ISB

Time Series Analysis to Forecast Air Quality for Mumbai

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Executive Summary

Air pollution is one of the most widespread problem in India today. Breathing bad quality air has robbed the country with its significant opportunity to grow, and has costed huge human and economic losses. Monitoring and forecasting the status and trends of ambient air quality to ascertain air quality standards is one of the important step to address this issue.

This report presents results of forecasting the Air Quality Index for the City of Mumbai for the month of January 2017 using time series analysis. The report highlights performance of various time series models built to forecast the AQI based on four major pollutants – PM10, PM2.5, SO_2 and NO_2 and using these results forecast the overall quality of air for Mumbai. The models are built using data driven and regression based techniques to obtain most accurate results. The performance evaluations of the adopted models are carried out on the basis of MAPE and RMSE. The results indicate that the models provide satisfactory predictions for the air quality parameters and can be used for practical assessment.

Air Quality Index

Air Quality Index is scale designed to help public understand what the air quality around them means to their health. AQI can play an important role in taking appropriate actions to control air quality such as

- Addressing Health issues -- Generating health alerts when the air pollution levels exceed the specified limits. Such alerts can be useful to specific population which are sensitive to air pollution e.g. people suffering from Asthma
- Better Urban and Aviation planning – A reliable forecast of the air quality can help the local authorities better with operational planning (such as aviation services), better planning of the cities (start of a major project such as Metro). The government can start providing incentives to people for promoting carpooling activities to reduce emission levels from automobiles.
- On-demand emission control program – Air quality standards exceed more on certain days as compared to other days of the year such as the week around Diwali. The availability of an accurate air pollution forecasts can help local authorities deploy 'on demand' services, thus avoiding the high cost of continuous emission control.

AQI determines the category of air - namely Good, Satisfactory, Moderately polluted, Poor, Very Poor, and Severe. For each concentration a sub-index is calculated and the worst sub-index determines the overall AQI. The AQ sub index and the AQI category are calculated as follows

AQI Category	AQI	Concentration range*							
		PM_{10}	$PM_{2.5}$	NO_2	O_3	CO	SO_2	NH_3	Pb
Good	0 - 50	0 - 50	0 - 30	0 - 40	0 - 50	0 - 1.0	0 - 40	0 - 200	0 - 0.5
Satisfactory	51 - 100	51 - 100	31 - 60	41 - 80	51 - 100	1.1 - 2.0	41 - 80	201 - 400	0.5 - 1.0
Moderately polluted	101 - 200	101 - 250	61 - 90	81 - 180	101 - 168	2.1 - 10	81 - 380	401 - 800	1.1 - 2.0
Poor	201 - 300	251 - 350	91 - 120	181 - 280	169 - 208	10 - 17	381 - 800	801 - 1200	2.1 - 3.0
Very poor	301 – 400	351 - 430	121 - 250	281 - 400	209 - 748*	17 - 34	801 - 1600	1200 -1800	3.1 - 3.5
Severe	401 - 500	430 +	250+	400+	748+*	34+	1600+	1800+	3.5+

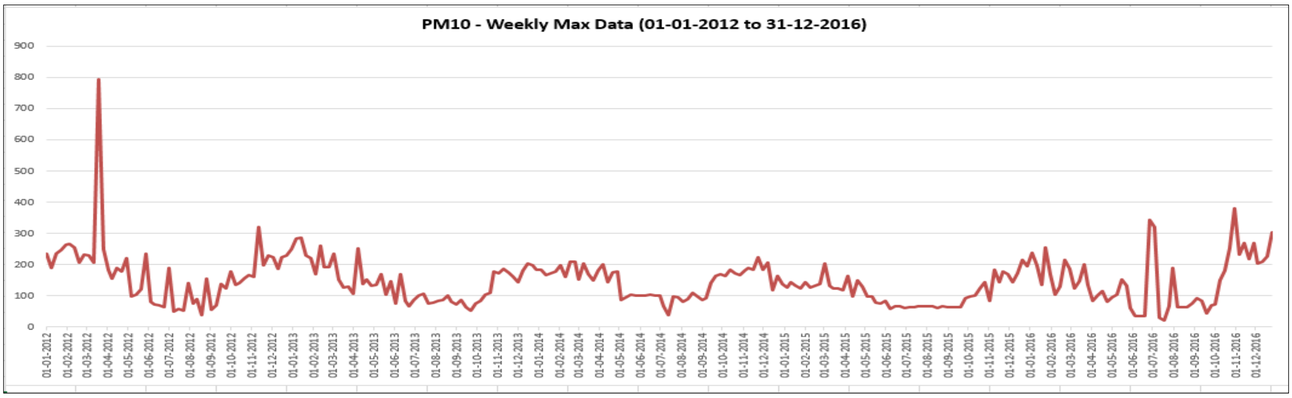
* CO in mg/m^3 and other pollutants in $\mu g/m^3$; 2h-hourly average values for PM_{10}, $PM_{2.5}$, NO_2, SO_2, NH_3, and Pb, and 8-hourly values for CO and O_3.

Data Collection and Pre-processing

The data is obtained from the official website of Central Pollution Board of India - http://www.cpcb.gov.in/CAAQM/frmUserAvgReportCriteria.aspx. Daily data is collected from 2012-16 for PM10, PM2.5 and from 2015-16 for NO2, SO2. Data is grouped into weeks and the MAX value for each concentration is calculated for each week. We used R for grouping the data and XLMiner for building models. The time series plot of each concentration (week wise) is shown in the forecasting methods section. Since missing values (for each pollutant) were less than 1% of the total data, we have used naïve forecast (current value is same as the last value).

Forecasting Methods

1. PM10



The time series shows constant trend along with monthly seasonal components. The data shows lot of local peaks and high fluctuations. A closer inspection shows that for a particular month, on an average the values are high for first 2 weeks and then decreases. We therefore have both weekly and monthly seasonality.

Data Pre-processing

Original dataset - 1810 records (daily records)
Dataset after pre-processing – 261 records (weekly max records)

Since data showed both weekly (approx. high during the first 2 weeks followed by low in the next 2 weeks) and monthly (12 months) seasonality, we partitioned the dataset keeping 209 records in training set and 52 records in validation set. We built models using seasonality = 52 periods.

Model Building

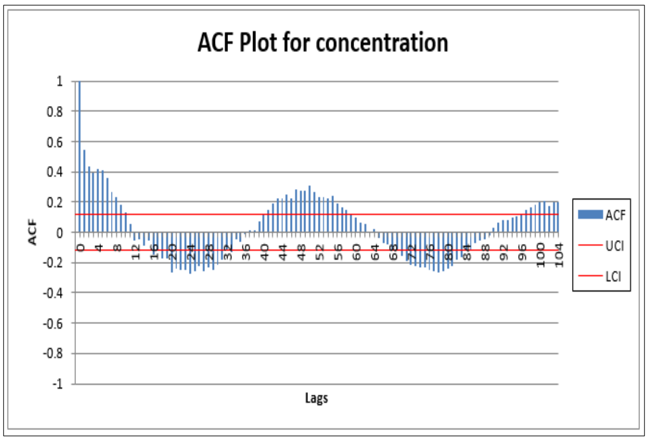
1. Regression Based Model

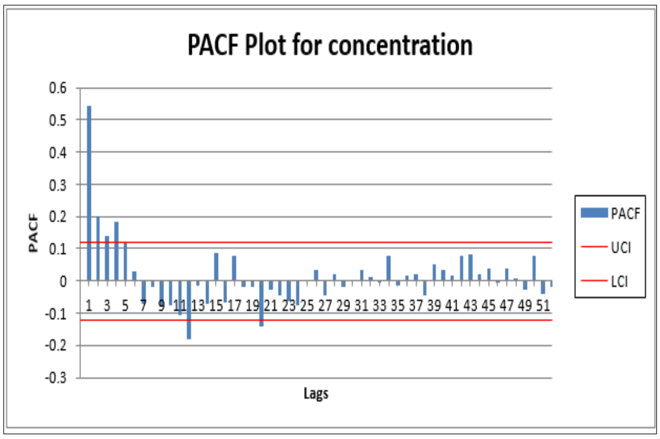
A regression based model with 53 dummy variables - for capturing weekly and monthly seasonality (53 because 2012 had 53 weeks)

$$\mathbf{Y = B_0 + B_1W_1 + B_2W_2 + \ldots + B_{52}W_{52}}$$

2. ARIMA Model

Observing the ACF and PACF plots of the response variable (PM10 concentration), it is observed that the data has seasonal component with period = 52. Also the past response values seem to influence the future values.





Observing the above plots and with some trial and error an ARIMA (1, 0, 0)(0, 1, 0) was built

p = 1 (Autoregressive component with lag = 1)   D = 1 (Differencing the series to remove the seasonality of period 52)

3. Holt-Winters Smoothing Model

Holt-Winters with no trend was used to build the smoothing model, with Alpha = 0.2287 and Gamma = 0.00167

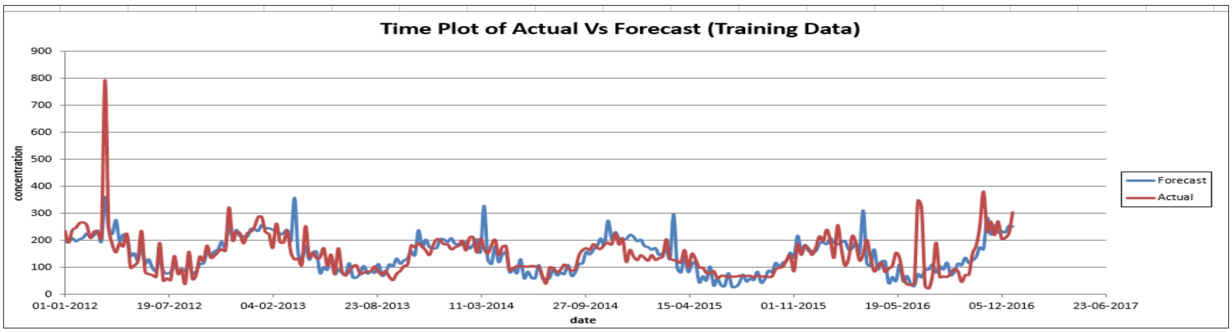
Summary Statistics for each Model (MAPE = Value*100 %)

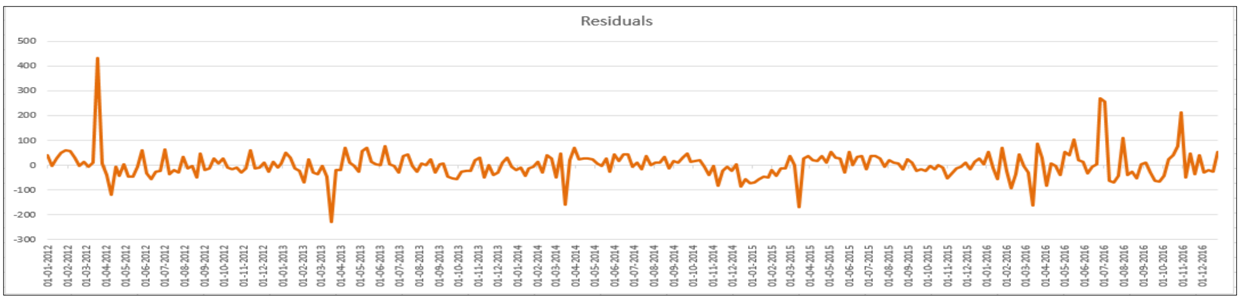
	Regression	ARIMA	Holt-Winters
Training RMSE	53.02768114	70.04075554	49.259
Validation RMSE	77.56252761	96.81452792	86.484
Training MAPE	0.239	0.349094358	0.227740633
Validation MAPE	0.505	0.374141367	0.371222532

	Regression	ARIMA	Holt-Winters
Overall RMSE	56.66185743	73.35485896	57.072
Overall MAPE	0.285957335	0.373654766	0.288243621

Overall **Holt-winters** shows good performance as compared to the other models. The validation set error was high for all 3 models because the validation set showed lot of irregularities and noise as compared to other time periods.

Performance chart for Holt-Winters

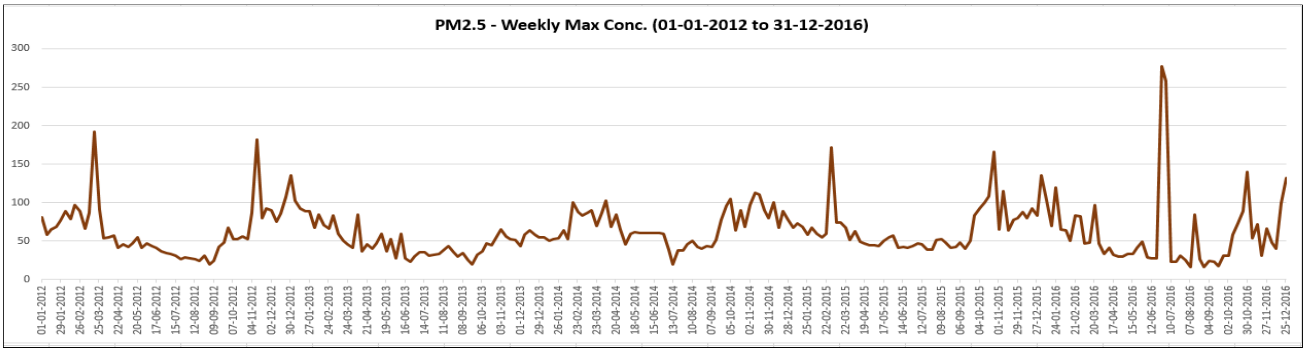




Forecast (max conc. of PM10) Using Holt-Winters (first 4 weeks for January 2017) and AQI values

Week	Forecast	LCI	UCI	AQI	AQI Category
1	250.2278	138.3684	362.0872	200	Moderately Polluted (very close to Poor)
2	264.4229	151.0364	377.8094	215	Poor
3	249.1286	133.5784	364.6788	199	Moderately Polluted (very close to Poor)
4	250.8748	132.4429	369.3067	201	Poor

2. PM2.5



The time series shows constant trend along with monthly seasonal components. Data shows lot of local peaks and high fluctuations (lots of noise). A closer inspection shows that for a particular month, on an average the values are high for first 2 weeks and then decreases. We therefore have both weekly and monthly seasonality.

Data Pre-processing

Original dataset - 1818 records (daily records)
Dataset after pre-processing – 261 records (weekly max records)

Since data showed both weekly (approx. high during the first 2 weeks followed by low in the next 2 weeks) and monthly (12 months) seasonality, we partitioned the dataset keeping 209 records in training set and 52 records in validation set. We built models using seasonality = 52 periods.

Model Building

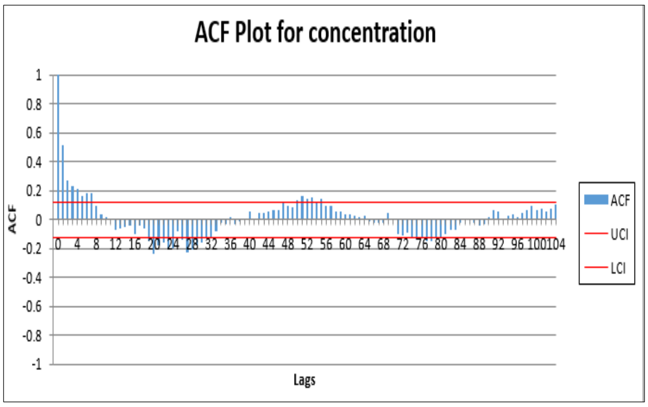
1. Regression Based Model

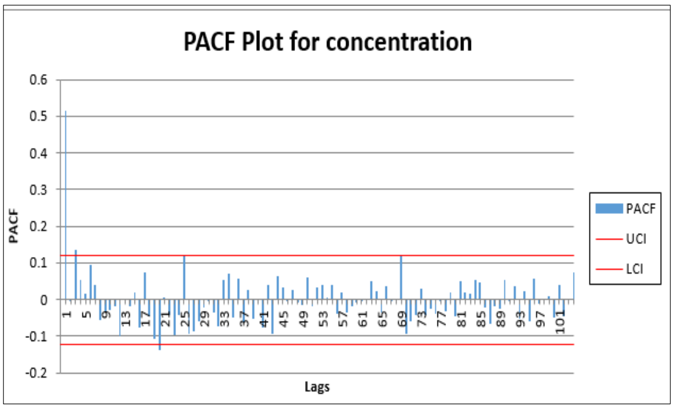
A regression based model with 53 dummy variables - for capturing weekly and monthly seasonality (53 because 2012 had 53 weeks)

$$Y = B_0 + B_1W_1 + B_2W_2 + \dots + B_{52}W_{52}$$

2. ARIMA Model

Observing the ACF and PACF plots the data has seasonal component with period = 52. Also the past response values seem to influence the future values.





Observing the above plots and with some trial and error an ARIMA (0, 1, 1)(0, 1, 0) was built

q = 1 (Moving Average component with lag = 1)   D = 1 (Differencing the series to remove the seasonality of period 52)

3. Holt-Winters Smoothing Model

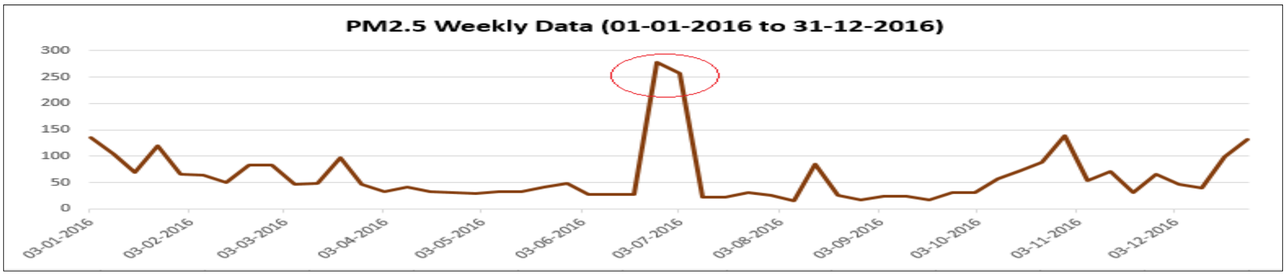
Holt-Winters with no trend was used to build the smoothing model, with Alpha = 0.22873 and Gamma = 0.001678

Summary Statistics for each Model (MAPE = Value*100 %)

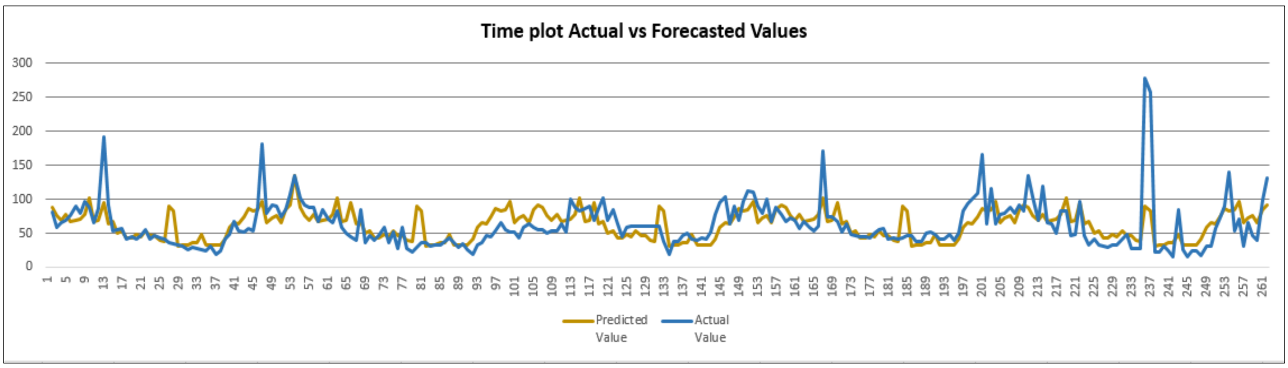
	Regression	ARIMA	Holt-Winters
Training RMSE	19.28526389	27.32768522	17.743
Validation RMSE	52.12149246	55.23588602	54.075
Training MAPE	0.233074184	0.311723055	19.38603856
Validation MAPE	0.548513279	0.510530249	51.35855654

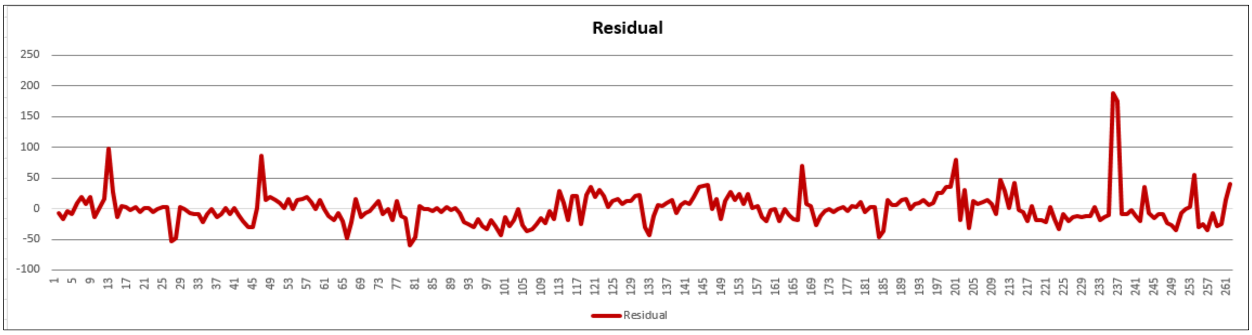
	Regression	ARIMA	Holt-Winters
Overall RMSE	27.03369632	37.26016105	29.273
Overall MAPE	0.30857935	0.40931849	0.300385568

Regression based model shows better performance as compared to the other models. The validation set error was high for all 3 models because it showed lot of noise as compared to other time periods. The graph below unusual spikes in the validation set. However we have not modified any of the data and have attempted to address these irregularities



Performance chart for Regression based model

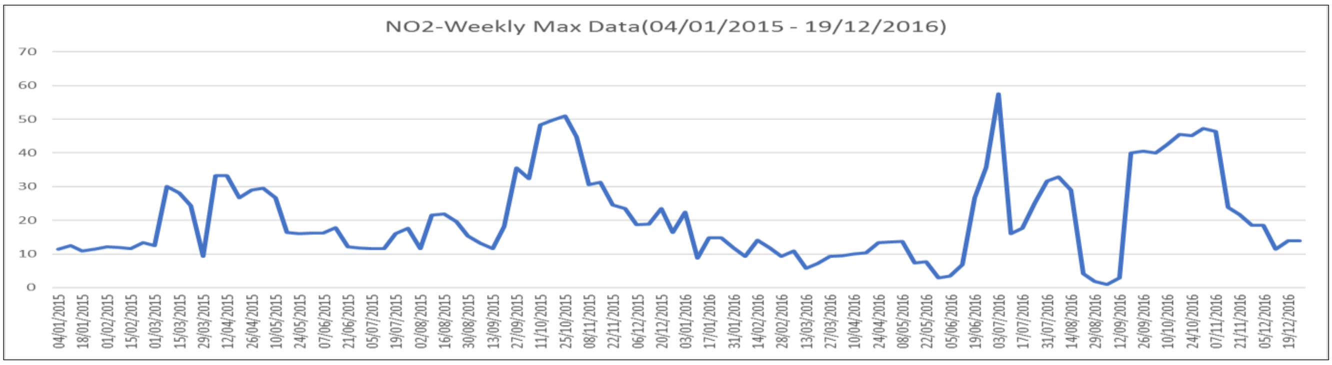




Forecast (max conc. of PM10) Using Regression based model (first 4 weeks for January 2017) and AQI values

Week	Forecasted Value	95% Prediction Intervals		AQI	AQI Category
		Lower	Upper		
1	88.182	22.78361443	153.5804	194	Moderately Polluted (very close to Poor)
2	75.294	9.89561443	140.6924	151	Moderately Polluted
3	68.858	3.45961443	134.2564	130	Moderately Polluted
4	77.604	12.20561443	143.0024	159	Moderately Polluted

3. NO2



Visual inspection of the time series shows no seasonality. It can be evidently seen that there is noise component present across the entire series along with level. We therefore proceed with a data-driven approach to model this pollutant.

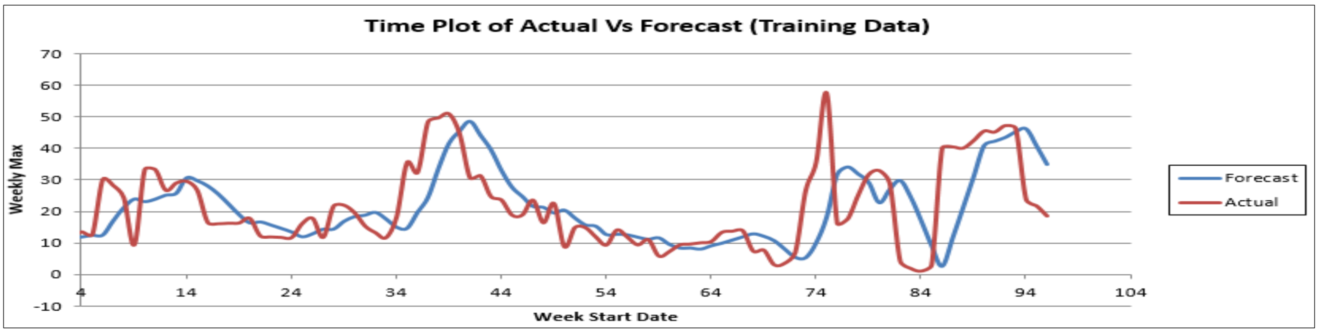
Data Pre-processing

Original dataset - 977 records (daily records)
Dataset after pre-processing – 104 records (weekly max records, considering the start of the week on a Sunday)
Training data set – 100 records
Validation data set – 4 records

Model building

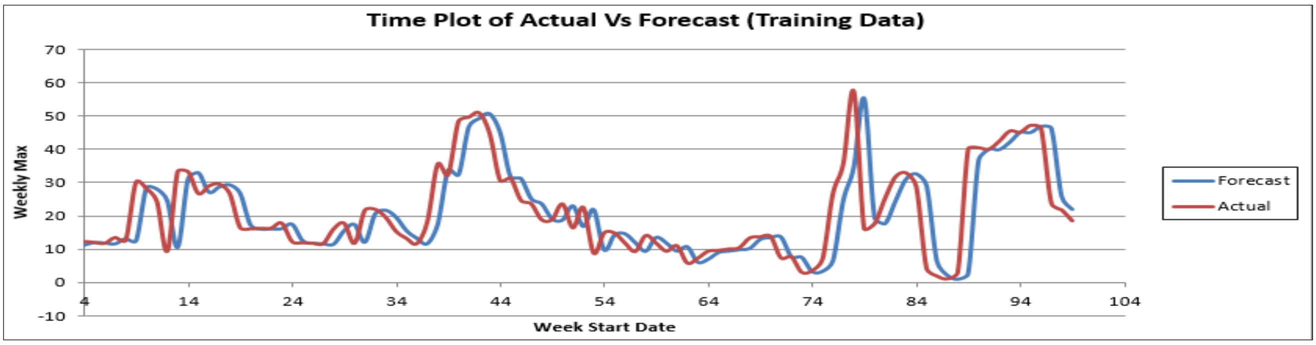
1. Moving Average

A moving average model with interval = 4.



2. Exponential

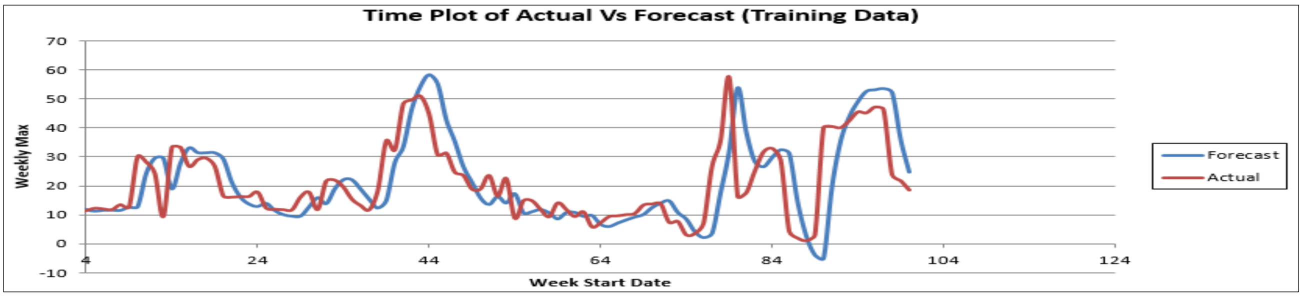
Alpha = 0.9100314



On trial and error, It was observed that with increasing value of alpha the MAPE and RMSE for the training and validation dataset were decreasing. Hence, we used the optimise option to obtain the most optimum alpha of 0.910031434.

3. Double Exponential

Alpha = 0.5, Beta = 0.3



Using a trial and error method, we came up with the values of alpha=0.5 and beta=0.3 which gave us minimum values for RMSE and MAPE for both training and validation dataset.

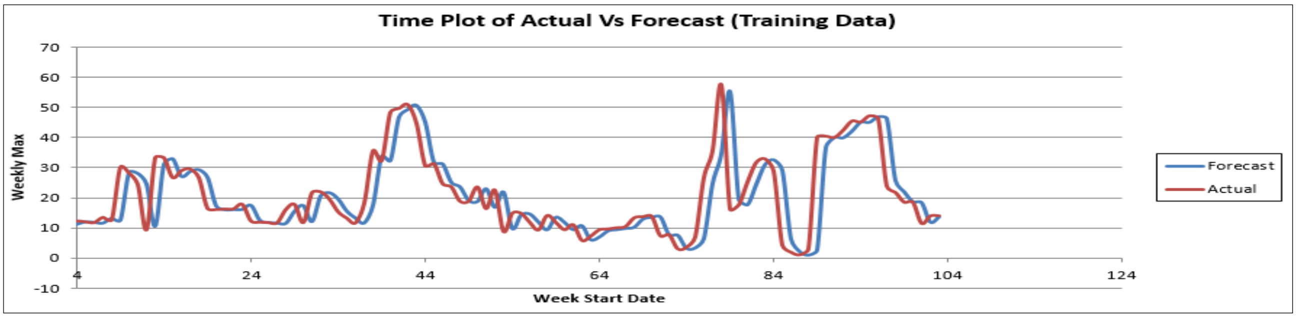
Summary Stats for each model (MAPE is in %)

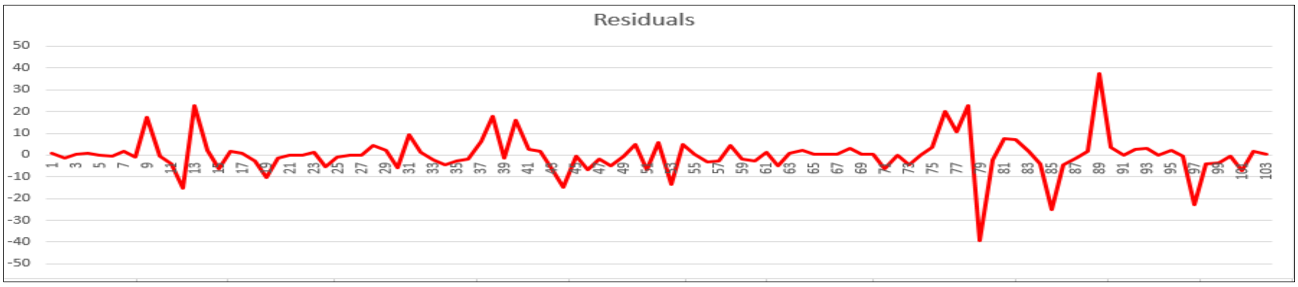
	MA(4)	Exponential	Double Exponential
Training RMSE	11.62127	9.114834	10.8855
Validation RMSE	13.3915	5.04815	7.429
Training MAPE	76.2921	37.3666	51.0676
Validation MAPE	96.8487	34.1106	38.9572

	MA(4)	Exponential	Double Exponential
Overall RMSE	11.4667	8.96534	10.727
Overall MAPE	74.9161	36.6848	50.4909

Exponential method gives us a good fit compared to the other models in terms of MAPE and RMSE.

Forecast performance of Exponential method

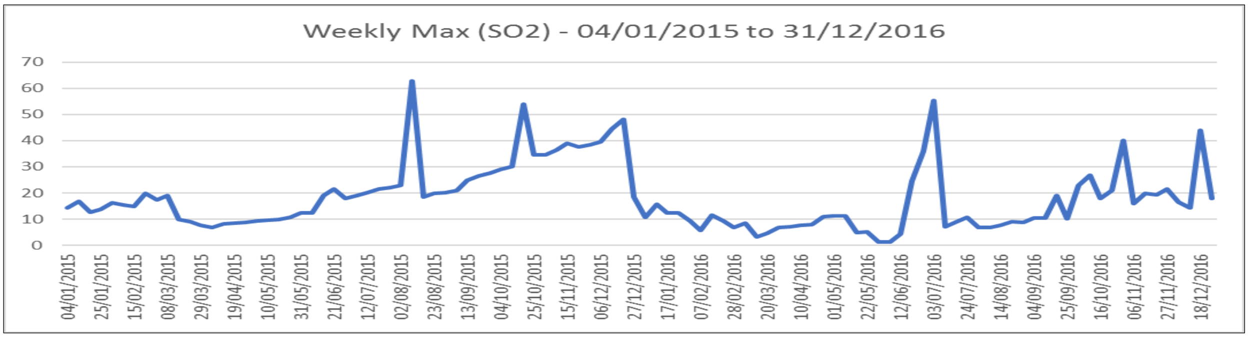




Forecast (max conc. Of NO2) using Exponential (first 4 weeks for January 2017) and AQI values

Week	Forecast	LCI	UCI	AQI	AQI Category
1	13.9394	-3.5476	31.4265	17	Good
2	13.9394	-9.7043	37.5832	17	Good
3	13.9394	-14.5607	42.4396	17	Good
4	13.9394	-18.7024	46.5813	17	Good

4. SO2



Time series plot shows hint of seasonality component around the end of the year from the month of Aug through December for both the years. We also observe the presence of noise patterns in the data. We proceed to apply both model-based and data driven approaches.

Data Pre-Processing

Original dataset - 977 records (daily records)
Dataset after pre-processing – 104 records (weekly max records, considering the start of the week on a Sunday)
Training data set – 100 records
Validation data set – 4 records
Seasonality = 52 period

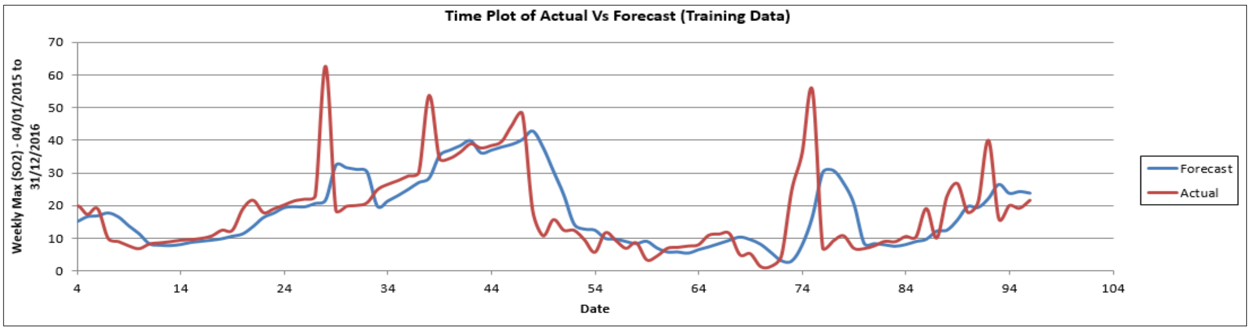
Model Building

1. Regression Model

A MLR model with 52 dummy variables for capturing weekly seasonality.

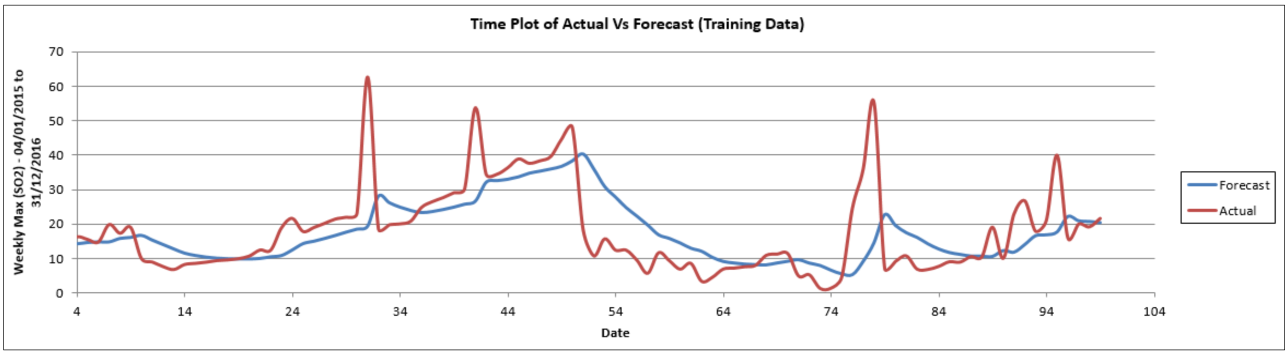
2. Moving Average

A moving average model with interval=4.



3. Exponential Method

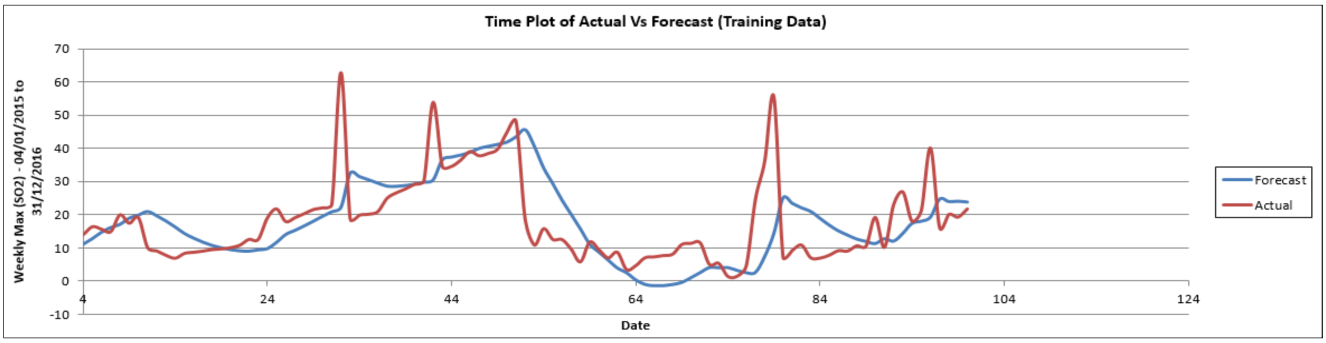
Alpha = 0.2



The forecast values from this model is not accounting for the seasonal variation in the data.

4. Double Exponential

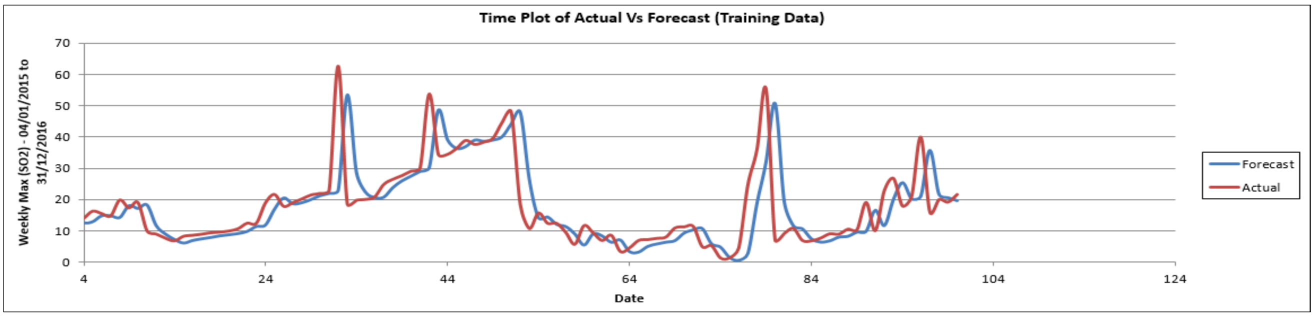
Alpha = 0.2, Beta = 0.15



With the trend component, the forecasted values fit better in comparison to the exponential model.

5. Holt-Winter's Model with Additive trend

Alpha = 0.2, Beta = 0.2, Gamma = 0.65



With the inclusion of seasonality component, we observe that Holt-Winter's model is able to account for all the components present in the data and is fitting most accurately to the data compared to the rest of the models. With a trial and error method, we arrive at the values of alpha, beta and gamma as 0.2,0.2,0.65 respectively.

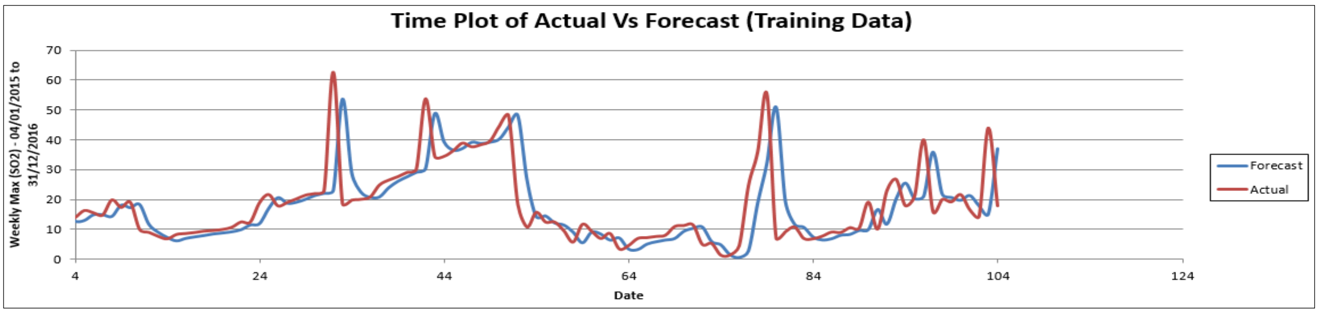
Summary Statistics of all the models (MAPE is in %)

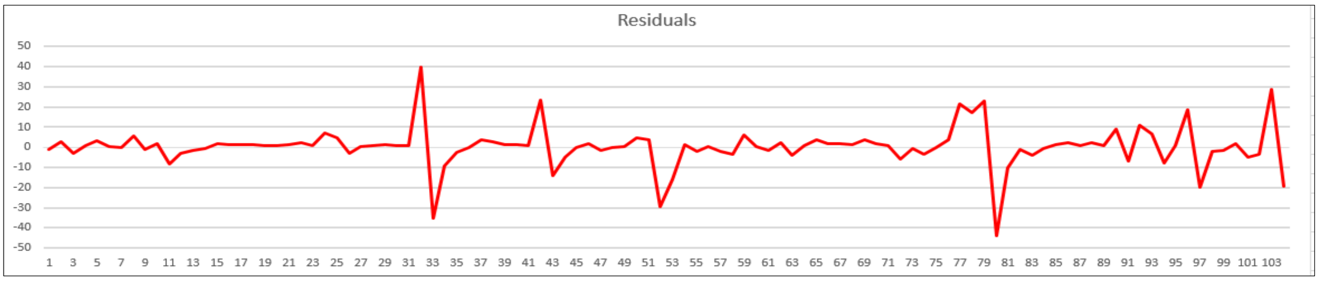
	Regression	MA(4)	Exponential	Double Exponential	Holt-Winter's
Training RMSE	7.2703	10.403	10.212	10.9805	9.884
Validation RMSE	23.0367	12.745	12.362	12.0378	12.117
Training MAPE	43.78062	51.3681	55.049	57.7878	38.3468
Validation MAPE	103.5323	28.6152	34.6813	51.5524	38.5963

	Regression	MA(4)	Exponentia	Double Exponential	Holt-Winter's
Overall MAPE	0.72175	0.507725	0.544138	0.573591	0.390587
Overall RMSE	7.611	10.557	10.356	11.072	10.286

Overall Holt-Winter's model with additive trend has been able to give the best fit to the data in comparison to the others.

Forecast performance of Holt-Winter's method





Forecast (max conc. of SO2) Using Holt-Winters (first 4 weeks for January 2017) and AQI values

Week	Forecast	LCI	UCI	AQI	AQI Category
1	23.4895	3.3292	43.6498	29	Good
2	23.7737	-3.2146	50.7622	30	Good
3	24.0579	-3.5144	51.6304	30	Good
4	24.3421	-3.9749	52.6593	30	Good

Overall Air Quality Index – Forecasted vs Actual

The forecasted values for each pollutant is used to calculate the sub-index AQI and the worst sub index is the AQI for the week for the city. We also compare the performance of the best models against the actual values for the month of January 2017.

Forecast Values

	Week1			Week2			Week3			Week4		
	Forecasted Conc.	Sub AQI	Overall AQI	Forecasted Conc.	Sub AQI	Overall AQI	Forecasted Conc.	Sub AQI	Overall AQI	Forecasted Conc.	Sub AQI	Overall AQI
PM10	250.2278	200	200	264.4229	215	214	249.1286	199	199	250.8748	201	201
PM2.5	88.182	194		75.294	151		68.858	130		77.604	159	
NO2	13.9394	17		13.9394	17		13.9394	17		13.9394	17	
SO2	23.4895	29		23.7737	30		24.0579	30		24.3421	30	

Actual Values

	Week1			Week2			Week3			Week4		
	Actual Conc.	Sub AQI	Overall AQI	Actual Conc.	Sub AQI	Overall AQI	Actual Conc.	Sub AQI	Overall AQI	Actual Conc.	Sub AQI	Overall AQI
PM10	270.92	221	250	200.96	167	197	244.99	197	257	252.65	203	230
PM2.5	105.02	250		88.96	197		106.97	257		99.03	230	
NO2	15.8	20		18.73	23		15.32	19		15.46	19	
SO2	15.57	19		29.42	37		20.51	26		21.77	27	

AQI Codes

Good (0–50)	Minimal Impact	Poor (201–300)	Breathing discomfort to people on prolonged exposure
Satisfactory (51–100)	Minor breathing discomfort to sensitive people	Very Poor (301–400)	Respiratory illness to the people on prolonged exposure
Moderate (101–200)	Breathing discomfort to the people with lung,	Severe (>401)	Respiratory effects even on healthy people

From the forecasted AQI, the overall air quality can be categorized as "Poor" for the month of January 2017. The results of these forecasted values satisfactorily concur with the actual scenario.

Conclusion and Recommendations

Forecasting the quality of air using time series analysis can enable the government authorities as well as people to characterise the concentration of different pollutants. Studying the seasonal and long term trends in the level of pollutants can help in analysing the impact of air quality on Health and Eco-system, empower people to take timely actions and better utilize the available resources. Forecasting results can help in understanding comprehensive seasonal air pollution scenario and relative contribution of different emission sources for various metropolitan cities under study.

The accuracy of the models can be further improved by investigating the unusual peaks in the concentration levels and understanding the cause of high fluctuations and noise. It is important to evaluate this as it can help to confirm whether the equipment and tools used to capture and collect data are not faulty. Also co-ordinated systems can be developed at the national level, giving insights regarding the pollution levels of different cities and their trends. Such systems can help the authorities to determine the correct course of action.

Appendix

1. Regression based model for PM10

Regression Model

Input Variables	Coefficient	Std. Error	t-Statistic	P-Value	CI Lower	CI Upper	RSS Reduction
Intercept	248.87	61.3781056	4.05470318	7.9E-05	127.631	370.109	4376912
W1	-41.685	68.6228082	-0.6074511	0.54443	-177.235	93.8648	15915.1
W2	-52.35	68.6228082	-0.7628659	0.4467	-187.9	83.1998	11470.4
W3	-55.5275	68.6228082	-0.8091697	0.41965	-191.077	80.0223	10574.7
W4	-56.4775	68.6228082	-0.8230135	0.41176	-192.027	79.0723	10613.9
W5	-55.03	68.6228082	-0.80192	0.42382	-190.58	80.5198	11687.1
W6	-45.1475	68.6228082	-0.6579081	0.51157	-180.697	90.4023	17003.4
W7	-51.2775	68.6228082	-0.747237	0.45605	-186.827	84.2723	14605.4
W8	-62.0775	68.6228082	-0.9046191	0.36706	-197.627	73.4723	10345.2
W9	-43.1325	68.6228082	-0.6285447	0.53057	-178.682	92.4173	20266.9
W10	-68.605	68.6228082	-0.9997405	0.31898	-204.155	66.9448	8863.85
W11	-91.825	68.6228082	-1.338112	0.18281	-227.375	43.7248	2440.74
W12	50.365	68.6228082	0.73393965	0.46409	-85.1848	185.915	114587
W13	-85.115	68.6228082	-1.2403311	0.21672	-220.665	50.4348	5275.79
W14	-48.9725	68.6228082	-0.7136476	0.47651	-184.522	86.5773	21825.1
W15	-114.89	68.6228082	-1.6742247	0.09609	-250.44	20.6598	325.962
W16	-82.395	68.6228082	-1.2006941	0.23169	-217.945	53.1548	7127.77
W17	-94.8975	68.6228082	-1.3828857	0.16868	-230.447	40.6523	3773.76
W18	-112.963	68.6228082	-1.6461364	0.10175	-248.512	22.5873	704.661
W19	-134.018	68.6228082	-1.9529585	0.05261	-269.567	1.53228	237.357
W20	-151.44	68.6228082	-2.2068464	0.02879	-286.99	-15.8902	2627.39

Residual DF	156
R^2	0.48896
Adjusted R^2	0.31861
Std. Error Estimate	61.3781
RSS	587694

2. ARIMA (1, 0, 0)(0, 1, 0) and Holt-Winters Smoothing Model for PM10

Parameters/Options	
AR	1
MA	0
Ordinary Difference	0
Seasonal model selected	Yes
Period	52
SAR	0
SMA	0
Seasonal Difference	1
Show Var/Covar Output	Yes
Show Forecasting Output	Yes
#Forecasts	52
Confidence Level	0.95
Show Residual Output	Yes

Parameters/Options	
Optimize Weights	Yes
Alpha (Level)	0.228736229
Gamma (Seasonality)	0.001678518
Season length	52
Number of seasons	4
Forecast	Yes
#Forecasts	52

ISB

3. Regression based model for PM2.5

Regression Model

Input Variables	Coefficient	Std. Error	t-Statistic	P-Value	CI Lower	CI Upper	RSS Reductio
Intercept	135.24	22.3221709	6.0585505	9.9E-09	91.1473	179.333	798912
W1	-58.78	24.9569458	-2.3552561	0.01975	-108.077	-9.48286	873.241
W2	-67.08	24.9569458	-2.6878289	0.00797	-116.377	-17.7829	178.72
W3	-66.435	24.9569458	-2.6619844	0.00858	-115.732	-17.1379	223.216
W4	-68.1325	24.9569458	-2.7300015	0.00706	-117.43	-18.8354	139.639
W5	-66.645	24.9569458	-2.6703989	0.00838	-115.942	-17.3479	227.127
W6	-64.0775	24.9569458	-2.5675217	0.01118	-113.375	-14.7804	423.674
W7	-59.2775	24.9569458	-2.3751905	0.01875	-108.575	-9.98036	944.874
W8	-57.7025	24.9569458	-2.3120818	0.02208	-107	-8.40536	1197.93
W9	-28.565	24.9569458	-1.1445711	0.25414	-77.8621	20.7321	8901.4
W10	-63.8475	24.9569458	-2.5583058	0.01147	-113.145	-14.5504	632.99
W11	-60.2475	24.9569458	-2.4140574	0.01693	-109.545	-10.9504	1092.22
W12	-41.4675	24.9569458	-1.6615615	0.09861	-90.7646	7.82964	5167.25
W13	-67.715	24.9569458	-2.7132727	0.00741	-117.012	-18.4179	421.594
W14	-59.345	24.9569458	-2.3778951	0.01862	-108.642	-10.0479	1445.53
W15	-83.1825	24.9569458	-3.3330401	0.00107	-132.48	-33.8854	86.1784
W16	-76.8725	24.9569458	-3.0802046	0.00245	-126.17	-27.5754	10.6081
W17	-87.7525	24.9569458	-3.5161554	0.00057	-137.05	-38.4554	350.377
W18	-89.515	24.9569458	-3.586777	0.00045	-138.812	-40.2179	521.356
W19	-84.175	24.9569458	-3.3728085	0.00094	-133.472	-34.8779	160.542
W20	-86.7375	24.9569458	-3.4754854	0.00066	-136.035	-37.4404	333.476
W21	-79.5975	24.9569458	-3.1893927	0.00172	-128.895	-30.3004	18.7484
W22	-88.66	24.9569458	-3.552518	0.0005	-137.957	-39.3629	524.087
W23	-83.54	24.9569458	-3.3473647	0.00102	-132.837	-34.2429	175.539
W24	-91.68	24.9569458	-3.6735264	0.00033	-140.977	-42.3829	916.619

Residual DF	156
R^2	0.51365
Adjusted R^2	0.35153
Std. Error Estim	22.3222
RSS	77731.6

4. ARIMA (0, 1, 1)(0, 1, 0) Holt-Winters Smoothing Model for PM2.5

Parameters/Options	
AR	0
MA	1
Ordinary Difference	1
Seasonal model selected	Yes
Period	52
SAR	0
SMA	0
Seasonal Difference	1
Show Var/Covar Output	Yes
Show Forecasting Output	Yes
#Forecasts	52
Confidence Level	0.95
Show Residual Output	Yes

Parameters/Options	
Optimize Weights	Yes
Alpha (Level)	0.228736229
Gamma (Seasonality)	0.001678518
Season length	52
Number of seasons	4
Forecast	Yes
#Forecasts	52

5. Exponential and Double Exponential model for NO_2

Parameters/Options	
Optimization Selected	Yes
Alpha (Level)	0.910031434
Forecast	Yes
#Forecasts	4

Parameters/Options	
Optimization Selected	No
Alpha (Level)	0.5
Beta (Trend)	0.3
Forecast	Yes
#Forecasts	4

6. Regression based model for SO_2

Input Variables	Coefficient	Std. Error	t-Statistic	P-Value	CI Lower	CI Upper	RSS Reduction
Intercept	12.39039	7.56860516	1.63707736	0.108155	-2.82731	27.60809	31717.47
t	0.114608	0.252006986	0.45478042	0.651317	-0.39209	0.621302	4925.495
W1	-5.845	12.65182723	-0.4619886	0.646474	-31.3774	19.68742	50.58169
W2	3.685392	10.39356981	0.354583865	0.724455	-17.2123	24.58306	210.9343
W3	-0.24422	10.29842514	-0.02371389	0.981179	-20.9506	20.46216	86.83714
W4	0.286176	10.20861608	0.028032837	0.977752	-20.2396	20.81197	104.9283
W5	-0.10343	10.12428462	-0.01021617	0.991891	-20.4597	20.25281	97.50132
W6	-2.48804	10.04556873	-0.2476753	0.805442	-22.686	17.70993	42.55151
W7	0.017353	9.972601371	0.001740062	0.998619	-20.0339	20.06861	101.6725
W8	1.292745	9.905509587	0.130507682	0.89671	-18.6236	21.20911	146.7066
W9	-1.33186	9.844413506	-0.13529122	0.892947	-21.1254	18.46166	72.97063
W10	0.258529	9.789425387	0.026409049	0.979041	-19.4244	19.94149	117.9921
W11	-7.00608	9.740648674	-0.719262	0.475467	-26.591	12.57881	0.088534
W12	-7.03569	9.698177087	-0.72546482	0.471689	-26.5352	12.46381	0.271729
W13	-6.61529	9.662093773	-0.68466466	0.496848	-26.0422	12.81165	0.558432
W14	-7.0299	9.632470524	-0.72981297	0.469051	-26.3973	12.33748	4.9497
W15	-6.20951	9.609367084	-0.64619342	0.521232	-25.5304	13.11142	4.020523
W16	-5.96412	9.592830559	-0.62172657	0.537064	-25.2518	13.32356	6.806035

Residual DF	48
R^2	0.651825
Adjusted R^2	0.281889
Std. Error Estimate	10.4939
RSS	5285.858

ISB

7. Exponential and Double Exponential for SO_2

Parameters/Options	
Optimization Selected	No
Alpha (Level)	0.2
Forecast	Yes
#Forecasts	4

Parameters/Options	
Optimization Selected	No
Alpha (Level)	0.2
Beta (Trend)	0.15
Forecast	Yes
#Forecasts	4

8. Holt-Winter's Model with Additive trend

Parameters/Options	
Optimize Weights	No
Alpha (Level)	0.2
Beta (Trend)	0.2
Gamma (Seasonality)	0.65
Season length	1
Number of seasons	100
Forecast	Yes
#Forecasts	4

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3. About National Air Quality Index - http://cpcb.nic.in/About_AQI.pdf
4. SAFAR – India (System of Air Quality and Weather Forecasting And Research) - http://safar.tropmet.res.in/RESEARCH-14-7-Details