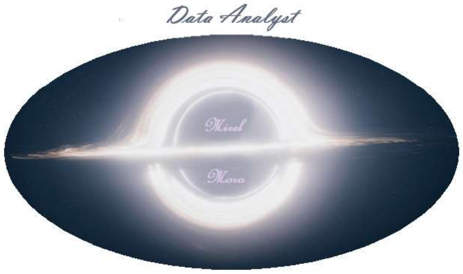
COGNITIVE CLASS.ai

IBM DIGITAL CREDENTIAL

FORECASTING AIR POLLUTION PARTICULATE MATTER (PM2.5)

MIREL MORA



CERTIFICATE APPLIED DATA SCIENCE CAPSTONE

APRIL 14, 2021

2 | Study Area and Methodology

2.1 Data set description

London is the capital and largest city of United Kingdom that is situated between the latitude of 52.3555° North and 1.1743° West. The data has been collected from London Air via the Openair project tools.

Openair is an R package developed for the purpose of analysing air quality data — or more generally atmospheric composition data. The package is extensively used in academia, the public and private sectors. The project was initially funded by the UK Natural Environment Research Council (NERC), with additional funds from Defra. The most up to date information on openair can be found in the package itself and at the book website here.

Openair tool provide a extensive access to UK air quality data. The networks includes:

- For importing data from the UK national network called Automatic Urban and Rural Network. This is the main UK network. (importAURN)]
- For accessing data from Air Quality Scotland network. (importSAQN)
- For accessing data from the Air Quality Wales network. (importWAQN)
- For accessing data from the Air Quality England network of sites. (importAQE)
- For accessing data from the Northern Ireland network of sites. (importNI)
- A simplified version of a function to give basic access to hourly European data based on Stuart Grange's package see.
- For accessing data from the sites operated by King's College London, primarily includ-

ing the The London Air Quality Network. (importKCL)

In this case, the networks used were UK national, Air Quality England and The London Air Quality.

2.2 Data cleaning

Data downloaded from three different network from Openair are combined into two data frames. The process is divide in the follow steps:

1. Extract data from Openair with R (Github - Jupyter)
2. Create a general data set with three networks (UK national, England and The London Air Quality).
3. Choosing stations (Stations in Greater London).
4. Filling missing values using Spatial interpolation.
5. Filling missing values using Panda method.

2.2.1 Extract data from Openair with R

Openair Tool works with programming language R. Openair has documents where explains how it works the package. It has been collected data from all stations in the United Kingdom for the years 2019 and 2020. It is generated two data set of 1495 stations around the United Kingdom. Data sets are divide into two groups that are particular and chronological data.

a) Particular data in the United Kingdom, England and London

b) Chronological data in the United Kingdom, England and London

2.2.2 Create a general data set with three networks

Generated one data frame with Particular data in the United Kingdom, England and London and another data frame with Chronological data in the United Kingdom, England and London using Pandas Library. Chronological data refers to that information, which quickly alters in a brief length of time. Particular parameters are values that change in area and time which cause changes within the concentration of air pollution 2.1.

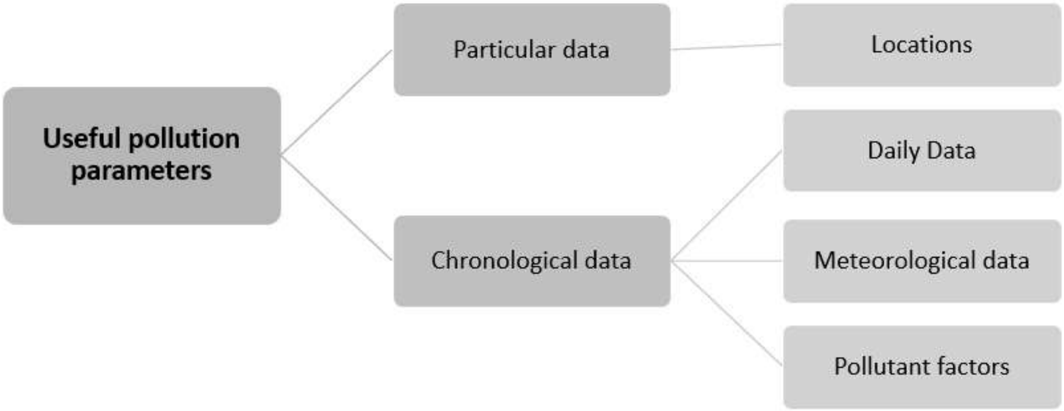
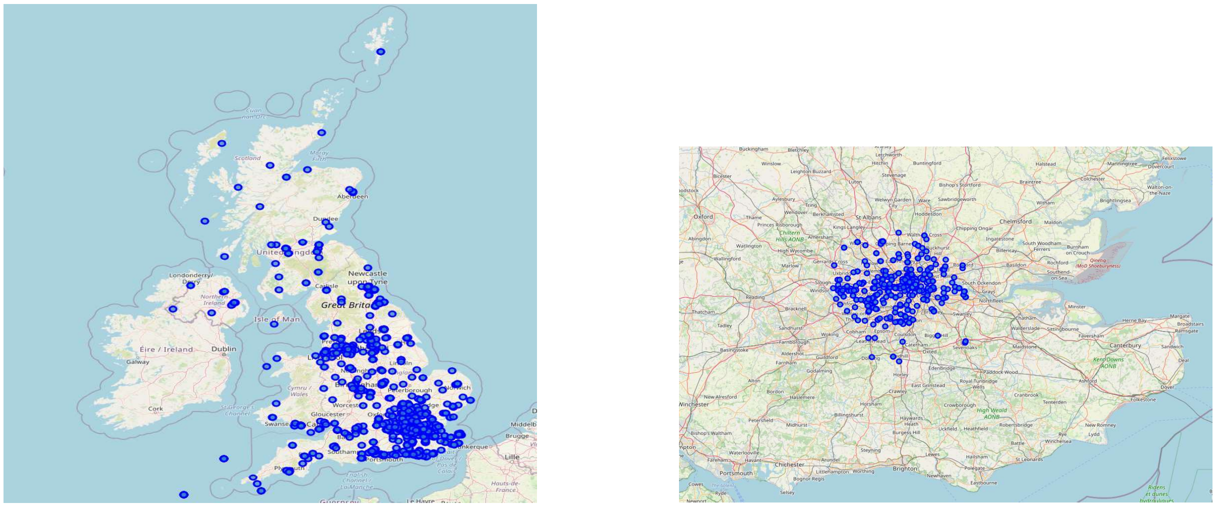


Figure 2.1: Data frames

2.2.3 Choosing stations (Stations in Greater London)

Two general data frame consider around 1495 stations. However, the project only is considering stations in London. So, the latitude between 51.20 to 51.20 and longitude from -0.55 and 0.20 is limited in the study and the rest of the stations are discarded.



(a) UK stations.

(b) Greater London stations .

Figure 2.2: Maps

Chronological data frame has different values like as site, code of station, date (date and hour), Oxides of Nitrogen (NO_x), Nitrogen Dioxide(NO_2), Nitric Oxide(NO), Ozone(O_3), Particulate Matter(PM_{10}) of 10 microns or less, Particulate Matter($PM_{2.5}$) of 2.5 microns or less, Volatile Component(v_{10}) of 10 microns or less, Volatile Component($v_{2.5}$) of 2.5 microns or less, Non-Volatile Component(nv_{10}) of 10 microns or less, Non-Volatile Component($nv_{2.5}$) of 2.5 microns or less, wind speed (ws), wind direction (wd), air temperature, Sulfur dioxide (SO_2), Carbon Monoxide (CO).

The stations should need to have more than 25% of total Particulate Matter($PM_{2.5}$) values and also a strong relationship with the Particulate Matter($PM_{2.5}$). So, it deleted stations that do not fulfil with features. Finally, the new data frame has 34 stations with the following values: code of station, date (date and hour), Oxides of Nitrogen (NO_x), Nitrogen Dioxide(NO_2), Nitric Oxide(NO), Particulate Matter(PM_{10}), wind speed (ws), wind direction (wd), air temperature.

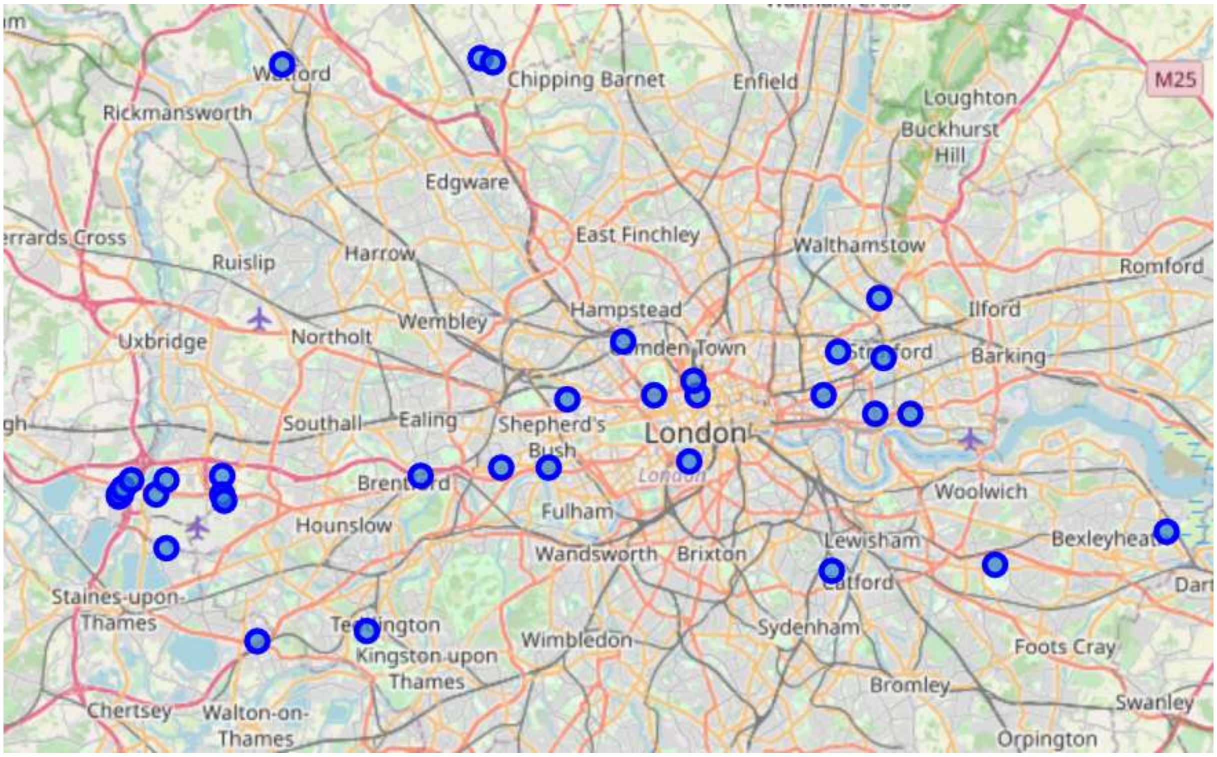
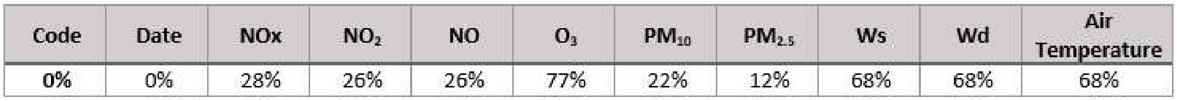


Figure 2.3: London Stations

2.2.4 Filling missing values using Spatial interpolation

The table 2.1 shows the percentage of missing values for each value in the Chronological dataframe.



Code	Date	NOx	NO_2	NO	O_3	PM_{10}	$PM_{2.5}$	Ws	Wd	Air Temperature
0%	0%	28%	26%	26%	77%	22%	12%	68%	68%	68%

Table 2.1: Percentage of missing before spatial interpolation

Applying interpolation spatial, the percentage of the missing values are found. This has two steps are the following calculate distance matrix and spatial interpolation of the nine nearest neighbours.

Distance matrix

It is used the library "scikit-learn" to calculate the distance matrix. Metric intended for two dimensional vector spaces and it is used the haversine distance because the particular data frame has latitude and longitude variables. The haversine formula determines the great-circle distance between two points on a sphere given their longitudes and latitudes.

Let the central angle Θ between any two points on a sphere be:

$$\Theta = \frac{d}{r} \tag{1}$$

where:

- d is the distance between the two points along a great circle of the sphere (see spherical distance),
- r is the radius of the sphere.

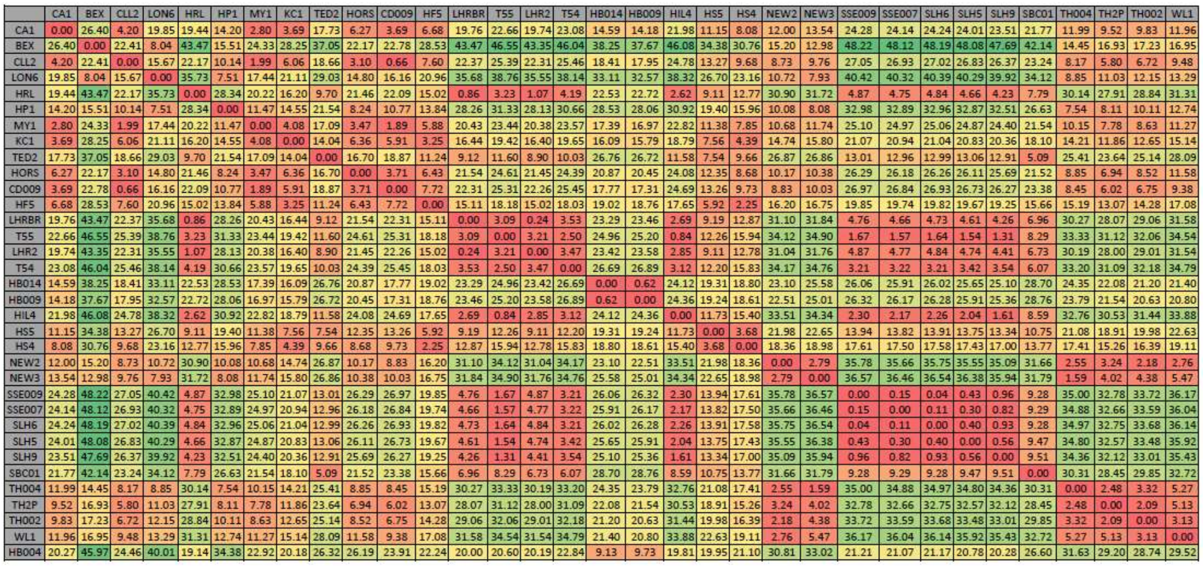
To find the distance, the haversine function hav(θ), applied above to both the central angle (θ) and the differences in latitude and longitude is.

$$\begin{aligned} d &= 2r \arcsin\left(\sqrt{\operatorname{hav}(\varphi_2 - \varphi_1) + \cos(\varphi_1)\cos(\varphi_2)\operatorname{hav}(\lambda_2 - \lambda_1)}\right) \\ &= 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \end{aligned} \tag{2}$$

where

- φ_1, φ_2 are the latitude of point 1 and latitude of point 2 (in radians),

- λ_1, λ_2 are the longitude of point 1 and longitude of point 2 (in radians).



	CA1	BEX	CLL2	LON6	HRL	HP1	MY1	KC1	TED2	HORS	CD009	HF5	LHRBR	T55	LHR2	T54	HB014	HB009	HIL4	HS5	HS4	NEW2	NEW3	SSE009	SSE007	SLH6	SLH5	SLH9	SBC01	TH004	TH2P	TH002	WL1
CA1	0.00	26.40	4.20	19.85	19.44	14.20	2.80	3.69	17.73	6.27	3.69	6.68	19.76	22.66	19.74	23.08	14.59	14.18	21.98	11.15	8.08	12.00	13.54	24.28	24.14	24.24	24.01	23.51	21.77	11.99	9.52	9.83	11.96
BEX	26.40	0.00	22.41	8.04	43.47	15.51	24.33	28.25	37.05	22.17	22.78	28.53	43.47	46.55	43.35	46.04	38.25	37.67	46.08	34.38	30.76	15.20	12.98	48.22	48.12	48.19	48.08	47.69	42.14	14.45	16.93	17.23	16.95
CLL2	4.20	22.41	0.00	15.67	22.17	10.14	1.99	6.06	18.66	3.10	0.66	7.60	22.37	25.39	22.31	25.46	18.41	17.95	24.78	13.27	9.68	8.73	9.76	27.05	26.93	27.02	26.83	26.37	23.24	8.17	5.80	6.72	9.48
LON6	19.85	8.04	15.67	0.00	35.73	7.51	17.44	21.11	29.03	14.80	16.16	20.96	35.68	38.76	35.55	38.14	33.11	32.57	38.32	26.70	23.16	10.72	7.93	40.42	40.32	40.39	40.29	39.92	34.12	8.85	11.03	12.15	13.29
HRL	19.44	43.47	22.17	35.73	0.00	28.34	20.22	16.20	9.70	21.46	22.09	15.02	0.86	3.23	1.07	4.19	22.53	22.72	2.62	9.11	12.77	30.90	31.72	4.87	4.75	4.84	4.66	4.23	7.79	30.14	27.91	28.84	31.31
HP1	14.20	15.51	10.14	7.51	28.34	0.00	11.47	14.55	21.54	8.24	10.77	13.84	28.26	31.33	28.13	30.66	28.53	28.06	30.92	19.40	15.96	10.08	8.08	32.98	32.89	32.96	32.87	32.51	26.63	7.54	8.11	10.11	12.74
MY1	2.80	24.33	1.99	17.44	20.22	11.47	0.00	4.08	17.09	3.47	1.89	5.88	20.43	23.44	20.38	23.57	17.39	16.97	22.82	11.38	7.85	10.68	11.74	25.10	24.97	25.06	24.87	24.40	21.54	10.15	7.78	8.63	11.27
KC1	3.69	28.25	6.06	21.11	16.20	14.55	4.08	0.00	14.04	6.36	5.91	3.25	16.44	19.42	16.40	19.65	16.09	15.79	18.79	7.56	4.39	14.74	15.80	21.07	20.94	21.04	20.83	20.36	18.10	14.21	11.86	12.65	15.14
TED2	17.73	37.05	18.66	29.03	9.70	21.54	17.09	14.04	0.00	16.70	18.87	11.24	9.12	11.60	8.90	10.03	26.76	26.72	11.58	7.54	9.66	26.87	26.86	13.01	12.96	12.99	13.06	12.91	5.09	25.41	23.64	25.14	28.09
HORS	6.27	22.17	3.10	14.80	21.46	8.24	3.47	6.36	16.70	0.00	3.71	6.43	21.54	24.61	21.45	24.39	20.87	20.45	24.08	12.35	8.68	10.17	10.38	26.29	26.18	26.26	26.11	25.69	21.52	8.85	6.94	8.52	11.58
CD009	3.69	22.78	0.66	16.16	22.09	10.77	1.89	5.91	18.87	3.71	0.00	7.72	22.31	25.31	22.26	25.45	17.77	17.31	24.69	13.26	9.73	8.83	10.03	26.97	26.84	26.93	26.73	26.27	23.38	8.45	6.02	6.75	9.38
HF5	6.68	28.53	7.60	20.96	15.02	13.84	5.88	3.25	11.24	6.43	7.72	0.00	15.11	18.18	15.02	18.03	19.02	18.76	17.65	5.92	2.25	16.20	16.75	19.85	19.74	19.82	19.67	19.25	15.66	15.19	13.07	14.28	17.08
LHRBR	19.76	43.47	22.37	35.68	0.86	28.26	20.43	16.44	9.12	21.54	22.31	15.11	0.00	3.09	0.24	3.53	23.29	23.46	2.69	9.19	12.87	31.10	31.84	4.76	4.66	4.73	4.61	4.26	6.96	30.27	28.07	29.06	31.58
T55	22.66	46.55	25.39	38.76	3.23	31.33	23.44	19.42	11.60	24.61	25.31	18.18	3.09	0.00	3.21	2.50	24.96	25.20	0.84	12.26	15.94	34.12	34.90	1.67	1.57	1.64	1.54	1.31	8.29	33.33	31.12	32.06	34.54
LHR2	19.74	43.35	22.31	35.55	1.07	28.13	20.38	16.40	8.90	21.45	22.26	15.02	0.24	3.21	0.00	3.47	23.42	23.58	2.85	9.11	12.78	31.04	31.76	4.87	4.77	4.84	4.74	4.41	6.73	30.19	28.00	29.01	31.54
T54	23.08	46.04	25.46	38.14	4.19	30.66	23.57	19.65	10.03	24.39	25.45	18.03	3.53	2.50	3.47	0.00	26.69	26.89	3.12	12.20	15.83	34.17	34.76	3.21	3.22	3.21	3.42	3.54	6.07	33.20	31.09	32.18	34.79
HB014	14.59	38.25	18.41	33.11	22.53	28.53	17.39	16.09	26.76	20.87	17.77	19.02	23.29	24.96	23.42	26.69	0.00	0.62	24.12	19.31	18.80	23.10	25.58	26.06	25.91	26.02	25.65	25.10	28.70	24.35	22.08	21.20	21.40
HB009	14.18	37.67	17.95	32.57	22.72	28.06	16.97	15.79	26.72	20.45	17.31	18.76	23.46	25.20	23.58	26.89	0.62	0.00	24.36	19.24	18.61	22.51	25.01	26.32	26.17	26.28	25.91	25.36	28.76	23.79	21.54	20.63	20.80
HIL4	21.98	46.08	24.78	38.32	2.62	30.92	22.82	18.79	11.58	24.08	24.69	17.65	2.69	0.84	2.85	3.12	24.12	24.36	0.00	11.73	15.40	33.51	34.34	2.30	2.17	2.26	2.04	1.61	8.59	32.76	30.53	31.44	33.88
HS5	11.15	34.38	13.27	26.70	9.11	19.40	11.38	7.56	7.54	12.35	13.26	5.92	9.19	12.26	9.11	12.20	19.31	19.24	11.73	0.00	3.68	21.98	22.65	13.94	13.82	13.91	13.75	13.34	10.75	21.08	18.91	19.98	22.63
HS4	8.08	30.76	9.68	23.16	12.77	15.96	7.85	4.39	9.66	8.68	9.73	2.25	12.87	15.94	12.78	15.83	18.80	18.61	15.40	3.68	0.00	18.36	18.98	17.61	17.50	17.58	17.43	17.00	13.77	17.41	15.26	16.39	19.11
NEW2	12.00	15.20	8.73	10.72	30.90	10.08	10.68	14.74	26.87	10.17	8.83	16.20	31.10	34.12	31.04	34.17	23.10	22.51	33.51	21.98	18.36	0.00	2.79	35.78	35.66	35.75	35.55	35.09	31.66	2.55	3.24	2.18	2.76
NEW3	13.54	12.98	9.76	7.93	31.72	8.08	11.74	15.80	26.86	10.38	10.03	16.75	31.84	34.90	31.76	34.76	25.58	25.01	34.34	22.65	18.98	2.79	0.00	36.57	36.46	36.54	36.38	35.94	31.79	1.59	4.02	4.38	5.47
SSE009	24.28	48.22	27.05	40.42	4.87	32.98	25.10	21.07	13.01	26.29	26.97	19.85	4.76	1.67	4.87	3.21	26.06	26.32	2.30	13.94	17.61	35.78	36.57	0.00	0.15	0.04	0.43	0.96	9.28	35.00	32.78	33.72	36.17
SSE007	24.14	48.12	26.93	40.32	4.75	32.89	24.97	20.94	12.96	26.18	26.84	19.74	4.66	1.57	4.77	3.22	25.91	26.17	2.17	13.82	17.50	35.66	36.46	0.15	0.00	0.11	0.30	0.82	9.29	34.88	32.66	33.59	36.04
SLH6	24.24	48.19	27.02	40.39	4.84	32.96	25.06	21.04	12.99	26.26	26.93	19.82	4.73	1.64	4.84	3.21	26.02	26.28	2.26	13.91	17.58	35.75	36.54	0.04	0.11	0.00	0.40	0.93	9.28	34.97	32.75	33.68	36.14
SLH5	24.01	48.08	26.83	40.29	4.66	32.87	24.87	20.83	13.06	26.11	26.73	19.67	4.61	1.54	4.74	3.42	25.65	25.91	2.04	13.75	17.43	35.55	36.38	0.43	0.30	0.40	0.00	0.56	9.47	34.80	32.57	33.48	35.92
SLH9	23.51	47.69	26.37	39.92	4.23	32.51	24.40	20.36	12.91	25.69	26.27	19.25	4.26	1.31	4.41	3.54	25.10	25.36	1.61	13.34	17.00	35.09	35.94	0.96	0.82	0.93	0.56	0.00	9.51	34.36	32.12	33.01	35.43
SBC01	21.77	42.14	23.24	34.12	7.79	26.63	21.54	18.10	5.09	21.52	23.38	15.66	6.96	8.29	6.73	6.07	28.70	28.76	8.59	10.75	13.77	31.66	31.79	9.28	9.29	9.28	9.47	9.51	0.00	30.31	28.45	29.85	32.72
TH004	11.99	14.45	8.17	8.85	30.14	7.54	10.15	14.21	25.41	8.85	8.45	15.19	30.27	33.33	30.19	33.20	24.35	23.79	32.76	21.08	17.41	2.55	1.59	35.00	34.88	34.97	34.80	34.36	30.31	0.00	2.48	3.32	5.27
TH2P	9.52	16.93	5.80	11.03	27.91	8.11	7.78	11.86	23.64	6.94	6.02	13.07	28.07	31.12	28.00	31.09	22.08	21.54	30.53	18.91	15.26	3.24	4.02	32.78	32.66	32.75	32.57	32.12	28.45	2.48	0.00	2.09	5.13
TH002	9.83	17.23	6.72	12.15	28.84	10.11	8.63	12.65	25.14	8.52	6.75	14.28	29.06	32.06	29.01	32.18	21.20	20.63	31.44	19.98	16.39	2.18	4.38	33.72	33.59	33.68	33.48	33.01	29.85	3.32	2.09	0.00	3.13
WL1	11.96	16.95	9.48	13.29	31.31	12.74	11.27	15.14	28.09	11.58	9.38	17.08	31.58	34.54	31.54	34.79	21.40	20.80	33.88	22.63	19.11	2.76	5.47	36.17	36.04	36.14	35.92	35.43	32.72	5.27	5.13	3.13	0.00
HB004	20.27	45.97	24.46	40.01	19.14	34.38	22.92	20.18	26.32	26.19	23.91	22.24	20.00	20.60	20.19	22.84	9.13	9.73	19.81	19.95	21.10	30.81	33.02	21.21	21.07	21.17	20.78	20.28	26.60	31.63	29.20	28.74	29.52

Figure 2.4: Distance Matrix of 34 stations

Spatial Interpolation

The methodology to find the nearest neighbours interpolation considering multiple stations is. Let's denote $S_i^1....S_i^k$ the k-nearest stations to S_i such as $d(S_i, S_i^1) < d(S_i, S_i^2) < .... < d(S_i, S_i^k)$. Finally, it calculated the mean from the 9 nearest stations.

$$X_t(S_i) = \frac{1}{K} \sum_{k=1}^{K} X_t(S_i^k) \tag{3}$$

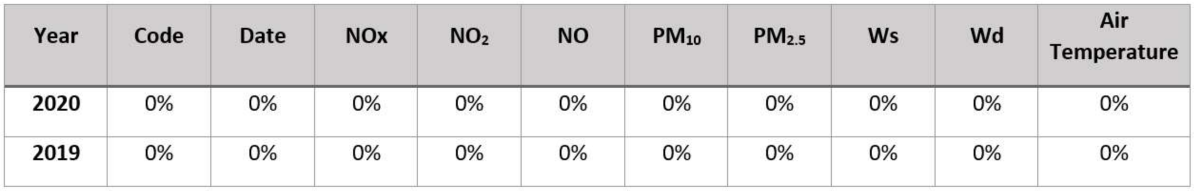
where $X_t(S_i)$ denotes the variable to be interpolated at a given point in time t and station S_i.

Year	Code	Date	NOx	NO$_2$	NO	PM$_{10}$	PM$_{2.5}$	Ws	Wd	Air Temperature
2020	0%	0%	0%	0%	0%	0%	0%	3.7%	3.7%	3.7%
2019	0%	0%	0%	0%	0%	0%	0%	4.8%	4.8%	4.8%

Table 2.2: Percentage of missing after spatial interpolation

2.2.5 Fill missing values using method in Panda

This is basically about the *'fillna'* function that is used in pandas, the method used is *'backfill'*. Finally, this method help to fill all the missing values in the data frame.



Year	Code	Date	NOx	NO_2	NO	PM_{10}	$PM_{2.5}$	Ws	Wd	Air Temperature
2020	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
2019	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 2.3: Percentage of missing after apply fillna function

3 Results and Discussion