Air Pollution in Madrid:

Have the policies established by the government been effective?

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Abstract

Within this study, researchers investigated the air quality in Madrid. First of all, data was cleaned and analyzed in the desired format, with the primary goals of prooving whether the policies established by the government have been effective and creating a model and forecast air quality in Madrid for the upcoming years. Several models were compared to find the best model. Forecasts show that, in accordance with the policies established up to 2018, air quality levels would continue to be stable. However, if these policies were turned over, researchers suspect that air quality might go worse.

Keywords: Hybrid Model, NO_2, Air Pollution, Madrid

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Hybrid Models: Air Pollution in Madrid

Introduction

When you arrive in Madrid by car, the first thing you can see is a black layer that covers the whole city; this is due to the amount of air pollution produced every day in Madrid. By 2014, there were already more than 6740 deaths in Spain due to air pollution. It is affecting our health and our planet, but we are still not doing anything about it. Over 50% of NO_2 emissions, one of the top three pollutants in Spain, are due to road traffic, what is said to affect the fetus in pregnant women and to be cancerogenic (Sánchez, 2018).

The Spanish government, as well as the European Union, have already tried to solve this problem by implementing some policies (Appendix 1), which can be divided into two different groups. From 2003 to 2015 the policies were mainly centred around pollution created by factories and companies. The Spanish government started restricting businesses production of certain gases, and in case they surpassed these limits, they had to pay high fees. From 2016 to 2018, the policies started affecting Madrid's citizens as individuals, meaning the restrictions were not only aimed at companies anymore. One of the most famous policies is the one from the city centre. The government restricted the access of cars to the city centre only allowing hybrid or electric cars to enter.

With this study, researchers' goal is to first look at the evolution of air pollution in Madrid, to see if there is any relation with the season or significant events. Further on, investigators aim to check whether the policies implemented by the government have been effective or not, and lastly to see how the future looks like.

The Data Set

The name of this dataset is "Air Quality in Madrid", retrieved from Kaggle. The original dataset has information about the levels of 17 different gases (Appendix 2) recorded in 24 stations (Appendix 3) located all over Madrid. The first thing the team did to prepare the data for analysis was to deal with the missing values, represented by "NA" in the original dataset. The final decision they reached was to replace them with zeros. Once they did this, they decided on what gases they would use for the study.

Investigators decided to focus on NO_2 for various reasons. Most of the policies implemented are centred around traffic, and traffic and high temperatures mainly produce NO_2. The European Union shares a concern around this gas, which is the reason why they stipulated the annual average of this gas should never exceed 40 micrograms per m3 (Sánchez, 2018), and Madrid has already overpassed this level in 62 occasions. This gas, being among the top three pollutants in Spain, made it the perfect candidate for the study.

The data was recorded by hours every day from 2001 to 2018. Researchers first decided to summarize the data by days, establishing the values as the mean NO_2 of all the hours per days. After retrieving some background information, the team found out that for every regulation implemented by the government or other institutions, the levels used are measured around the mean. Thus researchers decided also to use the mean. Daily data was making the analysis tedious, due to the lack of computational power, so researchers decided to summarize the data by weeks, again with the average values.

Once researchers had all the data divided by stations and NO_2 levels averaged per week, they selected the two stations that they would use for their model selection and forecast. For this reason, investigators decided to look at the maximum average per week values of all 24 stations. Having all of these values, investigators selected the highest and lowest maximum averages per week. The highest NO_2 level maximum average per week was recorded in Plaza de España, with a level of 137.3297 µg/m3 per week. The lowest NO_2 level was recorded in Casa Campo, with a level of 82.52845 µg/m3 per week. Casa Campo was mainly chosen to be able to compare results to Plaza de España.

Regarding the selection of the station, investigators decided to focus on Plaza de España and Casa Campo. They decided to focus on Plaza de España because it was the station most affected by the majority of the policies implemented, as it is located in the central district of Madrid. Thus, it is the station with the highest records of NO_2 concentrations, what worried investigators the most. Researchers decided to investigate Casa Campo as well because it is located in the outskirts of Madrid, making it the complete opposite station to Plaza de España, in the sense that there is not a lot of traffic nor laws established for that specific area. Another reason why researchers decided to select Casa Campo was that it has the lowest maximum average NO_2 level.

Exploring the Time Series

When looking at the whole data set (Appendix 4), researchers can see that the trend decreases in general. Around 2003 there is a peak in the NO_2 levels when the first policies that addressed air pollution were implemented. Around 2004 investigators can also see there is a big spike, due to the terrorist attack in Madrid on the 11th of March 2004. Terrorists placed butane bombs in trains near the Atocha station. When these exploded, butane was burned, and the chemical reaction produced NO_2, increasing the levels of this gas. From around 2007 onwards, the trend starts decreasing and then, around 2015, there is a bit of an increase that then starts getting constant. Taking a look at the time series from 2015 onwards (Appendix 5), there is a spike around 2016, when the policies that affected us as individuals where implemented. From then onwards, researchers can see that the maximums never reach the same level as in 2016 and that the minimums start getting constant.

When looking at the seasonality (Appendix 6) of this time series researchers can see that the levels of NO2 are higher at the beginning and the end of each year, meaning that in winter there seems to be more pollution than in summer. This could be due to the daily use of heaters and cars to drive to work. In summer, mainly in August, Madrid is less active, citizens are set on vacation mostly during this month of the summer. In the ACF plot (Appendix 7) the trend and seasonality can also be seen.

Model Selection

To select the model of Plaza de España researchers first tried different models, including ARIMA, linear regression, ETS, a neural network (NNAR), the benchmark methods and the hybrid model. To choose the best option of each model type investigators used the AICc, which measures the goodness of fit and simplicity of the model. After selecting the best models from each model type, without taking hybrid models into account, the team looked at the MAPEs, an error measure calculated as the average absolute percent error for each time period minus the actual values, divided by the actual values. Comparing this error measure, researchers concluded that the benchmark model of random walk with drift was giving the best model, meaning the models that were previously tested were not good enough, and the researchers should take the model one step further.

This step was the hybrid model. The best errors were given by a hybrid model of ARIMA, NNAR, Theta, STL and TBATS, but it only had a 0.1 difference with the MAPE of the hybrid model without TBATS, and it made the model much more complicated. At this point, researchers decided that for Plaza de España's station, they could give up that 0.1 and use the simpler hybrid model. Either way, they recommend that for stations with stronger seasonality the hybrid model should also include the TBATS model, as this model can detect season from different frequencies, as they saw in the case of Casa de Campo. (Appendix 8, 9)

The Hybrid Model

The best model found for the data set is a hybrid model of ARIMA, NNAR, Theta and STL. A hybrid model is composed of several models, and each model brings something different to it. In this case, ARIMA mainly gets the information from the past, NNAR is in charge of the non-linear relationship, Theta takes care of the long-term behaviour, and STL accounts for seasonality. (Appendix 10)

ARIMA Model

ARIMA stands for Autoregressive Integrated Moving Averages. ARIMA aims to describe the autocorrelations in the data, and it is used to describe only stationary time series. In this hybrid model, researchers use an ARIMA(1,1,1). The first number is the autoregression number that represents a linear combination of lagged values. As there is one autoregression, it means that the model is created by a multiple of its own previous value. The last number indicates the moving average, a linear combination of the lagged forecasting errors. In the case of this model, that is equal to one, meaning that the model is created by adding the error term to a multiple of the previous error value. To combine both of them, researchers need an intercept, given by the middle number. This shows the number of differentiations one must do to the original data to make it stationary, one of the assumptions required when fitting an ARIMA model. (Appendix 11)

Neural Network (NNAR(6,1,4))

A neural network is a complex model that works in the following way. First of all, lagged values are inputs that produce an output; this output is then the input of the hidden layer, which is in charge of figuring out the non-linear relationship. The output of this is the forecast. In the case of this model, investigators have an NNAR(6,1,4), where the 6 indicates that researchers have used 6 lagged values as inputs, meaning the inputs are the following: y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}, y_{t-5} and y_{t-6}. The 1 indicates stands for another input is a seasonal lag, in this case, y_{t-52} as this data is weekly and there are 52 weeks per year. The last number indicates the number of nodes that work out the non-linear relationship. For one-step forecasts, the model uses historical input, and for two steps forecasts, it uses the first step plus the historical data. The problem with the forecast using neural networks is that it is not based on a well-defined stochastic model. Therefore the model iterates to see the different forecasts researchers could have and from there it creates the prediction interval. (Appendix 12, 13)

Theta Model

The Theta Model modifies the local curvatures of the time series with the Theta-coefficient to the second difference of the original data. The smaller the value of the theta coefficient, the more it is approximated to a regression line. If the coefficient is low, it means that the fluctuations decrease and therefore, the differences between successive terms are decreased, leading to a better view of long-term trends in data. If the coefficient is high, there are more fluctuations created by the theta line, leading to an augmentation of the view of short-term behaviour. In this hybrid model, the goal of the theta model is to improve the view of long-term behaviour. When forecasting, the model deseasonalizes and decomposes the original data into different theta lines, which are extrapolated separately, and its forecasts are combined. In the case of this model, researchers used an ETS(A,N,N) to forecast each theta line. After combining the forecasts, the data is reseasonalized, leading to the final forecast. (Appendix 14)

STL Model

STL stands for Seasonal and Trend decomposition using LOESS, a method for estimating non-linear relationships. First of all, the model divides the original data into the seasonal component and the seasonally adjusted component, the one with no seasonality. In the case of this model, it fitted an ETS(A,N,N) in the seasonally adjusted component. The ANN means it detected no trend and no seasonality, only additive errors. For the seasonal component, it uses the benchmark method seasonal naive; this means it assumes that the seasonality does not change a lot through time and uses the last observed value from the same season. Afterwards, it combines both, and this gives us the model. (Appendix 15)

Forecast

Researchers forecasted 1,5 years, until the end of 2019, as this data ends in May of 2018 (Appendix 16). In the forecast, the trend keeps on being quite constant, and the seasonality is still represented. This means that the issue with air pollution is not getting worse if the conditions remained the same as in 2018, but many policies have been removed since then, meaning it is most probable that NO_2 levels will have increased again.

Conclusion

In conclusion, the NO_2 levels have decreased throughout the years, meaning the policies seem to have been useful. If the policies were still the same policies implemented in Madrid by 2018 the situation could improve, but taking into account that many policies have been removed, there is a big probability that the situation will get worse again, if no new policies are implemented shortly. Regarding the model, the best moment 1 model investigators could find is the hybrid of ARIMA, STL, Theta and NNAR, but the researchers believe that a moment 2 model could fit better the time series and could make better forecasts, as it will be able to manage the non-linear relationship much better. The moment 1 models are based around the mean, while the moment 2 models are designed around the variance of the data.

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Appendix

Appendix 1: Laws

2003

Spain:

- 27 December → Emission control of organic compounds.

Europe:

- 13 October → Scheme for trade in greenhouse gas emission rights in the community

2004

Spain:

- 12 March → Prior notification and registration of installations emitting volatile organic compounds is regulated in the community of Madrid
- 27 August → Regulation of greenhouse gas emission rights

Europe:

- 3 December → Reduction of ozone-depleting substances
- 15 December → Reduction to arsenic, cadmium, mercury, nickel and aromatic hydrocarbons

2005

Spain:

- 9 March → Regulation of greenhouse gas trade rights x2

Europe:

- 8 September → A review of the measures to be taken against the emission of gaseous and particulate pollutants from ignition engines, and regulation of the emission of gases from spark ignition engines fuelled with natural gas or liquefied petroleum gas

2006

Spain:

- 24 February → Prior notification and registration of installations emitting volatile organic compounds is regulated in the community of Madrid
- 9 May → Prior notification and registration of installations emitting volatile organic compounds is regulated in the community of Madrid

Europe:

- 18 July → Amending Annex IV = European Parliament Regulation and Council Regulation on persistent organic pollutants
- 14 December → Determining the respective emission levels allocated to the community

2007

Madrid only:

- 6 February → Regulation of prior notification and registration of installations emitting volatile organic compounds is regulated in the community of Madrid

Spain:

- 15 November → Air quality law and atmospheric protection

Europe:

- 27 March → Establishing a mechanism for allocating quotas to producers and importers of hydrochlorofluorocarbon
- 27 July → Amendment of the regulating the expulsion of ozone-depleting gases
- 19 December → Standard leakage control requirements for stationary refrigeration, air conditioning and heat pump equipment

2008

Spain:

- 21 September → Regulation of emitted gases causing ozone depletion

Europe:

- 2 April→ Minimum requirements and conditions for the mutual recognition of the certification of undertakings and personnel as regards fixed fire protection systems and fire extinguishers containing certain fluorinated gases of greenhouse effect
- 2 April → Minimum requirements for training programmes and conditions for the mutual recognition of staff training certificates with regard to air-conditioning systems for certain motor vehicles

2009

Madrid only:

- 12 March → Increased monitoring and control of industrial air pollution

Europe:

- 23 April → Law on member states' efforts to reduce their greenhouse gas emissions
- 21 October → Implementation of the method for recovering steams of furtive gasoline refueling of motor vehicles in the refueling stations

2010

Spain:

- 5 July → Greenhouse gas trading rights regulation act
- 5 November → Regulation of labelling and packaging of substances
- 29 December → Carbon dioxide geological storage law

Europe:

- 19 November → Limitation of emission of volatile organic compounds

2011

Spain:

- 13 May → Certain conditions are laid down for the control of emissions to air of oil refineries

Europe:

- 28 January → The catalogue of potentially polluting atmospheric activities is updated and the basic provisions for its implementation are
- 24 March → Regulation on essential uses for laboratory purposes and analysis in the union of regulated substances other than hydrochlorofluorocarbons
- 11 May → Emission performance standards for new light commercial vehicles are established as part of the union's integrated approach to reduce CO2 emissions from light commercial vehicles

2012

Spain:

- 14 January → Notification by the Kingdom of Spain of the extension of the deadline for reaching the limit values for NO_2 in three zones where air quality is to be assessed
- 19 July → Complements the legal regime on limiting emissions of volatile organic compounds in certain paints and varnishes

Europe:

- 29 May → Committee on the Environment, Public Health and Consumer Protection

2013

Spain:

- 8 February → Regulation of the direct granting of aid under the environmental incentive scheme for the purchase of commercial vehicles
- 29 October → Act establishing certain measures in the field of environmental taxation and adopting other tax and financial measures

Europe:

- 30 October → Decision confirming the average specific emissions of CO2 and the specific emissions targets applicable to tourism manufacturers

2014

Madrid only:

- 3 April → Of the councillor for the environment and regional planning, approving the community strategy for air quality and climate change in Madrid 2013-2020
- 22 December → Order of the councillor for the environment and regional planning laying down the regulatory basis for the granting of aid for the purchase of efficient, auxiliary and service light commercial vehicles

Spain:

- 29 April → Taxes on fluorinated greenhouse gases
- 12 December → Creates a mechanism for offsetting costs of indirect greenhouse gas emissions for companies in certain industrial sectors and subsectors that are considered to be exposed to a significant risk of carbon leakage

2015

Spain:

- 6 November → It regulates the acquisition of carbon credits from the plan of impulse to the environment, for the reduction of greenhouse gases in the installations of companies

Europe:

- 25 November → Limitation of emissions to air of certain pollutants from medium combustion plants

2016

Only Madrid:

- 13 June → More control in the field of environmental quality

Spain:

- 5 March → Measures to reduce the number of petrol vapours emitted during refuelling of vehicles

Europe:

- 30 May → Best available techniques for common water and waste gas treatment and management systems are established
- 3 November → Approval of the photovoltaic roof battery charger as an innovative technology for the reduction of CO_2 emissions
- 3 November → Approval of technological advances for electric cars to reduce the emission of gases
- 14 December → Emissions of gaseous pollutants into the atmosphere are reduced

2017

Only Madrid:

- 28 March → The commissioner of the government of the community of Madrid for the climate change is created
- 5 June → Laying down the regulatory basis for investment aid for the replacement of fossil fuel boilers by biomass-fired forest boilers
- 21 November → Adopted framework protocol for action during episodes of high contamination by NO_2

Spain:

- 28 July → Various royal decrees on industrial products and emissions are amended
- 22 December → Limitation of emissions to air of certain pollutants from medium combustion plants

2018

Only Madrid:

- Car limitation in the centre of Madrid

Spain:

- 6 July → Measures to reduce national emissions of certain air pollutants

Europe:

- 29 November → Technology approval in light commercial vehicles equipped with conventional combustion engines as an innovative technology for reducing CO2 emissions

Appendix 2: Gases

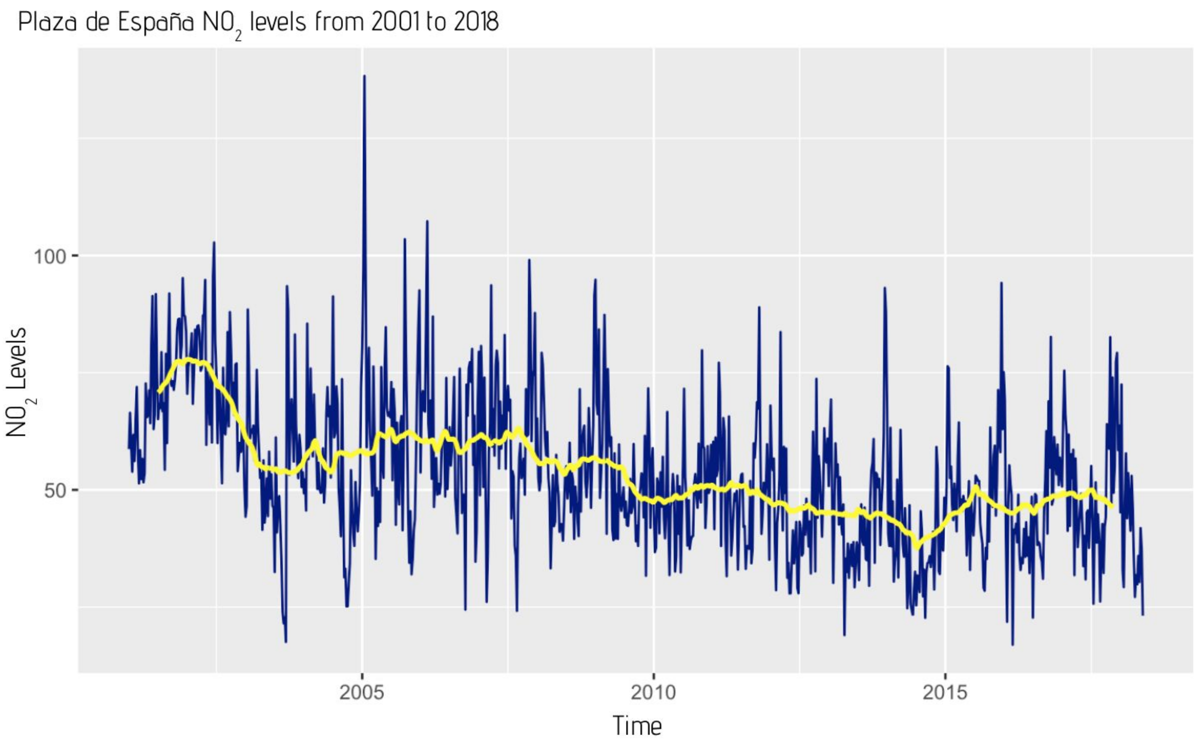
1. SO_2 - sulphur dioxide
2. CO - carbon monoxide
3. NO - nitric oxide
4. NO_2 - nitrogen dioxide
5. PM25 - particles smaller than 2.5 µm
6. PM 10 - particles smaller than 10 µm
7. NOx - nitrous oxides
8. O_3 - ozone
9. TOL - toluene (methylbenzene)
10. BEN - benzene
11. EBE - benzene
12. MXY - m-xylene
13. PXY - p-xylene
14. OXY - o-xylene
15. TCH - total hydrocarbons
16. CH4 - methane
17. NMHC - non-methane hydrocarbons

Appendix 3: Stations

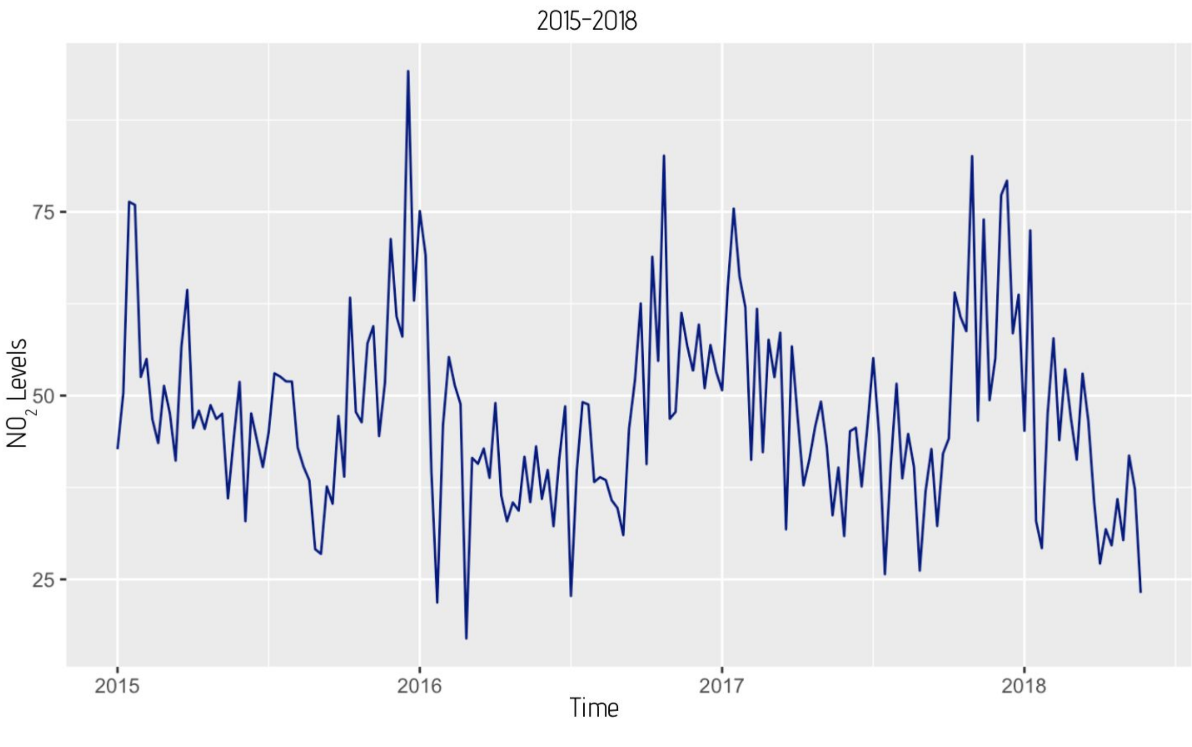
1. Pza. de España
2. Esc. Aguirre
3. Ramón y Cajal
4. Cuatro Caminos
5. Barrio del Pilar
6. Castellana
7. Pza. Castilla
8. Pza. del Carmen
9. Méndez Álvaro
10. Retiro
11. Moratalaz
12. Vallecas
13. Ens. Vallecas
14. Arturo Soria
15. Barajas Pueblo
16. Urb. Embajada
17. Sanchinarro
18. Tres Olivos
19. Juan Carlos I
20. Casa Campo
21. El Pardo
22. Fdez. Ladreda
23. Villaverde

24. Farolillo

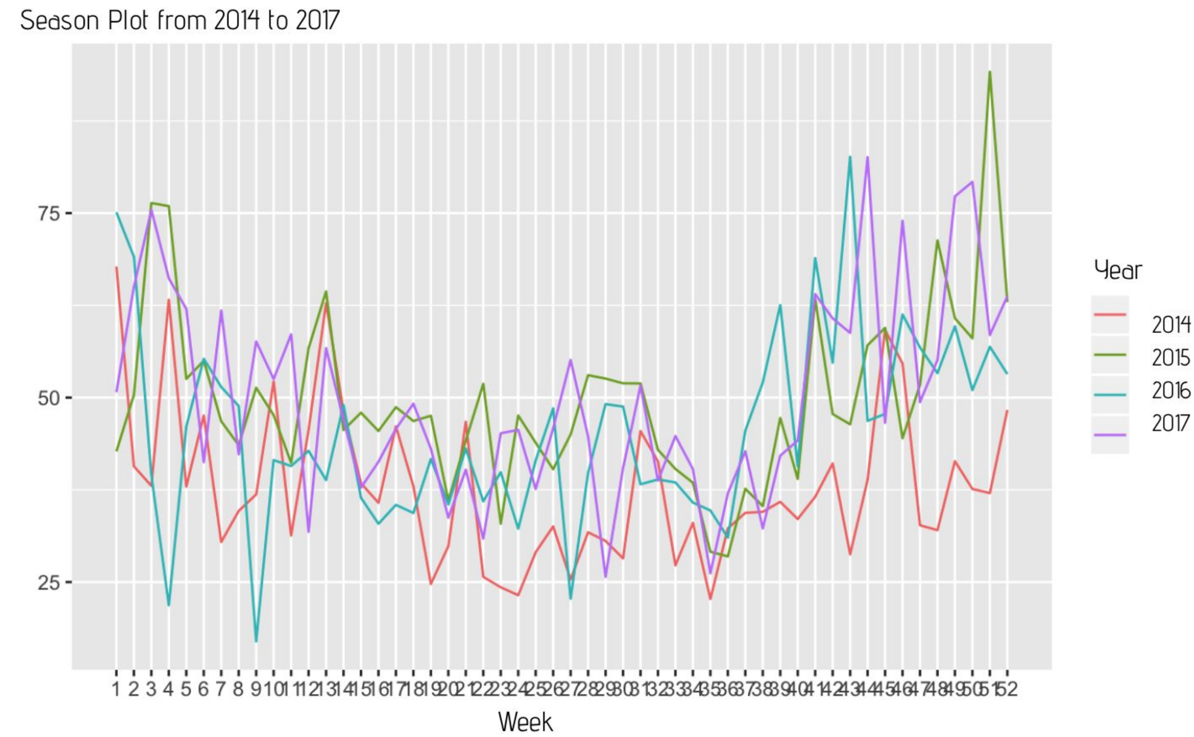
Appendix 4: Plaza de España NO_2 Levels from 2001 to 2018 Plot



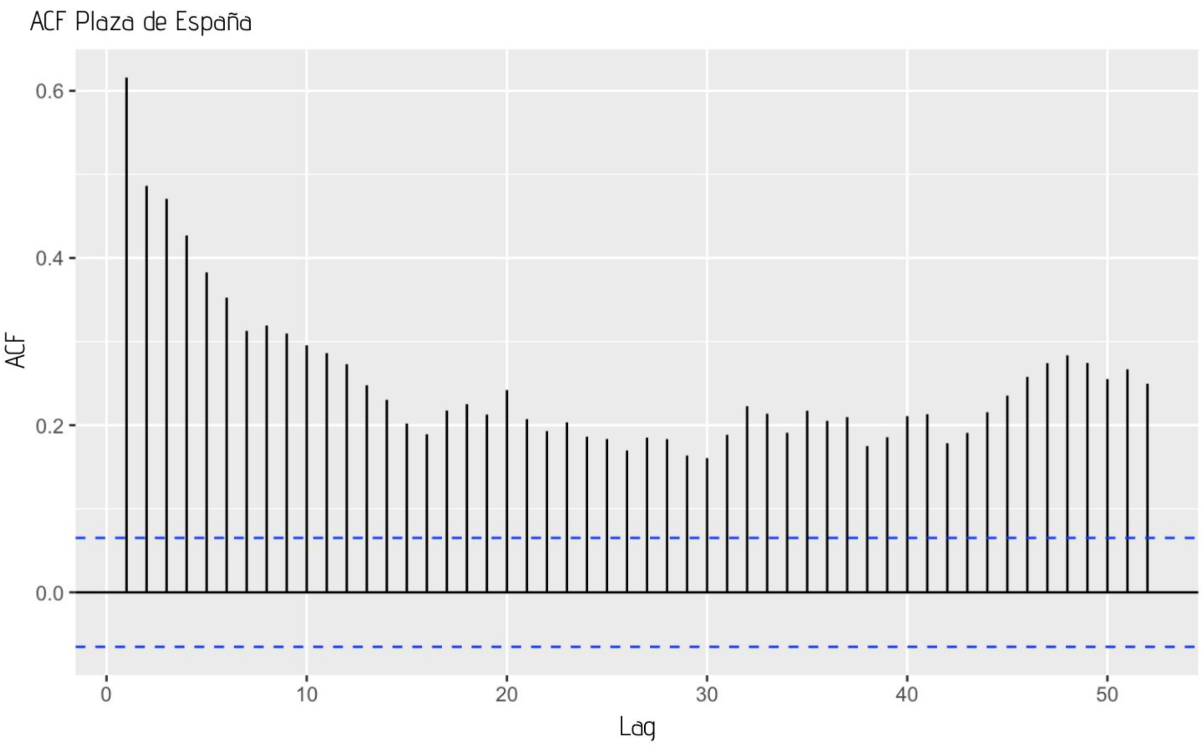
Appendix 5: Plaza de España NO_2 Levels from 2015 to 2018 Plot



Appendix 6: Plaza de España Season Plot from 2014 to 2017



Appendix 7: Plaza de España ACF Plot (first 52 lags)



Appendix 8: AICc and MAPE from Plaza de España Models

Model	AICc	MAPE	White noise	Normal
ARIMA(3,0,0)	7118,05			
ARIMA(3,0,1)	7107,94	28,89364	NO	NO
ARIMA(1,0,2)	7125,52	28,72317		
ARIMA(1,1,0)	7252,31			
ARIMA(0,1,2)	7113,57			
ARIMA(0,1,1)	7146,01			
ARIMA(2,1,0)	7175			
ARIMA(2,1,2)	7090,73	22,38095	NO	NO
ARIMA(1,1,1)	7108,65			
ARIMA(2,1,1)	7104,21			
ARIMA(3,1,2)	7087,75	22,42042	NO	NO
ARIMA(1,0,2), nonzero mean	7105,17			
ETS(A,N,N)	8516,913	22,88340	NO	NO
Average		32,12275	NO	NO
Random Walk		22,17561	NO	NO
Seasonal Naive		23,25896	NO	NO
Random Walk+drift		22,09100	NO	NO
TBATS(0.405, {2,1}, -, {<52,4>})		25,21437	NO	NO
ARIMA(1,0,3)+trend linear model	6279,13	53,33295	NO	NO

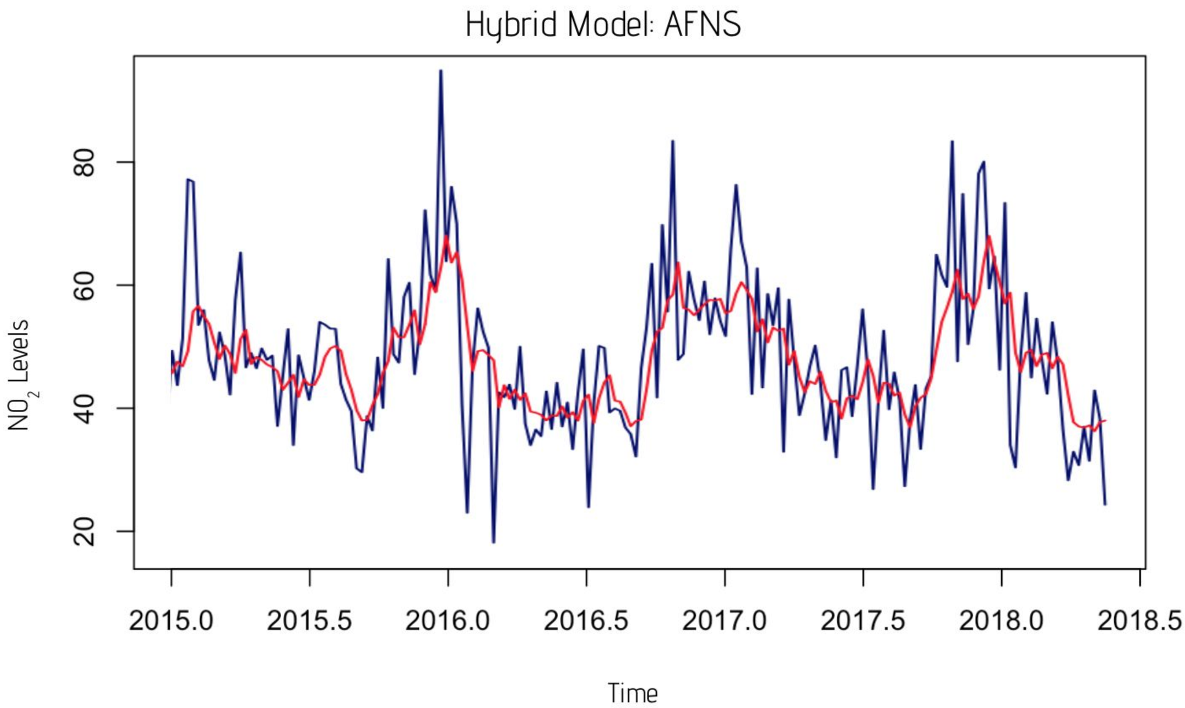
ARIMA(1,0,2)+trend linear model	6279,81	53,16958	NO	NO
NNAR(20,1,11)[52]		23,34536	NO	NO
Afnst Equal		19,78464	NO	NO
Afnst Insample		20,68277	NO	NO
Afns Equal		19,89509	NO	NO
Afns Insample		21,68913	NO	NO

Appendix 9: AICc and MAPE from Casa de Campo Models

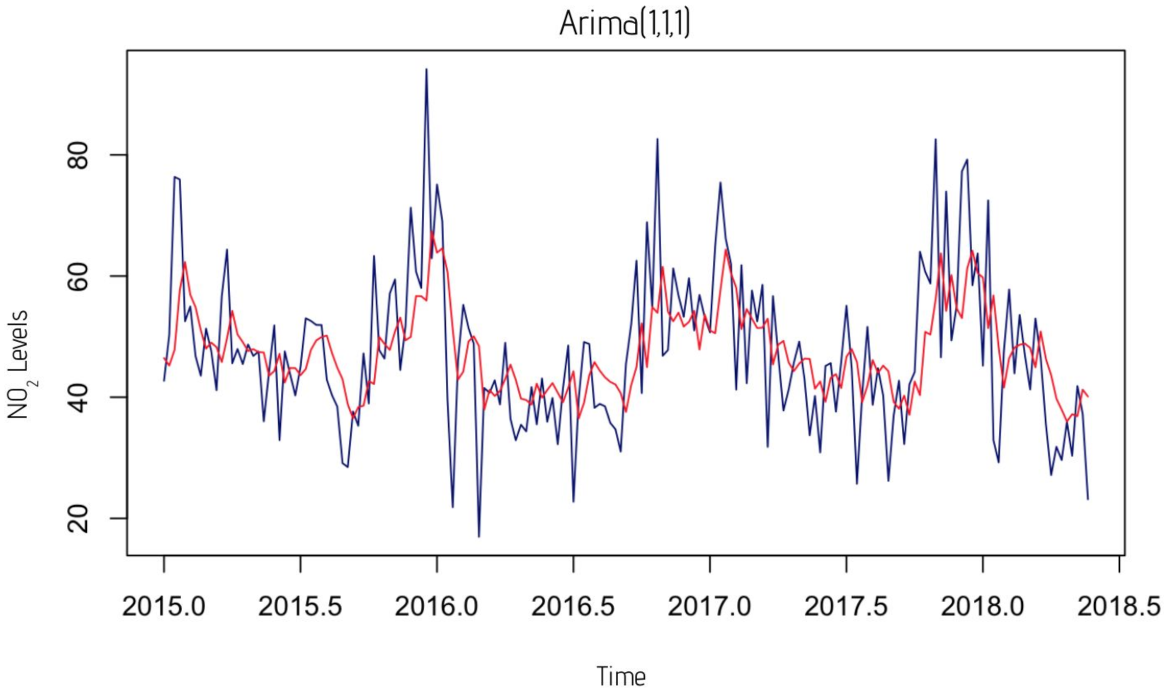
Model	AICc	MAPE	White noise	Normal
ARIMA(0,1,1)	6902,7		NO	NO
ARIMA(2,1,2)	6898,47		NO	NO
ARIMA(3,1,2)	6900,04		NO	NO
ARIMA(2,1,0)	6938,52		NO	NO
ARIMA(3,1,0)	6912,37		NO	NO
ARIMA(0,1,2)	6896,13		NO	NO
ARIMA(1,0,1)(2,1,1)[52]	6545,86		NO	NO
ARIMA (1,0,3)(2,1,1)[52]	6525,67		NO	NO
ARIMA (2,0,3)(3,1,1)[52]	INF			
ARIMA (1,0,1)(3,1,1)[52]				
ARIMA (2,0,1)(2,1,1)[52]				
ARIMA (1,0,3)(3,1,1)[52]				
ARIMA (2,0,3)(2,1,1)[52]				
Trend Regression		47,49947	NO	NO
Trend Regression + simple ds		115,85610	NO	NO
Trend+Seas Regression		32,42436	NO	NO
TBATS(0.579, {1,1}, -, {<52,4>})		30,06231	NO	NO
NNAR(12,1,7)[52]		111,44140	NO	NO
STL + ETS(A,N,N)		33,72410	NO	NO

Average	85,68642	NO	NO
Random Walk	183,04908	NO	NO
Seasonal Naive	41,45922	NO	NO
Random Walk + drift	193,84075	NO	NO
Afnst Equal	40,88777	NO	NO
Afnst Insample	51,99600	NO	NO
Afns Equal	58,98301	NO	NO
Afns Insample	51,84664	NO	NO

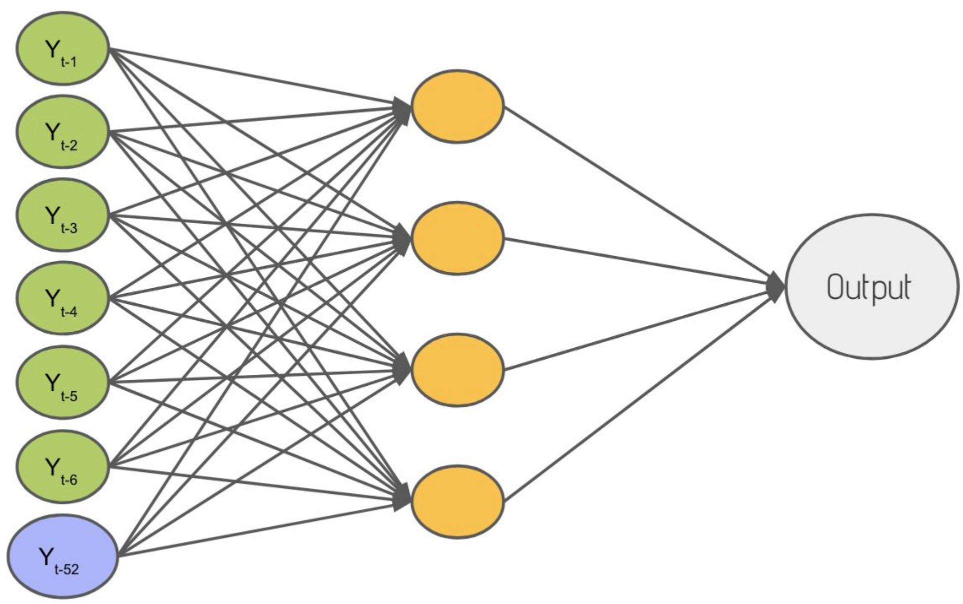
Appendix 10: Hybrid Model Fit



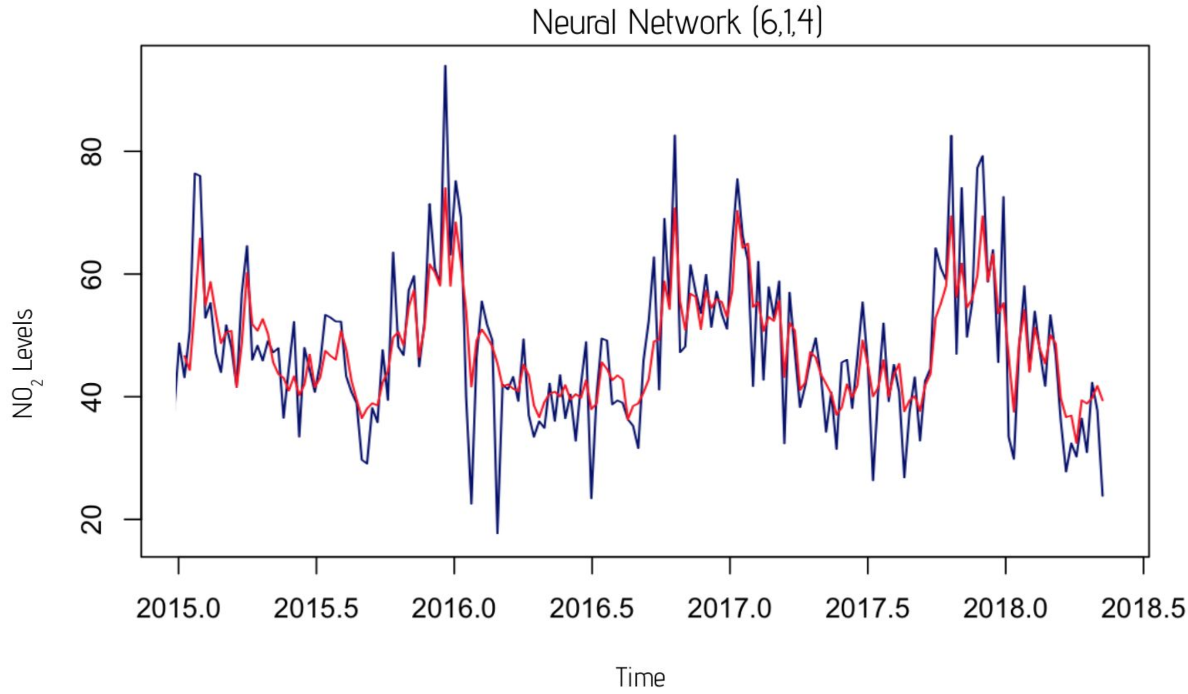
Appendix 11: Arima(1,1,1) Fit



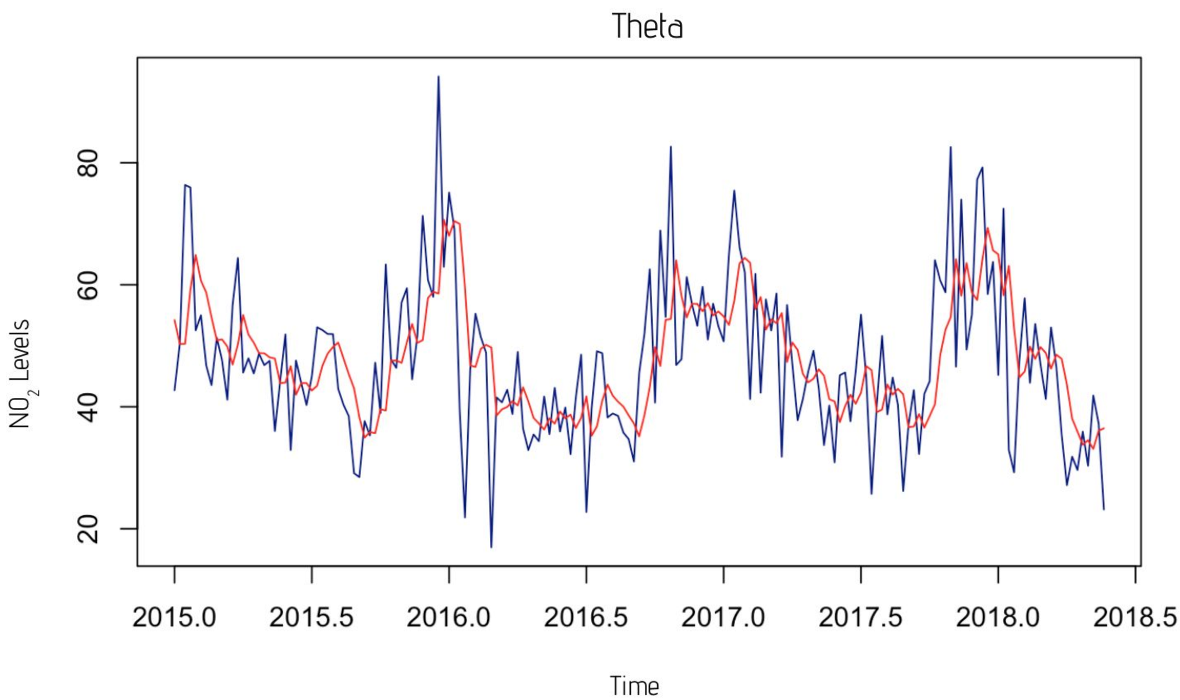
Appendix 12: NNAR(6,1,4)



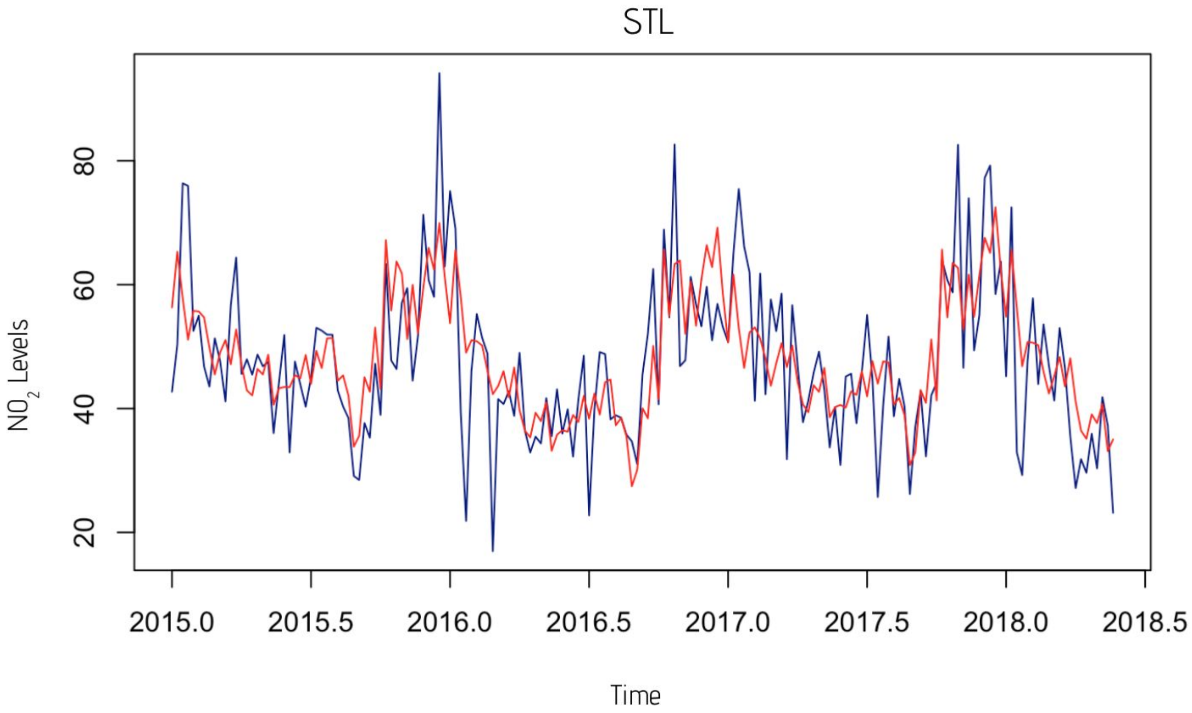
Appendix 13: Neural Network(6,1,4) Fit



Appendix 14: Theta Model Fit



Appendix 15: STL Model Fit



Appendix 16: The Forecast