermore, the correlation test depicted in Fig. 7 reveals that none of the features present a strong correlation, and some of them exhibit a negative correlation. Based on the results of these three tests, multivariate forecasting is not applicable. Therefore, it can be concluded that forecasting is performed using univariate techniques and implemented using methods that support these conditions.

4.3. Results of Simulation

This subsection discusses the results of the forecasts performed using the three proposed methods (ARIMA, EnKF, and UKF). The forecasting processes carried out by these methods require different approaches. These approaches are tailored to the characteristics of each method through hyperparameter tuning. Table 6 below provides details on the hyperparameter tuning.

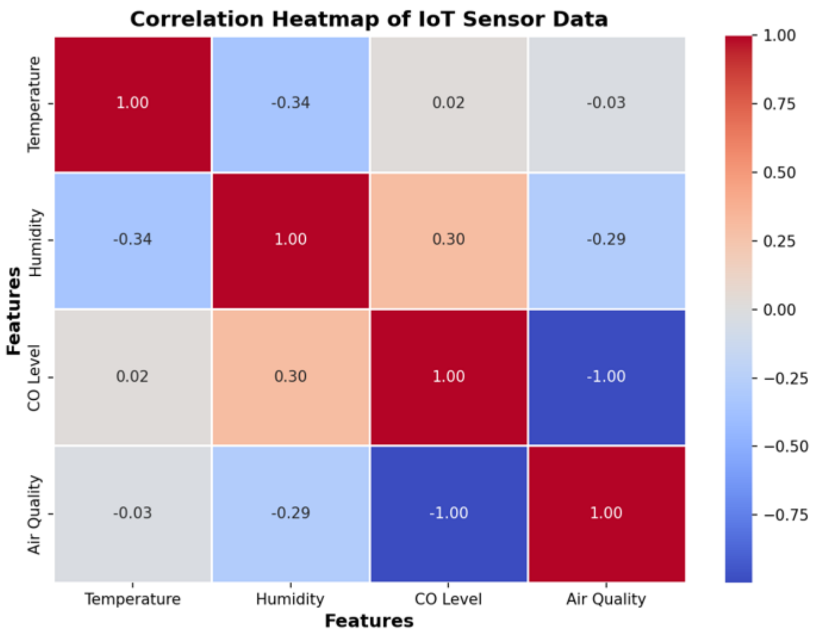

Figure 7. The Plot of Correlation

Table 6. Hyperparameter Tuning

Method	Hyperparameter	Value
ARIMA	p, d, q	(1, 1, 1)
EnKF	ensemble size	200
UKF	alpha	0.1
	beta	2.0
	kappa	1.0

Based on the table above, the forecasting process was performed on the CO feature, and the forecasting results are depicted in Fig. 8 below.

Fig. 8 above presents the forecasting results obtained using the three proposed methods. As can be observed in the figure, the forecasting results are excellent. This is indicated by a forecast line that closely approximates the actual values. Regarding the evaluation results, it can be noted that the ARIMA method achieved an RMSE of 8.44. Then, the EnKF and UKF forecasting methods successively produced RMSE values of 0.19 and 5.33, respectively. The results of the simulation test indicate that there is a significant difference between the ARIMA method and the other two methods (EnKF and UKF). The significance level obtained from the ARIMA and EnKF methods is 97.7 percent, while with the UKF method, the result is 36.8 percent. In the Table 7 below provides the details of evaluation metric.

Table 7. The Details of Evaluation

Method	MSE	RMSE
ARIMA	71.23	8.44
EnKF	0.036	0.19
UKF	28.40	5.33

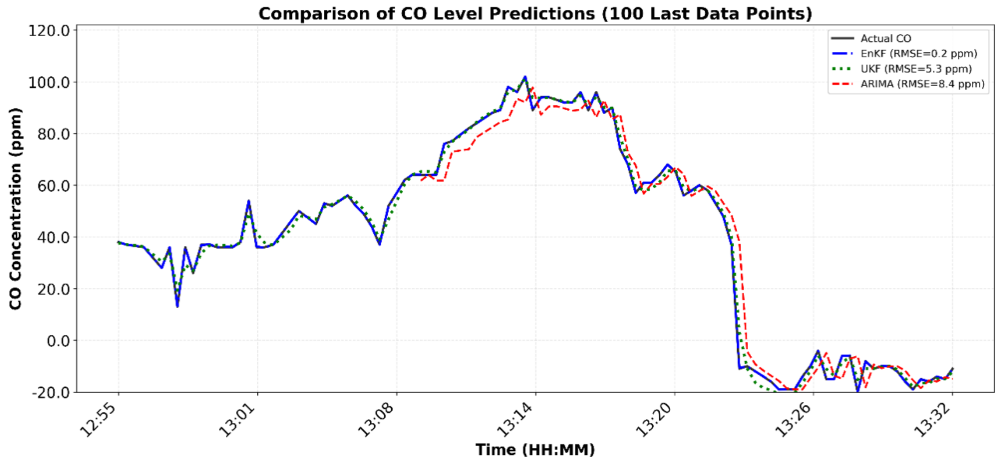

Figure 8. The Plot of Forecasting Result

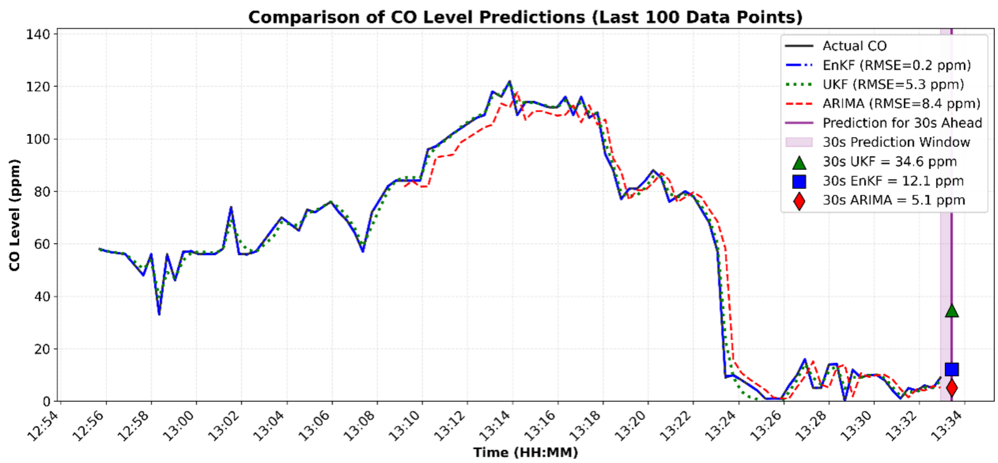

Figure 9. The Plot of Projected Value

Fig. 9 above illustrates the projected values generated by the three methods over the next 30 seconds. As indicated in the plot, the forecast values obtained mentioned that The ARIMA method forecasts a value of 5.1 ppm 30 seconds from now, the EnKF method forecasts 12.1 ppm, and the UKF method forecasts 34.6 ppm. Based on these results, only the EnKF method exhibited a slight deviation from the values obtained in previous measurements.

Based on the result of simulations conducted above, several factors can be identified as advantages of the EnKF method over the UKF method, including:

1. Spikes : EnKF with an ensemble can capture skewed distribution shapes, whereas UKF forces the distribution to remain symmetric, resulting in less-than-optimal corrections.
2. Drift baseline : Gradual changes in sensor offset are also easier for the EnKF to track because the ensembles provides a more diverse range of variations.
3. Parameter tuning : EnKF is more tolerant of less-than-ideal Q and R values.

5. Conclusions

Based on the results achieved during the design and development of an IoT-based indoor air quality monitoring device, as well as the forecasting using three methods (ARIMA, EnKF, UKF), the research objectives have been met and satisfactory results have been obtained. Furthermore, some of the key findings from this research include:

1. The indoor air quality monitor that has been developed works well and can send measurement data to the Arduino IDE and ThingSpeak web app.
2. In the forecasting simulation stage, the EnKF method outperformed the other methods.

Based on these results, future research could focus on increasing the number of sensors on the device, varying the experiment duration and location, and exploring different forecasting methods.

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Competing Interest

The authors declare that they have no known competing financial interests or personal relationship that could have appeared to influence the work reported in this paper.

Declaration of Generative AI Use

In preparing and executing this research, the authors utilized Generative AI to assist with developing ideas and coding. The result obtained from this tool were subsequently processed and corrected to ensure accountability.

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