The Relationship between Air Pollution and COVID-19-related deaths: An Application to three French Cities

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Abstract

We selected three major French cities (Paris, Lyon, and Marseille) to investigate the relationship between the COVID-19 outbreak and air pollution. Using Artificial Neural Networks experiments, we have determined the concentration of $PM_{2.5}$ and PM_{10} linked to COVID-19-related deaths. Our focus is on the potential effects of Particulate Matter in spreading the epidemic. The underlying hypothesis is that a pre-determined particulate concentration can foster COVID-19 and make the respiratory system more susceptible to this infection. The empirical strategy used an innovative Machine Learning methodology. In particular, through the so-called cutting technique in ANNs, we found new threshold levels of $PM_{2.5}$ and PM_{10} connected to COVID19: 17.4 µg/m^3 ($PM_{2.5}$) and 29.6 µg/m^3 (PM_{10}) for Paris; 15.6 µg/m^3 ($PM_{2.5}$) and 20.6 µg/m^3 (PM_{10}) for Lyon; 14.3 µg/m^3 ($PM_{2.5}$) and 22.04 µg/m^3 (PM_{10}) for Marseille.

Keywords: COVID-19, air pollution, Machine Learning, Artificial Neural Networks.

1. Introduction

As one of the most urgent threats on the planet, the World Health Organization (WHO) declared the Corona Virus Disease (COVID-19) as a global health emergency on March 12th 2020 (WHO, 2020a). At the world level and as of April 20th 2020, the WHO reported 157,847 confirmed deaths and 2,314,621 confirmed cases (WHO, 2020b). This virus spreads through three channels: saliva, nasal discharge, or airborne particles (Mitra et al., 2020). Even though most people infected recover without relying on advanced treatment, elderly and sensitive people present an important risk to develop serious and deadly illness (Mitra et al., 2020). The most effective way to prevent and reduce transmission worldwide is by washing hands and using alcohol-based hand sanitizer frequently. Indeed, experts are unanimous on the necessity to control and lower contact among the population, not only to protect uncontaminated individuals, but also to isolate the bearer of the virus. Most of the governments have understood that the quarantine strategy is necessary to keep the pathogen dynamic under control (Mitra et al., 2020).

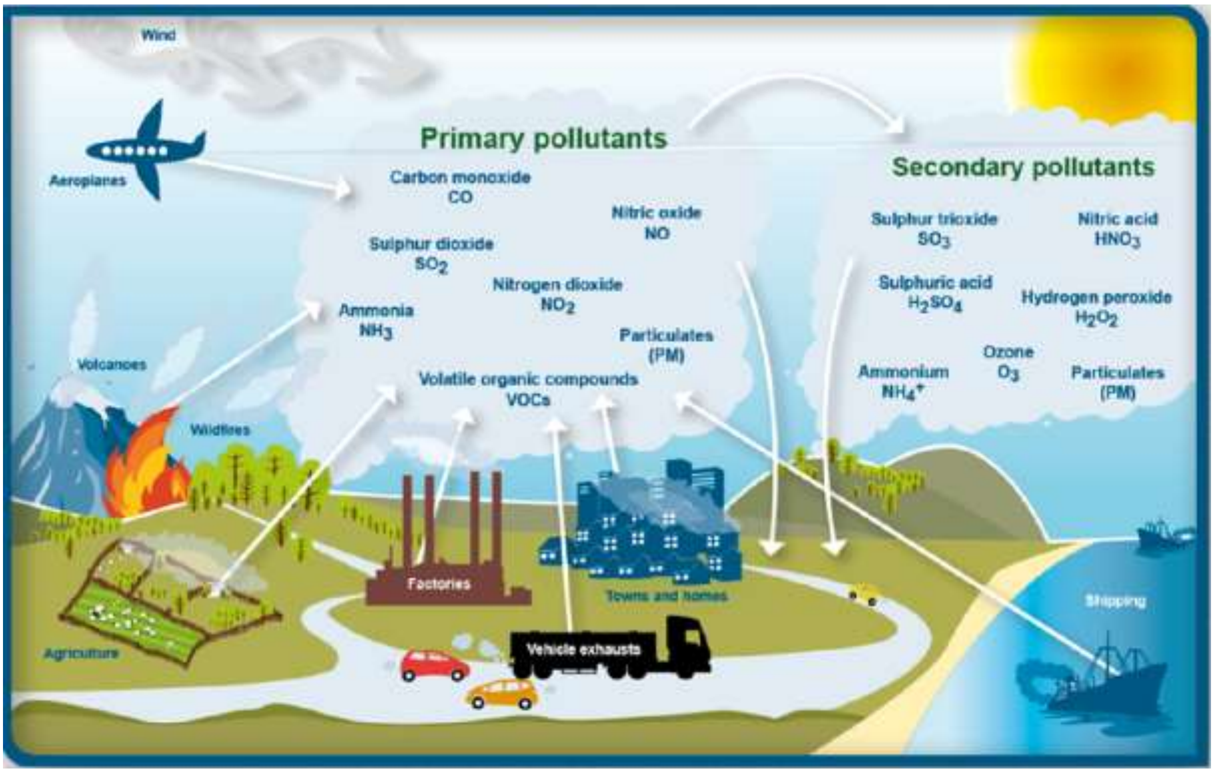
As the epicentre of the pandemic, China was the first country to completely shut-down commercial activities, restrict domestic and international travel, and impose a containment system on the population (Huang et al., 2020). Following that, similar policy measures were adopted by numerous countries, notably France. Beginning on March 17th 2020, the national containment measure decided by the French President, Emmanuel Macron, involved: closing of schools, colleges and universities; shutting down non-essential companies and sending workers home, restriction of public transport operations; forbidding gatherings and meetings in public spaces; requiring individuals to remain in their residence, aside from going out for necessities (Elysée, 2020). This state of sanitary emergency is not without major consequences. It is expected to seriously impact the world economy[1], without sparing the French economic growth. Numerous industries are impacted, especially tourism, catering, apparel, culture, aeronautic, and automotive sectors.

Economic activity is a well-known factor contributing to global environmental pollution because fuel combustion directly releases Greenhouse Gas (GHG) emissions into the atmosphere (Intergovernmental Panel on Climate Change (IPCC), 2007). In major world cities, air is considered polluted because high concentrations of harmful particles have been recorded

[1] According to the UN Department of Economic and Social Affairs (DESA, 2020), the COVID-19 pandemic has almost totally disrupted international trade. Thus, the global economy is expected to shrink around 1% in 2020 due to the COVID-19 pandemic (Mitra et al., 2020).

for years (Anjum, 2020). Among them, one finds generally primary pollutants[2] (methane, CH_4; carbon monoxide, CO; nitrogen dioxide, NO_2; sulphur oxides, SOx). However, important secondary pollutants (nitrogen dioxide, NO_2; ozone, O_3; sulphur trioxide, SO_3) can be recorded in densely populated cities. Furthermore, evidence of critical levels of small size components (PM_{10} and $PM_{2.5}$)[3] have also been confirmed in the two last decades. The Particulate Matter (PM) concentration is driven by vehicle engines and factories, and by fossil fuel combustion in general. It can also be formed by a reaction of several pollutants in the atmosphere, making PMs both primary and secondary pollutants. Figure 1 summarizes the main information regarding types and sources of air pollutants.

Figure 1: Types and origins of major air pollutants.



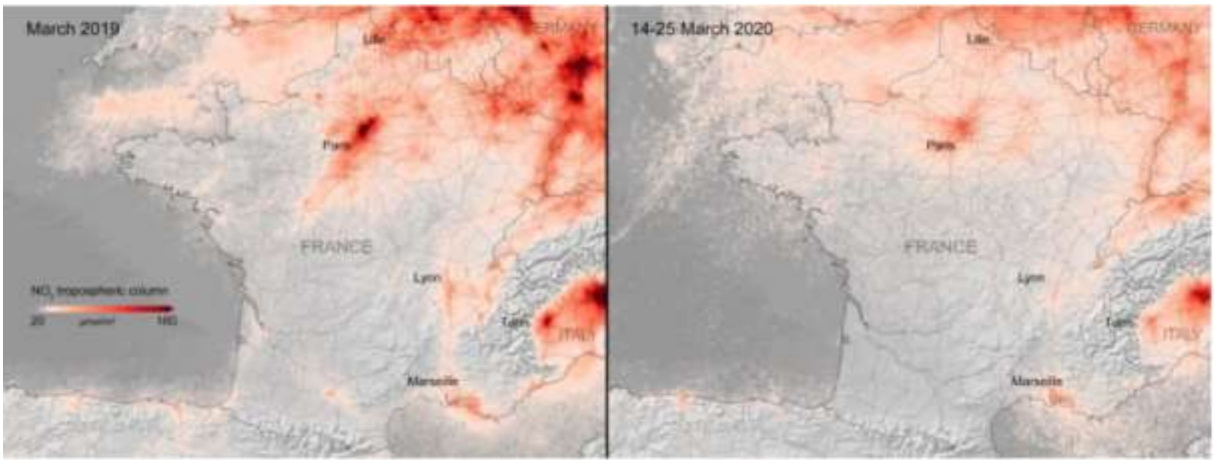
Source: (Helen, 2020).

[2] Primary pollutants refer to any type of pollutant that are directly emitted from a single source into the air including many sources including vehicles, coal-fired power plants, natural gas power plants, and biomass burning. They differ from secondary pollutants which are instead formed when two or more primary pollutants react with each other in the atmosphere.

[3] PM_{10} and $PM_{2.5}$ are ultrafine harmful particles pollution whose diameter is inferior to 0.1 and 0.025 mm, respectively.

Air pollution induces important health risks[4] for the population including respiratory, infections, asthma, chronic obstructive pulmonary disease, and lung cancer (Kim et al., 2018; Nunez, 2019). Therefore, mitigating this has become a key target for mayors of large cities. Recently, this issue has been growing for French cities. The Paris city council banned cars from using the roads near the Seine river in 2016. In Marseille, parking costs for non-residents increased when the city recorded pollution peaks in 2019. In Lyon, the council adopted a motion in 2020 to allow only less polluting vehicles to circulate when pollution peaks are confirmed. However, we must admit that none of these measures are comparable to the COVID-19 related shut-down. Interestingly, one unexpected externality of the COVID-19 lockdown is the significant lowering in both primary and secondary pollutant emissions, raising questions about the well-established relationship among human activities and air quality. Indeed, major French cities have experienced remarkable drops in air pollution, notably for PMs and NO_2 emissions as these pollutants come mainly from traffic. As shown in Figure 2, NO_2 level has drastically fallen in March 2020 when compared to the same period in 2019.

Figure 2: Reduction in NO_2 level in major French cities due to the COVID-19 lockdown (comparison between March 2019 and 14-25 March 2020).



Source: Balkan Green Energy News (2020).

Just before the mandatory containment measures (i.e., March 12th 2020), the WHO (2020b) reported 48 confirmed deaths and 2,269 confirmed cases. The Situation Report n. 98 on COVID-19 published by the WHO (2020c) indicated 22,821 confirmed deaths and 123,279 confirmed cases, as of April 27th 2020. Looking at the city level, confirmed deaths recorded a

[4] Air pollution contributed to 9% of deaths worldwide for the year 2017 which is equivalent to 7 million deaths (Anjum, 2020). Consequently, air pollution has been recognized as one of the world's important deaths drivers after high blood pressure, smoking and high blood sugar (Ritchie and Roser, 2019).

dramatic increase over the March 18th-April 27th period: from 14 to 1,387 in Paris; from 0 to 481 in Lyon; from 4 to 381 in Marseille (French National Public Health Agency, 2020). If the restriction of public and domestic transportation has resulted in obvious reductions of fuel combustion, several questions remain unanswered. Since there are no specific vaccines for COVID-19 for the moment, the ongoing COVID-19 crisis is currently far from being over.

The literature on this topic is very scarce and the few existing studies are quiet recent. Scientific literature highlighted that the exposure to air pollution matters for the spread of viral infection (Chen et al., 2010; Ye et al., 2016; Chen et al., 2017; Peng et al., 2020); notably with regard to the COVID-19 diffusion (Conticini et al., 2020; Setti et al., 2020; Wu et al., 2020). These latter studies concluded that air pollution is an effective determinant of the spread of COVID-19. However, the feedback channel remains less investigated. Mitra et al. (2020) studied the atmospheric CO_2 levels for the city of Kolkata (India) comparing the April 2019 and April 2020 periods. Focusing on Chinese provinces, Huang et al. (2020) analysed the variations in primary and secondary pollution emissions during the COVID-19 lockdown. Using a different method, Wang et al. (2020) explored the effects of emission reductions on air pollution due to decreased human activity during the Chinese COVID-19 outbreak. Overall, these research works unanimously show that the COVID-19 lockdown caused large emission reductions.

This research presents three novelty aspects. First, our results are the only ones currently able to demonstrate the concentration amount of PM_{10} and $PM_{2.5}$ capable of generating the adverse effect of Covid-19. Second, this paper fills the gaps in the literature and analyses the French case in a single study. Third, this study relies on the innovative Machine Learning (ML) methodology.

This study investigates the relationship between COVID-19 diffusion and air pollution for three major French cities. Having collected daily data on deaths, resuscitations, and hospitalizations for COVID-19 infection, we focus on two pollutants: PM_{10} and $PM_{2.5}$. We collected data on the largest and most recent available period for all cities: from March 18th to April 27th 2020 (41 consecutive days of observation).

The rest of this paper is organized as follows: Section 2 gives a brief review of the literature. Section 3 describes the data and the methodology employed. Section 4 presents the empirical results. Section 5 gives results' interpretation and discussion. Section 6 suggests concluding remarks and policy recommendations.

2. A Concise Literature Review

Because of its recent nature, the literature tackling the COVID-19-air pollution relationship is very seminal. While a few studies examined the Chinese and Indian cases, no study has been currently made public on the French case. This section aims at presenting research works performed at different scales (International, national/provincial, and city level). First, we introduce Anjum (2020)'s study making a broad overview on the international COVID-19 situation and its link with air pollution for major countries (China, India, France, Italy and the US). Second, we present the pioneer empirical research works performed by Huang et al. (2020) and Wang et al. (2020) and focusing on Chinese provinces. Third, we outline the contribution from Mitra et al. (2020) on the specific case of Kolkata city (India).

Anjum (2020) built a global assessment on COVID-19 restrictions and air pollution enhancements. Starting with an overview on the relationship between air pollution and respiratory diseases, the author compiled major public data reporting drastic reductions of air pollution for countries affected by COVID-19 virus spread. With a special focus on major cities in China, Lombardy (Italy), France, the US and India, Anjum (2020) relevantly suggested that the temporary nationwide lockdowns have first resulted in obvious significant reductions in air pollutions. However, at the end of the COVID-19 crisis, one cannot omit that restoring the normal situation may reverse air pollution trends.

Since Wuhan announced lockdown on January 23th 2020, a major part of human an economic activity has been prohibited. However, severe air pollution events continued to occur. The recent studies from Huang et al. (2020) and Wang et al. (2020) aim at explaining why severe air pollution were not avoided in China. To do so, they both estimated emissions reduction due to COVID-19 outbreak. Huang et al. (2020) analysed the variations in primary and secondary pollution emissions during the COVID-19 lockdown and underlined the link between these pollutants. Using a chemical transport modelling, they showed that haze events during the COVID-19 lockdown were driven by a global reduction of secondary pollution emissions. They linked it directly to the drop in transport. According to the authors, this induced a large decrease in Nitrogen oxides (NOx) emissions (primary pollutants) what led to an increase in O_3 and NO_3, decreasing most of secondary pollutants (but not all) and facilitating in turn the formation Particulate Matter (PM). Therefore, this comprehensive approach suggested that large (but imbalanced) reductions in primary pollutant emissions in China unexpectedly facilitated the formation of some secondary emissions pollutants, creating haze pollution. Finally, the authors bring an estimation of provincial emission reduction of primary and secondary pollutants. Upon them, nitrogen oxides (NOx) and Volatile Organic Compounds (VOCs) show the highest enhancements. To study $PM_{2.5}$ changes under emission reduction scenarios, Wang et al. (2020)

employed a Community Multiscale Air Quality model over the period from January 01 to February 12th 2020. Focusing on Chinese provinces, the authors found evidence that $PM_{2.5}$ concentrations decreased by 20% over this period. They engaged in further analysis in including the meteorological factor and suggested that the unfavourable weather conditions influenced the simulation results. Both studies highlight an interesting point: even though the COVID-19 lockdown produced large primary and secondary emissions reduction, this are temporary enhancements and it would not avoid severe air pollution degradation on the long-run in China. Therefore, there is a large room for improvements.

Focusing on the city of Kolkata (India), Mitra et al. (2020) compared the atmospheric CO_2 levels between April 2020 (lockdown phase) and April 2019 (pre-COVID-19 phase). Using data taken from 12 different locations, the authors observed significant variation of CO_2 levels between periods but no change between sites. Thus, as industries and transports represent the main determinants of CO_2 emissions, Mitra et al. (2020) interpreted this result as the direct lockdown effect due to COVID-19.

This literature review highlights two important points. First, since the COVID-19 crisis is currently far from being over, the few empirical works bring non-sophisticated results but seminal evidence. Second, at the time this paper was written, we found no empirical study investigating the relationship between COVID-19 pandemic expansion and air pollution for the French case. Our paper finds its empirical contribution in the literature by providing a first and preliminary study on major French cities. Furthermore, we rely on the innovative ML method to perform this analysis.

3. Data Collection and Methodology

3.1. Data Collection

To assess the relationship between COVID-19 diffusion and air pollution in France, we rely on daily data at city level.

We collected data on confirmed deaths (total and daily), resuscitations (daily), and hospitalizations (daily) due to COVID-19 for each selected department: Paris (the *Paris* department), Marseille (the *Bouches du Rhône* department), Lyon (the *Rhône* department). Data are compiled from the reports published by the French National Public Health Agency (Santé Publique France, 2020)[5] and updated with daily frequency.

[5] COVID-19 data are available at: https://www.santepubliquefrance.fr/

We computed air pollution concentrations levels for related 3 major French cities (Paris, Marseille, Lyon). By order, Paris is the most populated, followed by Marseille (2^{nd}), Lyon (3^{rd}) (French National Institute of Statistics and Information about the Economy (INSEE), 2020). We used 2 different pollutants: PM_{10} and $PM_{2.5}$ (expressed in $\mu g/m^3$). For each city and each pollutant, we collected and average the concentrations measures given by operating environmental monitoring stations. Having averaged hourly data for each city, we then calculated the daily arithmetic average. Thus, we obtained an averaged air pollution concentration for each day, each pollutant, and each city. Air pollution data are collated by the French Federation of Certified Associations for the air quality monitoring (Atmo France, 2020). This federation gathers all air quality monitoring institutes across the French territory. For Paris, air pollution data are taken from AirParif[6] based on information given by 40 environmental monitoring stations. For Marseille, air pollution data are taken from AtmoSud[7] using information from seven environmental monitoring stations. For Lyon, air pollution data are collected by Atmo Auvergne-Rhône-Alpes[8] using eleven environmental monitoring stations.

Because the unprecedented COVID-19 crisis is evolving every day, performing such study requires to compute the most recent and refined daily data on COVID-19 expansion and air pollution. Therefore, data span the largest and latest available period for all cities: from March 18^{th} 2020 to April 27^{th} 2020 (included); allowing us to observe the changes in our variables of interest during 41 consecutive days for each city. Notice that the choice of starting period was constrained by COVID-19 data availability. Indeed, the French National Public Health Agency (Santé Publique France) started to publicly provide daily estimations of COVID-19 expansion (deaths) for each department from March 18^{th} 2020 onwards.

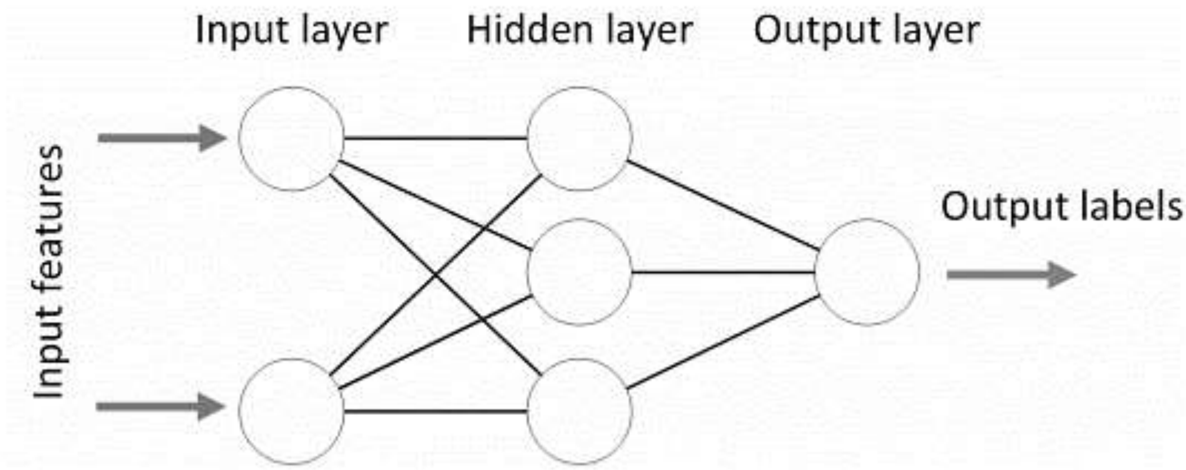
3.2. Methodology

After collecting the data and storing it in a database from which a well-defined structure can be extracted, we proceed with the search for the optimal ML algorithm. These techniques are subsequently adopted using the measurements collected in the previous phase. Our goal is to be able to train a machine so that it learns to perform certain operations in order to obtain the desired results without explicitly providing it with the necessary algorithm. The machine must be able to determine the links present in a dataset by developing a specific behaviour. This learned behaviour can then be used to make timely forecasts and estimates on new data. We use

[6] Air pollution data for Paris are available at: http://www.airparif.asso.fr/publications/
[7] Air pollution data for Marseille are available at : https://www.atmosud.org/donnees/acces-par-station
[8] Air pollution data for Lyon are available at: https://www.atmo-auvergnerhonealpes.fr/donnees/telecharger

a model of Artificial Neural Networks (ANNs) through the implementation of the AD-Designer platform. We use a series of neurons grouped in layers. Each layer receives inputs from the previous layer and supplies the outputs to the next layer. The initial layer, connected to the input data, is called the input layer, whilst the final layer, which provides the network output, is called the output layer. Among them, there can be various hidden layers, which can increase the complexity and potential of the network. An example of a layered network is shown in Figure 3.

Figure 3: ANNs example.



Source: our elaborations.

In our NN experiments, we define non-linear activation functions for each neuron. This function is applied to the output of the neuron before it is passed onto the next neuron. Usually, the same activation function is applied to neurons of the same layer. These functions are chosen according to needs, and allow us to model a non-linearity within the network. By superimposing a series of non-linear layers, we obtain an extremely sophisticated model capable of understanding even very complicated relationships. During the training phase, to correct the weights, we use a back-propagation technique. Starting from the output nodes, we use the various gradients for each layer, updating the weights accordingly, until reaching the input layer. Therefore, keeping in mind the characteristics of the available data and the NN estimation technologies, we outline a path that hopefully produces tangible results. The main objective is to define a model capable of carrying out predictive analysis of the quantity of PM_{10} and $PM_{2.5}$ that assists the spread of COVID-19. To carry out the experiments on the three selected French cities, we build ANNs, which are defined through a series of experimental tests. The training of the network takes place by providing it with a series of precise indications regarding the type of algorithm and recommended training. In particular, the difficulty in framing the best architecture of the NN is to find the balance between "Scaling Model" and "Unscaling Method". We therefore choose the combinations that minimizes errors concerning the number of layers that are activated by hyperbolic activation functions. Next, we carry out tests to optimize the algorithm that the machine has chosen to use. Through these tests, we analyze how long it takes (epochs) for the predictive error of estimate to decrease until it reaches a value close to zero. Our analysis proceeds through the performance of the "selections order" about the neurons used by the NN and we verify the distribution of data on the predictive regression line. Finally, we use the so-called cutting technique. In other words, we try to estimate a precise point in the neural transmission from the inputs (PM_{10} and $PM_{2.5}$ levels) to the target (number of deaths in the three French cities due to COVID-19). This identified point will describe the predictive concentrations of particulate matter, which leads to an increase in the number of deaths due to COVID-19.

To replicate the results obtained in Section 4, researchers must precisely follow all the steps in Table 1. In this way, we help scientists to quickly use the NNs in AD-Designer, Python or R to estimate the concentration of $PM_{2.5}$ and PM_{10} in other cities of the world.

All the steps in Table 1 are the result of many combinations and experiments carried out by the Authors.

Table 1: ANNs Experiment procedure.

1

ANNs METHOD	**Experiment**
Scaling layer	Mean and standard deviation
Perceptron layers	Hyperbolic Tangent
Unscaling layer	Minimum-Maximum
Bounding layer	Apply - Target (Deaths)

2

TRAINING STRATEGY	**Experiment**	**Type**
A loss index	Normalized squared error	L2 regularization method
An optimization algorithm	Quasi-Newton method	Very Hight

3

MODEL SELECTION	**Experiment**
Order selection	Incremental order algorithm

4

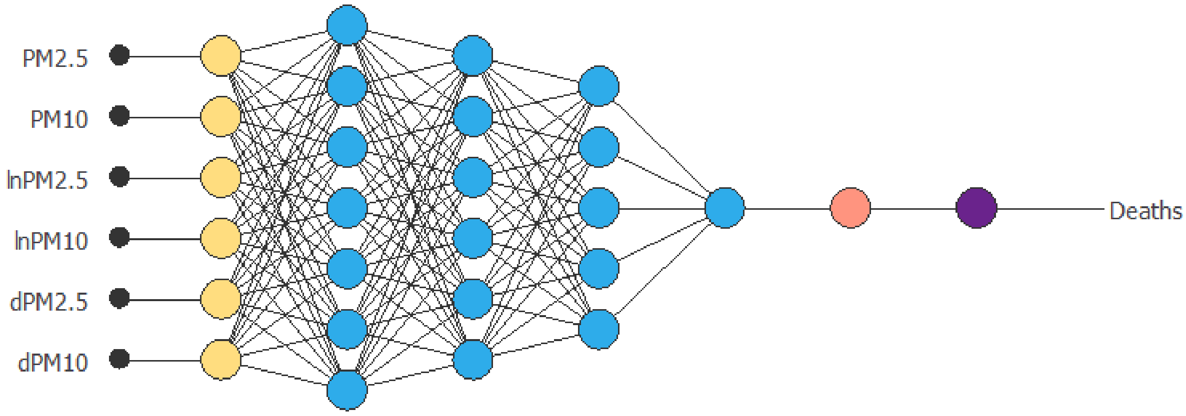
TESTING ANALYSIS	**Experiment**	**Type**
Sunburst ML	Expected Error	Node threshold: 512

Source: our elaborations.

4. Empirical Results

In this section, we show the results obtained for the French cities of Paris, Lyon, Marseille. The ANNs architecture used for each city is always the same (Figure 4). We expanded the data to allow the machine to be able to use a more efficient combination of information. We generated the logarithm of each variable (ln) and the first difference (d). Therefore, the inputs are $PM_{2.5}$, PM_{10} as well as their transforms. The target is represented by the Deaths variable, which represents the number of deaths in cities due to COVID-19.

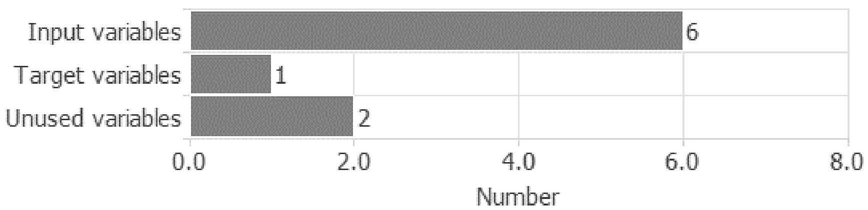
Figure 4: Our ANNs.



Source: our processing on command strings.

Since the architecture of the NN is the same for all the cities, the descriptive neural statistics are described below.

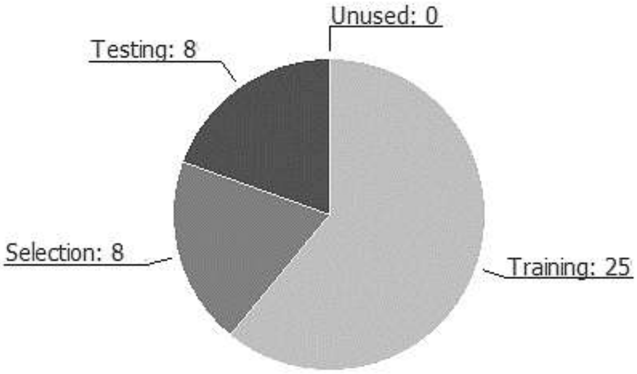
Table 2: Variables bars chart.



Source: our elaborations.

Table 2 represents the summary of the dataset used in our ANNs. The variables used are 9, of which six represent the input process, and one is the generated target. In Figure 5, we show the behaviour of the instances using a pie chart elaborated by our protocol.

Figure 5: Instances pie chart.



Source: our elaborations.

As we can see from Figure 5, the instances of the ML process were equal to 41. Those representing the training are 25 (60.9%). This result underlines how, compared to a choice of *n* projects, our model chose 25 out of 41 potential models. These are the ones that best suit the target. The result confirms that our choice is appropriate. The selection requests were eight (19%). The instances, therefore, selected the best possible NN process concerning the generated target. This result allows us to continue the processing. As for the testing instances, they were eight (19%). This value represents the result of the choice of numerous training models. Since it is the same and never less than the selection instances, this reinforces the previous findings. Finally, the number of unused instances is zero (0%). This result also confirms the effectiveness of our model. No anomalous values (which would have invalidated the results) were generated.

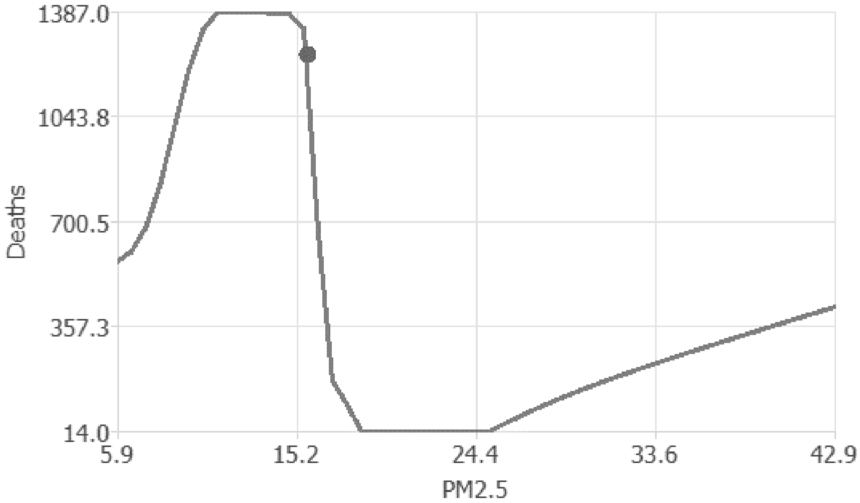
To facilitate the reading of the results obtained and ensure their replication by the scientific community, we have inserted the tests on NN in the Appendix. Below we show our estimation experiment on the concentration level of $PM_{2.5}$ and PM_{10} connected to the deaths during the COVID-19 epidemic in the three French cities. The system used is the “Plot Directional Output”. It is very useful to see how the outputs vary as a function of a single input, when all the others are fixed. This can be seen as the cut of the NN model along some input direction and through some reference point. We want to remind all readers that before proceeding with this experiment, we performed the NN through the “Perform Order Selection” and the “Perform Input Selection”.

- Paris[9][10]

[9] In Appendix: Perform inputs selection (PM_{10} and $PM_{2.5}$).

[10] In Appendix: Expected Error; Quasi-Newton method error history; Incremental order error plot.

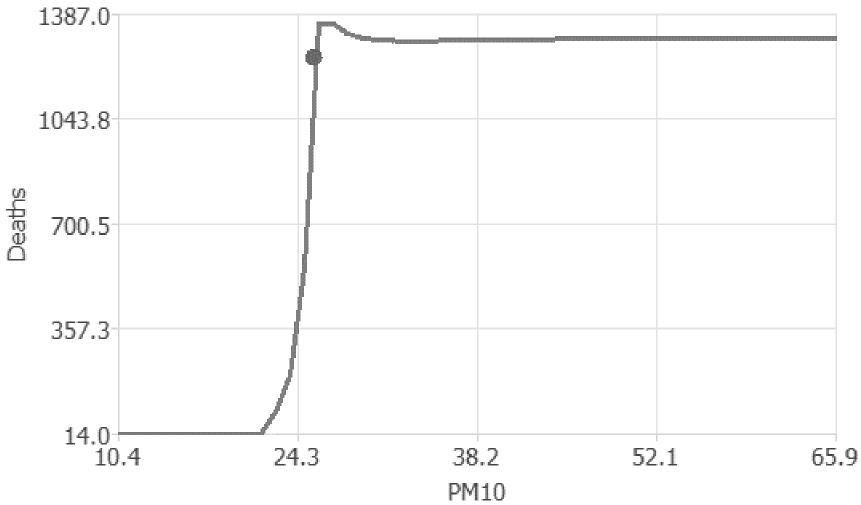
Figure 6: Deaths-$PM_{2.5}$ Directional Output.



Source: our elaborations.

Figure 6 shows the result of the first experiment. The cut-off signal in NN transmission from $PM_{2.5}$ input to the target Deaths has been precisely identified. It corresponds to the value of 17.4 $\mu g/m^3$. This value represents the threshold value for Paris. This value may be able to convey COVID-19 or accelerate its adverse health effects. In Figure 7, we analyse the effect compared to PM_{10}.

Figure 7: Deaths-PM_{10} Directional Output.



Source: our elaborations.

Figure 7 shows the result of the second experiment. The cut-off signal in NN transmission from PM_{10} input to the target Deaths has been identified as 29.6 $\mu g/m^3$. The result obtained is very interesting. Compared to Figure 6, the signal shows an exponentially increasing trend. This trend highlights how the containment measures and the lower circulation of polluting vehicles only affected $PM_{2.5}$. Subsequently, we carry out the Importance Test on $PM_{2.5}$ and PM_{10} compared to the number of deaths in Paris. With this test, we compare the effect of the two particulates connected to the deaths from COVID-19 (Figure 8).

Figure 8: Importance Test on Paris.

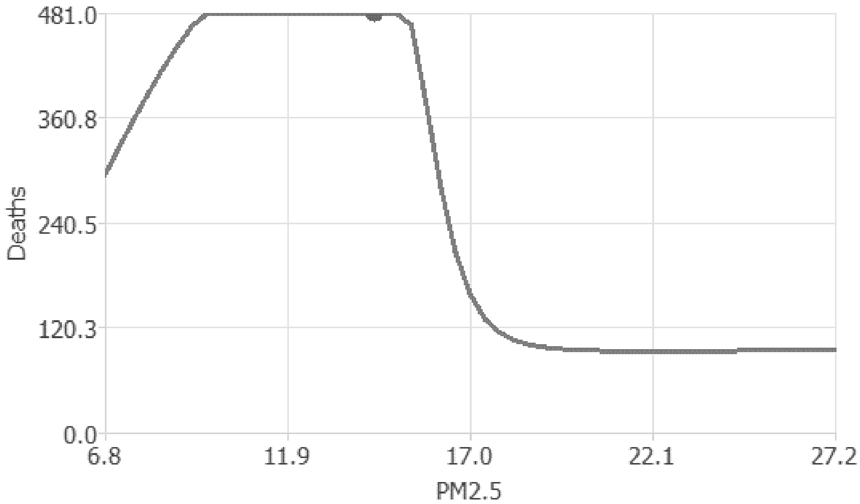
- Field Importance Test:
- **1**. PM10: **63.20**%
- **2**. PM2.5: **36.80**%

Source: our elaboration on BIG method.

Figure 8 shows the results obtained. Compared to $PM_{2.5}$, PM_{10} represents the variable whose threshold value is more strongly correlated with deaths from COVID-19. We can say that concentrations of 29.6 µg/m^3 of PM_{10} would be ideal for the spread of COVID-19. In addition, the adverse health effects caused by this type of particulate matter would aggravate COVID-19 disease.

- Lyon[11][12]

Figure 9: Deaths-$PM_{2.5}$ Directional Output.

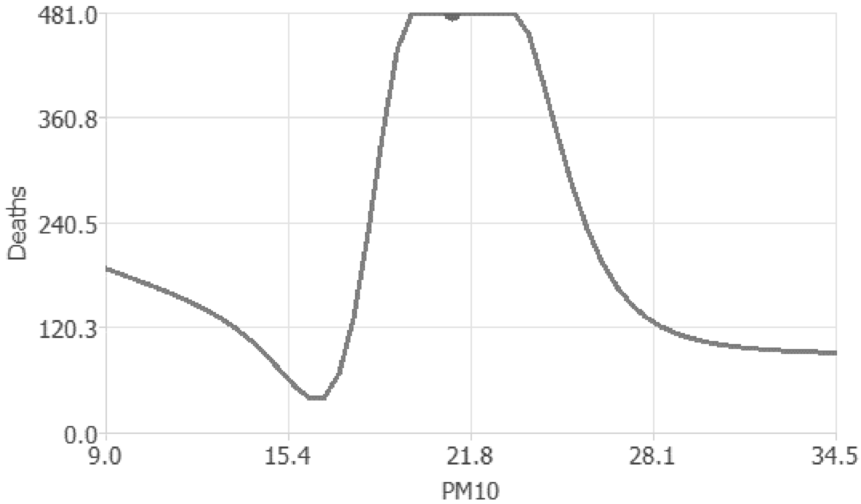


Source: our elaborations.

[11] In Appendix: Perform inputs selection (PM_{10} and $PM_{2.5}$).
[12] In Appendix: Expected Error; Quasi-Newton method error history; Incremental order error plot.

The results on the relationship between $PM_{2.5}$ concentration and deaths from COVID-19 are interesting. We can see that the highest number of deaths is reached at 15.6 μg/m^3. Since the recorded concentration of $PM_{2.5}$ on 27 April 2020 was 8.5 μg/m^3, our result is predictive. In other words, it is necessary to record values lower than those obtained by us to mitigate the number of Coronavirus deaths compared to the amount of $PM_{2.5}$. In fact, if a $PM_{2.5}$ level had been maintained at 15.6 μg/m^3, it is likely that the number of deaths would have been greater than the recorded total of 481. In Figure 9, we analyze the effect compared to PM_{10}.

Figure 9: Deaths-PM_{10} Directional Output.



Source: our elaborations.

Figure 9 shows the result of the second experiment in Lyon. The cut-off signal in NN transmission from PM_{10} input to the target Deaths has been identified as 20.6 μg/m^3. The value obtained should represent the concentration of PM_{10} able to exacerbate the number of deaths caused by COVID-19. We believe that the city of Lyon should limit the concentrations of this particulate to below the threshold value generated by our NN. Next, we estimate the levels of $PM_{2.5}$ and PM_{10}, with the Importance Test correlated to the number of deaths from COVID-19 (Figure 10).

Figure 10: Importance Test on Lyon.

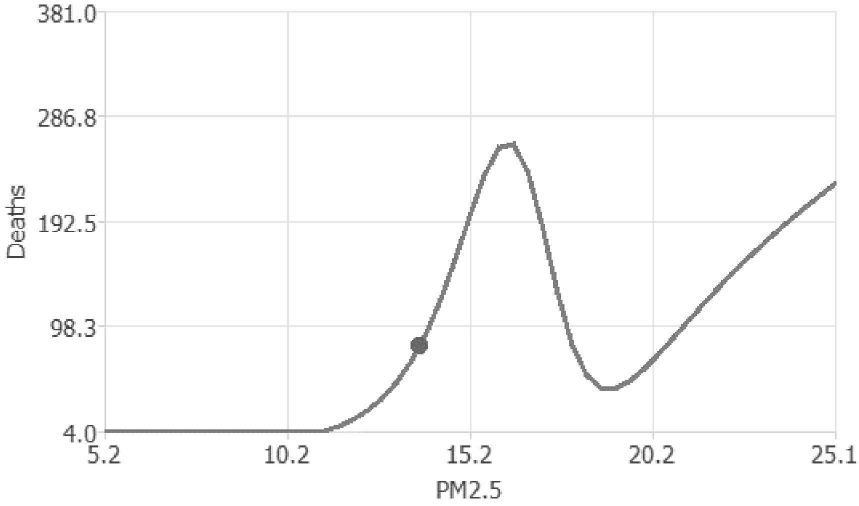
- Field Importance Test:
- **1**. PM10: **56.12**%
- **2**. PM2.5: **43.88**%

Source: our elaboration on BIG method.

The results obtained by the test from are interesting. COVID-19 deaths related to PM_{10} levels could be 56.12% compared to $PM_{2.5}$. Therefore, for Lyon, as for Paris, it is crucial to keep the concentration of PM_{10} below a specific threshold value. This was calculated to be 20.6 μg/m^3.

- Marseille[13][14]

Figure 11: Deaths-$PM_{2.5}$ Directional Output.

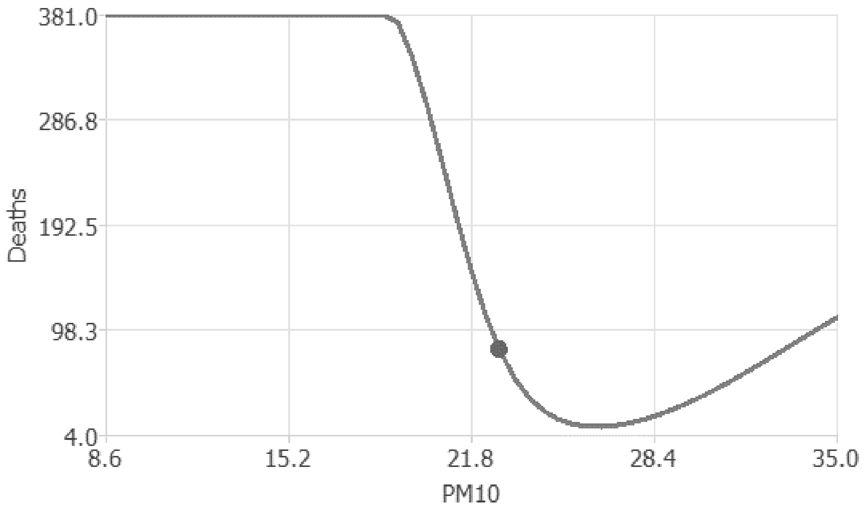


Source: our elaborations.

Figure 11 shows the result regarding the connection between $PM_{2.5}$ and deaths caused by COVID-19 in Marseille. The cut-off signal in NN transmission from $PM_{2.5}$ input to the target Deaths corresponds to the value of 14.3 μg/m^3. If the city exceeds this threshold in a pandemic situation, such as COVID-19, the adverse effects on health would be more significant. In Figure 12, we analyze the effect compared to PM_{10}.

Figure 12: Deaths-PM_{10} Directional Output.

[13] In Appendix: Perform inputs selection (PM_{10} and $PM_{2.5}$).
[14] In Appendix: Expected Error; Quasi-Newton method error history; Incremental order error plot.



Source: our elaborations.

The cut-off signal in NN transmission from PM_{10} input to the target Deaths has been identified as 22.04 μg/m^3. This result shows that adverse human health effects would amplify those from COVID-19 at this value. Next, we estimate the levels of $PM_{2.5}$ and PM_{10} with the Importance Test correlated to the number of deaths from Coronavirus (Figure 13).

Figure 13: Importance Test on Marseille.

- Field Importance Test:
- **1**. PM2.5: **79.01**%
- **2**. PM10: **20.99**%

Source: our elaboration on BIG method.

The results are different from those of Paris and Lyon. In fact, for Marseille, the cut off value of 14.3 μg/m^3 relative to $PM_{2.5}$ is the most important value. Compared to the value of PM_{10}, it would aggravate the health of the population in the presence of COVID-19, generating a greater number of deaths.

5. Summary of Results and Interpretations

Table 3: Summary Deaths-PM Directional Output.

City	**Population density**	**PM_{10}** μg/m^3 (threshold)	**$PM_{2.5}$** μg/m^3 (threshold)	**Importance**
Paris	21,616/km^2	29.6	17.4	63.2 % PM_{10}
Lyon	11,000/km^2	20.6	15.6	56.12% PM_{10}
Marseille	3,600/km^2	22.04	14.3	79.01 % $PM_{2.5}$

Source: our elaborations.

Table 3 summarizes the results obtained by our ML model with ANNs. In quantitative terms, the excess risk reported compared to our values is dramatic. In the city of Paris, an increase in PM_{10} concentration beyond the 29.6 μg/m^3 threshold could generate a 63.2% increase in mortality (in a COVID-19 pandemic), compared to an increase in $PM_{2.5}$. For Lyon, on the other hand, any value above 20.6 μg/m^3 in PM_{10} would generate an increase in deaths of 56.12%, compared to an increase in $PM_{2.5}$ concentrations. Finally, for Marseille, an increase in $PM_{2.5}$ concentrations above 14.3 μg/m^3 would generate a 79.01% increase in mortality compared to an increase in PM_{10} concentrations.

All the threshold values discovered are higher than the limits imposed by Directive 2008/50/EC of the European Parliament (Table 4).

Table 4: Our limit values compared to the maximum EU concentrations.

City	**PM_{10}** μg/m^3 (our threshold)	**$PM_{2.5}$** μg/m^3 (our threshold)	**Annual limit value (**μg/m^3**) (Directive (2008/50/EC - EU)**	**Difference between EU limit value and our threshold value** (μg/m^3)
Paris	29.6	17.4	40 PM_{10}; 25 $PM_{2.5}$	+10.4 PM_{10}; +7.6 $PM_{2.5}$
Lyon	20.6	15.6	40 PM_{10}; 25 $PM_{2.5}$	+19.4 PM_{10}; +9.4 $PM_{2.5}$
Marseille	22.04	14.3	40 PM_{10}; 25 $PM_{2.5.}$	+17.6 PM_{10}; +10.7 $PM_{2.5.}$

Source: our elaborations.

As we can see from Table 4, all our threshold values are lower than those of the EU. These findings are important in a COVID-19 pandemic situation. EU limit values for particulate matter (PM_{10} and $PM_{2.5}$) are excessively high. They are, on average, more significant than our threshold value for a value of 14.4 μg/m^3 (PM_{10}) and 9.2 μg/m^3 ($PM_{2.5}$). This result suggests a EU economic policy capable of reducing the limit values of emissions from fine particles. These limit values should respect our threshold value.

The relationship between our results and deaths from COVID-19 can be interpreted in the following way. The most likely explanation is that the levels of PM_{10} and $PM_{2.5}$ found in our study generate an inflammatory response in the lungs. However, key molecular events in response to PM exposure are involved in altering the homeostasis of cardiovascular physiology.

COVID-19 would seem to support a similar mechanism, inducing the rapid onset of a state of inflammation, with an equally rapid increase in inflammatory cytokines, comparable to that caused by short-term exposure to PM. Another interpretation of our results would confirm the hypothesis that particulate matter acts as a “carrier” in transporting the virus which coagulates on the surface of the particles over a longer distance. Particulates are at least a dozen times larger in diameter than the virus. This hypothesis, already advanced in the literature for some time on specific cases, would imply that the spread of the virus is facilitated, not by smog in general, but by fine particulates. Dominici et al. (2020) in a pre-review, found a correlation between fine dust pollution and coronavirus mortality. The increase of just one microgram per cubic meter of $PM_{2.5}$ would correspond to a 15% increase in the mortality rate due to the SARS-COVID-19 virus. According to the authors, the results obtained are statistically significant and robust, with a confidence interval of 95%. In a working paper, Becchetti et al. (2020) showed a link between the COVID-19 lethality index and air quality, regarding predisposition to pulmonary pathologies. Ogen (2020) analysed the relationship between NO_2 and COVID-19. He reviewed data from the ESA Sentinel 5P satellite and mapped the distribution of nitrogen dioxide in Europe in the months leading up to the pandemic. The results showed that 78% of the deaths from COVID-19 were concentrated in five areas located in northern Italy and central Spain. In these areas, there was a very high level of nitrogen dioxide.

The result of our study is different from those mentioned above. We have found a precise quantity of $PM_{2.5}$ and PM_{10} that can increase the probability of death in a COVID-19 context. These three French cities could serve as a study sample. In particular, we can say that all the cities in the world that have a population density similar to these three French cities, must keep the level of $PM_{2.5}$ and PM_{10} below the threshold values that we found.

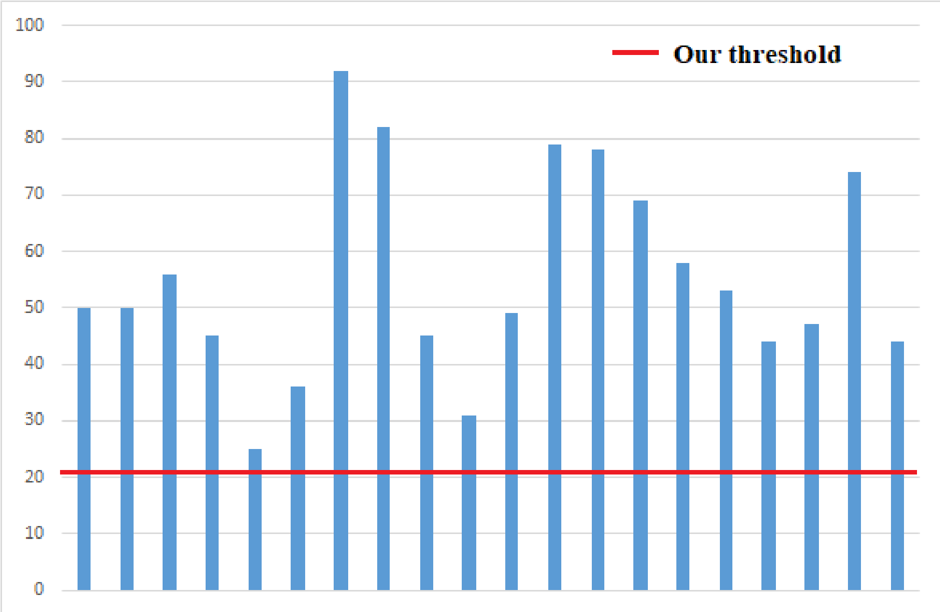
- Use of our threshold value: an example

Table 5: Our threshold value compared to Milan.

City	**Population density**	**COVID-19 deaths** (March 2020)	**PM_{10}** or **$PM_{2.5}$** $\mu g/m^3$ (February 25)	**Comparison city**	**Difference from our threshold value** ($\mu g/m^3$).
Milan	7,653/km^2	1,369	54 (PM_{10})	< Lyon	+30.4

Source: our elaborations.

Figure 14: PM_{10} $\mu g/m^3$ in Milan (average February values).



Source: our elaboration on SIAD-ARPA data.

Milan in February recorded PM_{10} values above our threshold level. Considering the incubation period (about 14 days), we can provide a positive correlation between the PM concentration data and the number of deaths in March. The high concentrations of PM during February could have increased the spread of the virus in Milan more than in other Italian cities. Atmospheric particulate matter may, therefore, have played a carrier role in COVID-19 (Chen et al., 2010; Ye et al., 2016; Chen et al., 2017; Peng et al., 2020). The positive correlation between PM_{10} and the number of deaths could also be due to another reason. Continuous exposure to fine particles causes sever inflammation of lung tissue. The angiotensin II converting enzyme (ACE-2) is involved in this inflammation process. This enzyme is also the key receptor through which the COVID-19 is able to enter into human cells.

6. Conclusions and policy implications

This study analyzed the relationship between particulate matter concentrations (PM_{10} and $PM_{2.5}$) and deaths from COVID-19 in three French cities. Through the use of an experiment in ML with ANNs, we estimated the threshold value of PM_{10} and $PM_{2.5}$, beyond which the number of deaths in the presence of COVID-19 would increase. The study takes into account the adverse health effects of the particulate objects of the study. Even in the absence of a pandemic situation, high concentrations of PM_{10} and $PM_{2.5}$ generate adverse effects and danger to human health. These tiny particles can be inhaled, reaching the deepest part of the human respiratory system. The finer fractions could filter even deeper into our body by travelling into the blood and reaching the cells. We have followed some research that affirms a correlation between air pollution and the spread of COVID-19. Starting from these hypotheses, we wanted to verify the possibility of determining precise values of PM_{10} and $PM_{2.5}$ which correspond to the optimal value for the diffusion of the coronavirus. We found that if the signal from the neural network (from input to output) is cut to a precise amount, there is a reduction in the number of coronavirus deaths in the three French cities studied. This result suggests that there are certain conditions which increase the likelihood of the spread and aggravation of the disease. The three cities taken as a statistical sample in this study have different population densities. We found that threshold values of $PM_{2.5}$ and PM_{10} were different among Paris, Lyon, and Marseille. In particular, the new threshold levels of $PM_{2.5}$ and PM_{10} connected to COVID19 are: 17.4 µg/m^3 ($PM_{2.5}$) and 29.6 µg/m^3 (PM_{10}) for Paris; 15.6 µg/m^3 ($PM_{2.5}$) and 20.6 µg/m^3 (PM_{10}) for Lyon; 14.3 µg/m^3 ($PM_{2.5}$) and 22.04 µg/m^3 (PM_{10}) for Marseille.

We believe, therefore, that this result can be replicated in any city that has a population density similar to one of the cities that we studied. The objective is to recommend environmental intervention policies aimed at limiting the concentrations of PM_{10} and $PM_{2.5}$ below the thresholds that we found. Pending further scientific confirmation, our threshold value could be considered a possible indirect indicator of the virulence of the COVID-19 epidemic. Our study could be beneficial in the event of a second wave of the pandemic. Policymakers are expected to keep PM_{10} and $PM_{2.5}$ concentrations in line with our threshold until a cure or vaccine is available.

Acknowledgments

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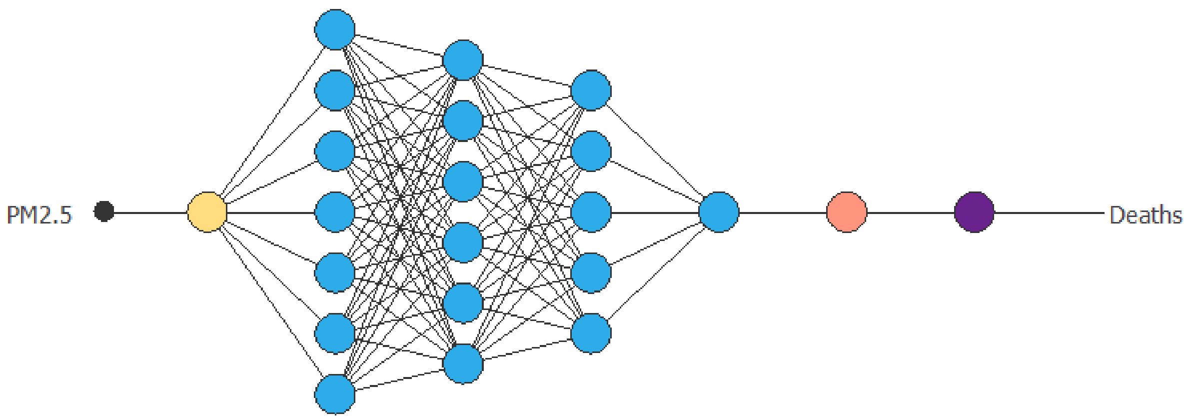
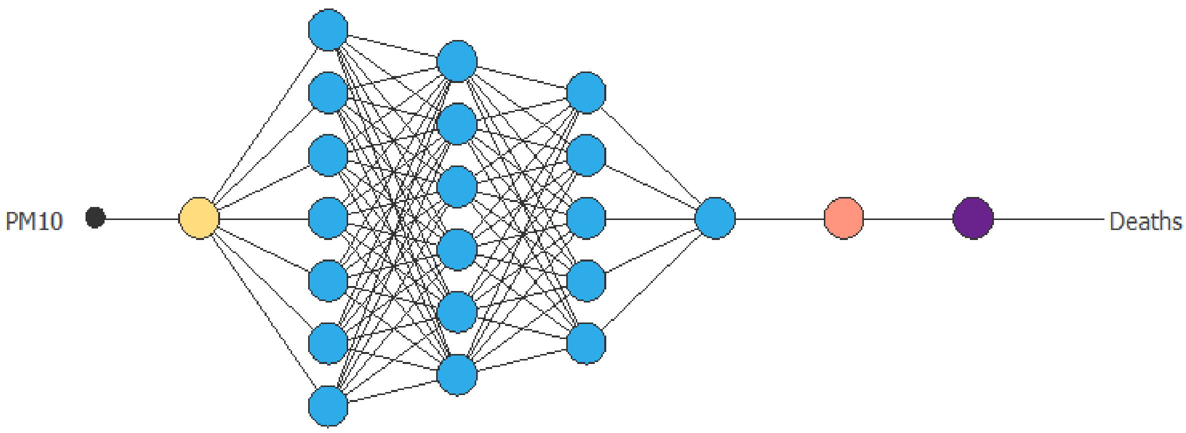
Appendix

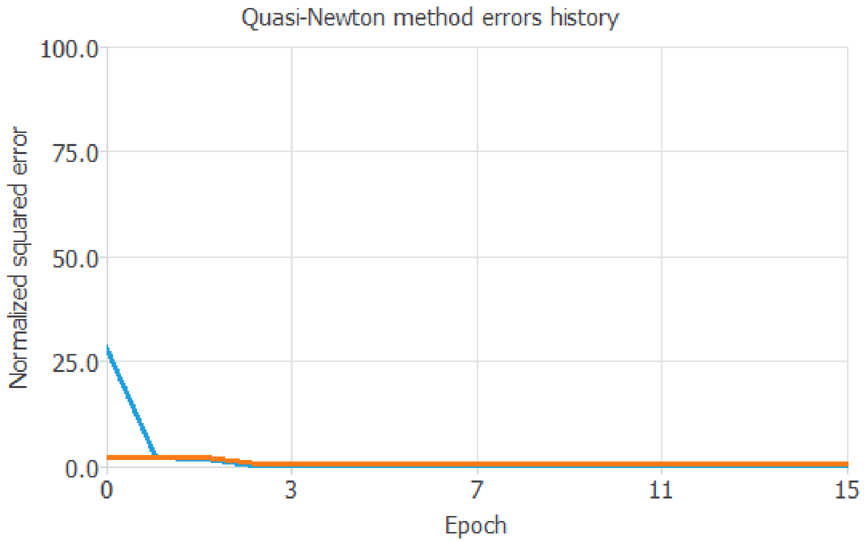
- Paris

a) ANNs Perform inputs selection (PM_{10} and $PM_{2.5}$).

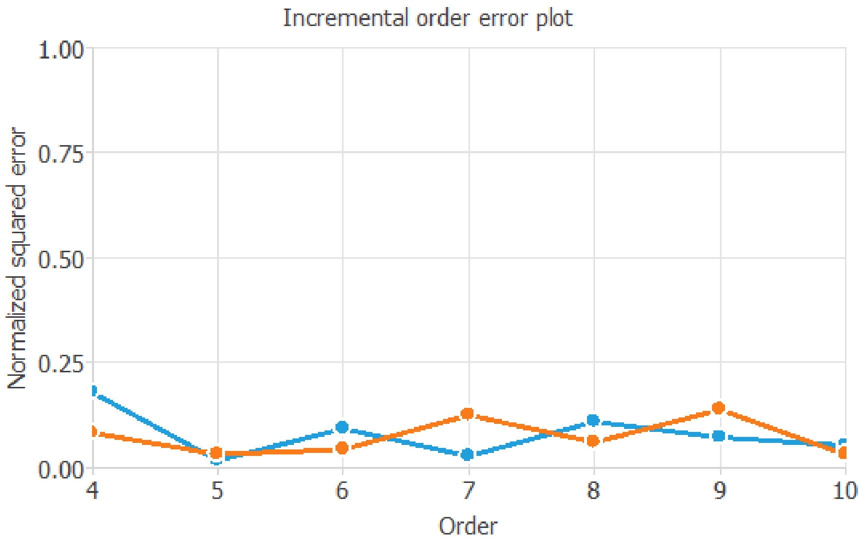




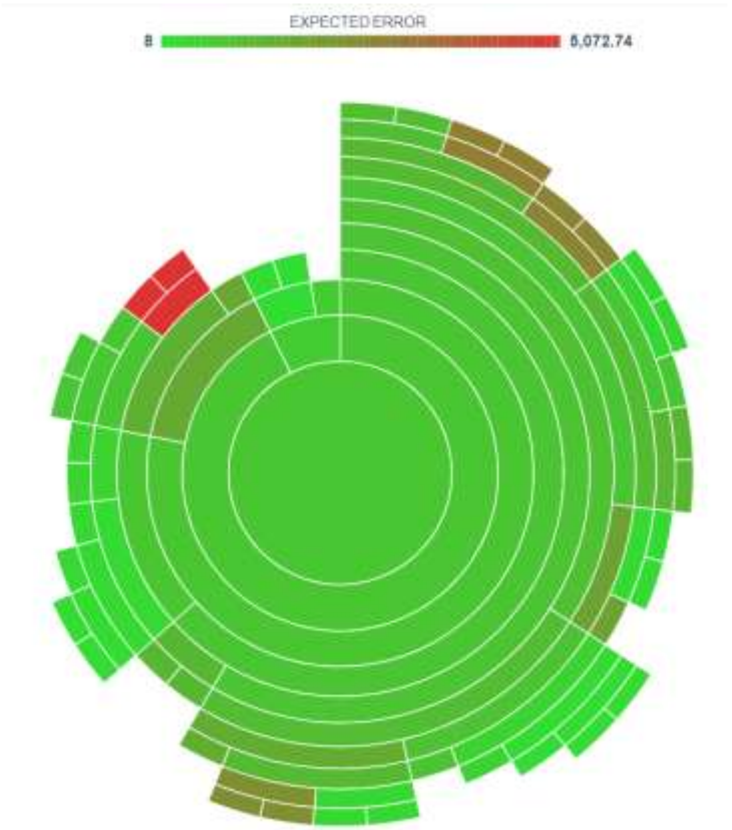
b) Training strategy: Perform Training



c) Model Selection

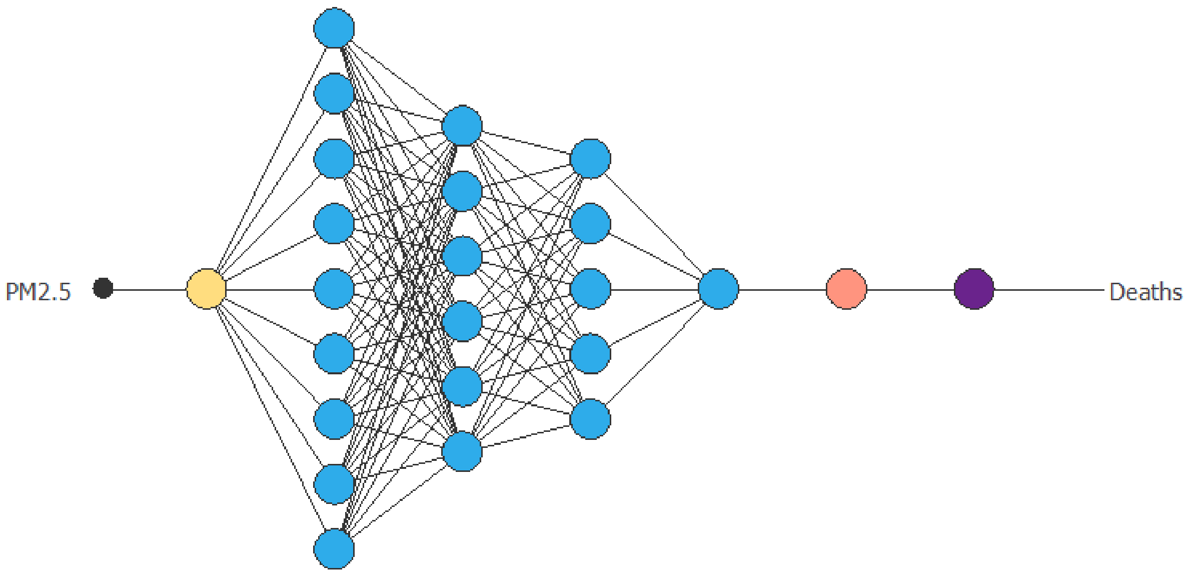


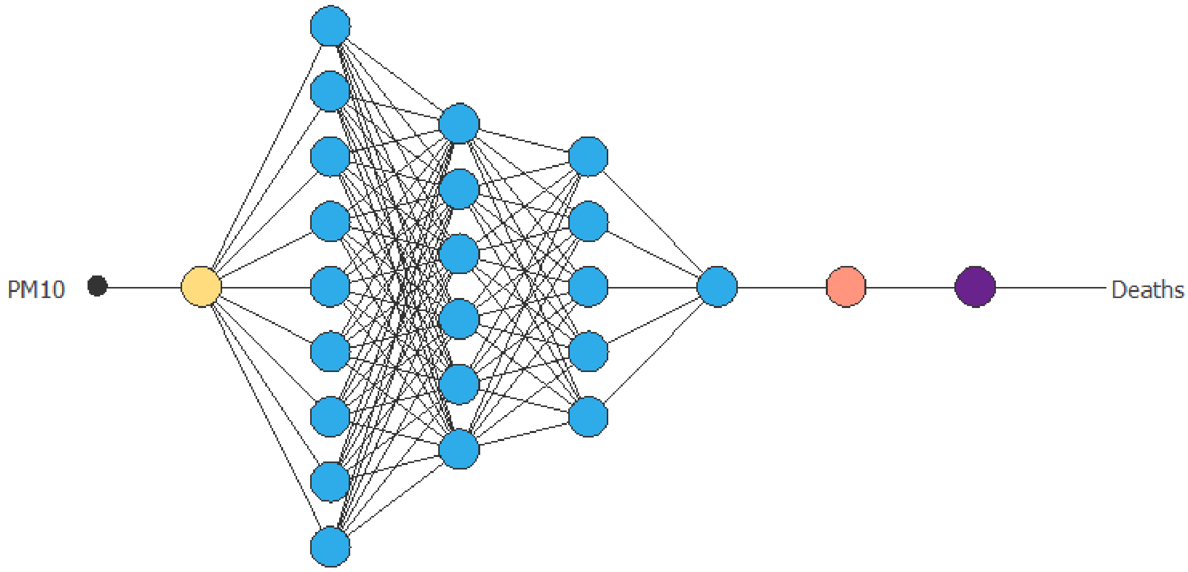
d) Testing Analysis



- **Lyon**

a) ANNs Perform inputs selection (PM_{10} and $PM_{2.5}$).





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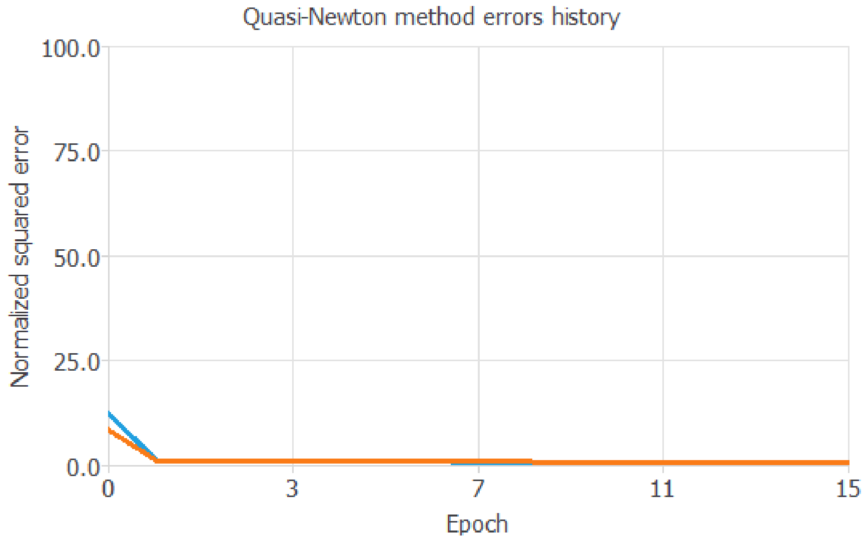

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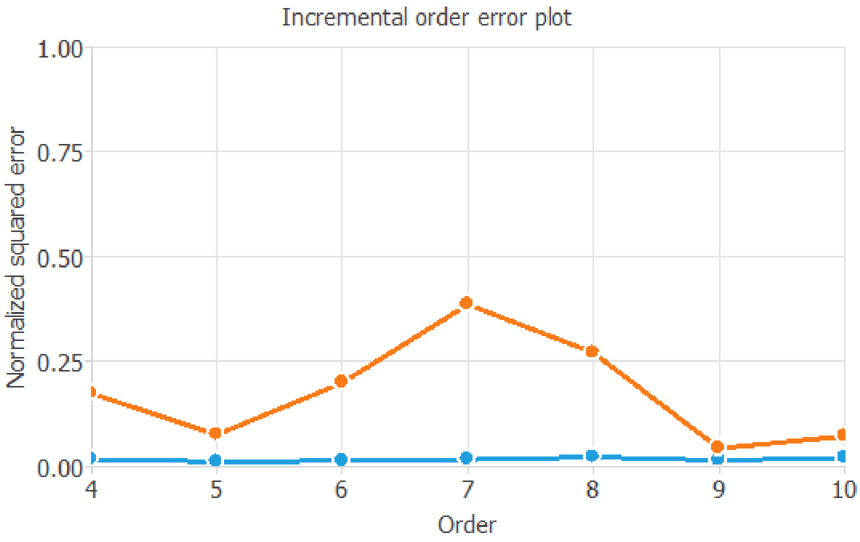
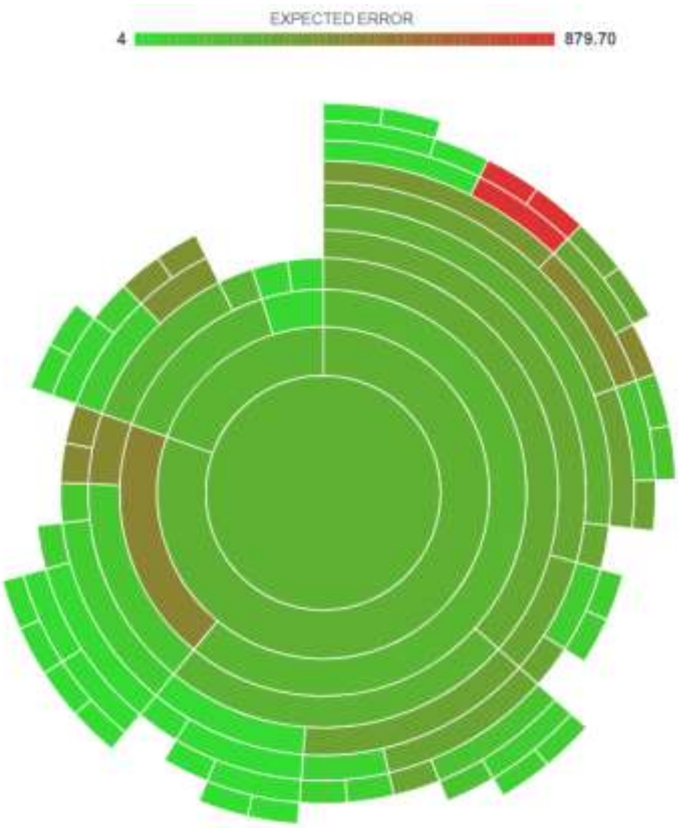
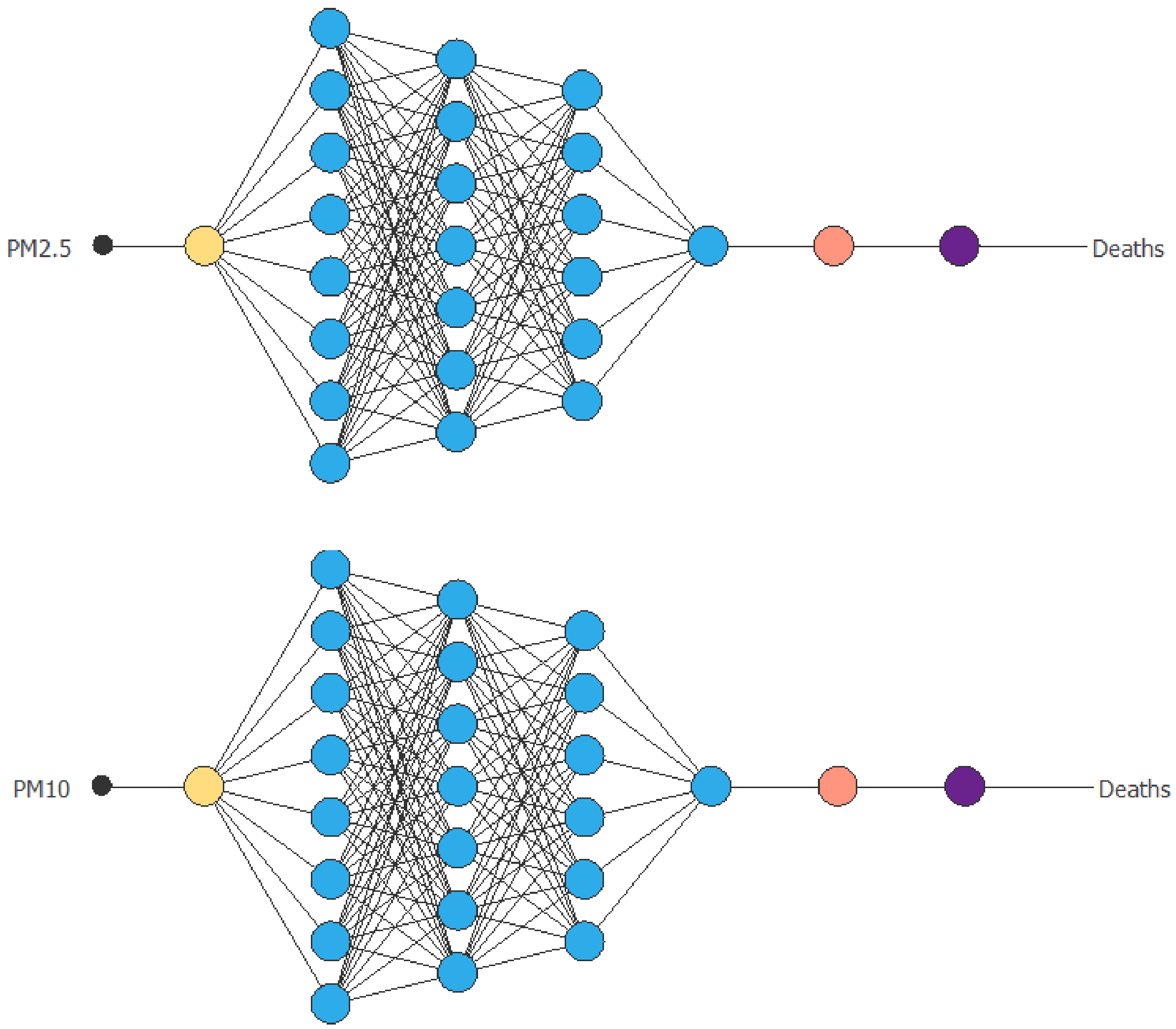


d) Testing Analysis

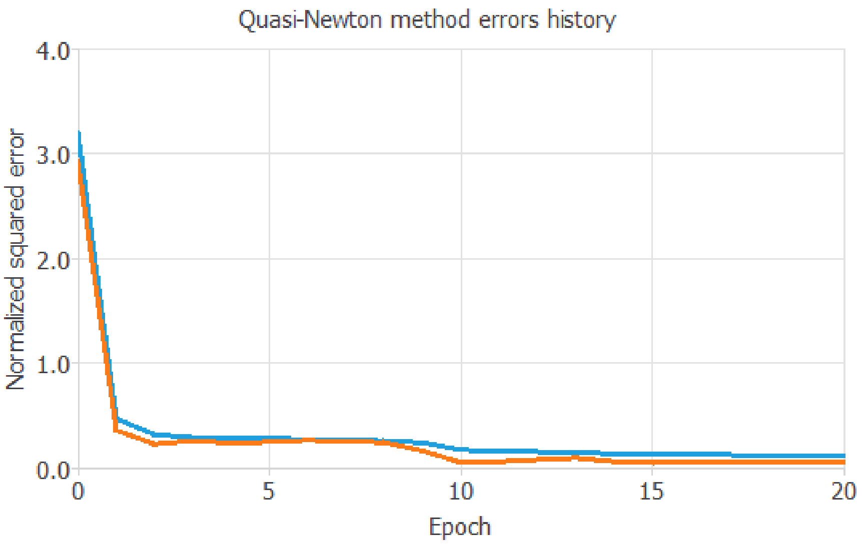


- Marseille

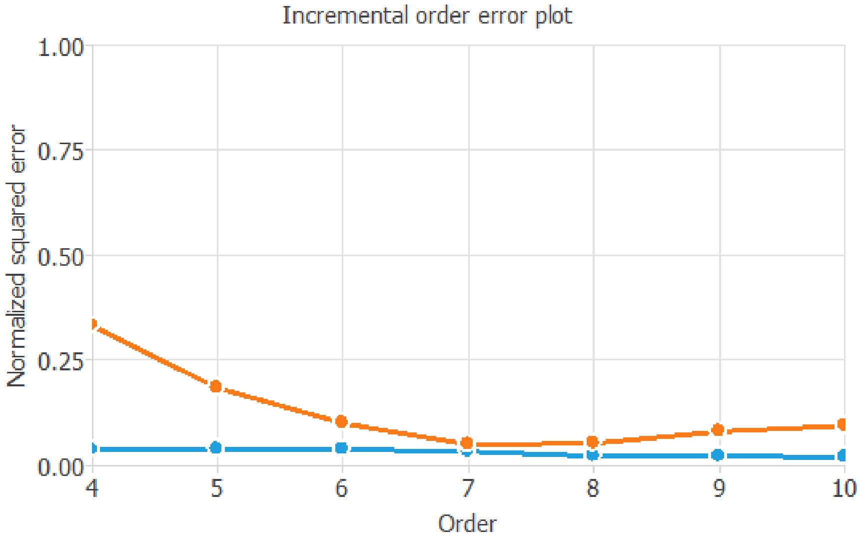
a) ANNs Perform inputs selection (PM_{10} and $PM_{2.5}$).



b) Training strategy: Perform Training



c) Model Selection



d) Testing Analysis