Regression-Based Predictive Modeling for Air Quality Parameters

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Abstract— Predictive Modeling is the solution for discovering data in areas of air pollution prediction in the urban area. The prediction of the dataset is always helpful in the visualization and monitoring of the dataset. The air quality prediction for the urban city is necessary for future alert and precaution for a human being to save from hazardous. The urban areas need more observations regarding the air quality level and its impact on human health because of urbanization. In this research paper, we predict the air quality levels concerning air pollutants for the year 2016 based on the known dataset captured by sensors mounted at different geographical areas for the year 2014 and 2015 for the urban areas of the country India. This work leads to develop the formulation of regression analysis for the air pollutants to predict the air pollutants for any year concerning any month and time slots of the day.

Keywords— Predictive Modeling, Air Quality, Air Pollutants, Prediction range

I. Introduction

Predicted values are calculated for observations withinside the pattern used to estimate the regression. Air pollution always remains the area of research needing relevant data capture and its analysis to create an environment that doesn't affect planet health keeping the parameters inside the permissible limits. Most of the air pollutants are generated with the energy used and production processes. The flaming fossil fuels are sources of releasing health dangerous chemicals and toxic gases into the air [1]. The air pollution increases the temperature which is currently popularly known as a global warning. The impact brings a drastic change in the environment and the climate. The unhealthy impact on human life is eye, skin, and lung irritation, blood disorder due to inhaling of toxic gases and micro/nano particles present in the environment. The impact of Air pollution leads to unhealthy to Infant of the city [2]. It is a desire to have some strict and wise initiatives to reduce and better control the environment to a safer level. The gross study of air pollutants and its prediction is extremely plenty essential to be told the particular deterioration within the quality of air. It also helps to understand the pattern of possible pollution in the air and respective measures can be taken for [3]. The present study is targeting the Air quality and its causes based on the databases available by the sensor nodes. It is important to understand that the Surat city is a highly developing city situated in the south region of Gujarat state. The city has the bank of River and close to the cove of Cambay. The air pollutants result in serious human health effects, it also associated with a large number of diseases for mankind [4]. Air Quality Index (AQI) is the Measurement of air quality [5]. The air pollutants are Nitrogen Dioxide (NO2) emission from fossil-fuel, Carbon Monoxide (CO), Ozone (O3). Other major pollutants are inhalable Particulate Matter (PM10 or PM2.5), Ammonia (NH3), and Lead (Pb)) [6]. Main Air pollutants elements are consist of six important components. It includes CO2, CO, NO2, SO2, O3, and PM. The main source of CO2 emissions are industries and vehicle engines [7].

II. Related Work

Lanzafame Rosario et al [8] have worked in November and December 2012, to operate and measure NO2, C6H6, and O3 pollutants around the city areas by different samplers based on some models. The fixed sampling sites are selected as monitoring stations for comparing the predicted values with the actual values generated from the passive samplers, with time data of the continual samplers were mediate as operate of the number of hours of dispersive sampler exposure. The ensuing correlation coefficients show that the indicative measurements for NO2, O3, and C6H6 can be with validity integrated with the certified systems. A. Järvinen et al [9] has measured air quality by setting up the particulate sensors at 2 positions of the urban areas. Consider the NO2 and PM2.5 for air quality measurement. The relationship between the Particulate maters was observed concerning the location of measurement stations which are the sources of emission of it. The work must be extended with air pollutants centric.

R. Lanzafame et al [10] have undertaken the issue of AQI adopted by the U.S. Environmental Protection Agency, to the metropolitan town of Catania. The period duration was 2010 to 2014 for analyzing air quality exploitation the information of pollution concentrations submitted by the Municipal Ecology and Environment Office. MinJeong Kim et al [10] have proposed a model which is independent of the seasons. The calculation was carried out for the parameters PM10 and PM2.5 of the year 2008 to 2009. They proposed an analysis using regression methodologies. Knowing prior to the worth of the AQI, are often a helpful support for the government, for the system of preventive health care, or to forestall the exposure of the population. The air quality prediction depends on the previous year's dataset.

III. Dataset and Analysis

Data collected using three sensors placed at three different locations in the city are recorded and obtained at regular intervals. Three sensors are arranged at different locations to record the Environmental variables data at regular intervals. These intervals are not uniform. Data filtration is applied and only interesting data are selected. These interested selected data are of consecutive years 2014, 2015. Three sensors S1, S2, and S3 are placed at three different regions available at Katargam, Pandesara, and RingRoad respectively of the city are observed and the difference among the sensor results for the Time-slots are achieved. The observations are categorized in three parts for each month and the pilot-data analysis for R-10-1(For October 2014) is shown in Table 1.

TABLE 1: AVERAGE PARAMETER OBSERVATION DIFFERENCE AMONG S2 AND S1 FOR OCTOBER-2014

Time	Temp	Hum	Dew	CO2	CO	NO2	CH4
12 to 5pm	4.499	-10.220	1.410	29.339	-0.501	0.3456	-115.82
5 to 8pm	1.824	-4.207	0.507	28.013	-0.441	0.0619	-133.27
8 to 10pm	1.034	-2.237	0.348	25.03	-0.729	0.0006	-322.36
10 to 12pm	0.701	-1.589	0.232	25.942	-1.176	0.0058	-556.63
12 to 6 am	1.100	-2.110	0.262	20.11	-0.821	0.0091	-293.81
6 to 9 am	2.120	-5.210	0.570	23.12	-0.731	0.0391	-198.71
9 to 12am	3.170	-7.820	1.110	26.81	-0.391	0.1792	-132.71

Similarly, the database analysis made for R-10-2 (For October 2015) is shown in Table 2. Both the tables are showing the data pertaining to the difference of Parameters for all seven Time-Slots among the sensors S2 and S1. Sensor S2 is related to the Pandesara region whereas the Sensor S1 is pertaining to Katargam region.

It can be depicted from Table 2 that, the temperature difference among the sensor S2 and S1 is positive for all time slots. It can be also observed that this temperature difference is due to the location of the Sensor S1. The location of sensor S1 is in Katargam region which is near to the riverside thus the temperature difference compared to the Pandesara region is lower. Moreover, the Pandesara region is an Industrial area and the density of Industries and traffic is also higher than the Katargam region. The difference of parameters among both the sensors is average for the individual time-slots. The average Humidity difference among the Sensors S2 and S1 is observed to be negative for all time slots. The average Dew difference among the Sensors S2 and S1 is observed to be positive for all time slots. The average CO2 difference among the Sensors S2 and S1 is observed to be positive for all time slots. The average CO difference among the Sensors S2 and S1 is observed to be negative for all time slots. The Average NO2 difference among the Sensors S2 and S1 is observed to be positive for all time slots. The Average CH4 difference among the Sensors S2 and S1 is observed to be negative for all time slots.

Considering Table 3, depicts the comparative parameter-wise observations in percentage between both the sensors for the month of October-2015. Following observations are observed for October-2015. Average Temperature is observed 12.92% higher during slot-1(12 to 5 pm) at sensor-1(Pandesara) compared to sensor-2 (Katargam Riverfront). It also depicts that the temperature at sensor-1 is higher compared to sensor-2 area during all slots observations. Humidity is observed to be 20.27% lower during slot-1 (12 to 5 pm) at sensor-1 compared to sensor-2. It also depicts that the Humidity at sensor-2 is higher compared to sensor-1 area during all slots observations. Average Dew is observed to be 4.52% higher during slot-1 (12 to 5 pm) at sensor-1(Pandesara) compared to sensor-2(Katargam Riverfront). It also depicts that the dew at sensor-1 is higher compared to sensor-2 area during all slots observations. CO2 is observed to be 7.46% higher during slot-1 (12 to 5 pm) at sensor-1(Pandesara) compared to sensor-2(Katargam Riverfront). It also depicts that the CO2 at sensor-1 is higher compared to sensor-2 area during all slots observations. CO is observed to be 36.68% lower during slot-4 (10 pm to 12 am) at sensor-1(Pandesara) compared to sensor-2(Katargam Riverfront). It also depicts that the CO at sensor-1 is lower compared to sensor-2 area during all slots observations. NO2 is observed to be 72.91% during Slot-1 (12 pm to 5 pm) at sensor-1(Pandesara) compared to sensor-2(Katargam Riverfront). It also depicts that the NO2 at sensor-1 is higher compared to sensor-2 area during all slots observations. CH4 is observed to be 164.05% higher during slot-4 (10 pm to 12 am) at sensor-1 (Pandesara) compared to sensor-2(Katargam Riverfront). It also depicts that the CH4 at sensor-1 is higher compared to sensor-2 area during all slots observations.

TABLE 2: AVERAGE PARAMETER OBSERVATION DIFFERENCE AMONG S2 AND S1 FOR OCTOBER-2015

Time	Temp	Hum	Dew	CO2	CO	NO2	CH4
12to5pm	4.799	-11.31	1.213	30.172	-0.493	0.4213	-126.82
5to 8pm	1.926	-4.371	0.507	29.062	-0.463	0.0723	-129.13
8to 10pm	1.123	-2.316	0.313	24.732	-0.801	0.0005	-298.44
10to 12pm	0.690	-1.563	0.242	26.732	-1.312	0.0061	-496.73
12to6 am	1.213	-2.213	0.273	21.321	-0.793	0.0087	-307.93
6 to9 am	2.214	-5.413	0.493	24.192	-0.697	0.0401	-189.93
9to12am	3.241	-8.124	1.211	25.792	-0.431	0.1632	-131.69

PM10 is observed to be higher during slot-1(12 to 5 pm) for October 2014 and 2015 for Sensor-2 compared to Sensor-1. For PM10, all observation slots depict higher values for Sensor-2 compared to Sensor-1. For 2014 and 2015, the maximum temperature difference in % is observed for PM10 among S2 and S1 is during slot-1. This is the same for both years. For 2014 and 2015, the minimum temperature difference in % is observed for PM10 among S2 and S1 is during slot-6. This is the same for both years.PM10 is observed to be higher during slot-1 (12 to 5 pm) for October 2014 and 2015 for Sensor-2 compared to Sensor-1. For PM10, all observation slots depict higher values for Sensor-2 compared to Sensor-1. For 2014 and 2015, the maximum temperature difference in % is observed for PM10 among S2 and S1 is during slot-1. This is the same for both years. For 2014 and 2015, the minimum temperature difference in % is observed for PM10 among S2 and S1 is during slot-6. This is the same for both years.

TABLE 3: PARAMETER OBSERVATION DIFFERENCE AMONG S2 AND S1 FOR OCTOBER-2015

Time	Temp	Hum	Dew	CO2	CO	NO2	CH4
12 to 5pm	**12.92**	**-20.27**	**4.52**	**7.46**	-16.80	**72.91**	-89.19
5 to 8pm	5.39	-7.62	1.95	7.19	-14.02	32.75	**-55.23**
8 to 10pm	3.25	-3.89	1.22	6.08	-21.26	**0.46**	-78.29
10 to12pm	**2.03**	**-2.58**	**0.95**	6.56	**-36.68**	5.45	**-164.05**
12to 6 am	3.58	-3.43	1.07	**5.23**	-22.16	7.73	-101.70
6 to 9 am	6.53	-8.80	1.93	5.93	-19.48	35.64	130.49
9to 12am	9.55	-13.21	4.15	6.32	**-12.05**	28.24	-90.48

TABLE 4: PM10 and PM2.5 S1 and S2 COMPARATIVE OBSERVATIONS FOR 2014 AND 2015

PM10			PM2.5		
Slot	**2014**	**2015**	**Slot**	**2014**	**2015**
12 to 5pm	**28.11**	**29.83**	12 to 5pm	**7.23**	**7.60**
5 to 8pm	18.79	19.76	5 to 8pm	6.27	6.40
8 to 10pm	14.34	14.63	8 to 10pm	5.94	6.12
10 to 12pm	14.22	14.46	10 to 12pm	5.72	5.94
12 to 6 am	15.93	16.43	12 to 6 am	5.98	6.11
6 to 9 am	**12.78**	**13.42**	6 to 9 am	**5.69**	**5.81**
9 am to 12	17.93	18.97	9 am to 12	5.76	5.98

A. Temperature and Humidity

The comparative observations for two years 2014 and 2015 are shown as per table 5. The observations show the temperature difference among the two sensors S1 and S2. This is also represented in Chart 4.10. Maximum temperature difference among sensors-S1 and S2 are observed for the slot-12 to 5 pm. in the case of both years 2014 and 2015.

The minimum difference among both the sensors is observed during the slot 10 am to 12 pm. This is also a common slot for both years 2014 and 2015. It is also observed that Humidity sensor S1 higher than sensor S2 for all slots, whereas Temperature defines differently.

TABLE 5: % DEFFERENCE AMONG S1 AND S2 COMPARATIVE OBSERVATIONS FOR 2014 AND 2015

[A] TEMPRATURE			[B] HUMIDITY		
Slot	**2014**	**2015**	**Slot**	**2014**	**2015**
12to 5pm	**12.11**	**12.92**	12to5pm	**-21.31**	**-20.27**
5 to 8pm	5.10	5.39	5 to 8pm	-10.4	-7.62
8to 10pm	2.99	3.25	8to10pm	-4.66	-3.89
10to12pm	**2.07**	**2.03**	10to12pm	**-2.78**	**-2.58**
12to 6 am	3.24	3.58	12to 6 am	-4.35	-3.43
6 to 9 am	6.25	6.53	6 to 9 am	-12.68	-8.80
9am to 12	9.34	9.55	9am to 12	-14.54	-13.21

The percentage difference among both slots is observed highest during slot-1 and lowest during slot-4. Trends for temperature and humidity difference are observed as shown in chart1[a] and 1[b].

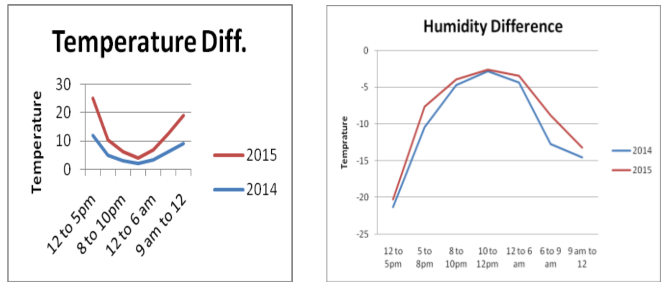

Chart 1[a]: Temperature difference among S1 and S2 for the year 2014 and 2015. [b]: Humidity difference among S1 and S2 for the year 2014 and 2015.

B. Comparative Range of Parameters for 2014 and 2015

It is important to note from the results obtained and shown in Tables 5, which depicts that certain patterns are observed for all parameters and the results are within a certain range for two years of results. Following important inferences are observed for the years 2014 and 2015 among the results of Sensors S1, S2, and S3. For every time slot results obtained for every parameter are higher in 2015 compared to 2014. The pattern is identical for every parameter. Sensors S1 and S2 comparative study for 2014 shows range difference which is identical in pattern compared to 2015. Max and Min's ranges are obtained for every parameter using the results of 2014 and 2015. These ranges are tested for known data of parameters for the year 2016 and the accuracy of the range is verified as depicted in the following section. For known results of any of the sensors out of three sensors, the predicted value of any parameter for a given slot and month can be predicted and verified.

C. Parameter wise prediction Range

Considering the range obtained, month-wise, the prediction range model is developed. The parameter-wise range for all sensors is obtained based on the data for every month. The parameter-wise range for every slot is generated. The base data is considered for the Sensor-2 and based on the Sensor-2 data, the rest data for Sensor-1 and Sensor-3 are generated using the predicted model.

Month: October:

Parameter: Temperature:

As shown in Table 6, the results obtained for Parameter, Temperature are shown slot-wise. Comparative changes are observed for all three sensors. It is observed that for temperature range results for Base sensor-2, the Observations obtained for 2014 and 2015 areas per following range:

Slot-1: S2[37.14, 37.16] $S1_R$[12.11,12.91]-ve. $S3_R$[10.31, 11.19]-ve
Slot-2: S2[35.74, 35.77] $S1_R$[5.10,5.38]-ve. $S3_R$[3.23, 3.60]-ve
Slot-3: S2[34.61, 34.66] $S1_R$[2.99,3.24]-ve. $S3_R$[1.05, 1.39]-ve
Slot-4: S2[33.92,33.95] $S1_R$[2.07,2.03]-ve. $S3_R$[0.09, 0.15]-ve
Slot-5: S2[30.17, 30.19] $S1_R$[3.65,4.02]-ve. $S3_R$[1.43, 1.90]-ve
Slot-6: S2[31.12, 31.14] $S1_R$[6.81,7.11]-ve. $S3_R$[4.66, 5.05]-ve
Slot-7: S2[33.35, 33.37] $S1_R$[9.51,9.71]-ve. $S3_R$[7.50, 7.79]-ve

TABLE 6: TEMPERATURE PARAMETER RANGE FOR SENSORS-S2, S1, S3.

Month: October -2014

Parameter:(Average)Temperature

Time Slot	Base Result - S2	% Diff. in S1 for 2014 (In -ve)	% Diff. in S3 for 2014 (in –ve)
12 to 5pm	37.14	12.11	10.31

5 to 8pm	35.74	5.10	3.23
8 to 10pm	34.61	2.99	1.05
10 to 12pm	33.92	2.07	0.09
12 to 6 am	30.17	3.65	1.43
6 to 9 am	31.12	6.81	4.66
9 to 12 pm	**33.35**	9.51	7.50

Month: October -2015

Parameter:(Average)Temperature

Time Slot	Base Result - S2	% Diff. in S1 for 2014 (In -ve)	% Diff. in S3 for 2014 (in –ve)
12 to 5pm	37.16	12.91	11.19
5 to 8pm	35.77	5.38	3.60
8 to 10pm	34.66	3.24	1.39
10 to 12pm	33.95	2.03	0.15
12 to 6 am	30.19	4.02	1.90
6 to 9 am	31.14	7.11	5.05
9 to 12 pm	**33.37**	9.71	7.79

D. Slot wise Parameter Prediction Range

To obtain the prediction values for all other sensors using the formula:

Slot-1:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-1}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.1211*$S2_{t1}$), $S2_{t2}$- (0.1291*$S2_{t2}$)] $_{SLOT-1}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.1031*$S2_{t1}$), $S2_{t2}$- (0.1119*$S2_{t2}$)] $_{SLOT-1}$

Slot-2:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-2}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.0510*$S2_{t1}$), $S2_{t2}$- (0.0538*$S2_{t2}$)] $_{SLOT-2}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.0323*$S2_{t1}$), $S2_{t2}$- (0.0360*$S2_{t2}$)] $_{SLOT-2}$

Slot-3:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-3}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.0299*$S2_{t1}$), $S2_{t2}$- (0.0324*$S2_{t2}$)] $_{SLOT-3}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.0105*$S2_{t1}$), $S2_{t2}$- (0.0139*$S2_{t2}$)] $_{SLOT-3}$

Slot-4:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-4}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.0207*$S2_{t1}$), $S2_{t2}$- (0.0203*$S2_{t2}$)] $_{SLOT-4}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.0009*$S2_{t1}$), $S2_{t2}$- (0.0015*$S2_{t2}$)] $_{SLOT-4}$

Slot-5:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-5}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.0365*$S2_{t1}$), $S2_{t2}$- (0.0402*$S2_{t2}$)] $_{SLOT-5}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.0143*$S2_{t1}$), $S2_{t2}$- (0.0190*$S2_{t2}$)] $_{SLOT-5}$

Slot-6:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-6}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.0681*$S2_{t1}$), $S2_{t2}$- (0.0711*$S2_{t2}$)] $_{SLOT-6}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.0466*$S2_{t1}$), $S2_{t2}$- (0.0505*$S2_{t2}$)] $_{SLOT-6}$

Slot-7:

Temperature Range for Sensor-S2: [$S2_{t1}$, $S2_{t2}$] $_{SLOT-7}$

Temperature Range for Sensor-S1: [$S2_{t1}$- (0.0951*$S2_{t1}$), $S2_{t2}$- (0.0971*$S2_{t2}$)] $_{SLOT-7}$

Temperature Range for Sensor-S3: [$S2_{t1}$- (0.0750*$S2_{t1}$), $S2_{t2}$- (0.0779*$S2_{t2}$)] $_{SLOT-7}$

As shown in Table 7, the results obtained for Parameter, Humidity are shown slot-wise. Comparative changes are observed for all three sensors (% difference). It is observed that for temperature range results for Base sensor-2, the Observations obtained for 2014 and 2015 is:

Slot-1:S2[55.80,55.07] $S1_R$[21.31,20.27]-ve.$S3_R$[20.58,20.60]-ve
Slot-2: S2[57.32, 56.65] $S1_R$[10.40, 7.62]-ve.$S3_R$[9.67, 7.62]-ve
Slot-3: S2[59.59, 59.17] $S1_R$[4.66, 3.89]-ve.$S3_R$[3.99, 4.03]-ve
Slot-4: S2[61.52, 61.23] $S1_R$[2.78, 2.58]-ve.$S3_R$[2.17, 2.58]-ve
Slot-5: S2[63.79, 63.62] $S1_R$[4.35, 3.43]-ve.$S3_R$[3.91, 3.88]-ve
Slot-6:S2[60.72, 60.53] $S1_R$[12.68, 8.80]-ve.$S3_R$[12.11,12.09]-ve
Slot-7:S2[58.47, 58.21] $S1_R$[14.54,13.21]-ve.$S3_R$[14.09,14.05]-ve

The slot-wise Range for Humidity is observed to be for the month of October for year 2014 and 2015 which are our training dataset. The predicted range will be categorized based on this obtained dataset difference in percentage values.

TABLE 7: Humidity Parameter Range for Sensors-S2 and corresponding range for S1 and S3.

	Month: October - 2014	Parameter: Humidity		Month: October -2015	Parameter: Humidity	
Time Slot	Base Result - S2	% Diff. at S1 for 2014 (In -ve)	% Diff. at S3 for 2014 (In -ve)	Base Result - S2	% Diff. at S1 for 2015 (In -ve)	% Diff. at S3 for 2015
12 to 5pm	55.80	**-21.31**	-20.58	55.07	**-20.27**	-20.60
5 to 8pm	57.32	-10.4	-9.67	56.65	-7.62	-9.70
8 to 10pm	59.59	-4.66	-3.99	59.17	-3.89	-4.03
10 to 12pm	61.52	**-2.78**	-2.17	61.23	**-2.58**	-2.19
12 to 6 am	63.79	-4.35	-3.88	63.62	-3.43	-3.91
6 to 9 am	60.72	-12.68	-12.09	60.53	-8.80	-12.11
9 to 12 pm	58.47	-14.54	-14.05	58.21	-13.21	-14.09

Slot-Wise Prediction for Parameter-Humidity will be-

Slot-1:

Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-1
Humidity Range for Sensor-S1:
[S2t1- (0.2131*S2t1), S2t2- (0.2027*S2t2)] SLOT-1
Humidity Range for Sensor-S3:
[S2t1- (0.2058*S2t1), S2t2- (0.2060*S2t2)] SLOT-1

Slot-2:

Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-2
Humidity Range for Sensor-S1:
[S2t1- (0.1040*S2t1), S2t2- (0.0762*S2t2)] SLOT-2
Humidity Range for Sensor-S3:
[S2t1- (0.0967*S2t1), S2t2- (0.0762*S2t2)] SLOT-2

Slot-3:

Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-3
Humidity Range for Sensor-S1:
[S2t1- (0.0466*S2t1), S2t2- (0.0389*S2t2)] SLOT-3
Humidity Range for Sensor-S3:
[S2t1- (0.0399*S2t1), S2t2- (0.0403*S2t2)] SLOT-3

Slot-4:

Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-4

Humidity Range for Sensor-S1:
[S2t1- (0.0278*S2t1), S2t2- (0.0258*S2t2)] SLOT-4
Humidity Range for Sensor-S3:
[S2t1- (0.0217*S2t1), S2t2- (0.0219*S2t2)] SLOT-4

Slot-5:
Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-5
Humidity Range for Sensor-S1:
[S2t1- (0.0435*S2t1), S2t2- (0.0343*S2t2)] SLOT-5
Humidity Range for Sensor-S3:
[S2t1- (0.0388*S2t1), S2t2- (0.0391*S2t2)] SLOT-5

Slot-6:
Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-6
Humidity Range for Sensor-S1:
[S2t1- (0.1268*S2t1), S2t2- (0.0880*S2t2)] SLOT-6
Humidity Range for Sensor-S3:
[S2t1- (0.1209*S2t1), S2t2- (0.1211*S2t2)] SLOT-6

Slot-7:
Humidity Range for Sensor-S2: [S2t1, S2t2] SLOT-7
Humidity Range for Sensor-S1:
[S2t1- (0.1454*S2t1), S2t2- (0.1321*S2t2)] SLOT-7
Humidity Range for Sensor-S3:
[S2t1- (0.1405*S2t1), S2t2- (0.1409*S2t2)] SLOT-7

IV. CONCLUSION AND FUTURE ENHANCEMENT

The air quality prediction helps in safeguarding the people of the country of the areas. The prediction range can be obtained based on the past dataset with regression analysis. The work forecast the formulas for the prediction of temperature and humidity of air quality. In the future, we can predict the other air pollutants also and can check the accuracy of predicted values percentage-wise, and can judge whether the predicted values are accurate or not with respect to what level of accuracy.

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