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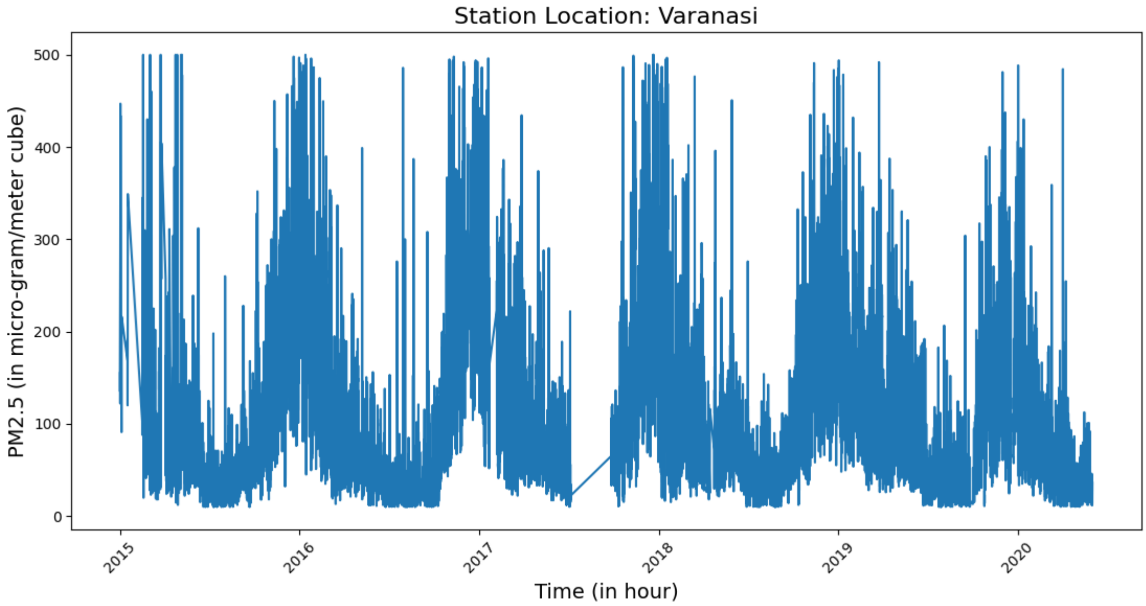
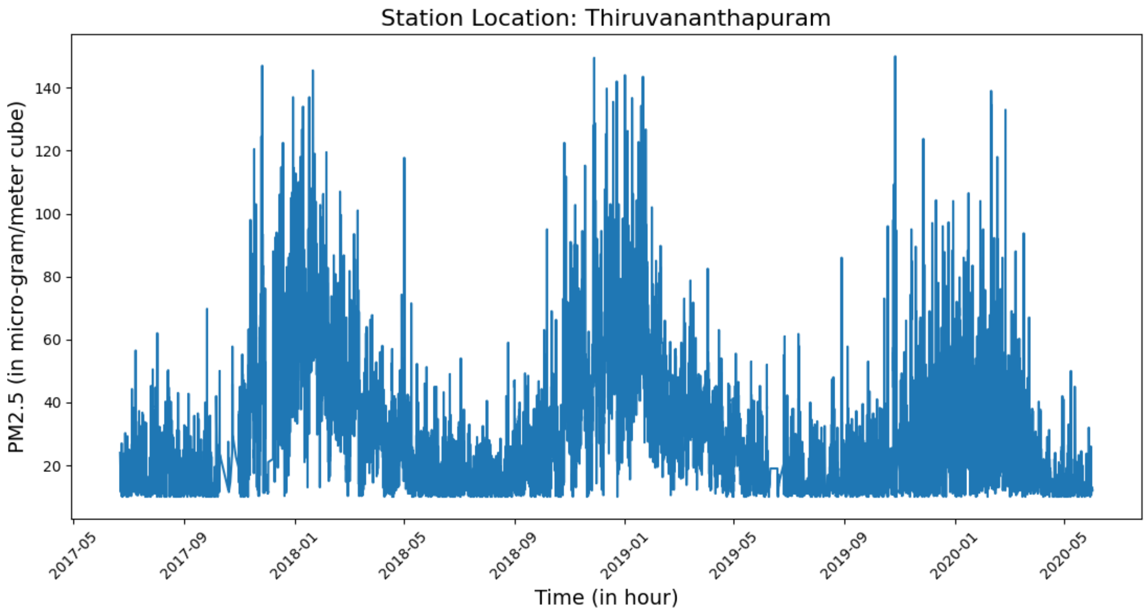
7 Appendix

7.1 Line plot of input data:





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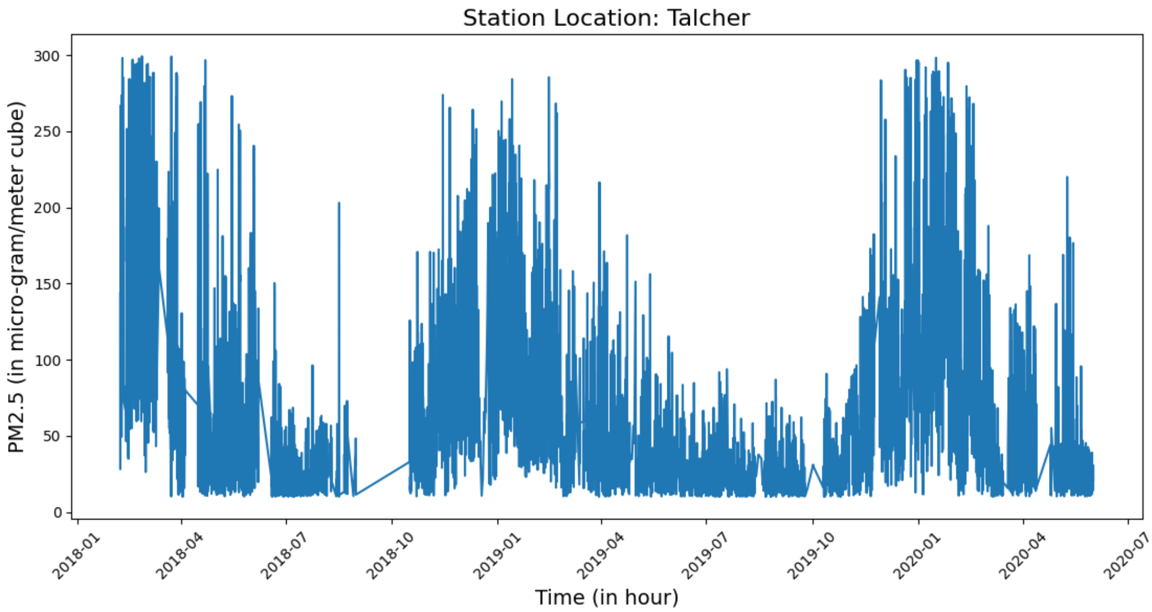
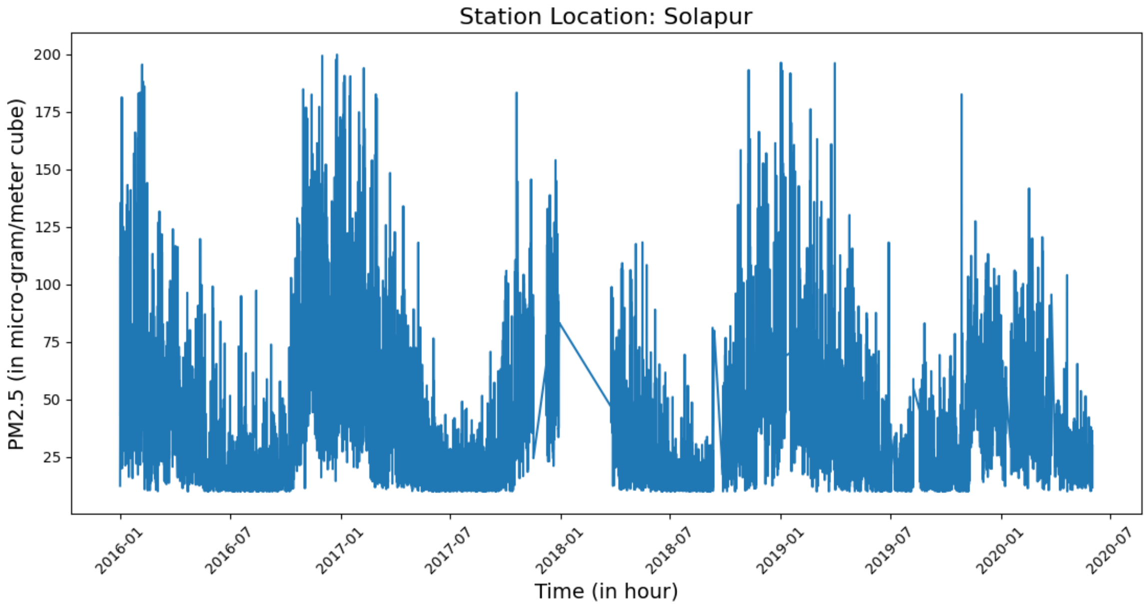
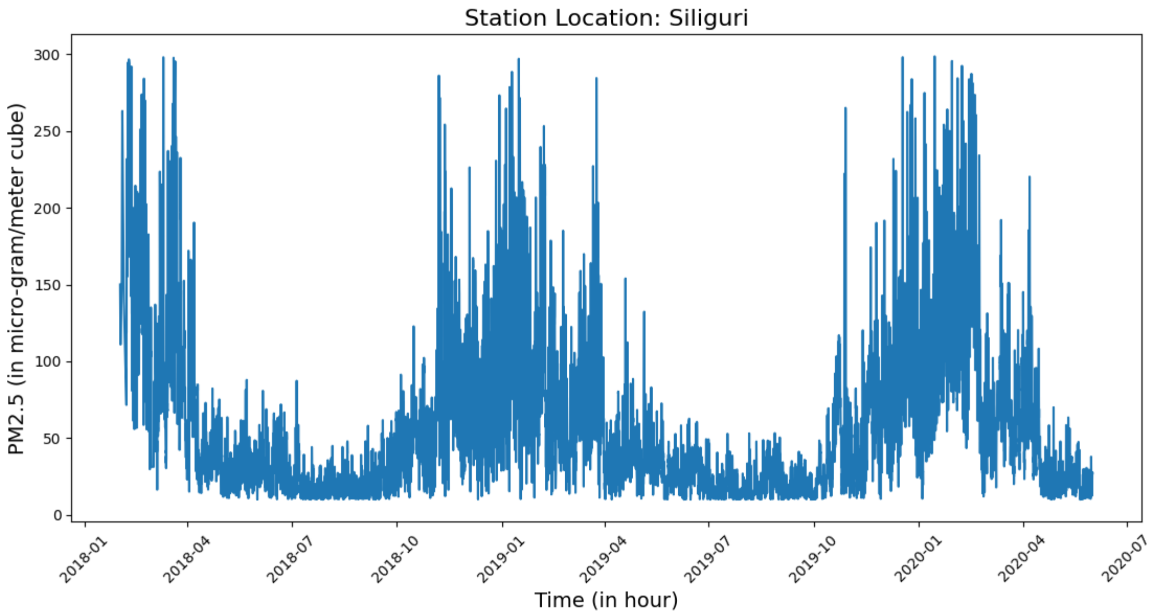
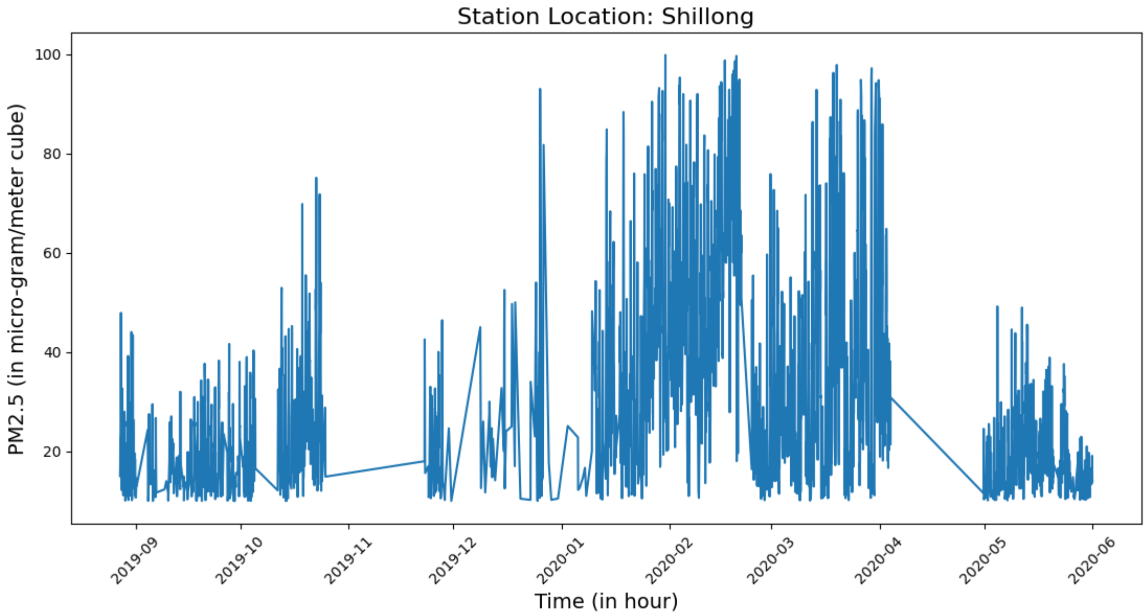
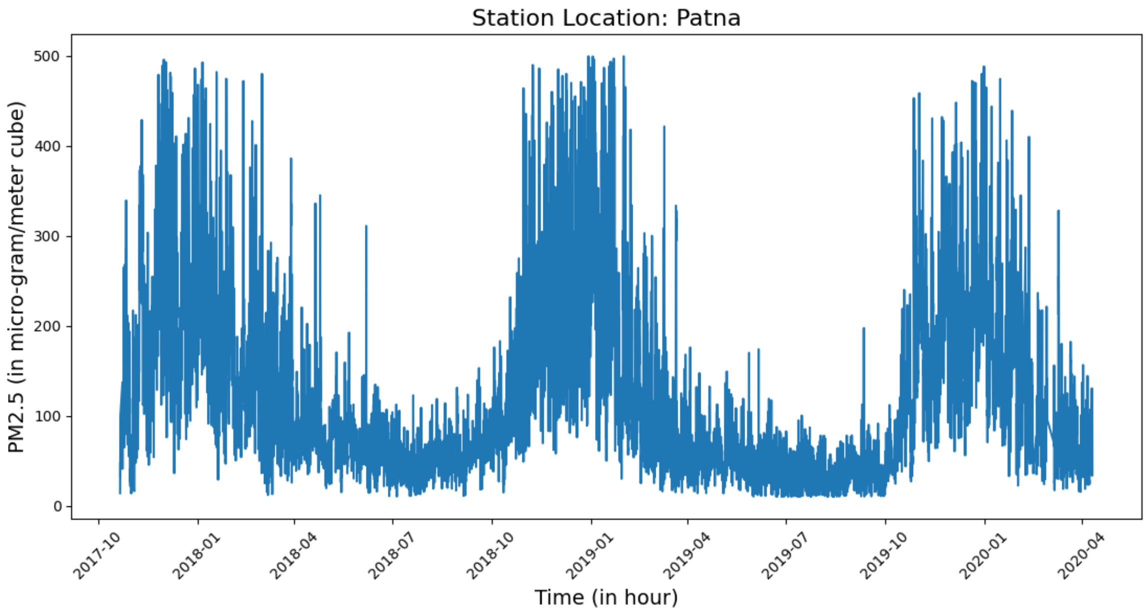

Station Location: Talcher
PM2.5 (in micro-gram/meter cube)
0
50
100
150
200
250
300
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
Time (in hour)

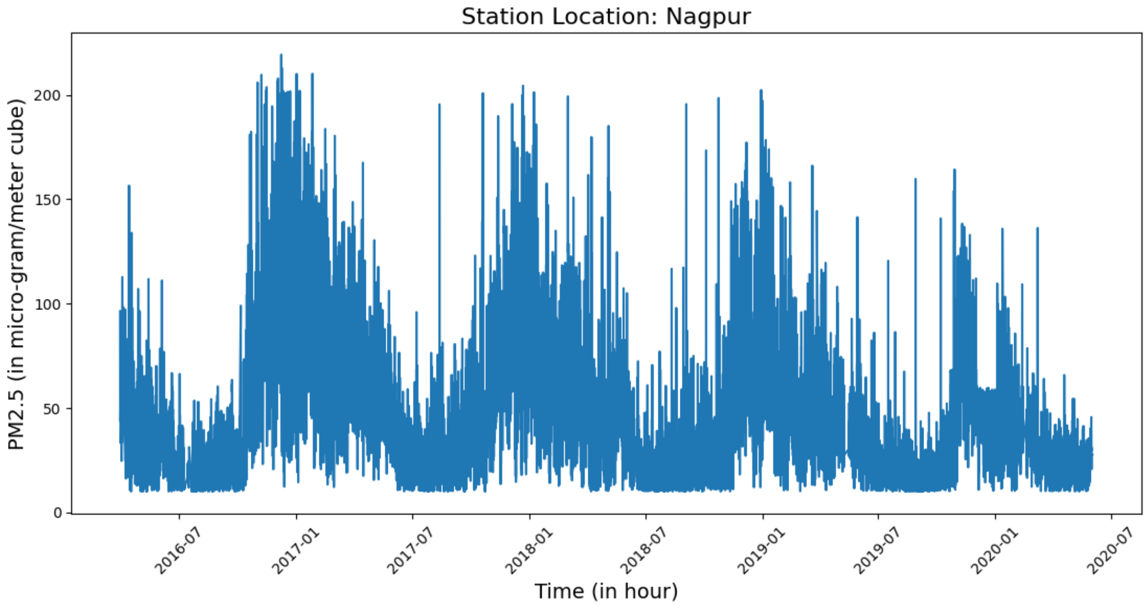

Station Location: Solapur
PM2.5 (in micro-gram/meter cube)
25
50
75
100
125
150
175
200
2016-01
2016-07
2017-01
2017-07
2018-01
2018-07
2019-01
2019-07
2020-01
2020-07
Time (in hour)

`

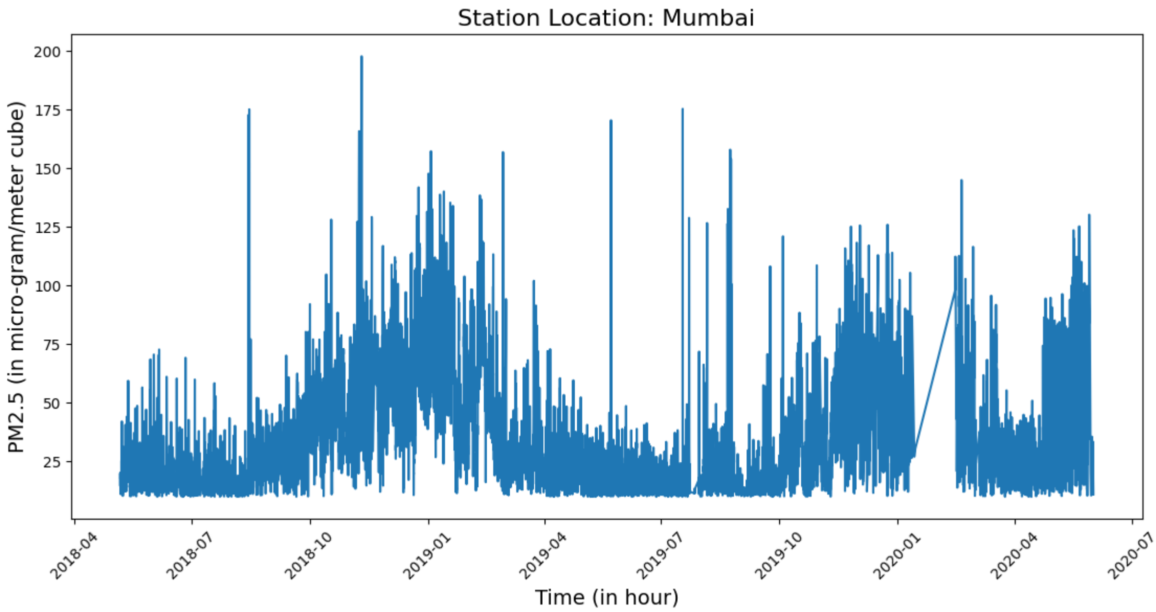

Station Location: Siliguri
PM2.5 (in micro-gram/meter cube)
300
250
200
150
100
50
0
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
Time (in hour)

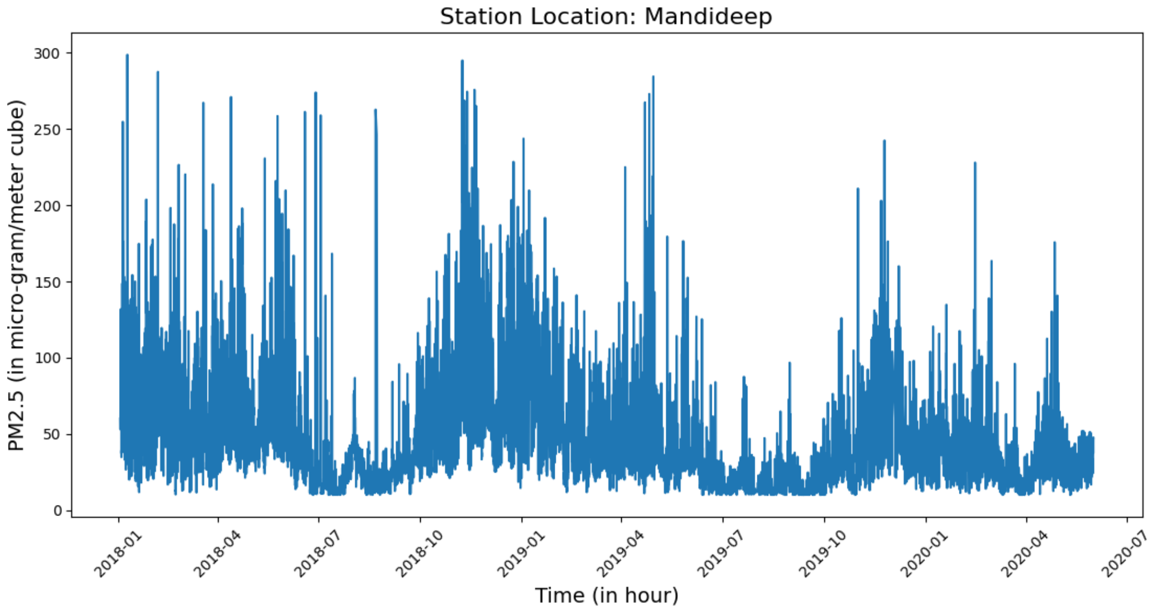

Station Location: Shillong
PM2.5 (in micro-gram/meter cube)
100
80
60
40
20
2019-09
2019-10
2019-11
2019-12
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
Time (in hour)

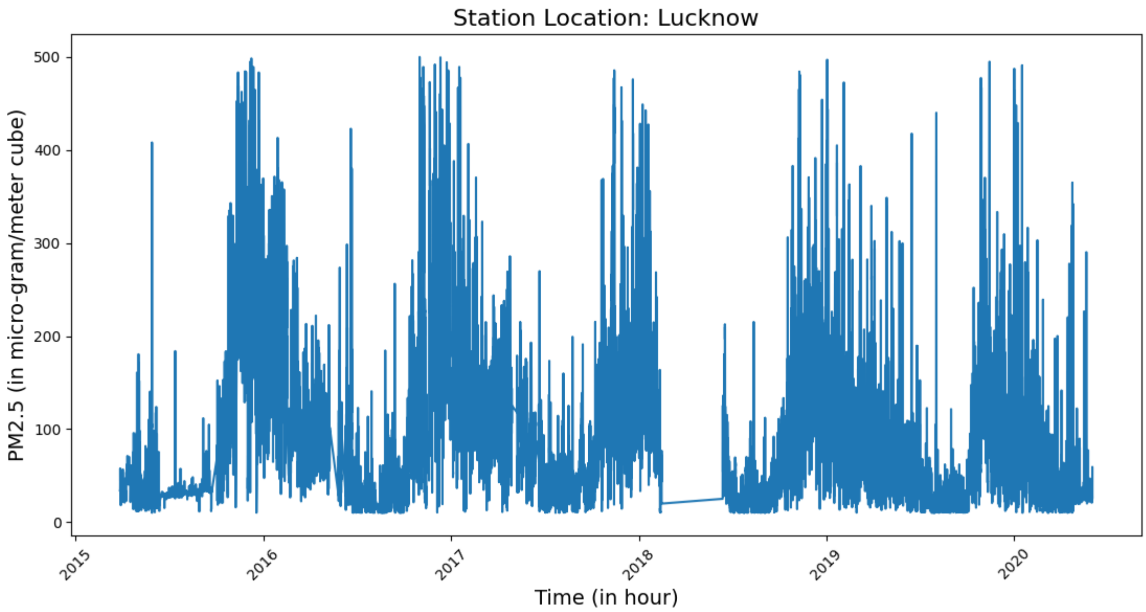

Station Location: Patna
PM2.5 (in micro-gram/meter cube)
0
100
200
300
400
500
2017-10
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
Time (in hour)

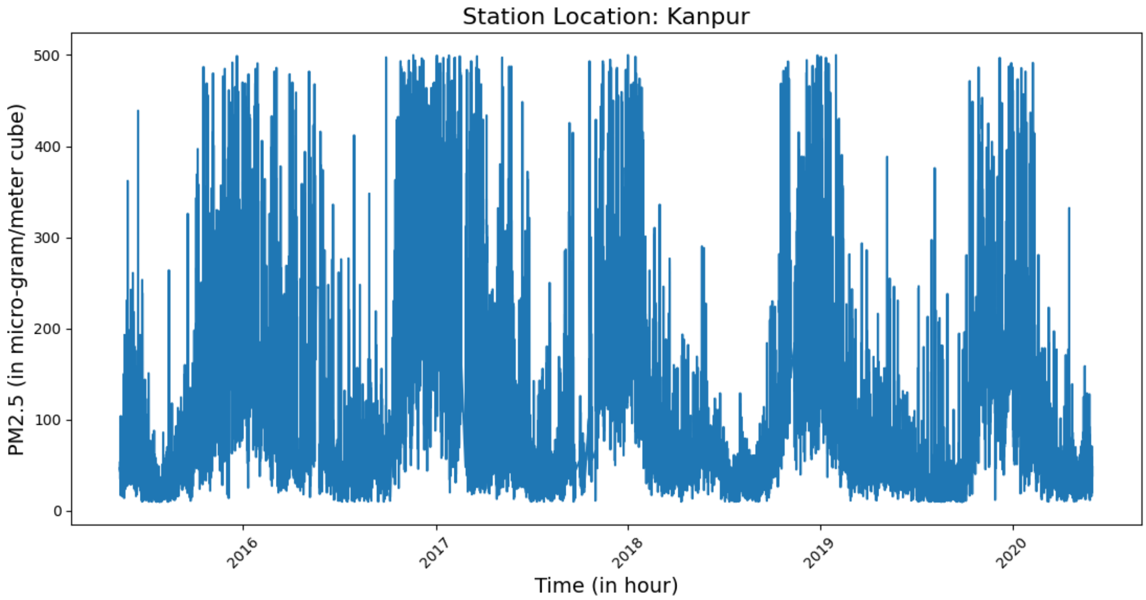

Station Location: Nagpur
PM2.5 (in micro-gram/meter cube)
0
50
100
150
200
2016-07
2017-01
2017-07
2018-01
2018-07
2019-01
2019-07
2020-01
2020-07
Time (in hour)

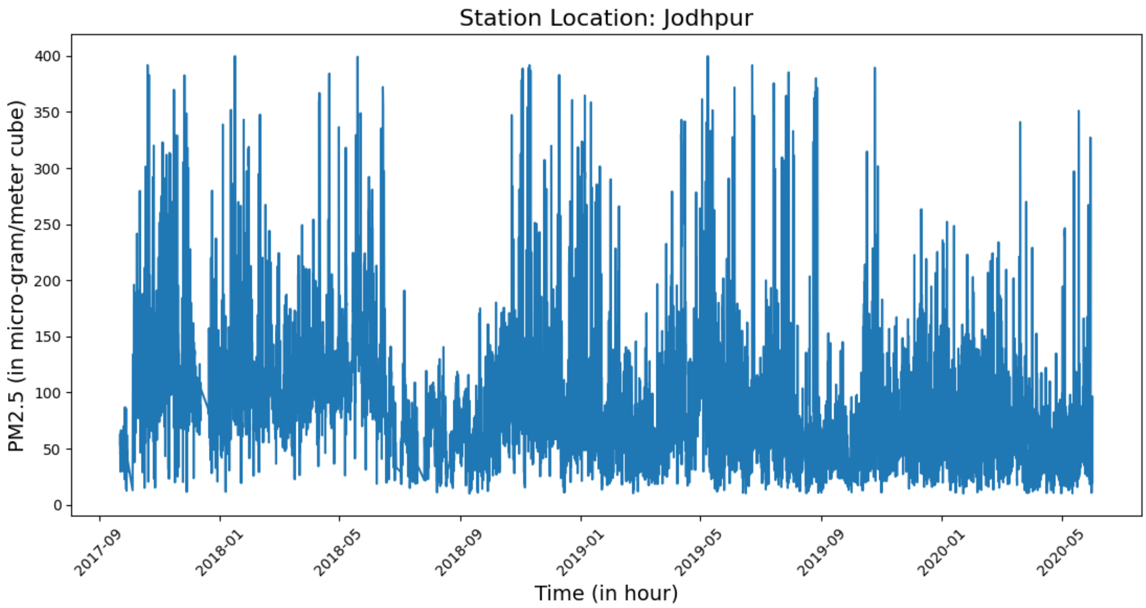
`

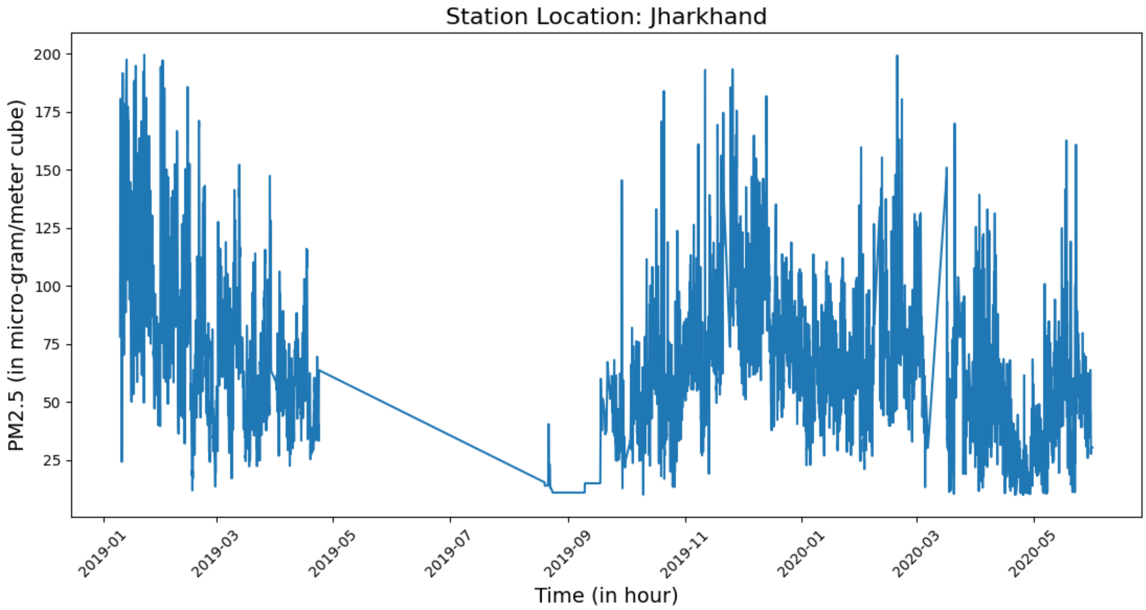

Station Location: Mumbai
PM2.5 (in micro-gram/meter cube)
200
175
150
125
100
75
50
25
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
Time (in hour)

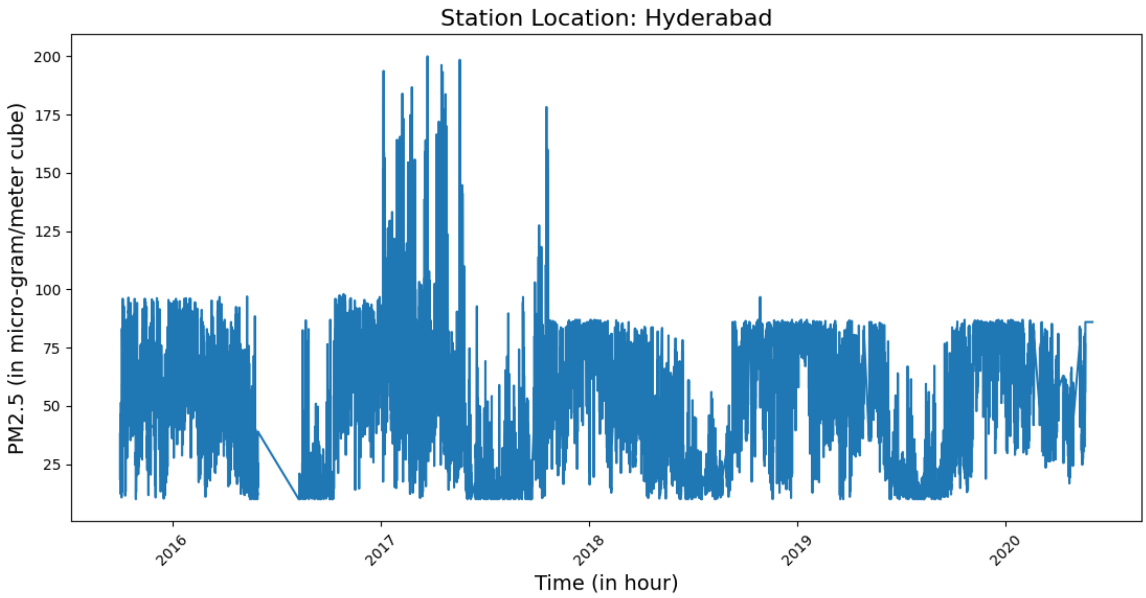

Station Location: Mandideep
PM2.5 (in micro-gram/meter cube)
300
250
200
150
100
50
0
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
Time (in hour)

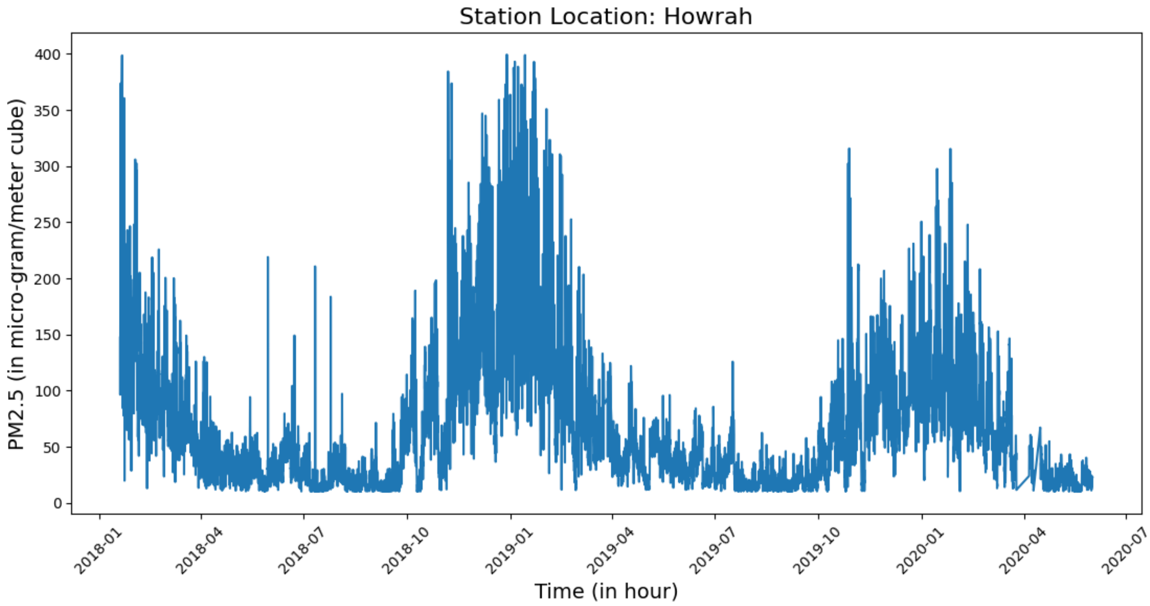

Station Location: Lucknow
PM2.5 (in micro-gram/meter cube)
0
100
200
300
400
500
2015
2016
2017
2018
2019
2020
Time (in hour)

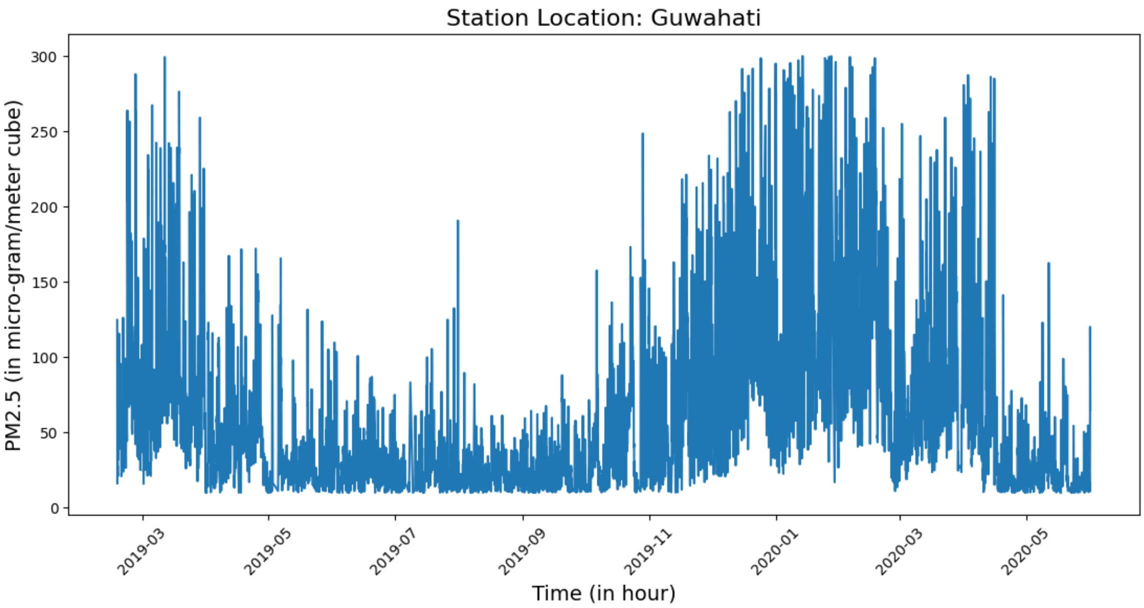

Station Location: Kanpur
PM2.5 (in micro-gram/meter cube)
0
100
200
300
400
500
2016
2017
2018
2019
2020
Time (in hour)

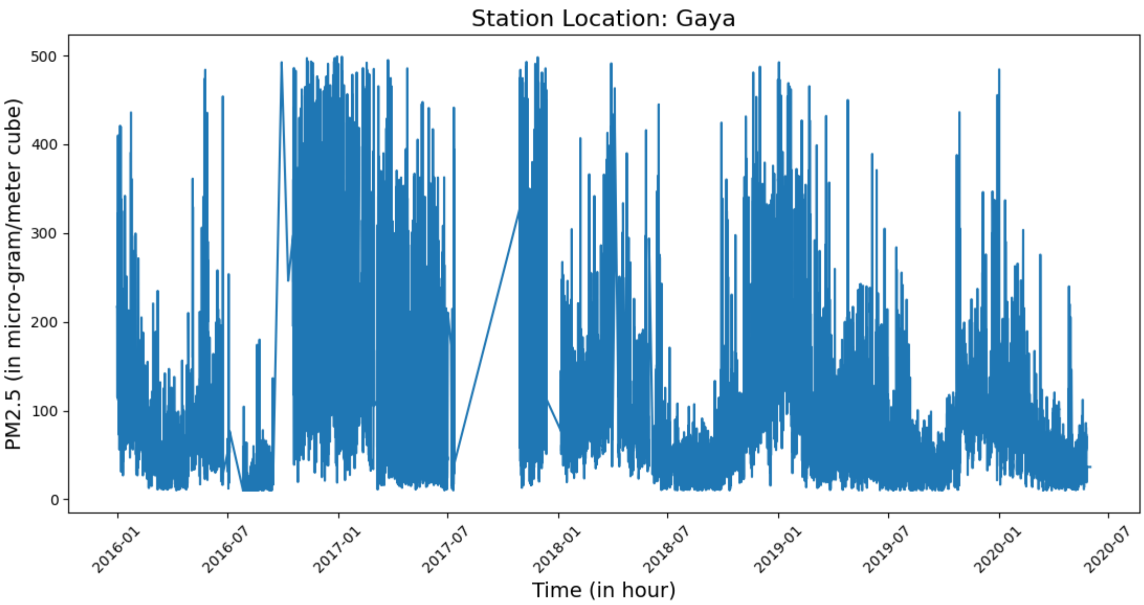

Station Location: Jodhpur
PM2.5 (in micro-gram/meter cube)
0
50
100
150
200
250
300
350
400
2017-09
2018-01
2018-05
2018-09
2019-01
2019-05
2019-09
2020-01
2020-05
Time (in hour)

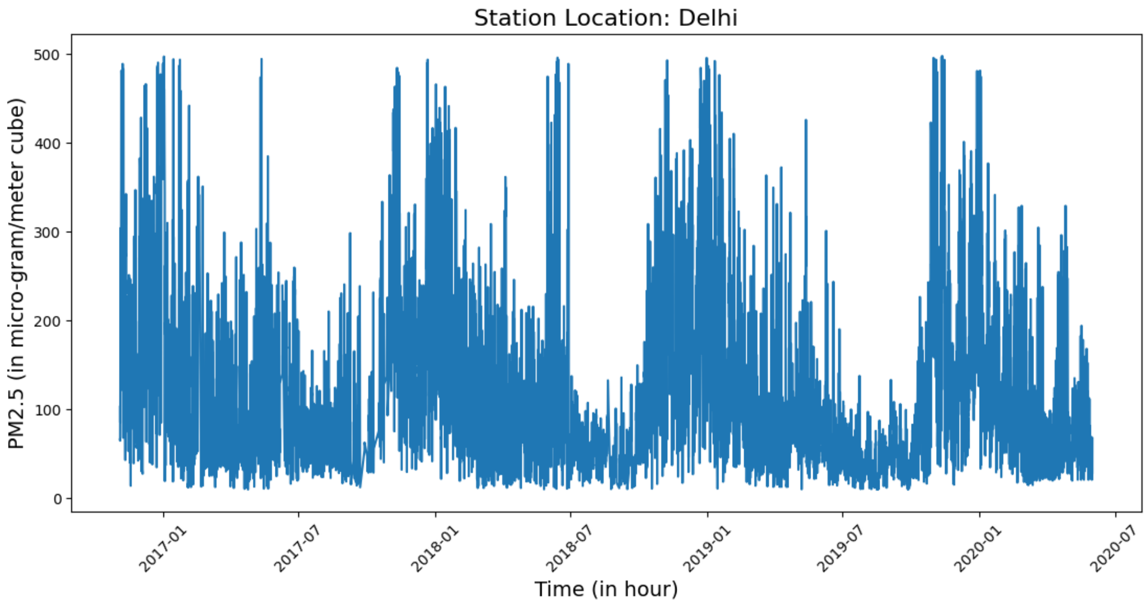

Station Location: Jharkhand
PM2.5 (in micro-gram/meter cube)
25
50
75
100
125
150
175
200
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01
2020-03
2020-05
Time (in hour)

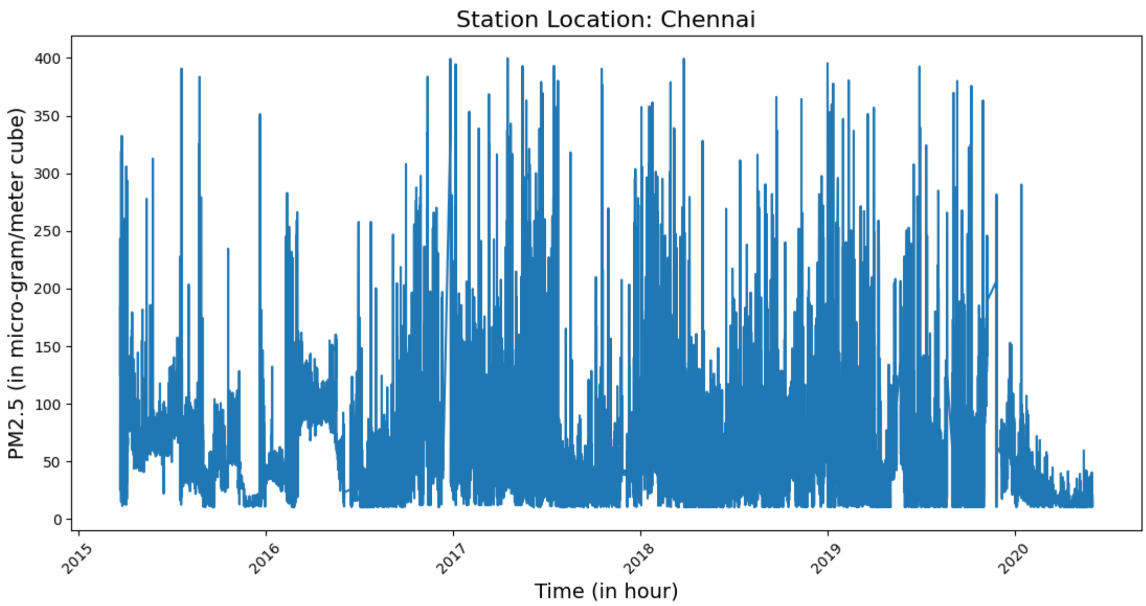

Station Location: Hyderabad
PM2.5 (in micro-gram/meter cube)
200
175
150
125
100
75
50
25
2016
2017
2018
2019
2020
Time (in hour)

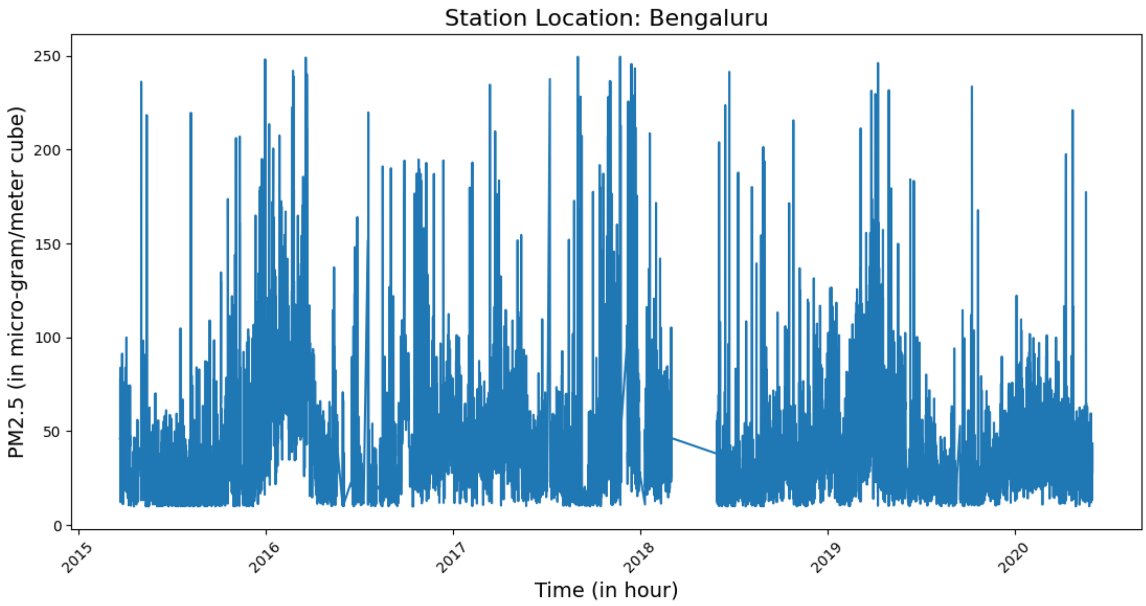

Station Location: Howrah
PM2.5 (in micro-gram/meter cube)
400
350
300
250
200
150
100
50
0
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
Time (in hour)

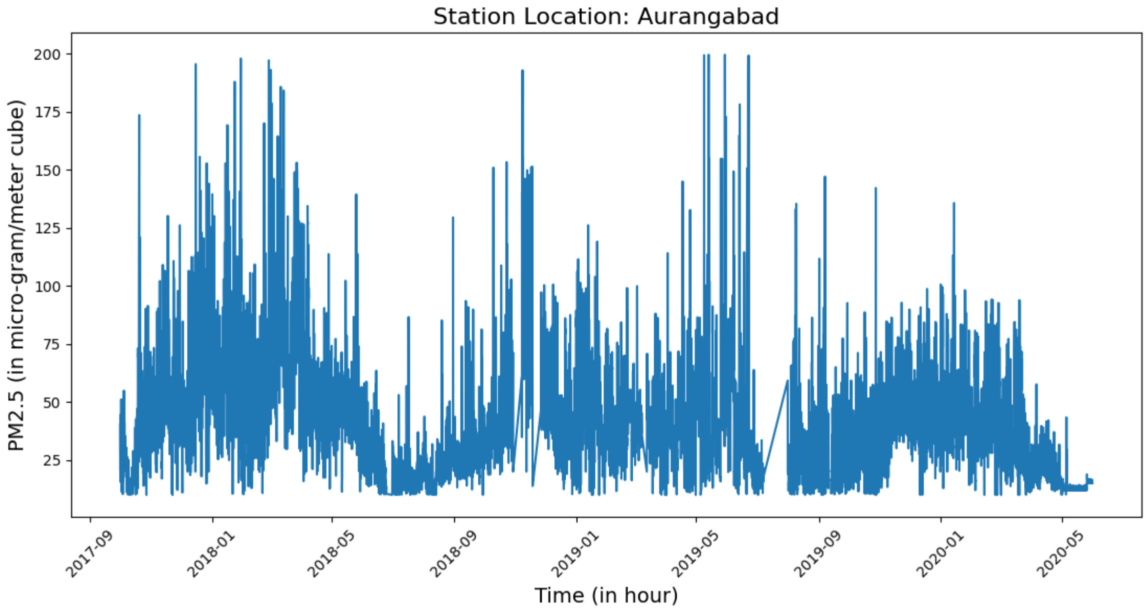

Station Location: Guwahati
PM2.5 (in micro-gram/meter cube)
Time (in hour)
300
250
200
150
100
50
0
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01
2020-03
2020-05


Station Location: Gaya
PM2.5 (in micro-gram/meter cube)
Time (in hour)
500
400
300
200
100
0
2016-01
2016-07
2017-01
2017-07
2018-01
2018-07
2019-01
2019-07
2020-01
2020-07

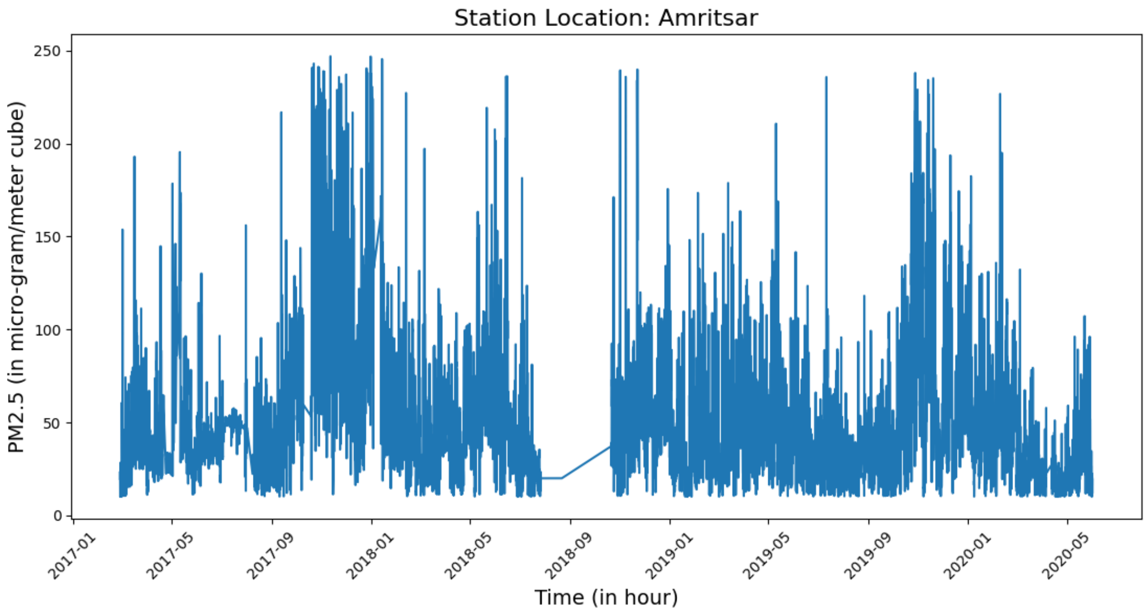

Station Location: Delhi
PM2.5 (in micro-gram/meter cube)
Time (in hour)
0
100
200
300
400
500
2017-01
2017-07
2018-01
2018-07
2019-01
2019-07
2020-01
2020-07


Station Location: Chennai
PM2.5 (in micro-gram/meter cube)
Time (in hour)
0
50
100
150
200
250
300
350
400
2015
2016
2017
2018
2019
2020

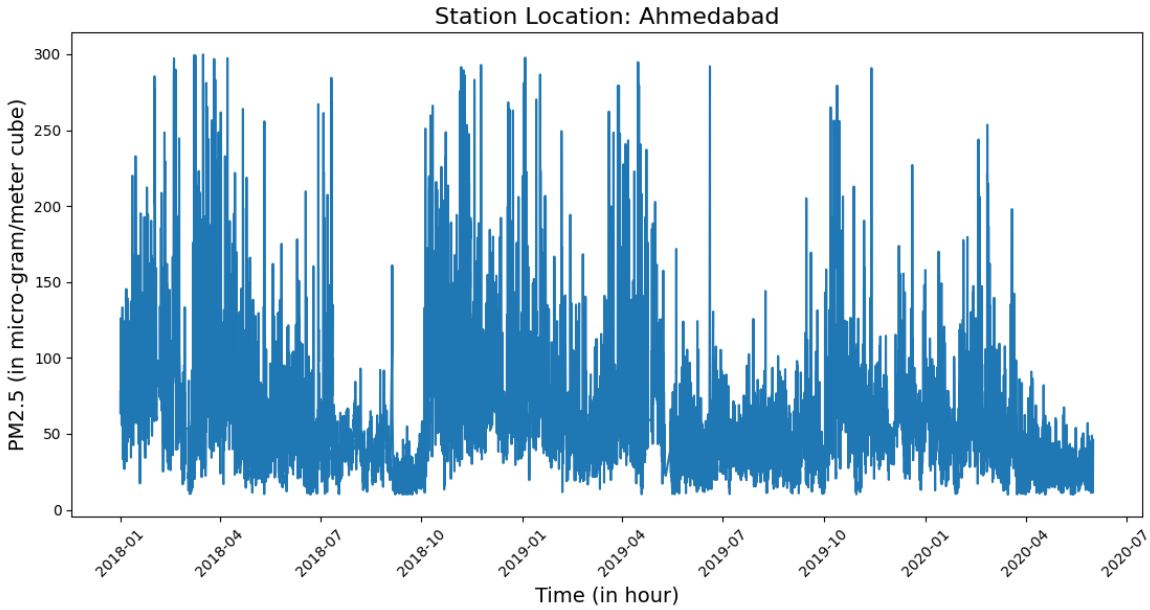

Station Location: Bengaluru
PM2.5 (in micro-gram/meter cube)
0
50
100
150
200
250
2015
2016
2017
2018
2019
2020
Time (in hour)


Station Location: Aurangabad
PM2.5 (in micro-gram/meter cube)
25
50
75
100
125
150
175
200
2017-09
2018-01
2018-05
2018-09
2019-01
2019-05
2019-09
2020-01
2020-05
Time (in hour)

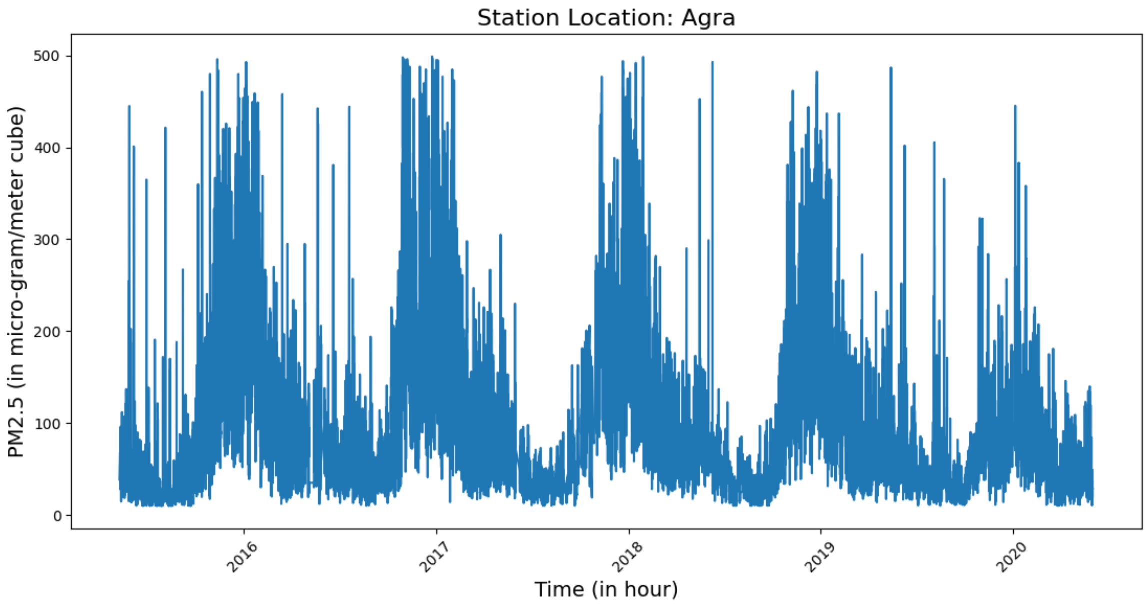
`

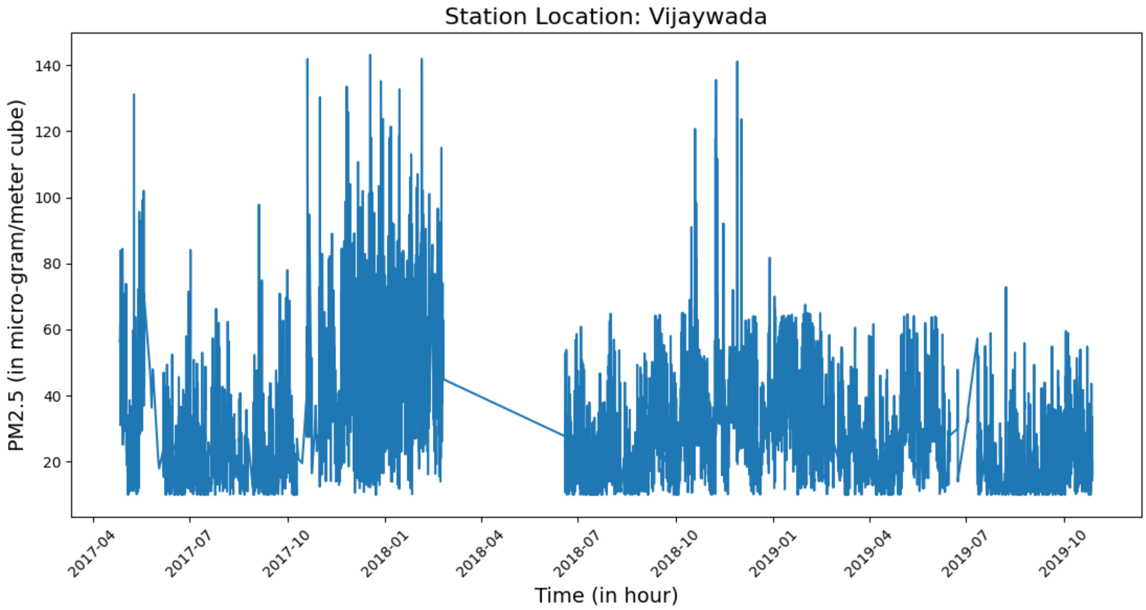


Station Location: Amritsar
PM2.5 (in micro-gram/meter cube)
0
50
100
150
200
250
2017-01
2017-05
2017-09
2018-01
2018-05
2018-09
2019-01
2019-05
2019-09
2020-01
2020-05
Time (in hour)



Station Location: Ahmedabad
PM2.5 (in micro-gram/meter cube)
0
50
100
150
200
250
300
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
2020-01
2020-04
2020-07
Time (in hour)


Station Location: Agra
PM2.5 (in micro-gram/meter cube)
0
100
200
300
400
500
2016
2017
2018
2019
2020
Time (in hour)


Station Location: Vijaywada
PM2.5 (in micro-gram/meter cube)
20
40
60
80
100
120
140
2017-04
2017-07
2017-10
2018-01
2018-04
2018-07
2018-10
2019-01
2019-04
2019-07
2019-10
Time (in hour)

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