International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-4, February 2020

Identification of Carbon Monoxide Levels

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Abstract: ***With ever rising emission of pollutant gases from different sources like factories, auto mobiles and power, it is a subject of emerging concerns that some strong measures are required to monitor and control these pollutant. Breathing of these gases may cause serious harmful effects to anyone. In these gases, Carbon Monoxide (CO) is often called "Silent Killer" as being colour-less, odour-less and poisonous, it is undetectable by humans. When inhaled it, it deprives blood stream of oxygen and suffocates its victim. In this paper we are proposing a simple system to monitor Carbon Monoxide (CO). Carbon Monoxide (CO) detectors are used to detect CO. This paper also discusses analysis of amount of these CO based a data set from Kaggle and prediction of possible amount of CO in air using regression. The prediction accuracy which is measured as RMSE is 0.17766.***

Keywords : pollutant monitoring, pollution, air quality, pollution control, CO emission.

I. INTRODUCTION

Emerging concerns about pollution and its effects on environment as well as on human health has given a push to activities to control it. It requires different ways to collect, monitor and analyze levels of pollutant in air. Carbon monoxide (CO) - a colorless, odorless, tasteless, and toxic air pollutant—is produced in the incomplete combustion of carbon-containing fuels, such as gasoline, natural gas, oil, coal, and wood. The largest source of CO [9] is vehicle emissions. Breathing the high concentrations of CO [1] [8] typical of a polluted environment leads to reduced oxygen (O2) transport by hemoglobin and has health effects that include headaches, increased risk of chest pain for persons with heart disease, and impaired reaction timing. Vehicle emissions led to increased and unhealthful ambient CO concentrations cities. With the introduction of emissions controls by different government organization like EPA (in U.S.), particularly automotive catalysts, estimated CO emissions from all sources decreased by some considerable amount.

Revised Manuscript Received on February 28, 2020.
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In this paper, we are proposing a system to monitor and analyze CO amount in air. The system consists of two parts:

1. Device : It consists of MQ - 7 sensor connected to ADC of Atmega 32A micro controller. It takes reading with specific delays and sends it through medium like wifi or gsm (whichever available) to cloud server. The reading taken and transmitted by sensor are in parts per million (PPM).
2. Cloud : Cloud consist of centralized or distributed system depending upon geographical convenience. Its task is simply to collect and store readings from devices at different locations. Further, these reading can be used to analyse and visualize different pattern. This can be useful to evaluate different factors causing increase or decrease in amount of CO in air. Also using linear regression, it is possible to predict what can be future values to make different emission control policies.

II. HOW CO AFFECTS HUMAN BODY

The CO molecule is made up of a carbon and an oxygen atom. CO has a density similar to air. But, its density rises when it is produced because of heat caused by combustion. When it cools down, it starts circulating as same as ambient air. Oxygen molecules enter the lungs through respiration and are transported to cells throughout the body by attaching to hemoglobin in the blood by circulation. CO poisoning can affects due to shorter exposure to high level or prolonged exposure to low levels of Carbon Monoxide [10,11]. CO molecules attach to hemoglobin far more readily than oxygen. Thus, when CO molecules present in environment are inhaled and interfere with circulation of oxygen, by attaching itself to hemoglobin, throughout the body, it can cause harmful effects as given in table below.

Table- II: Name of the Table that justify the values

CO Concentration (in PPM)	Symptoms
50	No adverse effects with 8 hours of exposure.
800	Headache, nausea, and dizziness after 45 minutes of exposure; collapse and unconsciousness after 2 hours of exposure
1,000	Loss of consciousness after 1 hour of exposure
6,400	Headache and dizziness after 1-2 minutes of exposure; unconsciousness and danger of death after 10-15 minutes of exposure

III. TYPES OF CO DETECTORS

Carbon Monoxide (CO) detectors are devices that monitor the amount of CO in the air over a given period of time. Thereare three types of CO detectors present [3].

A. Biomimetic CO Detector

Biomimetic CO detectors mimic how hemoglobin reacts in biological organisms to Carbon Monoxide. A biomimetic sensor monitors infrared light that is passed through a disc of synthetic hemoglobin that darkens in the presence of CO.
Thus, as CO concentrations increase, the light signal becomes weak, which triggers the alarm.
Biomimetic detectors are low cost. They require a low current draw to operate. But, these detectors are susceptible to false alarms if environmental conditions fluctuate outside peak operating ranges.

B. Metal Oxide Semiconductor CO detector

In Metal Oxide Semiconductor (MOS) detector technology, using an electric current, a tin dioxide semiconductor is heated with some fixed time intervals. When semiconductor reaches its operating temperature, it is starts changing its resistance in the presence of carbon monoxide. Once the resistance change reaches to a threshold value, it sounds the alarm.

MOS detectors are more expensive to purchase and operate than other types of sensors. This type of sensor requires high current draw in order to heat metal oxide. Furthermore, MOS detectors are susceptible to false alarms in the presence of some common household chemicals or gases other than CO.

C. Electrochemical CO detector

Electrochemical sensor uses a combination of a platinum electrode and acid that lead to a reaction between CO and the oxygen in the air. This reaction produces an electric current. When CO is present in the air, the current output increases above a given threshold and so the alarm is sounded. CO detectors using electrochemical sensors are commonly used in industrial applications. These detectors are reliable, require a low current draw, and are highly responsive to CO.

IV. DEVICE

Device has MicroChip Atmega32A at it's core. In our prototype, device uses MQ - 7 CO detection sensor to take readings. It is connected to ADC of Atmega32A.

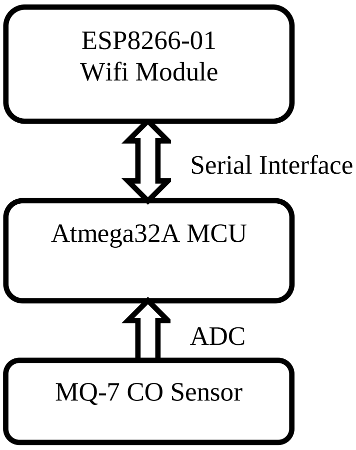

Fig. 1. Example of a figure caption. (*figure caption*)

In our prototype, we have used ESP8266-01 Wifi Module for connectivity. It is connected to UART interface of Atmega32A. It connects to Access Point and sends detected readings to cloud server through internet. Also we can use any medium to send data to cloud server. Fig. 1 shows the architecture diagram of the device. Following hardware components are used for device:

.
Microchip Atmega 32A Microcontroller.

Fig. 2: Microchip Atmega 32A Microcontroller

The Microchip Atmega32A is a low-power CMOS 8-bit microcontroller. It is based on the AVR enhanced RISC architecture. It can achieve throughputs close to 1MIPS per MHz.
It has 32 K Bytes of In-System Self Programmable Flash Program Memory, 1 K Bytes of EEPROM and 2 K Bytes of internal SRAM. Also, it has on chip ADC and serial interface support for UART, SPI, TWI protocols.

1. ESP8266-01 Wifi module.

Fig. 3: ESP8266-01 Wifi Module

ESP8266 is a complete and self-contained Wi-Fi network solutions that can carry software applications. It has built-in TCP/IP protocol stack. Supporting UART interface, it can provide wifi access to microcontorller based application. It can work in both P2P or soft-AP modes. There is a set of AT commands that allow communication with it for MCU. Built-in cache memory will help improve system performance and reduce memory requirements.
2. MQ – 7 CO detector/sensor:

Fig. 4: MQ – 7 CO detector/sensor

MQ-7 [4] gas sensor is Metal Oxide Semiconductor (MOS) CO detector. It make detection by method of cycle high and low temperature, and detect CO at low temperature (heated by 1.5V). The sensor’s conductivity gets higher along with the CO gas concentration rising. At high temperature(heated by 5.0V), it cleans the other gases adsorbed at low temperature.
Given below is test ckt of MQ - 7 as given in its datasheet:

Retrieval Number: D1137029420 /2020©BEIESP
DOI: 10.35940/ijitee.D1137.029420
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

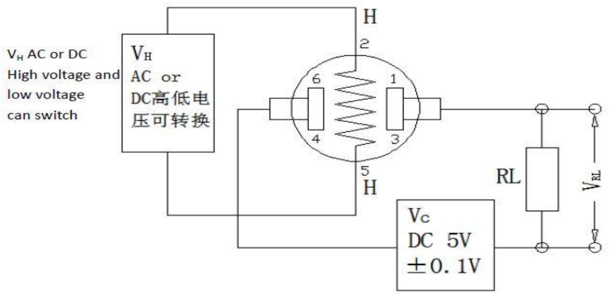

Fig. 5: MQ -7 CO detector test circuit

Diagram below shows sensitivity curve of MQ-7 sensor as in its datasheet:

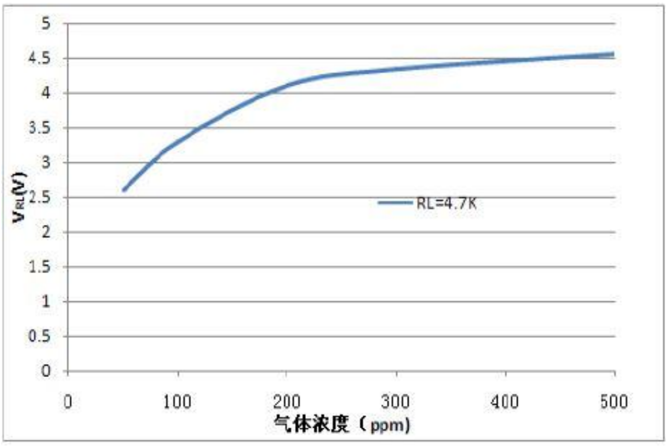

Fig. 6: MQ-7 sensitivity curve

To ease the calculation we plotted simple regression plot:

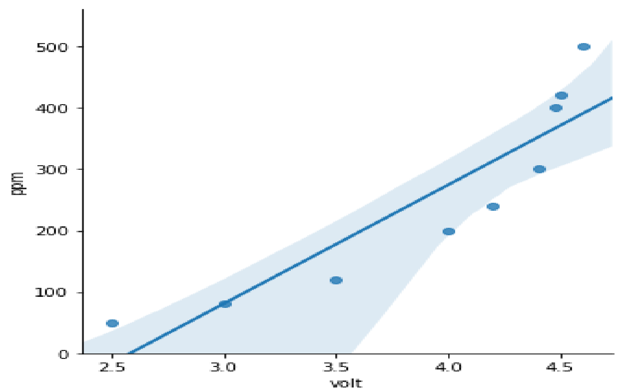

Fig. 7: MQ – 7 reading calculation plot

With y-intercept being 193.803 and co-efficient -500.89, we can calculate CO (in ppm) as,

CO = -500.89 + reading (V) * 193.803

V. RESULT ANALYSIS AND DISCUSSION

A. Description

We picked a dataset 'US Pollution 2000-2016' [5] from Kaggle which is extracted from Environmental Protection Agency (EPA), USA by @sogun. The complete dataset is available at https://www.kaggle.com/sogun3/uspollution.

Dataset includes reading taken at different point across USA from 2000-2016 with details of place and time.

It provides details of four pollutant namely, CO, NO_2, SO_2 and ground level O_3. Each pollutant has its five metrics of description. For instance, for CO:

- CO Units : The units measured for CO.
- CO Mean : The arithmetic mean of concentration of CO within a given day.
- CO AQI : The calculated air quality index of CO within a given day.
- CO 1st Max Value : The maximum value obtained for CO concentration in a given day.
- CO 1st Max Hour : The hour when the maximum CO concentration was recorded in a given day.

CO units value is “parts per million” for all records.

B. Understanding the dataset.

The dataset includes readings taken at different points (address) in 47 states in USA. With state California having highest count of 49 address, followed by Pennsylvania 21and so on. With some state like Hawaii having single address record. Plot below describes number of address present in different states.

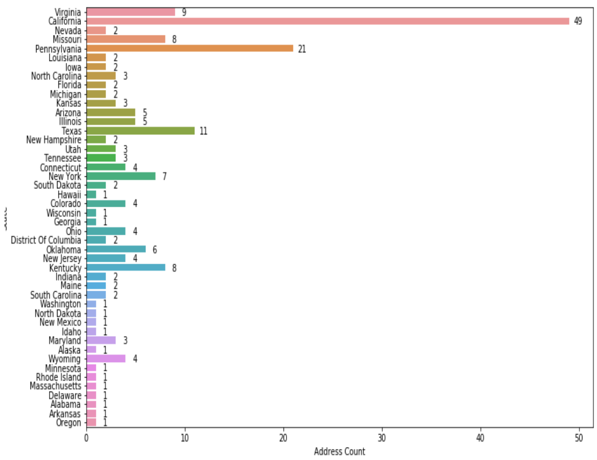

Fig. 8: Count plot for no. of address in states

The dataset consist of records from 2000-01 to 2016-05. However, for all addresses the data is not present from 2000 to 2016-05. It varies by amount of period in which reading were taken for different addresses. For example,

Address	Start Date	End Date
1415 Hinton Street, Texas	01-01-2000	31-03-2016
14306 PARK AVE., VICTORVILLE, CA, California	19-01-2000	31-03-2016
NO. B'HAM,SOU R.R., 3009 28TH ST. NO., Alabama	01-12-2013	31-05-2016
2 YARMOUTH ROAD, RG&E Substation, New York	31-01-2011	31-12-2011
200TH STREET AND SOUTHERN BOULDVARD Pfizer Lab, New York	23-01-2007	30-04-2016

Table 2: Range of dates at which records are present

The plot below describes the number of records present year-wise.

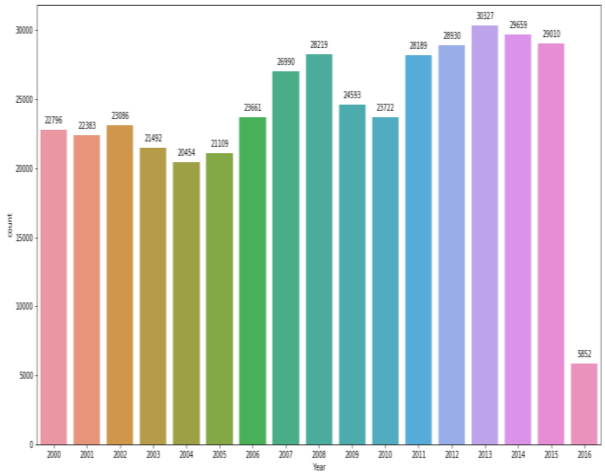

Fig.9: Number of records year-wise

The variation in number of records is because the varying ranges of dates at which records are present. Thus, we have records of 196 points (addresses) in 47 states across USA in dataset.

VI. RESULT ANALYSIS AND DISCUSSION

A. Analysing the data.

The dataset can be analyzed in different ways to provide different insights in data gathered at different points. This can help monitor and regulate pollution in different areas.

The table below gives year - wise high polluting sites along with month where mean of CO Mean reading was high.

Address	State	CO Mean	Month
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	7.15	2000-12
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	4.78	2001-10
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	5.42	2002-01
80 E. 'J' ST., CHULA VISTA	California	4.50	2003-10
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	4.33	2004-01
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	4.14	2005-12
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	4.04	2006-02
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	4.30	2007-12
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	2.79	2008-10
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	3.76	2009-12
14306 PARK AVE., VICTORVILLE, CA	California	3.56	2010-06
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	2.96	2011-01
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	3.44	2012-01
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	2.60	2013-12
1061-A Leesville Ave	Louisiana	2.12	2014-01
14306 PARK AVE., VICTORVILLE, CA	California	2.06	2015-12
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	1.71	2016-02

Table 3: Maximum captured CO mean value in year

We can observe that most of site are from state California.

The table below gives year - wise one of low polluting sites along with month where mean of CO Mean reading was low.

Address	State	CO Mean	Month
1005 INDUSTRIAL ROAD	Nevada	0.00208	2001-10
1005 INDUSTRIAL ROAD	Nevada	0.00208	2002-02
1005 INDUSTRIAL ROAD	Nevada	0.00208	2003-01
1061-A Leesville Ave	Louisiana	0.00208	2004-12
1210 N. 10TH ST.,JFK RECREATION CENTER	Kansas	0.00208	2005-02
1029 ETHEL ST, CALEXICO HIGH SCHOOL	California	0.00208	2006-08
1061-A Leesville Ave	Louisiana	0.00020	2007-08
1061-A Leesville Ave	Louisiana	0.000652	2008-03
Queens College 65-30 Kissena Blvd Parking Lot#6	New York	0.000021	2009-06
1059 Arnold Road	Pennsylvania	0.002084	2010-04
NCore - North Cheyenne Soccer Complex	Wyoming	0.000041	2011-08
NCore - North Cheyenne Soccer Complex	Wyoming	0.000041	2012-07
2500 1ST STREET, N.W. WASHINGTON DC	District of Columbia	0.000021	2013-11
NCore - North Cheyenne Soccer Complex	Wyoming	0.000479	2014-07
NCore - North Cheyenne Soccer Complex	Wyoming	0.001214	2015-06
10TH AND MARNE STREETS	Pennsylvania	0.00208	2016-03

Table 4: Minimum captured CO mean value in year

For further analysis we picked address '14306 PARK AVE., VICTORVILLE, CA' which is address of 'Mojave Desert Air Quality Management' in California State. It covers most of time period. So, we get a good amount of data to train our linear regression model. Also, it appears in max table at year 2015.

It covers every month from 2000-01 to 2016-03. But from count, it can be observed that some records are missing for some months. The most probable solution would be filling these missing records with mean value.

However, we applied group by (using Month) on entire record with mean (average) function for regression model training data set. Thus adding missing record would not change month-wise CO Mean values.

Plot below shows number of records present month wise in year 2015.

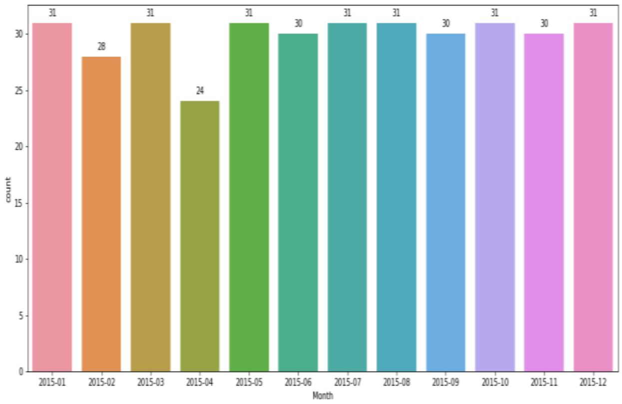

Fig. 10: Number of records month wise in year 2015.

We examined characteristics of CO Mean of selected address for December 2014 and in year 2015 month-wise. For month April 2015 having missing records from 07 April to 12 April the CO Mean values are filled with mean values of CO Mean of existing records.

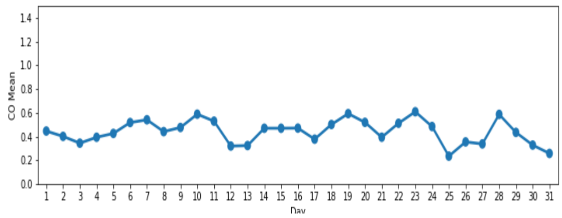

Fig. 11: Characteristics of CO Mean in month 2014-12

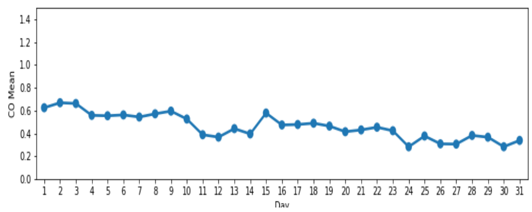

Fig. 12: Characteristics of CO Mean in month 2015-01

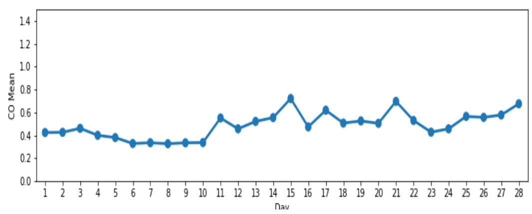

Fig. 13: Characteristics of CO Mean in month 2015-02

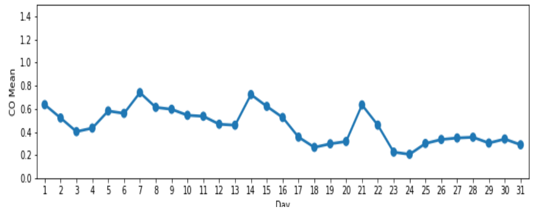

Fig. 14: Characteristics of CO Mean in month 2015-03

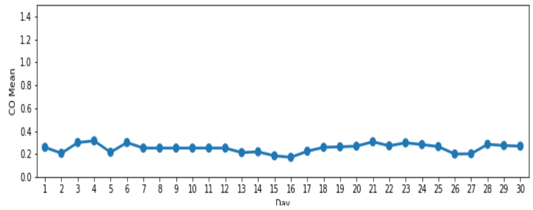

Fig. 15: Characteristics of CO Mean in month 2015-04

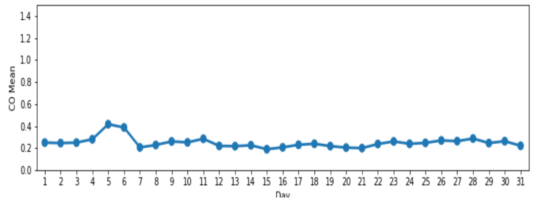

Fig. 16: Characteristics of CO Mean in month 2015-05

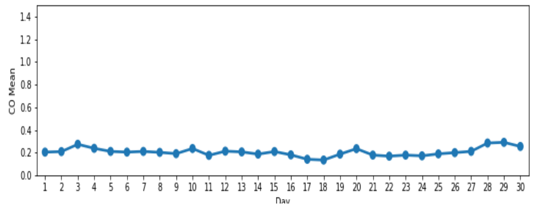

Fig. 17: Characteristics of CO Mean in month 2015-06

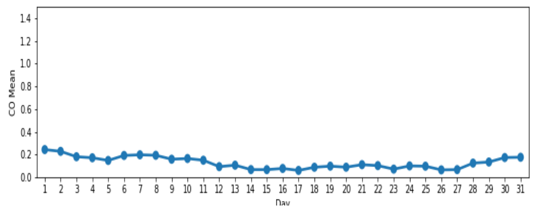

Fig. 18: Characteristics of CO Mean in month 2015-07

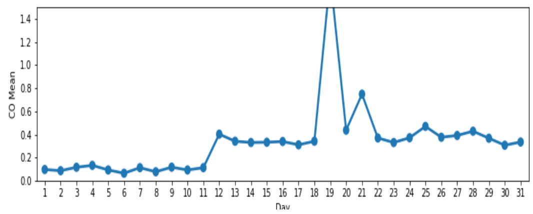

Fig. 19: Characteristics of CO Mean in month 2015-08

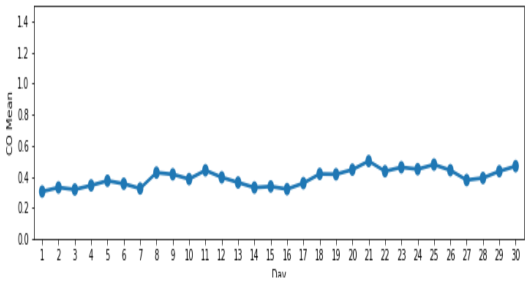

Fig. 20: Characteristics of CO Mean in month 2015-09

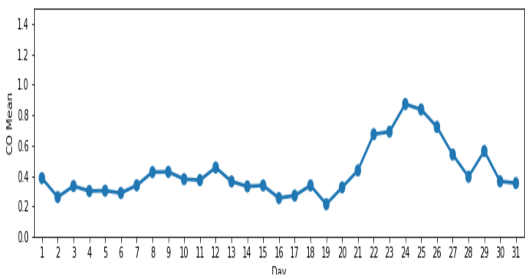

Fig. 21: Characteristics of CO Mean in month 2015-10

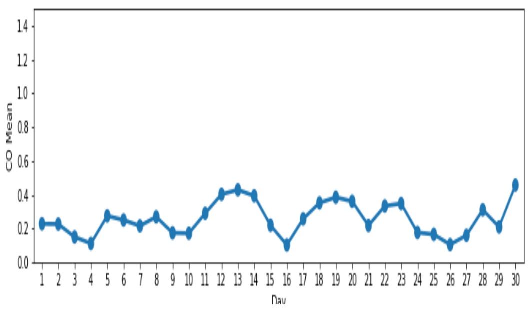

Fig. 22: Characteristics of CO Mean in month 2015-11

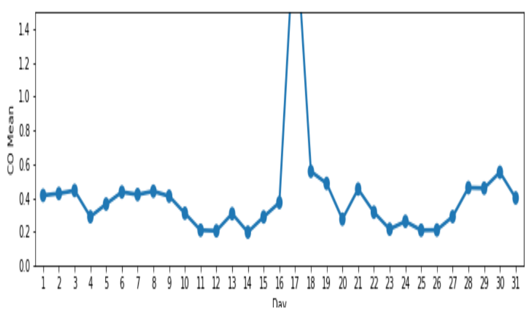

Fig. 23: Characteristics of CO Mean in month 2015-12

As it can be observed, the range of values in an year varies. Actually, these values vary by different season as in Winter they reach near to 0.8 ppm while in Summer it stays near to 0.4 ppm.

This happens because of phenomenon called inversion [6]. In USA, there are four seasons - Winter (December to February), Spring (March to May), Summer (June to August) and Autumn (September to November).

The boxplot below describes how CO Mean values vary by season. It is plotted over a complete season cycle (from 2014-12 to 2015-11).

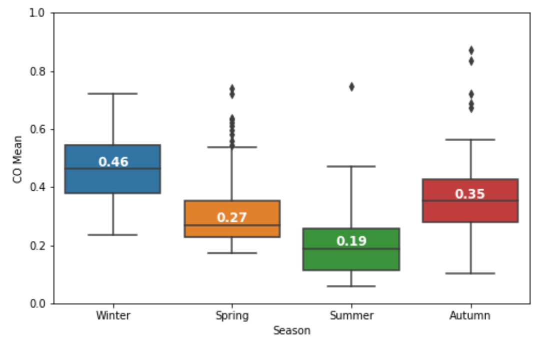

Fig. 24: Distribution of CO Mean values over different seasons

The median value for winter is high is 0.46 ppm which goes down to 0.19 in summer, rising back in autumn to 0.35 ppm.

Also, the same phenomenon makes influence over the time at which Maximum reading (CO Max) was recorded. Box plot below shows how hour at which maximum value was recorded varies.

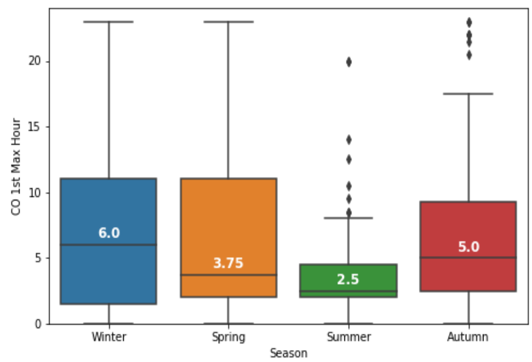

Fig. 25: Distribution of CO Mean values over different seasons

Most of the values occur to be in hours when there is dark (night or early morning). However, considering median values, for winter it is late to 06:00 A.M. while for summer it is recorded early at 02:30 A.M.

Geographical distribution of CO Mean can provide how CO levels are distributed regionally (state-wise) in different states. Plots below show geographical (state-wise) distribution of CO levels season-wise in season cycle from 2014-12 to 2015-11. Mean of CO values was calculated for every record in all present states season-wise.

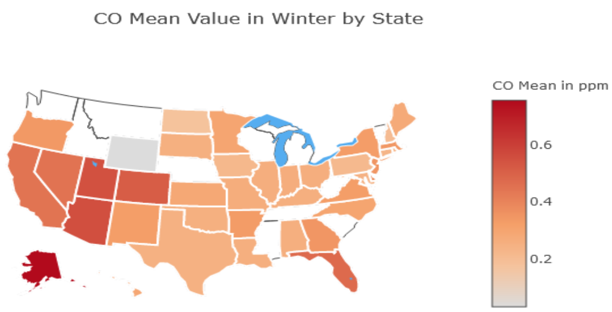

Fig. 26: Distribution of CO Mean in Winter by state

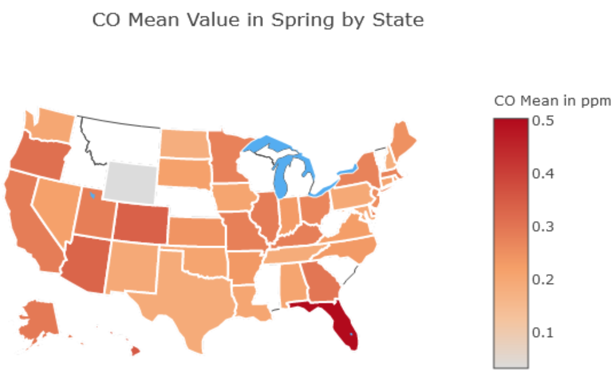

Fig. 27: Distribution of CO Mean in Spring by state

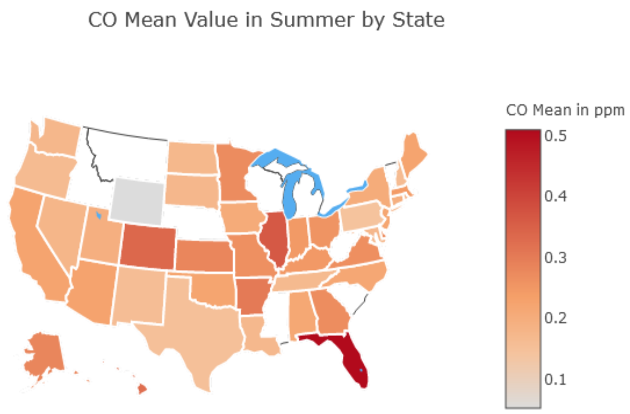

Fig. 28: Distribution of CO Mean in Summer by state

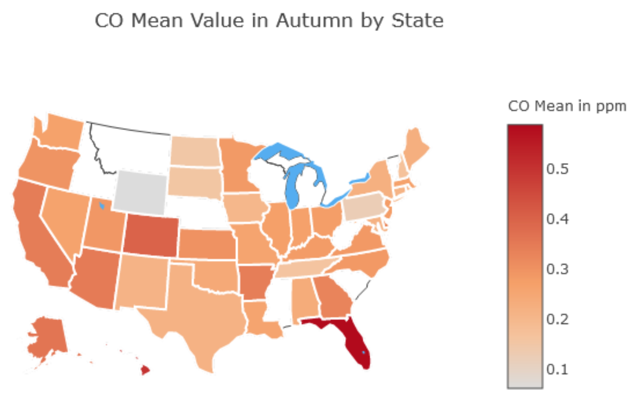

Fig. 29: Distribution of CO Mean in Autumn by state

The CO Mean values in maps for Winter are considerably high than for Summer.

So, in above ways, the data captured and sent by devices at different points can be used to analyze and view insights in data that can provide as an input or bias for government organization to create environmental regulation policies.

B. Prediction using Linear Regression.

In statistics, linear regression [7] is a linear approach for modelling the relationship between a scalar dependent variable y and one or more independent variables Xi. We modeled a linear regression model over CO Mean (in ppm) against MonthID. Month had a string format was converted to numeric form monthID such that the Month at which record started (2000-01 in this case) is marked at 0.

Following function did mapping between month to MonthID.

```
# start is first month in record of given address is of form
'2000-01'
# tofind is input feature for which the CO Mean values
is to be predicted is of form '2018-11'
def toID(tofind,start):
    startY = int(start.split('-')[0])
    startM = int(start.split('-')[1])
    tofindY = int(tofind.split('-')[0])
    tofindM = int(tofind.split('-')[1])
    id = 12 - startM
    id += (tofindY – startY) - 1 )) * 12
    id += tofindM
    return id
```

The data was split into 3/4rd and 1/4th subpart. 3/4rd split was used to train the linear regression model while 1/4th was used to test it.

Plot below show trained linear regression model.

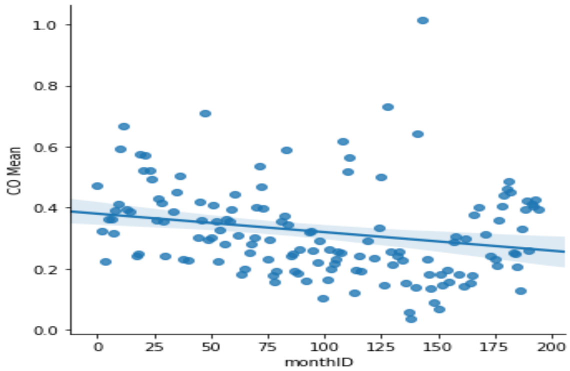

Fig. 30: Trained linear regression model

Actual and Predicted results are shown in Table 5.

Actual_Result	Prediction	Difference
0.170932173	0.356639544	-0.185707371
0.18106429	0.281424746	-0.100360455
0.221262054	0.343294983	-0.122032929
0.325724683	0.360885541	-0.035160857
0.150266717	0.305687584	-0.155420867
0.147643516	0.3032613	-0.155617784
0.892879183	0.294162736	0.598716448
0.391567194	0.354819831	0.036747362
0.42807115	0.359672399	0.068398751
0.123299484	0.319638716	-0.196339232
0.567365607	0.365131537	0.20223407
0.5342284	0.36695125	0.16727715
0.353398183	0.340262128	0.013136055
0.225504613	0.274752465	-0.049247852
0.940810339	0.292949594	0.647860745
0.72082079	0.351180405	0.369640385
0.170511645	0.325704425	-0.15519278
0.395835911	0.357852686	0.037983225
0.225597323	0.300835016	-0.075237694
0.33803755	0.308720439	0.029317111
0.518967645	0.37301696	0.145950685
0.295119339	0.27778532	0.017334019
0.314384387	0.322065	-0.007680613
0.358665694	0.275965607	0.082700086
0.202378032	0.346934409	-0.144556377
0.439358339	0.278998462	0.160359877
0.135337258	0.283244459	-0.1479072
0.280765367	0.355426402	-0.074661035
0.518151274	0.335409561	0.182741714
0.384309226	0.361492112	0.022817114
0.2183286	0.298408732	-0.080080132

0.163613726	0.312359864	-0.148746139
0.374687097	0.34147527	0.033211827
0.271526629	0.287490455	-0.015963826
0.067197371	0.285670742	-0.218473371
0.36549275	0.370590676	-0.005097926
0.170814484	0.325097854	-0.154283371
0.204835968	0.295982449	-0.091146481
0.148128321	0.314179577	-0.166051256
0.280933033	0.331770135	-0.050837102
0.163678581	0.30932701	-0.145648429
0.326386452	0.277178749	0.049207703
0.319776071	0.306900726	0.012875346
0.320334468	0.377869527	-0.05753506
0.370090567	0.371197247	-0.00110668
0.3273785	0.37968924	-0.05231074
0.262260774	0.35421326	-0.091952486
0.234297183	0.289916739	-0.055619556
0.544380548	0.307507297	0.236873252

Table 5: Actual and Predicted result

The Y-intercept of model was 0.38029581. The coefficient for CO Mean was -0.00060657. Thus, the amount of CO decreases by 0.00060657 for every next month. But, this can be updated as with new values over time, the model will be updated. The prediction accuracy is measures as RMSE (Root Mean Squared Error) is 0.17762 which is acceptable.

The testing data features were used to predict values of CO Mean for test monthIDs. Plot below shows distribution of difference between predictions and test data labels (test labels - prediction).

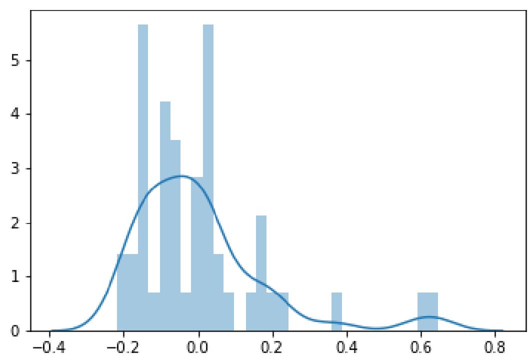

Fig. 31: Distribution of test_labels – prediction(test_feature) values

As the peak for Kernel Density Estimation (KDE) lies near to 0, we can say that model choice of linear regression was right.

VII. FUTURE SCOPE

The system is created for Carbon Monoxide. But, the system can be scalable for any pollutant types like Nitrogen dioxide (NO_2), Sulphur Dioxide(SO_2) or Ground level Ozone (O_3). This can help to predict future pollutant levels in air. And so, to control pollution levels.

VIII. CONCLUSION

Air pollution is having adverse effects from respiratory disease to harmful greenhouse effects. It is important to create a system to monitor and control their emissions. We have a created a system to monitor, analyze and predict CO levels in air. This can be used to identify how different factors emit CO in air. Also, system can be used to help make better regulation policies. The prediction carried out by regression gives prediction accuracy of RMSE 0.17766 which is in the acceptable range. This way our environment can be protected. The implementation cost is very less as commodity hardware and open source software is used.

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