PREDICTING AIR POLLUTANT LEVELS NEAR MAJOR CONSTRUCTION ZONES IN DOWNTOWN TORONTO: Interim Report

by

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INTRODUCTION:

Air pollution is the greatest environmental burden to human health. It contributes to over eight million premature deaths globally every year, of which 14,400 are in Canada [1]. Two ways people cause air pollution are constant use of an automobile for transportation and high energy consumption. Thankfully, both can be reduced through urban densification, the process of increasing the density of people living in urban areas. When implemented along with accessible public transit, urban densification reduces the distance people need to travel for work and leads to a lower average energy consumption due to the efficiency of high-density buildings [2]. It is also associated with a reduced land take, which allows for greater availability of land for agriculture, nature, and biodiversity.

Urban densification often requires a major construction overhaul. This is especially true for projects that require deep pits to be dug, such as for high-rise buildings or underground transportation. These plans can lead to construction lasting up to a decade long [3]. As a result of the heavy machinery, increased congestion on the roads, and the release of particles (like dust) into the air, major construction sites lead to an increase in air pollutant levels. A case study in Qingyuan, China, found the daily concentration of total suspended particulates (TSP) near a construction site increased by 42.24%. It also saw a 16.27% increase in particulate matter 2.5 (PM2.5), which refers to particles that are 2.5 microns or less in width [4]. PM2.5 pose the greatest health risks, since due to their small size, they can lodge deeply into the lungs [5]. So, while there are long-term benefits to urban densification, the short-term decline in air quality caused by construction sites is worrying.

Air quality is popularly measured with the US Air Quality Index (AQI). This index considers the following pollutants: Ozone (O3), PM2.5, PM10, Carbon Monoxide (CO), Sulfur Dioxide (SO2) and Nitrogen Dioxide (NO2) [6]. Weather forecast providers display the AQI value for a given location, usually for an entire city. However, due to environmental and location-based factors, such as major construction, the given AQI value may not be representative of all sub-regions within a given location [4].

LITERATURE REVIEW:

Construction Sites Large Impact on Particulate Emissions

Article Title: *An Inventory of Particulate Emissions from Open Sources* [7]

Authors: *John S. Evans and Douglas W. Cooper*

This article from the Harvard School of Public Health looks at different open sources of air pollution – those stationary sources too great in extent to be controlled through enclosure or ducting – and their overall contribution to national particulate emissions in 1976. Due to the lack of particulate measuring devices at-the-time, the authors instead constructed formulae to estimate the yearly Total Suspended Particulate (TSP) emissions from each of the open sources. They found that construction activities represented 3.8% (22 X 10^6 ton) of total particulate emissions from open sources.

Negative Health Effects

Article Title: *Increased mortality in COPD among construction workers exposed to inorganic dust* [8]

Authors: *I.A. Bergdahl, K. Tore´n, K. Eriksson, U. Hedlund, T. Nilsson, R. Flodin, B. Ja¨rvholm*

The aim of the study was to find out if exposure to inorganic dust and other air pollution increase the mortality from chronic obstructive pulmonary disease (COPD). Over 300,000 Swedish male construction workers were followed and analyzed from 1971 to 1999. They found that the fraction of COPD among the exposed attributable to any airborne exposure was estimated as 10.7% overall and 52.6% among people who have never smoked. This means that of all the workers who developed COPD and never smoked before, 52.6% of the cases were due to exposure to airborne emissions. While this study only looked at construction workers' health, residents in dense urban areas undergoing construction would also be exposed to similar airborne particles.

Variability from Construction Activity and Weather

Article Title: *An Estimation on Overall Emission Rate of Fugitive Dust Emitted from Road Construction Activity* [9]

Authors: *Yu-Min Chang, Tien-Chin Chang, and Wang-Kun Chen*

This article from 1999 looks at estimating the overall emission rate of total suspended particulates (TSP) caused by road construction in Taiwan. They found that dust emissions often vary substantially from day to day depending on the level of activity, the specific operations and the prevailing meteorological conditions, making it difficult to assess the total contribution of such emissions to the air pollution levels of a city or region**.**

Since the current measuring devices near Yonge and Eglinton capture real-time meteorological and noise values (which can be used to estimate construction activity), there exists an opportunity to address the variability this study brings up in understanding emission rates.

Increased Emissions During Working Hours

Article Title: *Degradation in urban air quality from construction activity and increased traffic arising from a road widening scheme* [10]

Authors: *Anna Font, Timothy Baker, Ian S. Mudway, Esme Purdie Christina Dunster, Gary W.Fuller*

In this 2014 study of road work construction in London, England, PM_{10} increased during the construction period up to 15 μg m^{-3} during working hours compared to concentrations before the road works. This breached the EU PM_{10} limit value (LV).

This shows the emission rate of particulate matter increases during construction hours, so-much-so that environmental regulations are broken.

Ontario Environmental Protection Act and Current Air Dispersion Models

In Ontario, businesses must follow the air quality regulations set out by the Environmental Protection Act [11]. These include limits to particulate matter emissions. Penalties can range from $1,000 per day for less serious violations such as failure to submit a quarterly report, to $100,000 per day for the most serious violations, including a spill with a significant impact.

Also outlined in the act are current ways to determine/model air dispersion models: the AERMOD/AERMET models and the ASHRAE method of calculation. AERMOD Modeling System is a steady-state plume model that incorporates air dispersion based on planetary boundary layer turbulence structure and scaling concepts, including treatment of both surface and elevated sources, and both simple and complex terrain.

Using these recommended models, I can compare the performance of our highest-performing model against the current industry-standard.

Toronto Dust Control By-Law

In Toronto, City Council has decided that the Dust Control by-law will not apply to municipal works, construction occurring on commercial and industrial properties, nor will it apply to the construction of a multi-residential building, subdivision, or mixed-use development [12].

This is relevant to this thesis, as we are looking at the air pollutant levels in large construction hubs in downtown Toronto. These construction sites are likely some of the biggest dust producers yet are given an exemption from the city.

Previous Attempt to Model Air Pollutant Levels near Construction Sites

Article Title: *The Correlation Analysis between Air Quality and Construction Sites: Evaluation in the Urban Environment during the COVID-19 Pandemic* [13]

Authors: *Haoran Li, Ali Cheshmehzangi, Zhiang Zhang, Zhaohui Su, Saeid Pourroostaei Ardakani, Maycon Sedrez, Ayotunde Dawodu*

This 2022 study aimed to find the correlative relationship between seven air quality indicators (i.e., the air quality index, PM2.5, PM10, O3, NO2, SO2, and CO) and the number of construction sites in Hangzhou, China. They used non-linear regression models to estimate the number of construction sites. Then, based on guideline values of air parameters provided by the Chinese criteria and standard, the recommended maximum number of construction projects can be defined. The model did not generalize to other districts, however, and the lack of meteorological data was considered a limitation that needs to be addressed.

Methods for Multivariate Time Series Analysis

Book Title: *Elements of Multivariate Time Series Analysis* [14]

Author: *Gregory C. Reinsel*

Unlike univariate time series, which look at a single variable over time, multivariate time series feature a vector of *k* variables observed over time. The goal with modelling multivariate time series is to accurately describe the relationship amongst the *k* variables and how they impact each other's future values. The vector autoregressive and moving average models are both successful modelling techniques to use for multivariate time series problems. VAR, VMA, and VARMA models all require the time series variables to be stationary (i.e. not show seasonality, see *Dickey-Fuller Test*)

Vectorized Auto-Regressive (VAR) Model

In the VAR model, each variable has an equation modelling its evolution over time. It includes the variable's lagged (past) values, the lagged values of the other variables in the model, and an error term. In general, a *p*th-order VAR refers to a VAR model which includes lags for the last *p* time periods, and can be written as:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t,$$

Where c is a k-vector of constants (intercept of the model), A_i is a time-invariant (k x k)-matrix, y_{t-i} are that variable's value i time periods earlier, and e_t is a k-vector of error terms.

Vectorized Moving-Average (VMA) Model

A moving average model states that the current value of a variable is linearly dependent on the current and past error terms. Unlike the VAR model that includes lagged values of the variables, a VMA model only uses past error terms in a regression-like model.

Vectorized Auto-Regressive Moving-Average (VARMA) Model

This model combines both the VAR and VMA model. It historically performs better then one of those models separately because it combines the VAR model's ability to build relationships between the various variables and the VMA model's ability to capture long-term trends within each of the variables.

Augmented Dickey-Fuller Test

Article Title*: Testing Time Series Data for Stationarity* [15]

Author: *Rizwan Mushtaq*

Testing time series data for stationarity is important, as VAR, VMA, and VARMA models all require multivariate time series data to be stationary in order to be successful. Data is considered non-stationary if it exhibits trending behaviour in the mean. A formal test of stationarity exists, called the *Augmented Dickey-Fuller (ADF) Test*. If the critical value from the ADF test is less than 0.05, the null hypothesis (data is non-stationary) can be rejected, so the data would be considered stationary. If a time series variable is non-stationary, you can take its first-order differences and retry the ADF test.

Granger Causality Test

Article Title: *Granger Causality* [16]

Author: Anil Seth

Granger causality is a statistical concept of causality that is based on prediction. A variable *X* "Granger-causes" a different variable *Y* if past values of *X* contain information that helps predict *Y* above and beyond the information contained in past values of *Y* alone. The Granger Causality test in a multivariate time series looks at each pairwise comparison between variables *X* and *Y* and computes a p-value. If the p-value is smaller than 0.05, then it can be said that variable *X* granger-causes variable *Y*. This test is useful in multivariate time series, since any variables that do not granger-cause a variable you are trying to predict can be removed from the problem, avoiding redundancy and improving the training times of models.

RESEARCH QUESTIONS

Through review of past literature and identifying the gaps in research, the following two research questions that will guide the thesis have been determined:

1. What effect do the active working hours and meteorological conditions have on the daily air pollutant levels near major, urban construction zones?
2. Using weather forecasts and construction work schedules, can future air pollutant levels near major, urban construction zones be accurately predicted?

PROGRESS TO DATE:

The following progress has been achieved on a 40-day subset of the measured data, taken at 1-hour intervals. Future work includes using a greater range of data and a variety of chosen time intervals.

Visualizing Data

One of the first steps that should be done when working with a time series problem is to plot the data. Through visual inspection, you can estimate which variables are not helpful for forecasting, as well as beginning to notice which variables appear to show seasonality (i.e. are not stationary). For example, visual inspection was done on the 40-day dataset [Appendix a], and the categories *Latitude*, *Longitude*, and *Elevation* were a constant value (as expected). Because they do not change, they provide no information on future pollutant values, and were removed from the dataset. *AQI* was also removed, as it is not a measured variable, but rather a value equated from already measured variables and therefore redundant for forecasting.

Remove Seasonality from Data

As the VAR, VMA, and VARMA models require stationary data, the Augmented Dickey and Fuller Test was performed on the data. PM_{10}, CO_2, *CO*, and *temperature* were all determined as non-stationary [Figure i]. First-order differences of these variables were taken and the ADF test was repeated, resulting in all variables now being stationary [Figures ii & iii].

```
Results of Dickey-Fuller Test for column: PM10
ADF Test Statistic          -2.002195
P-Value                      0.285612
# Lags Used                 21.000000
# Observations Used        937.000000
Critical Value (1%)         -3.437348
Critical Value (5%)         -2.864630
Critical Value (10%)        -2.568415
dtype: float64

Conclusion:
Fail to reject the null hypothesis
```

Figure i – ADF test results for PM_{10}

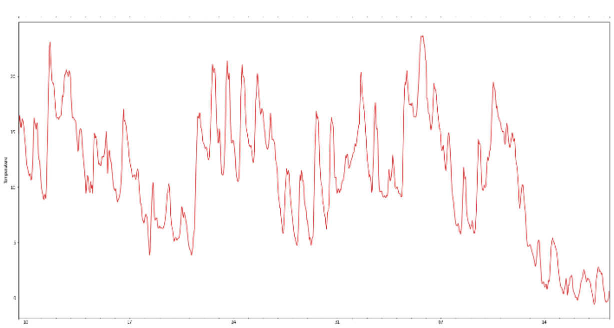

Figure ii - Temperature before differencing

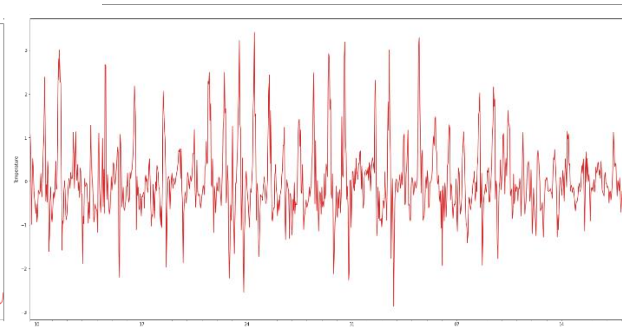

Figure iii - Temperature after differencing

Granger Causality Test

Now that the data has been made stationary, the Granger Causality test can be performed [Figure iv]. The diagonal values in the output matrix pairing the same variable against itself should be 1, since no new past values are being introduced (the variable's own past values are already considered in the test). For other entries in the output matrix, a value less than 0.05 means the variable in the y-column granger-causes the variable in the x-column. If a variable does not granger-cause another, it suggests it is not useful for predicting the other variable. This can be used in the future to reduce the number of input variables for the models.

	Noise_LEQ_x	PM10_x	CO2_x	CO_x	PM1_x	PM2_x	\
Noise_LEQ_y	1.0000	0.4224	0.0000	0.0000	0.4928	0.4386	
PM10_y	0.0547	1.0000	0.0000	0.0000	0.0000	0.0000	
CO2_y	0.0000	0.0030	1.0000	0.0000	0.0016	0.0022	
CO_y	0.0000	0.0069	0.0000	1.0000	0.0005	0.0009	
PM1_y	0.1644	0.0000	0.0000	0.0000	1.0000	0.0028	
PM2_y	0.0828	0.0000	0.0000	0.0000	0.0091	1.0000	
Noise_Max_y	0.0000	0.4629	0.0000	0.0000	0.4704	0.4586	
NO2_y	0.0000	0.0000	0.0000	0.0000	0.0495	0.0777	
O3_y	0.0000	0.0000	0.0000	0.0000	0.1259	0.0897	
Humidity_y	0.0000	0.0000	0.0000	0.0000	0.0373	0.0381	
NO_y	0.0000	0.0019	0.0000	0.0000	0.0053	0.0021	
Pressure_y	0.0000	0.6197	0.0000	0.0000	0.0007	0.0040	
Wind_Speed_y	0.0000	0.0939	0.0005	0.0008	0.6213	0.6481	
Wind_Gust_y	0.0000	0.1119	0.0005	0.0007	0.6151	0.6460	
Wind_Direction_y	0.0471	0.0981	0.0036	0.1366	0.1457	0.1286	
Temperature_y	0.0000	0.0148	0.0000	0.0000	0.0094	0.0060	

Figure iv - Granger-Causality Test results

Selecting Best AIC Lag Order

Using the Python library *statsmodels*’ built-in *select_order* function, the best lag order selections were automatically computed, looking up to a max of 20 lags for each variable. Because we are working with the VAR model first, only the *AIC* column values are being considered. The optimal lag order is the one that returns the lowest *AIC* value, which in our case was 3 [Figure v]. This means the VAR model will consider the past 3 values for each of the input variables when predicting future values.

	AIC	BIC	FPE	HQIC
0	37.55	37.63	2.023e+16	37.58
1	5.546	6.950	256.1	6.081
2	3.225	5.952*	25.17	4.265*
3	3.015*	7.063	20.42*	4.558
4	3.098	8.468	22.22	5.145
5	3.091	9.784	22.16	5.643
6	3.108	11.12	22.63	6.163
7	3.244	12.58	26.13	6.804
8	3.342	14.00	29.08	7.405
9	3.508	15.49	34.74	8.075
10	3.701	17.00	42.79	8.773
11	3.769	18.39	46.61	9.344
12	3.906	19.85	54.68	9.986
13	4.026	21.29	63.28	10.61
14	4.169	22.76	75.27	11.26
15	4.315	24.23	90.36	11.91
16	4.420	25.65	104.6	12.52
17	4.578	27.13	128.4	13.18
18	4.609	28.49	139.8	13.71
19	4.742	29.94	169.6	14.35
20	4.851	31.37	202.6	14.96

Figure v - Results from statsmodel's select_order function

Training the VAR Model / Building the Model Equations

With the optimal lag order selected, the training set of the data (70%) was used to train the VAR model. It takes ~11min to complete, resulting in a complete set of model equations for each of variables. An example of PM_1’s equations can be seen in Appendix ii.

Forecasting Results

The trained VAR model was then used to create a 1-day and 1-week forecast prediction of the air pollutant values (PM_1, $PM_{2.5}$, PM_{10}, *CO*, CO_2, O_3, *NO, and* NO_2) using the test dataset. The mean absolute percentage error (MAPE), margin of error (ME), mean absolute error (MAE), mean percentage error (MPE), root-mean-square error (RMSE), and correlation (CORR) between the predicted and actual values were calculated [Figure vii]. They will be used to compare future runs to determine the highest performing model.

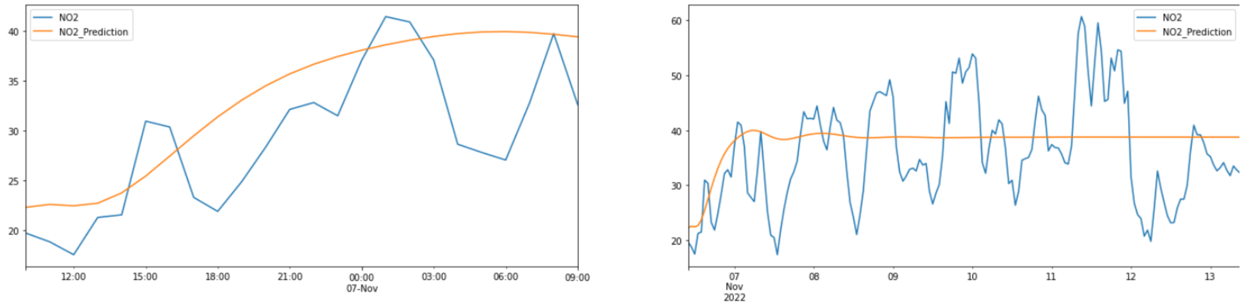

Figure vi - 1-day and 1-week NO2 prediction vs actual value

	mape	me	mae	mpe	rmse	corr
PM1	inf	1.853575	2.111090	inf	2.530453	0.611120
PM2	17.331819	1.989492	2.594064	16.965842	3.128912	0.564874
PM10	6.457709	2.275834	3.294240	5.997512	3.988757	0.556457
CO	0.132780	26.588006	34.338467	0.107091	42.559803	-0.183050
CO2	0.020581	3.517002	9.442154	0.007716	11.616441	0.099484
O3	0.134342	-4.058265	5.311808	-0.086003	6.060802	0.913305
NO	0.263652	2.734396	3.048794	0.241239	3.711800	0.425104
NO2	0.194002	4.109820	5.209666	0.161511	6.261514	0.760920

Figure vii - Performance metrics for model's 1-day predictions

As seen in *Figure vi*, the predictive performance of the VAR model can achieve some success with short-term forecast, but longer-term forecasts tend to converge to a consistent value. This suggests the model could be oversimplified, preferring to choose a variable's mean value. With future models (VMA, VARMA) incorporating a moving-average component, hopefully the daily peaks and troughs can be recognized by the model and considered when making forecasts.

FUTURE WORK:

While the current progress was achieved using the original 40-day dataset, future progress will use an updated dataset which includes measurements taken from July 2022 to January 2023 (and can be continually updated as each month passes). This updated dataset also includes several time intervals of each measured variable (1-hour, 15-min, 1-min).

The plan moving forward is to continue training and testing models to find the highest performing predictor. This includes trying different combinations of the following:

- Model types (VMA, VARMA, etc.)
- Training data sizes (1 month, 3 months, etc.)
- Data time interval (1hr, 15min, 1min)
- Prediction ranges (1day, 1 week, 2 weeks, 1 month)

Another key metric to consider is the number of input variables being used to train the model. It took 11 minutes to train a simple VAR model with only about 30 days worth of data. With more complicated models (VARMA) and larger datasets, this training time will only increase, making the testing procedure slow. To combat this, one can reduce the number of input variables used in training, speeding up the overall training process. Ways to select which variables to remove include:

- Choosing the variables with the highest p-values from the Granger-Causality test
- Performing Sensitivity Analysis on the variables to determine their importance in forecasting

Finally, the same process can completed on the data from the devices outside of the major construction zones. Whether a difference exists between forecasting performance, as well as the importance of individual variables, will be examined. The top-performing model will also be compared to existing forecasting tools, such as weather websites or the AERMOD/AERMET models outlined in the Environmental Protection Act.

Schedule

TASK	**DEADLINE**
Determine best performing model	February 20th
Sensitivity Analysis + Reduce Input Variables	March 15th
Compare to Existing Forecast Tools	March 30th
Final Presentation	April 7th
Final Document	April 14th

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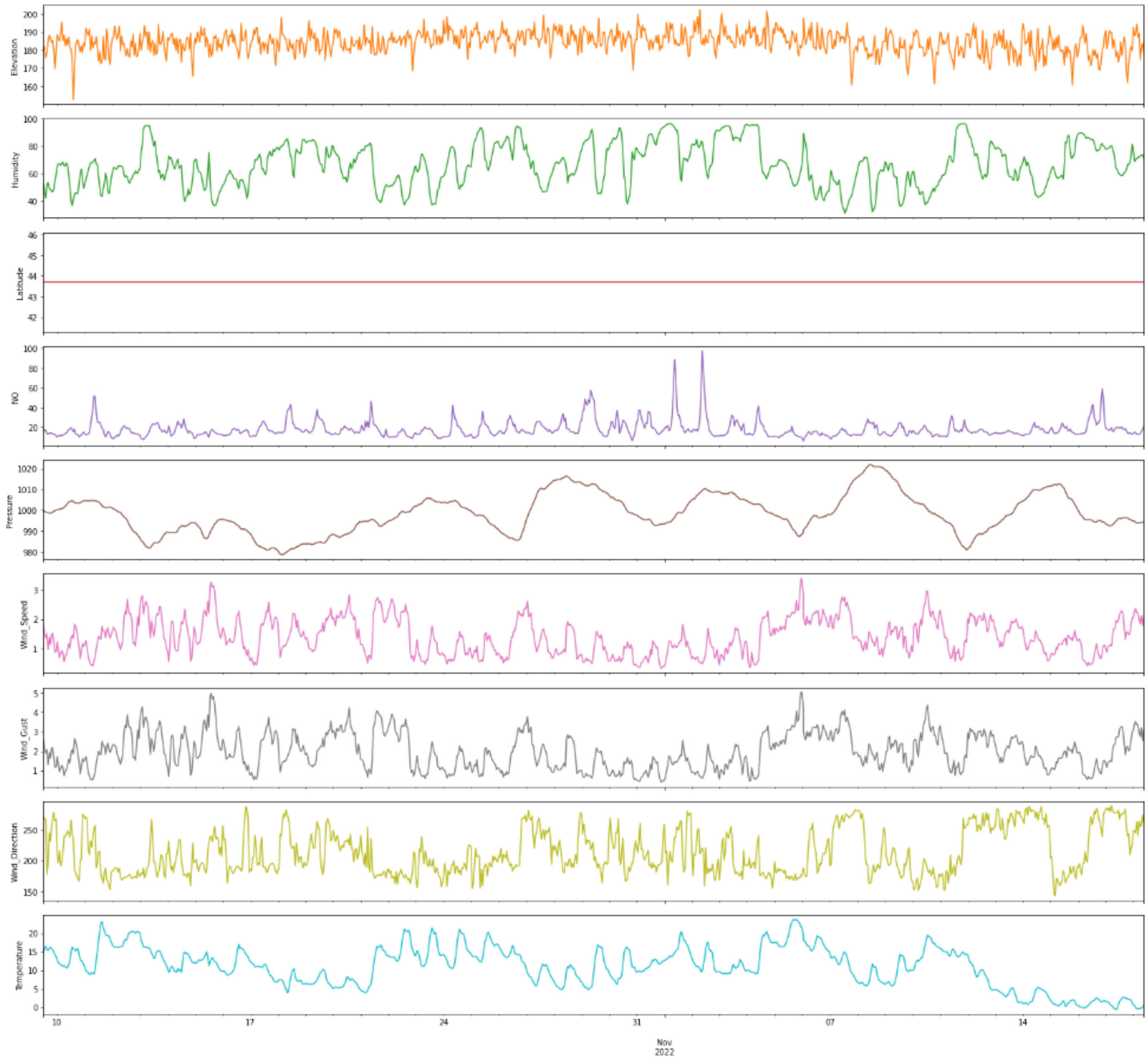
LIST OF FIGURES

APPENDIX:

[i] Visual Plot of 40-day, 1hr interval data


Elevation
Humidity
Latitude
NO
Pressure
Wind_Speed
Wind_Gust
Wind_Direction
Temperature
10
17
24
31
07
14
Nov
2022

[ii] VAR model equations for PM_1

Results for equation PM1

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	2.1981	0.194	11.321	0.000	1.818	2.579
L1.Noise_LEQ	0.3280	0.265	1.237	0.216	-0.192	0.848
L1.PM10	-0.1924	0.203	-0.950	0.342	-0.590	0.205
L1.CO2	0.0341	0.077	0.444	0.657	-0.116	0.184
L1.CO	0.0005	0.025	0.020	0.984	-0.048	0.049
L1.PM1	1.5505	0.318	4.884	0.000	0.928	2.173
L1.PM2	0.0643	0.352	0.182	0.855	-0.626	0.755
L1.Noise_Max	-0.3021	0.278	-1.087	0.277	-0.847	0.243
L1.NO2	-0.0152	0.118	-0.129	0.898	-0.247	0.217
L1.O3	0.0791	0.098	0.805	0.421	-0.114	0.272
L1.Humidity	-0.0528	0.133	-0.398	0.691	-0.313	0.207
L1.NO	-0.0524	0.123	-0.424	0.671	-0.294	0.190
L1.Pressure	-0.0052	0.265	-0.020	0.984	-0.526	0.515
L1.Wind_Speed	1.4232	0.467	3.047	0.002	0.508	2.339
L1.Wind_Gust	-1.2287	0.380	-3.232	0.001	-1.974	-0.484
L1.Wind_Direction	-0.0031	0.024	-0.131	0.896	-0.050	0.043
L1.Temperature	-0.3041	0.229	-1.330	0.184	-0.752	0.144
L2.Noise_LEQ	-0.1568	0.319	-0.492	0.623	-0.782	0.468
L2.PM10	0.4750	0.213	2.231	0.026	0.058	0.892
L2.CO2	-0.0038	0.117	-0.033	0.974	-0.232	0.225
L2.CO	-0.0031	0.026	-0.121	0.904	-0.053	0.047
L2.PM1	-0.3634	0.322	-1.128	0.260	-0.995	0.268
L2.PM2	-0.7483	0.337	-2.222	0.026	-1.408	-0.088
L2.Noise_Max	0.1693	0.261	0.648	0.517	-0.343	0.681
L2.NO2	-0.0105	0.157	-0.067	0.947	-0.318	0.297
L2.O3	-0.0710	0.133	-0.534	0.593	-0.331	0.189
L2.Humidity	0.0853	0.149	0.571	0.568	-0.208	0.378
L2.NO	-0.0099	0.159	-0.062	0.950	-0.321	0.302
L2.Pressure	-0.0114	0.380	-0.030	0.976	-0.756	0.733
L2.Wind_Speed	-1.6517	0.366	-4.509	0.000	-2.370	-0.934
L2.Wind_Gust	0.9566	0.368	2.596	0.009	0.234	1.679
L2.Wind_Direction	0.0058	0.037	0.158	0.875	-0.066	0.077
L2.Temperature	0.3304	0.239	1.380	0.168	-0.139	0.800
L3.Noise_LEQ	-0.0532	0.337	-0.158	0.875	-0.714	0.608
L3.PM10	-0.1145	0.232	-0.493	0.622	-0.569	0.340
L3.CO2	-0.0209	0.085	-0.245	0.806	-0.188	0.146
L3.CO	0.0047	0.025	0.191	0.848	-0.044	0.053
L3.PM1	-0.0528	0.292	-0.181	0.856	-0.625	0.519
L3.PM2	0.2977	0.372	0.800	0.424	-0.432	1.028
L3.Noise_Max	0.0163	0.298	0.055	0.956	-0.568	0.601
L3.NO2	0.0246	0.116	0.212	0.832	-0.203	0.252
L3.O3	0.0087	0.076	0.113	0.910	-0.141	0.159
L3.Humidity	-0.0241	0.119	-0.202	0.840	-0.258	0.210
L3.NO	0.0230	0.123	0.186	0.852	-0.219	0.265
L3.Pressure	0.0107	0.255	0.042	0.967	-0.489	0.510
L3.Wind_Speed	-0.9193	0.354	-2.598	0.009	-1.613	-0.226
L3.Wind_Gust	0.8599	0.281	3.062	0.002	0.309	1.410
L3.Wind_Direction	-0.0009	0.030	-0.029	0.976	-0.059	0.057
L3.Temperature	-0.0689	0.221	-0.313	0.755	-0.501	0.363