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Low Cost IoT Based Air Quality Monitoring Setup Using Arduino and MQ Series Sensors With Dataset Analysis

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Abstract

This paper talks about cost effective Arduino based Air Quality Monitoring setup using MQ series sensors which are quite suitable to install in both indoor and outdoor provided that properly calibrated before installing. There are many MQ series sensors out of which MQ135 and MQ7 have been considered here as MQ135 is able to detect ammonia, carbon dioxide, alcohol or even smoke and MQ7 help to calculate Carbon Monoxide alone and these two sensors are quite suitable for the application and considered.

Government of India has taken enough measures already to minimize the air being polluted. The whole setup can be made as a compact device with low cost and can be used as a carry-in device such that awareness is brought among the people of how's the air quality level of the area surrounded by the person either indoor or outdoor. Adverse effects of air pollution lead to respiratory problems, skin diseases etc., Moreover, the data collected by these sensors will be pushed to the cloud on back end, say here Thingspeak is chosen and there are many open source IoT supporting platforms. At the end, data analysis was done on the dataset collected from the setup which is installed at various places across the VIT University, Vellore. This analysis helps in deeper understanding of the air quality status such that people will be aware of what will happen if the same air quality continues for a longtime.

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Keywords: IoT; MQ135 Sensor; MQ7 Sensor; Thingspeak; Machine Learning; PPM (parts per million);

1. Introduction

Air pollution is not new to everyone. Just like any other pollutions, air pollution has serious effects on human health. It is quite important to be aware of this pollution level in our surroundings. With serious demand in vehicles and transport these days, knowingly or unknowingly there is a gradual increase in the level of pollution which results in respiratory and skin diseases. Not only the case of vehicles, but also with the deforestation, the air quality index is worsening day to day. Just like, the temperature of a specified location can be known, the air quality index can also be known with the help of an Internet of Things [4]. Affordable sensors have been considered here and calibrated

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properly to bring the accurate values. As IoT helps to project the values to the cloud and the values can be read anywhere from online. Instead of simply fetching the values from the sensors placed at a location and calibrated with respect to the location installed, Data analysis is made which gives a clear idea of the status and conditions of the pollution data fetched so far. The reason to go for data analysis is to know that if the same pollution continues for a long time without any proper measures taken [5]. The units for the Air Pollution are taken PPM (parts per million) here. The raw data fetched from the sensors is properly converted to PPM in the Arduino code and necessary help is taken from sensor datasheets. The proposed work makes use of affordable development kit boards which is reliable and cost-effective [9]. Proper calibration of the sensors used and establishing proper mathematical background while converting the raw data to the PPM units is maintained. At the end, results will be pushed to the mobile application or to a computer about the air quality index [3].

2. Related Work

Before understanding the setup, it is important to know the levels of air quality which affects human beings [4]. The table 1 mentioned below give as a clear insight that level 0-50PPM and 51-100PPM are good to humans. Any of above these ranges are totally harmful to people.

Table 1. Air Quality Index

Range (PPM)	Status
0-50	Good
51-100	Moderate
100-150	Unhealthy for sensitive groups
151-200	Unhealthy
201-300	Very Unhealthy
301-500	Hazardous

The paper cited at [1] has used LCD to show the values of Air quality being measured. If the paper is based on IOT, our usual intention is to show the sensors values converting to PPM (parts per million) on cloud or web but they showed it on LCD module which incurs additional cost. The paper cited at [2] has not properly calibrated the sensors because the readings shown are 300 PPM. As per the table 1 mentioned, 300 PPM is deadly dangerous. The paper cited at [3], also projected wrong PPM values and its clear indication that they haven't calibrated the sensor as mentioned in the Procedure section. The paper cited at [4] has used two sensors where the heater element inside the sensors will draw more current which arduino can't deliver enough and hence it needs an additional battery and they didn't use it so obviously the output is unpredictable and the values they claimed were not correct [8].

3. Procedure

The important step is to convert the Sensor raw data output into PPM (Parts per million). If these equations included in arduino code, then final output will be in PPM only [6].

3.1. Equations

Before finding the $\omega(R_0)$ value, the sensor readings gives $\beta(R_s)$ in fresh air and it is not that the scale considered in figure 1 is a logarithmic scale [8].

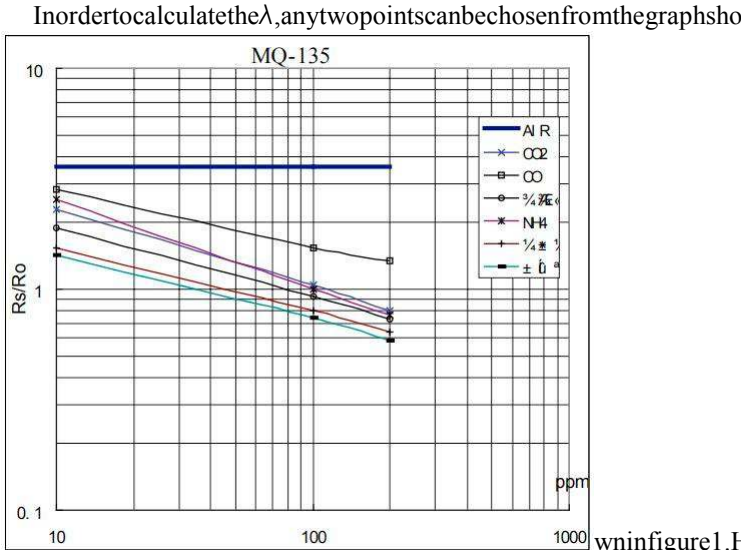
The following derivations can be calculated from Figure 1

$$\mu = \lambda\chi + \tau \quad (1)$$

The above equation 1 should be considered as below equation 2 as the figure 1 is on logarithmic scale

$$\log_{10}\mu = \lambda * \log_{10}\chi + \tau \quad (2)$$

Fig. 1. R_s/R_0 Vs PPM



Now in figure 1. Here, CO_2 line (10, 2.2) and (200, 0.8) are considered. This graph is taken from MQ135 datasheet and it is generated by subjecting the sensor exclusive to various PPM levels of the gases. Now, λ can be written as [8]

$$\lambda = \frac{\log(y_2) - \log(y_1)}{\log(x_2) - \log(x_1)}$$

To obtain the equation 4, apply logarithmic quotient rule to the equation 3,

$$\lambda = \log\left(\frac{y_2}{y_1}\right) \tag{3}$$

$$\lambda = \log\left(\frac{y_2}{y_1}\right) \tag{4}$$

Now passing the values (10, 2.2) and (200, 0.8) to equation 4

$$\lambda \Rightarrow \frac{\log(0.8/2.2)}{\log(200/10)} \tag{5}$$

$$\lambda = -0.3376 \tag{6}$$

After finding the slope λ , y-intercept τ is calculated by considering the above data

$$\log(\mu) = \lambda * \log(\chi) + \tau \tag{7}$$

$$\tau \Rightarrow \log(0.8) - (-0.3376) * \log(200) \tag{8}$$

$$\tau \Rightarrow 0.6799 \tag{9}$$

After finding λ and χ , gas concentration can be found for any ratio with the following formula:

$$\log(\chi) = \frac{\log(\mu) - \tau}{\lambda} \tag{10}$$

χ can be obtained from above equation 10 by applying inverse logarithmic function, hence

$$\chi = 10^{\frac{\log \mu - \tau}{\lambda}} \tag{11}$$

Using equation 11, our final intention is to convert the raw data given by the sensor into PPM and this equation will be given in arduino code.

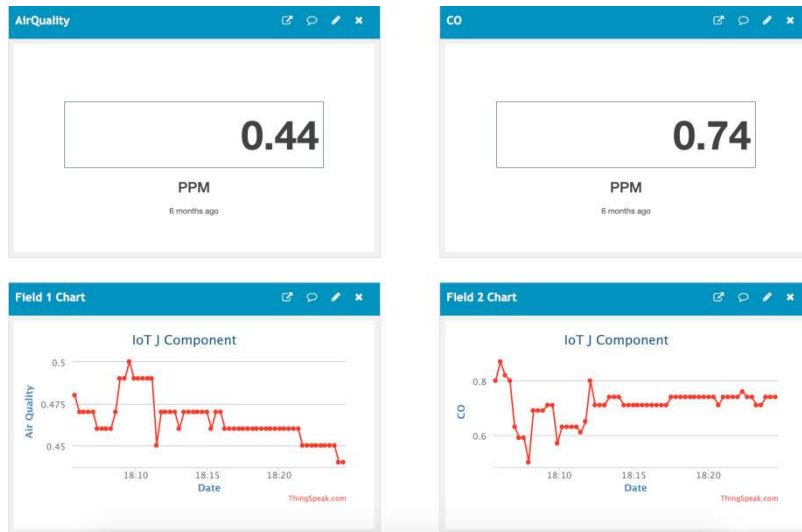


Fig. 2. Output on Thingspeak

4. Results

Arduino Uno doesn't have Wi-Fi capability. So, ESP-01 is used to enable Wi-Fi for the Arduino Uno. This will push the data output from Arduino Uno to Thingspeak and it will be auto visualized with built-in tools which is shown in figure 2. Air quality level graph goes high in day time due to vehicle movements and average value 0.15 PPM shown in figure 2 is absolutely safe [4]. While plotting the results, DHT 11 Temperature and humidity sensor is also considered.

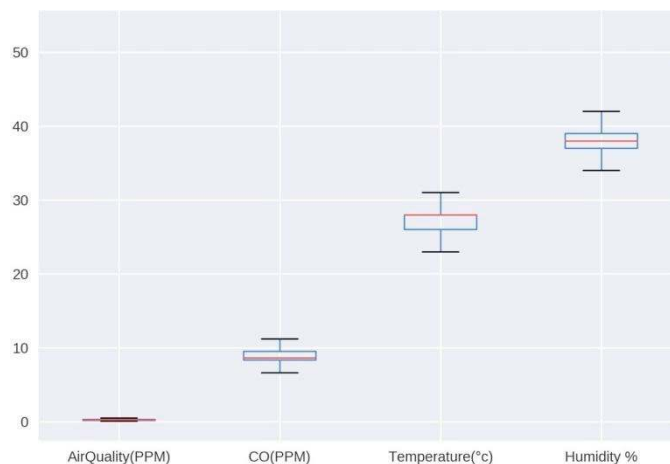


Fig. 3. Box Plot

The median of values present in the dataset can be identified from the plot shown in figure 3 [10]. This is then used for further observation. It is observed that the values of air quality is between 0 to 10 PPM at the region where the experiment is carried out which found to be safe from Table 1. The values of CO are around 9 PPM which is a little high but people will not suffer from any adverse effects. The temperature also has value between 20-30 and humidity percentage is around 40%.

From Histogram plot shown in figure 4, maximum and minimum values over a period for every data point is obtained. Most of the Air Quality values are between 0 and 1, which indicate not very high values of pollution. For

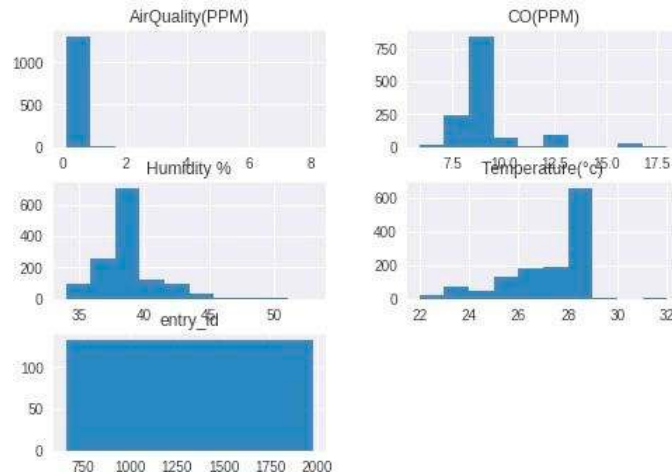


Fig. 4. Histogram of the dataset

the values of Carbon Monoxide, most of the values are between 7.5 which also indicates moderate values of CO. The entry id Histogram can be ignored as it is of no significance. The temperature values are also mostly between 28 and 30 degrees which indicated room temperature. As for humidity %, most of the values seem to be between 35 and 40 which seem to be little high. From the plots shown in fig 5, the data can be easily viewed for every datapoint over

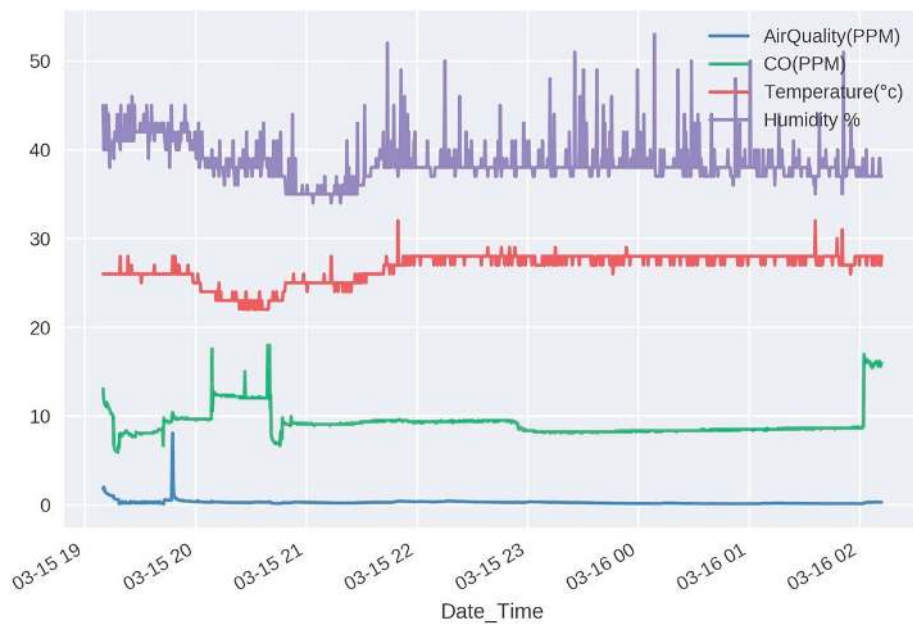


Fig. 5. Line Plot of the data

a period of time. This is done after outliers are removed so it becomes easy to draw conclusions from this data. It is found that AirQuality values were higher on some days but dropped down and varied a lot initially [5]. This coincided

with the root mean square error for every data point is as follows. The dipping of Temperature values which is a major point to note. The CO values did not change much but considerably varied with variation of Temperature which is also a point to be noted. As for the Humidity values, they do not seem to have a lot of relation with the rest of the variables.

- rmse value for AirQuality (PPM) is 0.08274985657405932
- rmse value for CO (PPM) is 2.8055052798658817
- rmse value for Temperature (c) is 1.4761492661822175
- rmse value for Humidity is 1.706479462754771

This indicates a relatively good performance of the model, especially for the Air Quality Values. For this analysis, Jupyter Notebook hosted on Google Co-Laboratory is used. A GPU was used to train the model and reduce computation time. The data was collected by combination of four sensors kept in and around the University for a few days. Continuous data was collected before saving it to a storage device over the cloud. For any dataset, pre-processing is the most important step [6]. The first step was to parse the timestamp generated from the device and make it into a format usable by the model. This was done using the following code. The second step was to remove outliers from the data and fill missing values. This was done by replacing the missing value with a value from the same column which would ensure that the values did not get skewed completely. The third step was to remove outliers. From data visualization, it was seen that there was a recurring value -999 which could be the sensor output when the sensor was switched off and these redundant values were removed [7].

5. Conclusion

So, using low cost arduino setup, accurate PPM values can be projected using the equations shown in 3.1 section. While training the model the 'Vector Auto Regression model' was found to be the best choice to train this model. For VAR(1), each variable is a linear function of lag 1 values and so on. Such a model in general implies that every variable depends on every other variable and thus the VAR model in the end can be written as a series of individual models. The VAR model can also be estimated by estimating each equation separately. Many models were tested and even an LSTM was considered and it was found that the VAR gave the best results in the form of root mean square error.

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