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The relationship between air pollution and COVID-19-related deaths: An application to three French cities

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ABSTRACT

Being heavily dependent to oil products (mainly gasoline and diesel), the French transport sector is the main emitter of Particulate Matter (PMs) whose critical levels induce harmful health effects for urban inhabitants. We selected three major French cities (Paris, Lyon, and Marseille) to investigate the relationship between the Coronavirus Disease 19 (COVID-19) outbreak and air pollution. Using Artificial Neural Networks (ANNs) 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 (PM) 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 (ML) 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 COVID-19: 17.4 $\mu g/m^3$ ($PM_{2.5}$) and 29.6 $\mu g/m^3$ (PM_{10}) for Paris; 15.6 $\mu g/m^3$ ($PM_{2.5}$) and 20.6 $\mu g/m^3$ (PM_{10}) for Lyon; 14.3 $\mu g/m^3$ ($PM_{2.5}$) and 22.04 $\mu g/m^3$ (PM_{10}) for Marseille. Interestingly, all the threshold values identified by the ANNs are higher than the limits imposed by the European Parliament. Finally, a Causal Direction from Dependency (D2C) algorithm is applied to check the consistency of our findings.

1. Introduction

As one of the most urgent threats on the planet, the World Health Organization (WHO) declared the Coronavirus Disease 19 (COVID-19) as a global health emergency on March 12th 2020 [1]. At the world level and as of April 20th 2020, the WHO reported 157,847 confirmed deaths and 2,314,621 confirmed cases [2]. This virus spreads through three channels: saliva, nasal discharge, or airborne particles [3]. 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. 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 [3].

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 [4]. 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

Abbreviations: ANNs, Artificial Neural Networks; CMAQ, Community Multiscale Air Quality; CO, Carbon Monoxide; CH_4, Methane; COVID-19, Coronavirus Disease 19; D2C, Causal Direction from Dependency; GAM, Generalized Additive Model; GHG, Greenhouse Gas; ML, Machine Learning; NO_2, Nitrogen Dioxide; NOx, Nitrogen Oxides; O_3, Ozone; $PM_{2.5}$, Particulate Matter with an aerodynamic diameter < 2.5 µm; PM_{10}, Particulate Matter with an aerodynamic diameter < 10.0 µm; SO_2, Sulfur Dioxide; SO_3, Sulphur Trioxide; SOx, Sulphur Oxides; VOC, Volatile Organic Compounds.

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public spaces; requiring individuals to remain in their residence, aside from going out for necessities [5]. 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. Although there is no possible comparison, looking at the COVID-19-related deaths recording gives a broad picture of the health consequences of that virus in France. Just before the mandatory containment measures (i.e., March 12th 2020), the WHO [6] reported 48 confirmed deaths and 2269 confirmed cases. The Situation Report on COVID-19 published by the WHO [2]indicated 22,821 confirmed deaths and 123,279 confirmed cases, as of April 27th 2020.

Economic activity is a well-known factor contributing to global environmental pollution because fuel combustion directly releases Greenhouse Gas (GHG) emissions into the atmosphere [7]. In the most densely populated cities, air pollution recorded high concentrations measures up to the point where the physical health of the population is now directly threatened [8,9]. Nowadays, primary pollutants[2] (methane, CH_4; carbon monoxide, CO; nitrogen dioxide, NO_2; sulphur oxides, SO_x) and secondary pollutants (nitrogen dioxide, NO_2; ozone, O_3; sulphur trioxide, SO_3) display systematically significant levels in urban areas. But another environmental concern is drawing the attention from researchers: the critical concentration of small size components (PM_{10} and $PM_{2.5}$)[3] in major cities. Factories and house heating are important driver of these particles. However, in major European cities, transport is widely recognised to be the main source of this local pollution inducing specific health effects for urban inhabitants [10]. Far from being a local concern, mega-cities in the developing world are also facing identical challenges.

The origin of PMs emissions come from road traffic as it relies almost exclusively on oil products (gasoline and diesel) [11]. In urbanized areas, these particles have recorded a constant growth over the past decades with detrimental impacts on human health [12,13]. Tightly linked to this view, it raises the question of the traffic congestion in big cities: beside inducing longer transport durations, it increases fuel consumption and carbon emissions[4], while not allowing efficient travels [14,15]. Consequently, much attention has been focused on planning urban areas capable of properly lowering traffic congestion (i.e., public transport, incentives for bike users and private vehicles restrictions) as well as introducing low-carbon energy sources with direct applications to transport mobility [8,16,17]. Nonetheless, cleaner alternative fuels insignificantly contribute to the energy supply, and appear domestically unavailable in most of the urban areas. Accordingly, transport needs on fossil fuels have not decreased over time[5]. Thus, climate change issues are still burning as oil products dependence for road traffic remains critical [12]. Dealing with direct exhaust congestion and pulmonary health diseases, the municipalities are now questioning the nature and the way fossil energy is consumed by road transport. To get a broad overview on the needs of petroleum-based fuels for combustion, one must look at the growth trend in car ownership. In 2010, 700 million light duty vehicles, automobiles, light trucks, SUVs (Sport Utility Vehicles) and minivans, were on roadways in the world. By 2030, these numbers are projected to increase 1.3 billion, and by 2050, it may reach 2 billion vehicles [18]. Controlling for the population size, car ownership rates reached 0.48 cars per capita in Europe in 2010, which is strongly higher than China (with 0.03 cars per capita) but remains lower than the US (0.76 cars per capita) for the same year [19]. Being the core of PMs emissions in major French cities, the consumption of imported oil products for transport recorded a drastic rise since 1970′s. Thus, one key sustainability challenge emerges: how can we allow efficient transportation services within cities with acceptable environmental externalities? To address the PMs problem at its major source, the French government committed to the ambitious goal of enhancing the share of renewable energy in the transport sector to 15% by 2030, in which biofuels will take a major share [20][6]. However, an important limit remains: when world agricultural prices rose (as it was the case in the aftermath of the 2008 crisis), biofuels are blamed for the threat they can potentially create for food security, and are often pushed to the background [21]. Meanwhile, France is experiencing a burning debate relative to the taxation of fossil fuels [21]. Indeed, diesel benefits from a lower tax rate compared to gasoline, explaining why diesel engines are predominant in the French car fleet. Facing the need to internalize its environmental and health externalities, the French Cour des Comptes [22]suggested the creation of new incentives towards diesel consumption reduction. Presented as controversial, this project has nonetheless induced large-scale demonstrations across the territory, worsening the public acceptance of future fuel tax reforms.

One crucial concern associated with the emission of PMs is that it induces important health risks[7] for the population including respiratory, infections, asthma, chronic obstructive pulmonary disease, and lung cancer [23,24]. Because of their small sizes and light weight, it is said that these fine particles tend to longer subsist in the air than larger ones and can penetrate deep into the lungs and the circulatory system [25]. This is in line with Boldo et al. [26] who performed a huge Health Impact Assessment (HIA) on 23 European cities and estimated that 16,926 premature deaths from all causes could be prevented if long-term exposure to $PM_{2.5}$ levels were reduced to 15 μg/m^3 in each city. Therefore, solving the poor air quality issue 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. NO_2 level has drastically fallen in March 2020 when compared to the same period in 2019.

[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 [3].

[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.

[4] As an illustration, the International Road Transport Union (IRU, 2012) estimated that more than 100 billion litres of wasted fuel (corresponding to 250 billion tonnes of CO_2 equivalent) were attributed to traffic congestion in the American cities for the year 2004. Far from being unique, European and (especially) French cities also experience important congestion issues.

[5] According to British Petroleum (BP, 2012), the share of biofuels in world liquid fuel is expected to not exceed 4% by 2030.

[6] Earlier, the 2009 Renewable Energy Directive (RED) had set the share of biofuels in the energy supply mix for road transportation should reach 10% by 2020 for each member state (European Parliament and Council, 2009).

[7] Air pollution contributed to 9% of deaths worldwide for the year 2017 which is equivalent to 7 million premature deaths [9]. Consequently, air pollution has been recognized as one of the world's important deaths drivers after high blood pressure, smoking and high blood sugar[75].

In addition, several investigations applied on various cases confirmed that the public and domestic transportation's restriction has resulted in obvious reductions of fuel combustion. Just before the mandatory containment measures (i.e., March 12th 2020), the WHO [2] reported 48 confirmed deaths and 2,269 confirmed cases. The Situation Report n. 98 on COVID-19 published by the WHO [6] indicated 22,821 confirmed deaths and 123,279 confirmed cases, as of April 27th 2020. Looking at the city level, confirmed deaths recorded a 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 [27]. 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.

Since it clearly appears that there are remarkable differences in terms of the rate of COVID-19 spread in the world, it would be relevant to assess the potential influence of atmospheric pollution as a contributing factor to COVID-19 mortality [28]. As a response, a few seminal studies have been recently conducted on various cases with multiple pollutants types Wu et al. [29] on the USA; Yongjian et al. [30] on China; Travaglio et al. [31] on England; Setti et al. [32] on Italy; Conticini et al. [33]) and Putrino et al. [34] on Italy). These empirical investigations confirmed the existence of a significant association between air pollution and COVID-19 cases or mortality, making poor air quality an additional co-factor of COVID-19 lethality. This finding is in line with the scientific literature highlighting that the exposure to air pollution matters for the spread of various viral infections [35–38]. The underlying hypothesis is that a pre-determined particulate concentration can foster COVID-19 and make the respiratory system more susceptible to this infection. In fact, airborne particles could serve as carrier of pathogens, making the viral infection spread more harmful [32]. Fernandes [39] provided two scenarios. The first hypothesizes that GDP growth takes a hit, ranging from 3 to 5% depending on the country. In the second one, GDP can fall as much as 10%. The economic costs of a recession are unequally distributed. Le Quéré et al. [40] calculated that, at their peak, CO_2 emissions in individual countries decreased by −26% on average during the COVID-19 forced confinement.

An in-depth review of the literature highlights that no study has been performed on the French case so far, even though French cities experienced a dramatic COVID-19 outbreak. In fact, confirmed deaths recorded a huge 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 [27]. To the best of our knowledge, no estimated threshold of $PM_{2.5}$ and PM_{10} connected to COVID-19 fatality was found. Knowing that the ongoing COVID-19 crisis is currently far from being over, the complexity of such topic requires urgent investigations. Being a fruitful research direction, demonstrating the air pollution-COVID-19 relationship could partially explain the efficiency of national lockdown measures. In addition, identifying the atmospheric co-factors (i.e., the polluting emissions linked to fossil energy combustion by transport) enabling the COVID-19 virus to spread across the urban population would help policymakers to control its epidemic diffusion with more efficiency.

This research seeks to contribute to the literature by bringing three novelty aspects. First, this paper fills the gap in the literature and proposes the first empirical assessment on the relationship between air pollution and COVID-19-related-deaths in France. To do so, we collected different sets of unique data on Particulate Matter (PM_{10} and $PM_{2.5}$) and COVID-19-related-deaths over the largest and most recent available period (from March 18th to April 27th 2020 representing 41 consecutive days of observation) for three major French cities (Paris, Lyon and Marseille). Second, following the empirical strategy employed by an emerging air pollution-virus epidemic literature [41–45], this study applies Artificial Neural Networks (ANNs) experiments and used a Machine Learning (ML) approach. Then, to check the consistency of our results, we perform a D2C (Causal Direction from Dependency) algorithm capable of predicting the existence of a direct causal link between two variables in a multivariate setting. Third and overall, this paper represents the first empirical estimation of threshold levels of $PM_{2.5}$ and PM_{10} connected to COVID-19. Hence, our empirical findings are the only ones currently able to significantly demonstrate the concentration amount of PM_{10} and $PM_{2.5}$ capable of generating the adverse effect of COVID-19. Bringing high information value for policy purposes, this study is believed to create new research opportunities connected to environmental and health issues.

This paper investigates the relationship between air pollution and COVID-19 diffusion for three major French cities (Paris, Lyon and Marseille). We focus on two pollutants (PM_{10} and $PM_{2.5}$) over the most available and recent period for all cities: from March 18th to April 27th 2020.

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

2. Literature review

Being at the core of air pollution in major cities, the consumption of oil products (mostly gasoline and diesel) for road transport elicits important environmental and health externalities. Because of its recent nature, the literature tackling the COVID-19-air pollution relationship is very seminal.

A first strand of studies assessed the impact of COVID-19 on environmental pollution. A second group of research considered air pollution as a determining factor of COVID-19 lethality.

2.1. Studies on the effect of COVID-19 shut-down and air pollution

This sub-section aims at presenting research works performed at different scales (international, national/provincial, and city level). First, Anjum [9] made a broad overview on the international COVID-19 situation and its link with air pollution for major countries (China, India, France, Italy and the USA). Second, we present some recent empirical research performed by Huang et al. [4] and Wang et al. [46] and focusing on Chinese provinces. Third, we outline the contribution of Mitra et al. [3] on the specific case of Kolkata city (India).

Anjum [9]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 USA, and India, Anjum [9] 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. [4] and Wang et al. [46] 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. [4] 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 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, NOx and Volatile Organic Compounds (VOCs) show the highest enhancements. To study $PM_{2.5}$ changes under emission reduction scenarios, Wang et al. [46] employed a Community Multiscale Air Quality (CMAQ) 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. [3] 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. [3] interpreted this result as the direct lockdown effect due to COVID-19.

Mele and Magazzino [47] analyzed the relationship between economic growth, polluting emissions, and COVID-19 deaths, finding a causal link amongst PM2.5, CO 2, NO 2 emissions, and COVID-19 deaths.

2.2. Studies considering air pollution as a contributing factor to COVID-19-related-deaths

This sub-section displays the relevant studies tackling the atmospheric determinants of population's vulnerability to COVID-19.

Wu et al. [29] explored the pre-existing conditions that increase the risk of death due to COVID-19. They investigated whether long-term exposure to $PM_{2.5}$ can be associated with an increased COVID-19 fatality in the USA. They collected data from 3,000 counties up to April 22th 2020 and employed a negative binomial mixed model. Having controlled for confounding factors including population size, age, and weather, the results indicate that an increase of only 1 $\mu g/m^3$ in $PM_{2.5}$ is associated with an 8% increase in the COVID-19 death rate. Yongjian et al. [30] explored the relationship between air pollutants and the infection caused by COVID-19 in China. Focusing on 120 cities over the period January 23th to February 29th 2020, the authors applied a Generalized Additive Model (GAM) on six air pollutants ($PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, and O_3) and linked it with COVID-19 confirmed cases. Results highlighted significantly positive associations of $PM_{2.5}$, PM_{10}, NO_2, O_3 and COVID-19 confirmed cases. Indeed, a 10-$\mu g/m^3$ increase in $PM_{2.5}$, PM_{10}, NO_2, and O_3 is associated with a 2.24%, 1.76%, 6.94%, and 4.76%, increase in daily COVID-19 cases, respectively.

Pansini and Fornacca [48] investigated the geographical character of COVID-19 and its correlation with several annual satellite and ground indexes of air quality in China, Iran, Italy, Spain, France, Germany, UK, and the USA. They registered more viral infections in the areas afflicted by high $PM_{2.5}$ and NO_2 values. Higher mortality was also correlated with relatively poor air quality. Travaglio et al. [31] showed that levels of multiple poor air quality markers, including nitrogen oxides (NOx) and sulphur dioxide (SO_2), are associated with increased numbers of COVID-19-related deaths throughout England, after an adjustment for population density.

Working on the Italian case, Setti et al. [32] highlighted the association between the number of PM_{10} daily limit value exceedances, registered in the period 10th February-29th February 2020, and the number of COVID-19 infected persons updated at 3rd March 2020. Empirical findings confirmed the existence of a direct relationship between the number of persons infected by COVID-19 and the PM_{10} concentration levels in specific areas of Italy. Focusing on Northern Italy, Conticini et al. [33]examined the correlation between the atmospheric pollution and the high level of COVID-19 lethality. Results provided evidence that people living in an area with high levels of pollutants are more susceptible to develop chronic respiratory conditions and suitable to infective agents. Furthermore, air pollution was suggested to partially explain the differences in mortality in this region.

Nonetheless, these studies unanimously call for a careful interpretation of the results. As mentioned in Contini and Costabile [28], misleading estimations are plausible mainly due to the different strategies used for counting deaths related to COVID-19 in the world. Table 1 summarizes the main information of this seminal literature.

This literature review highlights three important points based on which novelty aspects can be drawn. First, temporary nationwide lockdowns have resulted in obvious reductions in air pollutions across the world. Remaining tough significant in major cities, high PMs concentration levels find their source in the combustion of important volumes of fossil fuels (mainly gasoline and diesel) for domestic and commercial road transport. In France, urban municipalities are questioning the well-established transport-pollution relationship, restoring the potential of cleaner fuels (notably biofuels), and the power of diesel and gasoline taxation in fighting against oil products externalities. Second, a few past empirical works brought non-sophisticated results but very seminal evidence on the feedback air pollution-COVID-19 channel. In fact, all studies concluded that a wide range of

Table 1
Previous air pollution-COVID-19 empirical assessments.

Author(s)	Country	Sample period	Air pollution variable(s)	Evidence on the effect of air pollution on COVID-19 lethality
Wu et al. [29]	3087 counties in the USA	Up to April 22th 2020	$PM_{2.5}$	Yes
Yongjian et al. [30]	120 cities in China	January 23th-February 29th 2020,	$PM_{2.5}$, PM_{10}, SO_2, CO, NO_2 and O_3	Yes
Travaglio et al. [31]	120 sites in England	February 1st to April 8th 2020	NO_2, NO_x and O_3	Yes
Setti et al. [32]	8 Italian regions	10th February-29th February 2020,	PM_{10}	Yes
Conticini et al.[33]	Northern Italy	March 15th 2020 onward	PM_{10}, $PM_{2.5}$, O_3, SO_2 and NO_2	Yes

Source: our elaborations.
Notes: "Yes" means that a significant correlation between air pollution levels and COVID-19 cases/mortality is confirmed.

determinants are potentially involved in the spread of COVID-19 (such as age, population density, social habits, and the restrictive measures applied). But the original point stands elsewhere: these investigations also unanimously confirmed the correlation between atmospheric conditions and COVID-19 cases, making poor air quality an additional co-determinant of COVID-19 lethality. Third, starting from this observation, no empirical estimation of the threshold levels has been carried out so far. Obviously, this critical lack in the literature concerns many countries but specifically the French case, for which the COVID-19 situation resulted in dramatic consequences. Accordingly, our paper finds its empirical contribution by providing pioneer threshold levels estimations of $PM_{2.5}$ and PM_{10} connected to COVID-19 on major French cities (Paris, Marseille, and Lyon). Another novelty aspect is methodological. We refer to the emerging literature on the relationship among air pollution and virus epidemic diffusion [41–45] to rely on a ML methodology. Given the complexity of our research question, we apply ANNs experiments with univariate input and output. Then, to check the deep consistency of our results, a D2C Causal Direction from Dependency algorithm capable of predicting the existence of a direct causal link between two variables in a multivariate setting is performed. Though their limitations, our results are thought to represent a fruitful research direction whose direct implications would help policymakers.

3. Data collection and methodology

3.1. Data collection

The consumption of oil products (mainly gasoline and diesel) for road transport is at the source of an important concentration of PM in urban areas. Our focus is on the potential effects of these harmful particles in spreading the current COVID-19 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. Hence, to empirically assess this relationship, we rely on daily data at city level.

First, 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 (2nd), Lyon (3rd) (French National Institute of Statistics and Information about the Economy (INSEE), 2020). We used two types of Particulate Matter: PM_{10} and $PM_{2.5}$ (expressed in $\mu g/m^3$) whose concentration in urban cities is directly linked to the combustion of fossil fuels for road traffic [11]. 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[8] based on information given by 40 environmental monitoring stations. For Marseille, air pollution data are taken from AtmoSud[9] using information from seven environmental monitoring stations. For Lyon, air pollution data are collected by Atmo Auvergne-Rhône-Alpes[10] using eleven environmental monitoring stations.

Second, 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)[11] and updated with daily frequency.

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 18th 2020 to April 27th 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 18th 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.

The particular complexity and non-linearity of the relationships associated with air pollution suggest the use of a more flexible tool than usual. Boznar et al. [49], Cigizoglu and Kisi [50], Pasero and Mesin [51], Zhang [52], and Zhang et al. [53] have shown that NNs are adaptive structures capable of correctly estimating environmental and energy problems. NNs are capable of "learning" the solution of the issues starting from known examples. We use a model of Artificial Neural Networks (ANNs) through the implementation of the AD-Designer platform, following the recent contributions of Magazzino et al. [54] and Mele and Magazzino [55]. 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.

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

[8] Air pollution data for Paris are available at: http://www.airparif.asso.fr/publications/

[9] Air pollution data for Marseille are available at : https://www.atmosud.org/donnees/acces-par-station

[10] Air pollution data for Lyon are available at: https://www.atmo-auvergnerhonealpes.fr/donnees/telecharger

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

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 2. *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 2 are the result of many combinations and experiments carried out by the Authors.

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 (Fig. 1). 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.

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

As shown by the variables bars chart, the variables used are 9, of which six represent the input process, and one is the generated target. The instances pie chart reveals that 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".

5. - Paris[12][13]

Fig. 2 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 μg/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 Fig. 3, we analyze the effect compared to PM_{10}.

The cut-off signal in NN transmission from PM_{10} input to the target Deaths has been identified as 29.6 μg/m^3. The result obtained is very interesting. Compared to Fig. 2, 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 field importance test on $PM_{2.5}$ and PM_{10} compared to the number of deaths in Paris. This test represents an answer to a question. The algorithm asks the machine, for each variable, its weight on another variable (*Deaths*). The question has an answer in a range of 0–1, which is then processed in percentage terms. 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 5.

6. - Lyon[14][15]

The results on the relationship between $PM_{2.5}$ concentration and deaths from COVID-19 are interesting (Fig. 4). 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 Fig. 5, we analyze the effect compared to PM_{10}.

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. According to the test results, 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.

7. - Marseille[16][17]

Fig. 6 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

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

Table 2
ANNs experiment procedure.

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

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

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

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

Source: our elaborations.

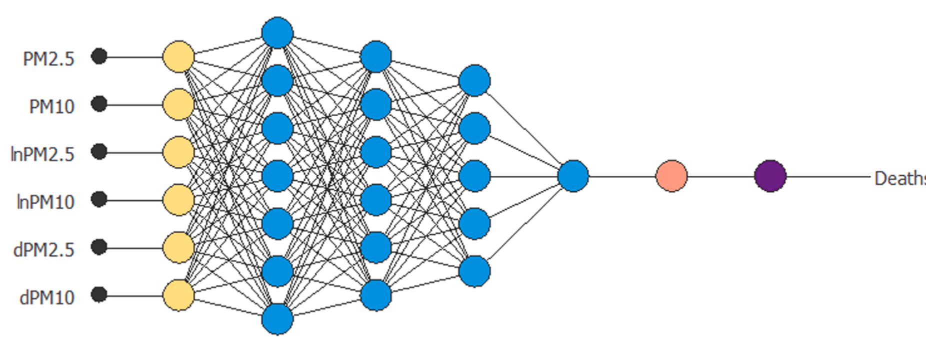


Fig. 1. Our ANNs. Source: our processing on command strings.

more significant. In Fig. 7, we analyze the effect compared to PM_{10}.

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. Both the predicted confidence intervals and the combination of instances between the inputs and the target are different from previous

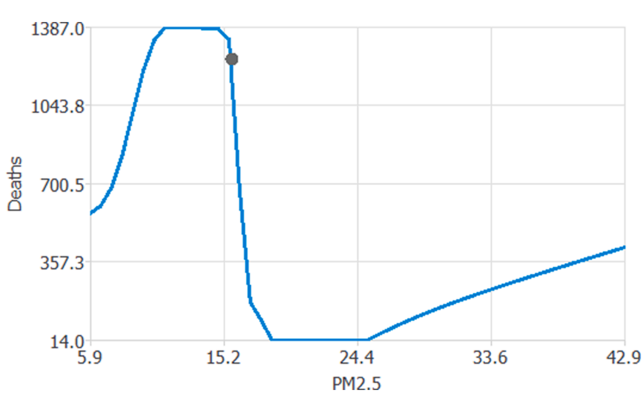


Fig. 2. Deaths-$PM_{2.5}$ Directional Output. Source: our elaborations.

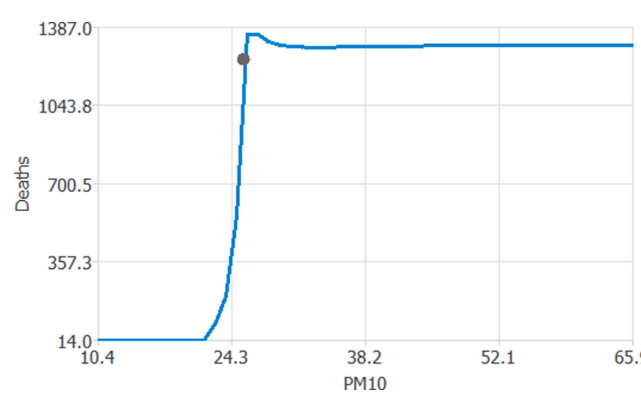


Fig. 3. Deaths-PM_{10} Directional Output. Source: our elaborations.

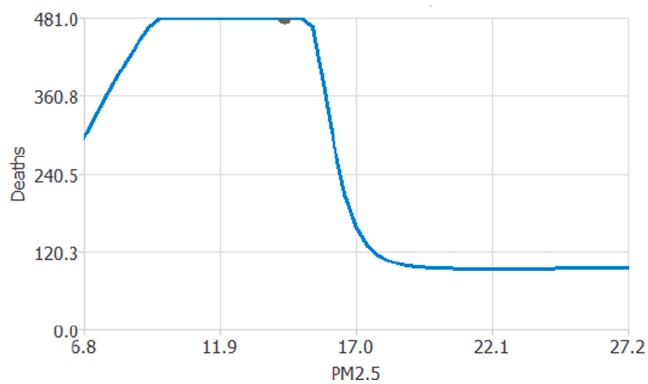


Fig. 4. Deaths-$PM_{2.5}$ Directional Output. Source: our elaborations.

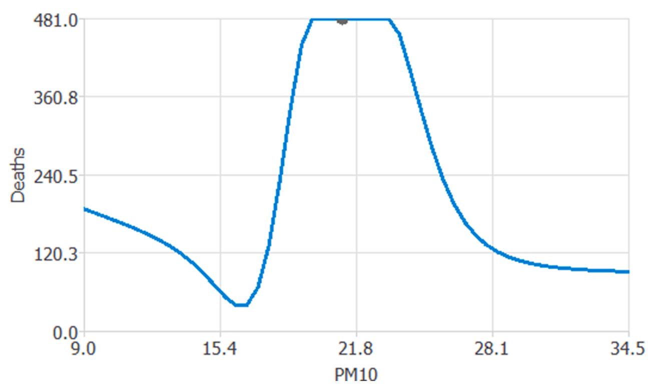


Fig. 5. Deaths-PM_{10} Directional Output. Source: our elaborations.

tests. Also the values results are different from those of Paris and Lyon. In fact, for Marseille, the cut off value of 14.3 $\mu g/m^3$ 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.

Now, we test the results obtained with the ANNs methodology through a different model. This choice is consistent with the definition of a scientific experiment. In fact, an experiment is correct when it can be tested through a different method and reproducible by all researchers. Therefore, we use an algorithm in ML that can generate causal effects between the variables. Following Pearl [56–59], we use a D2C algorithm on Proportion-based causality using the Oryx 2.0.8 software and the same dataset used for ANNs analysis. However, since an algorithm in ML needs many variables (remembering that the data is not interpreted as a time series), we will carry out mathematical transformations. Thus, in addition to the logarithmic transformation and the first difference already carried out in the previous analysis, we generate the square of the selected variables, and the first difference (calculated in logarithmic terms).

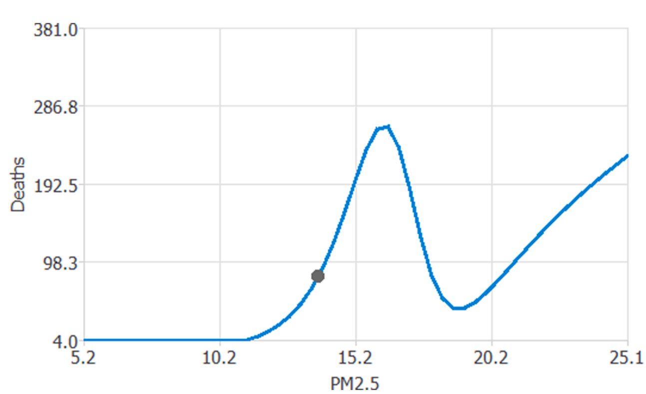


Fig. 6. Deaths-$PM_{2.5}$ Directional Output. Source: our elaborations.

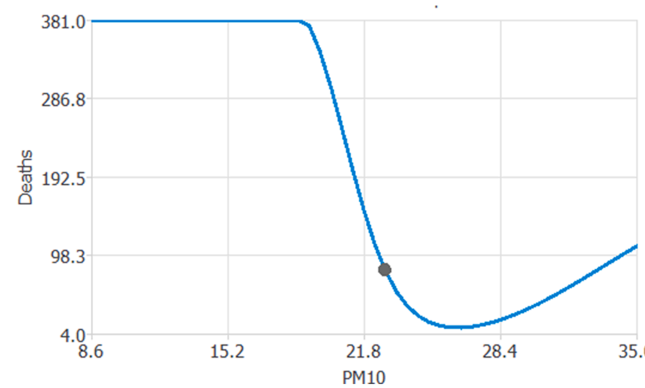


Fig. 7. Deaths-PM_{10} Directional Output. Source: our elaborations.

We perform a Machine Learning analysis, following the process shown in Fig. 8.

Starting from the dataset used for ANNs analysis, we increase the variables through mathematical transformations to obtain a large

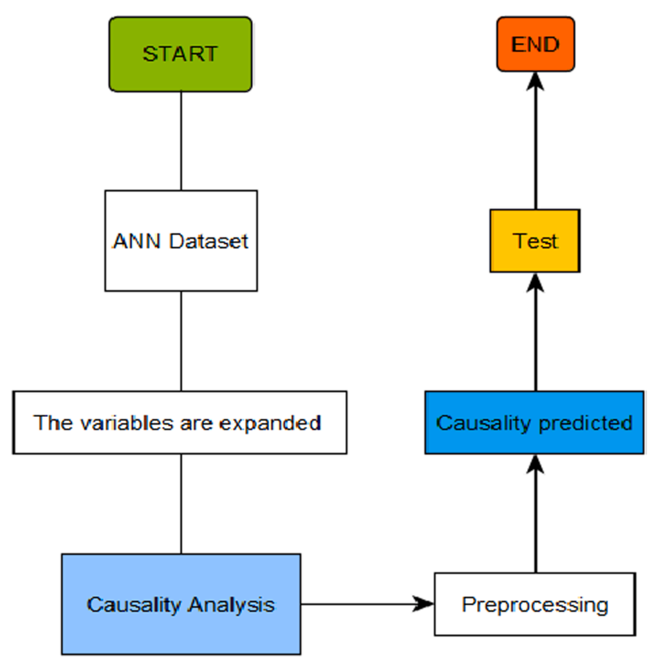


Fig. 8. ML D2C process. Source: our elaborations.

Table 3
Rank of predictor and significant causality results for Paris.

Rank of Predictor	Number of repetitions	Percentage (%)	AC	AUPRC
$PM_{2.5} \rightarrow PM_{10}$	17,985	0.89	4.949	False
$PM_{2.5} \leftarrow PM_{10}$	17,549	0.89	4.784	False
$lnPM_{2.5} \rightarrow lnPM_{10}$	18,161	0.89	4.745	False
$lnPM_{2.5} \leftarrow lnPM_{10}$	18,542	0.89	4.197	False
$dPM_{2.5} \rightarrow dPM_{10}$	18,665	0.89	4.187	False
$dPM_{2.5} \leftarrow dPM_{10}$	17,464	0.89	4.122	False
$sPM_{2.5} \rightarrow sPM_{10}$	17,952	0.89	4.125	False
$sPM_{2.5} \leftarrow sPM_{10}$	17,465	0.89	4.896	False
$d.lnPM_{2.5} \rightarrow d.lnPM_{10}$	17,651	0.89	4.191	False
$d.lnPM_{2.5} \leftarrow d.lnPM_{10}$	19,455	0.89	4.965	False
$PM_{2.5} \rightarrow$ Deaths	21,756	0.89	4.100	True
$PM_{2.5} \leftarrow$ Deaths	21,479	0.89	4.105	False
$lnPM_{2.5} \rightarrow$ lnDeaths	16,984	0.89	4.204	False
$lnPM_{2.5} \leftarrow$ lnDeaths	15,665	0.89	4.255	False
$dPM_{2.5} \rightarrow$ dDeaths	17,854	0.89	4.125	True
$dPM_{2.5} \leftarrow$ dDeaths	16,249	0.89	4.202	False
$sPM_{2.5} \rightarrow$ sDeaths	19,845	0.89	4.265	False
$sPM_{2.5} \leftarrow$ sDeaths	19,454	0.89	4.122	False
$d.lnPM_{2.5} \rightarrow$ d.lnDeaths	17,446	0.89	4.122	False
$d.lnPM_{2.5} \leftarrow$ d.lnDeaths	17,445	0.89	4.122	False
$PM_{10} \rightarrow$ Deaths	17,945	0.89	4.365	True
$PM_{10} \leftarrow$ Deaths	18,654	0.89	4.125	False
$lnPM_{10} \rightarrow$ lnDeaths	18,465	0.89	4.125	False
$lnPM_{10} \leftarrow$ lnDeaths	19,542	0.89	4.136	False
$dPM_{10} \rightarrow$ dDeaths	19,451	0.89	4.795	True
$dPM_{10} \leftarrow$ dDeaths	18,544	0.89	4.862	False
$sPM_{10} \rightarrow$ sDeaths	19,456	0.89	4.264	False
$sPM_{10} \leftarrow$ sDeaths	21,949	0.89	4.166	False
$d.lnPM_{10} \rightarrow$ d.lnDeaths	20,495	0.89	4.102	False
$d.lnPM_{10} \leftarrow$ d.lnDeaths	20,948	0.89	4.105	False

Notes: AC: Average Causality value; AUPRC: Area Under the Precision Recall Curve. True: P-Value < 0.05. False: P-Value ≥ 0.05. Number of repetitions: number of retries (0 and 1) carried out by the machine. Percentage (%): expected success rate compared to an opposite event.

Table 4
Rank of predictor and significant causality results for Lyon.

Rank of Predictor	Number of repetitions	Percentage (%)	AC	AUPRC
$PM_{2.5} \rightarrow PM_{10}$	17,894	0.80	4.646	False
$PM_{2.5} \leftarrow PM_{10}$	17,852	0.80	4.546	False
$lnPM_{2.5} \rightarrow lnPM_{10}$	18,111	0.80	4.546	False
$lnPM_{2.5} \leftarrow lnPM_{10}$	18,565	0.80	4.646	False
$dPM_{2.5} \rightarrow dPM_{10}$	18,749	0.80	4.466	False
$dPM_{2.5} \leftarrow dPM_{10}$	18,162	0.80	4.495	False
$sPM_{2.5} \rightarrow sPM_{10}$	17,429	0.80	4.495	False
$sPM_{2.5} \leftarrow sPM_{10}$	17,422	0.80	4.949	False
$d.lnPM_{2.5} \rightarrow d.lnPM_{10}$	17,411	0.80	4.498	False
$d.lnPM_{2.5} \leftarrow d.lnPM_{10}$	18,412	0.80	4.949	False
$PM_{2.5} \rightarrow$ Deaths	20,545	0.80	4.195	True
$PM_{2.5} \leftarrow$ Deaths	20,555	0.80	4.498	False
$lnPM_{2.5} \rightarrow$ lnDeaths	17,165	0.80	4.495	False
$lnPM_{2.5} \leftarrow$ lnDeaths	17,166	0.80	4.984	False
$dPM_{2.5} \rightarrow$ dDeaths	17,495	0.80	4.495	True
$dPM_{2.5} \leftarrow$ dDeaths	17,162	0.80	4.202	False
$sPM_{2.5} \rightarrow$ sDeaths	17,165	0.80	4.495	False
$sPM_{2.5} \leftarrow$ sDeaths	17,166	0.80	4.100	False
$d.lnPM_{2.5} \rightarrow$ d.lnDeaths	18,522	0.80	4.100	False
$d.lnPM_{2.5} \leftarrow$ d.lnDeaths	18,522	0.80	4.100	False
$PM_{10} \rightarrow$ Deaths	18,523	0.80	4.949	True
$PM_{10} \leftarrow$ Deaths	18,852	0.80	4.115	False
$lnPM_{10} \rightarrow$ lnDeaths	19,520	0.80	4.115	False
$lnPM_{10} \leftarrow$ lnDeaths	19,412	0.80	4.119	False
$dPM_{10} \rightarrow$ dDeaths	19,444	0.80	4.491	True
$dPM_{10} \leftarrow$ dDeaths	19,521	0.80	4.495	False
$sPM_{10} \rightarrow$ sDeaths	19,226	0.80	4.295	False
$sPM_{10} \leftarrow$ sDeaths	20,212	0.80	4.198	False
$d.lnPM_{10} \rightarrow$ d.lnDeaths	20,196	0.80	4.195	False
$d.lnPM_{10} \leftarrow$ d.lnDeaths	20,559	0.80	4.195	False

Notes: AC: Average Causality value; AUPRC: Area Under the Precision Recall Curve. True: P-Value < 0.05. False: P-Value ≥ 0.05. Number of repetitions: number of retries (0 and 1) carried out by the machine. Percentage (%): expected success rate compared to an opposite event.

dataset necessary for our D2C algorithm. Subsequently, the causality model is processed, and we analyze those variables significant for us. Once the D2C commands are imported into the Oryx software, the analysis generates the causalities mentioned above typical of a ML process. Finally, we carry out the ML test (AC and AUPRC) to verify the correctness of the algorithm.

In Tables 3-5, we show the causality and significance tests to determine the relationship between the variables object of the study on Paris, Lyon, and Marseille. In the model, *n* filtered factors were used. The self-learning machine worked in the following way. It started from a set of commands with functionality still to be preset. Subsequently, ten classifiers were trained and tested to achieve the predictive causal link between variables. These ten classifiers worked through a binary calculation sequence, alternating the values [0] with [1].

As we can see from the results, the algorithm worked by performing on average over 18,500 repetitions for each combination of causality between our variables. The closing percentage of the calculation, within the average of the repeats, has always been higher than 80%. Hence, our algorithm has ever completed each cycle for each pair of variables. The value of the Average Causality is uniform for all the pairs. As regards the significance of the results of predictive causality, we parameterized the AUPRC. It was divided into True or False with respect to a P-Value lower or higher than 5%. We obtained that only a causal relationship is significant within the AUPRC analysis. It is attributable to a unidirectional causality running from $PM_{2.5}$ to Deaths, PM_{10} to Deaths, $dPM_{2.5}$ to dDeaths, and dPM_{10} to dDeaths. These results clearly confirm the choice of the variables of the ANNs model. Besides, we have to underline that the causality predictive relationship is also present in the variation over time between the particulates and the COVID-19 deaths. This result would confirm the hypothesis that the threshold values found in the ANNs could influence the continuation of the pandemic and deaths. Although there may be many causes of deaths, the link of predictive causality has recorded a solid relationship between pollutants and deaths from COVID-19. We believe that, at least for a value higher than 80% (percentage in the tables), high levels of fine particulate matter have caused the aggravation of COVID-19 patients, generating death.

Table 5
Rank of predictor and significant causality results for Marseille.

Rank of Predictor	Number of repetitions	Percentage (%)	AC	AUPRC
$PM_{2.5} \rightarrow PM_{10}$	17,945	0.85	4.195	False
$PM_{2.5} \leftarrow PM_{10}$	17,894	0.85	4.195	False
$lnPM_{2.5} \rightarrow lnPM_{10}$	17,954	0.85	4.195	False
$lnPM_{2.5} \leftarrow lnPM_{10}$	17,191	0.85	4.195	False
$dPM_{2.5} \rightarrow dPM_{10}$	17,951	0.85	4.195	False
$dPM_{2.5} \leftarrow dPM_{10}$	17,951	0.85	4.984	False
$sPM_{2.5} \rightarrow sPM_{10}$	17,495	0.85	4.892	False
$sPM_{2.5} \leftarrow sPM_{10}$	17,952	0.85	4.918	False
$d.lnPM_{2.5} \rightarrow d.lnPM_{10}$	17,165	0.85	4.129	False
$d.lnPM_{2.5} \leftarrow d.lnPM_{10}$	17,456	0.85	4.929	False
$PM_{2.5} \rightarrow$ Deaths	19,516	0.85	4.140	True
$PM_{2.5} \leftarrow$ Deaths	19,511	0.85	4.135	False
$lnPM_{2.5} \rightarrow$ lnDeaths	17,951	0.85	4.274	False
$lnPM_{2.5} \leftarrow$ lnDeaths	17,565	0.85	4.916	False
$dPM_{2.5} \rightarrow$ dDeaths	17,165	0.85	4.625	True
$dPM_{2.5} \leftarrow$ dDeaths	17,915	0.85	4.272	False
$sPM_{2.5} \rightarrow$ sDeaths	18,411	0.85	4.995	False
$sPM_{2.5} \leftarrow$ sDeaths	18,116	0.85	4.651	False
$d.lnPM_{2.5} \rightarrow$ d.lnDeaths	18,116	0.85	4.174	False
$d.lnPM_{2.5} \leftarrow$ d.lnDeaths	17,812	0.85	4.195	False
$PM_{10} \rightarrow$ Deaths	17,198	0.85	4.326	True
$PM_{10} \leftarrow$ Deaths	17,116	0.85	4.123	False
$lnPM_{10} \rightarrow$ lnDeaths	17,165	0.85	4.795	False
$lnPM_{10} \leftarrow$ lnDeaths	18,116	0.85	4.895	False
$dPM_{10} \rightarrow$ dDeaths	18,196	0.85	4.552	True
$dPM_{10} \leftarrow$ dDeaths	18,516	0.85	4.862	False
$sPM_{10} \rightarrow$ sDeaths	18,116	0.85	4.954	False
$sPM_{10} \leftarrow$ sDeaths	19,862	0.85	4.955	False
$d.lnPM_{10} \rightarrow$ d.lnDeaths	19,156	0.85	4.175	False
$d.lnPM_{10} \leftarrow$ d.lnDeaths	19,478	0.85	4.199	False

Notes: AC: Average Causality value; AUPRC: Area Under the Precision Recall Curve. True: P-Value < 0.05. False: P-Value ≥ 0.05. Number of repetitions: number of retries (0 and 1) carried out by the machine. Percentage (%): expected success rate compared to an opposite event.

8. Summary of results and interpretations

Table 6 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.

As we can see from Table 7, all our threshold values are lower than those of the EU. These findings are important in a COVID-19 pandemic

Table 6
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.

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. [60] 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. [61] showed a link between the COVID-19 lethality index and air quality, regarding predisposition to pulmonary pathologies. Ogen [62] 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.

Table 7
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.

Table 8
Our threshold value compared to Milan.

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

Source: our elaborations.

9. - use of our threshold value: An example

Milan in February recorded PM_{10} values above our threshold level (Table 8). 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 (Fig. 9). 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 [35–38]. 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.

10. Conclusions and policy implications

Road transport displays important fossil fuel needs whose combustion is a leading driver of Particulate Matter (PM) concentrations in high populated cities worldwide. Far from being spared, French cities have been experiencing critical air pollution levels (notably PM_{10} and $PM_{2.5}$) for the last two decades, inducing chronic adverse health effects for urban inhabitants. While taking a dramatic dimension, several municipalities are calling for an urgent introduction of low-carbon fuels for

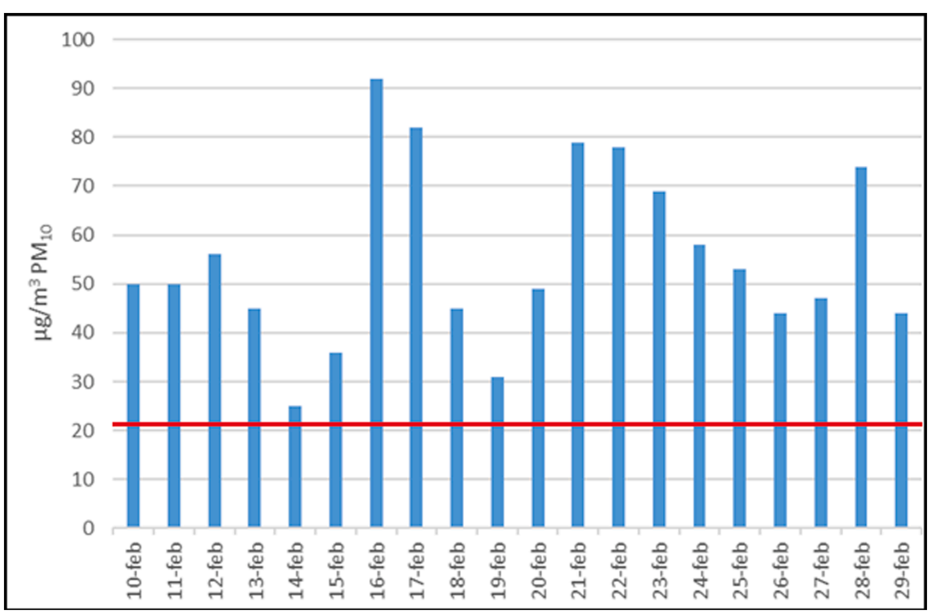


Fig. 9. PM_{10} µg/m^3 in Milan (average February values). Source: our elaboration on SIAD-ARPA data.

road transport in complement with a more efficient regulation of urban travels within cities. The purpose of this paper aims is to analyse the potential effects of these harmful particles in spreading the current COVID-19 epidemic in France. The underlying hypothesis is that a pre-determined particulate concentration can foster COVID-19 and make the respiratory system more susceptible to this infection.

This study investigated the empirical relationship between particulate matter concentrations (PM_{10} and $PM_{2.5}$) and deaths from COVID-19 in three French cities (Paris, Marseille and Lyon). To do so, we collected and averaged the concentrations measures given by operating environmental monitoring stations for each city and each pollutant. Then, we merged it with the daily reports on COVID-19-related-deaths provided at city level. 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. Then, we checked the consistency of our results using a D2C algorithm capable of predicting the existence of a direct causal link between two variables in a multivariate setting. 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 [63–65]. They can be inhaled and penetrate deep into the lungs and the circulatory system, travelling into the blood and reaching the cells [25]. Numerous scientific studies have shown that particle exposure can induce various health effects including heart or lung disease, non-fatal heart attacks, irregular heartbeat, aggravated asthma, decreased lung function, and increased respiratory symptoms such as irritation of the airways, coughing, or difficulty breathing [66–70]. Thus, reducing the exposure to high PMs concentrations levels could prevent thousands of premature deaths [26,71]. Meanwhile, the most common symptoms of COVID-19 illness are fever, cough, and fatigue, while other symptoms include sputum production, headache, haemoptysis, diarrhoea, dyspnoea, and lymphopenia [4,46,72–74]. By comparing these symptoms, we notice that PMs and COVID-19 induce both adverse respiratory effects causing deaths in the worst cases. But it should be mentioned that unlike PMs, the COVID-19 infection may rapidly induce deaths or severe complications. Linking air pollution and COVID-19 fatality refers to the empirical assessment of a crucial hypothesis: a pre-determined particulate concentration could foster COVID-19 and make the respiratory system more susceptible to this infection. As potential carriers of pathogens, airborne particles could make the viral infection spread more harmful [32]. Meaningful for future environmental and health policies, such empirical analysis is believed to bring additional findings regarding the atmospheric co-factors of COVID-19 lethality. 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. These findings have been corroborated by the D2C algorithm whose results confirmed the direct relationship between air pollution and COVID-19-related deaths. It is interesting to note that all the threshold values identified by the ANNs are higher than the limits imposed by the European Parliament. From the point of view of the European economic policy, raising environmental standards may require a quantification and balance between the interest in protecting public health and promoting economic growth.

In line with previous studies, our results showed evidence of a direct relationship between air pollution and COVID-19 mortality in France, confirming previous research regarding environmental factors involved in viral infection spread. This could partially explain the efficiency of national lockdown measures and provide useful implications for the prevention of this virus. 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. With its limits, our study underlines the necessity to recommend further environmental intervention policies 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. Another significant point drawn from this analysis is that it could bring useful information 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. To address this problem at its major source, a particular attention should be payed to the consumption of oil products (gasoline and diesel) for road transport in urban areas. Adequate urban planning is suggested to solve the chronic traffic congestion experienced by French cities. In addition, promoting low-carbon (biofuels), active (walking and cycling) and collective (bus and subway) transport modes for short-distance travels may lower the fleet's size of motor vehicles in French cities, reducing thus its petrol needs and harmful PMs emissions.

CRediT authorship contribution statement

Cosimo Magazzino: Conceptualization, Methodology, Software, Supervision. **Marco Mele:** Visualization, Investigation, Validation, Writing - review & editing. **Nicolas Schneider:** Data curation, Writing - original draft.

Declaration of Competing Interest

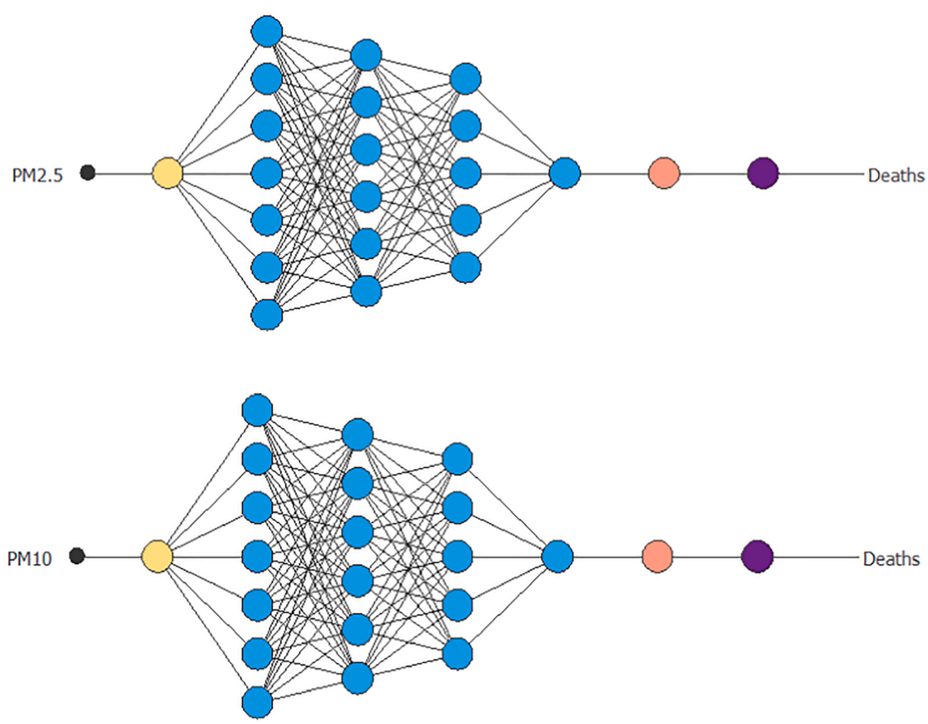
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

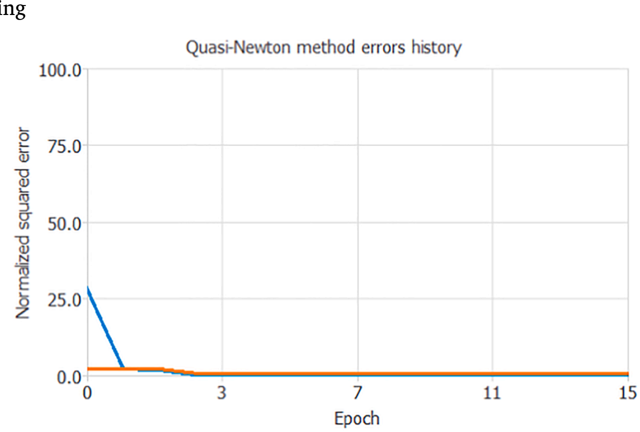
- *Paris*

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

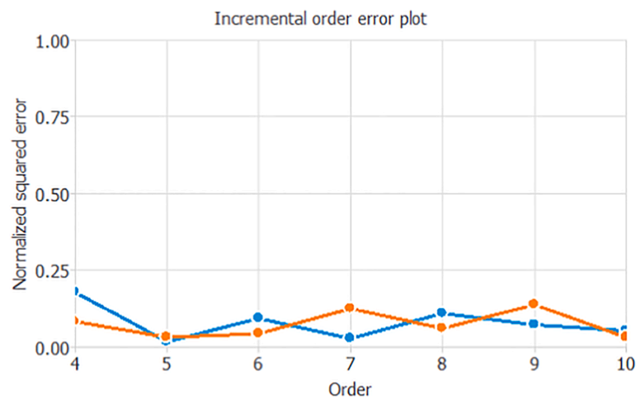
	Inputs number	Perceptrons number	Activation function
1	1	7	HyperbolicTangent
2	7	6	HyperbolicTangent
3	6	5	Linear
4	5	1	Linear



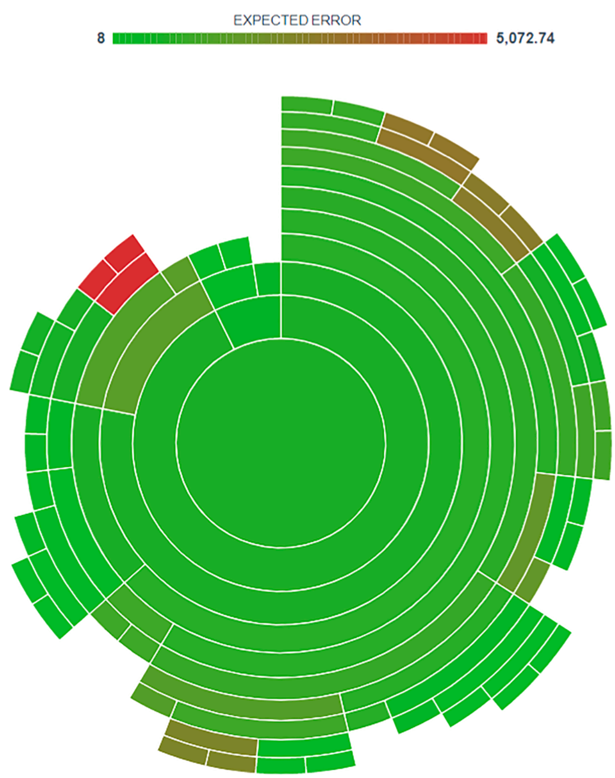
b) Training strategy: Perform Training



c) Model Selection



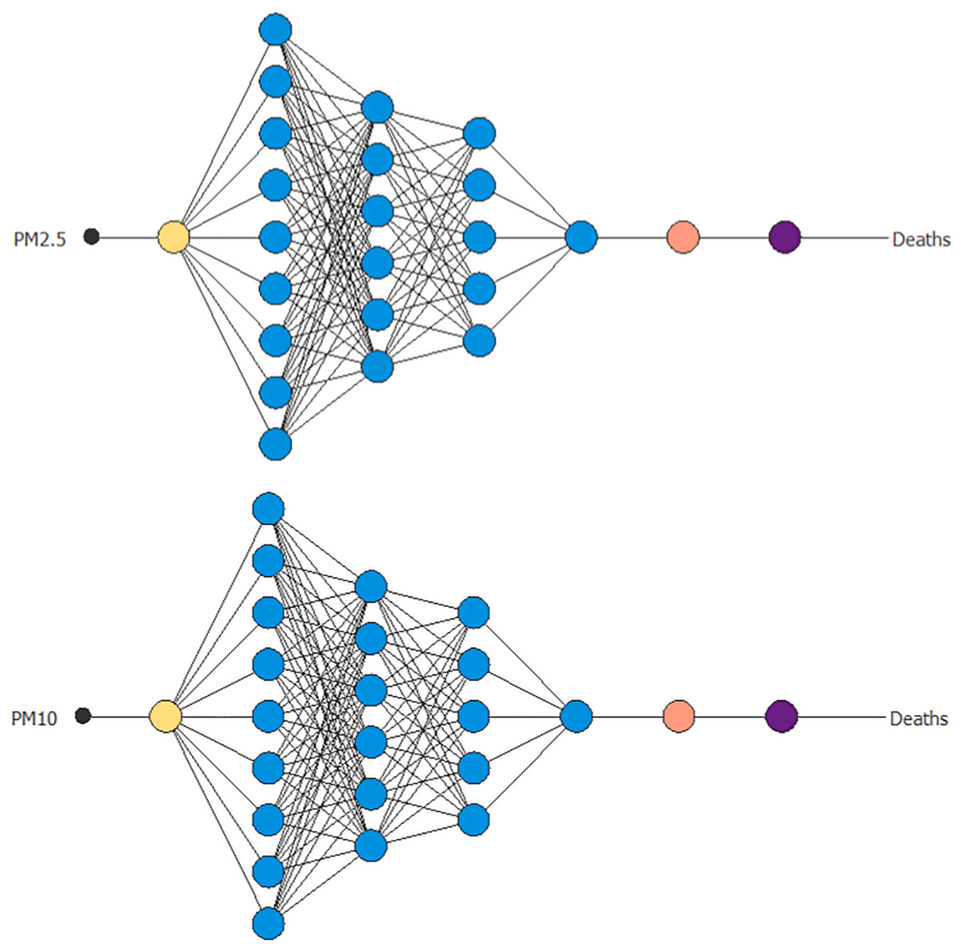
d) Testing Analysis (Paris: circular flow with final error of 1.96)



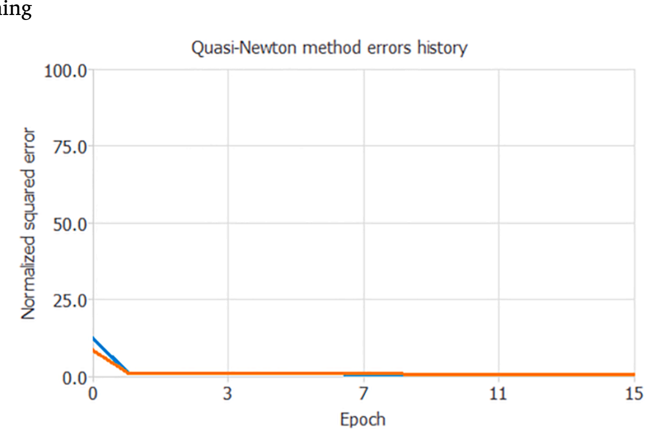
- Lyon

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

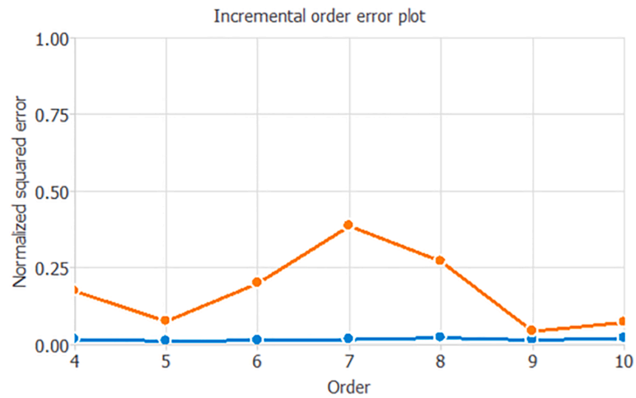
	Inputs number	Perceptrons number	Activation function
1	1	9	HyperbolicTangent
2	9	6	HyperbolicTangent
3	6	5	HyperbolicTangent
4	5	1	Linear



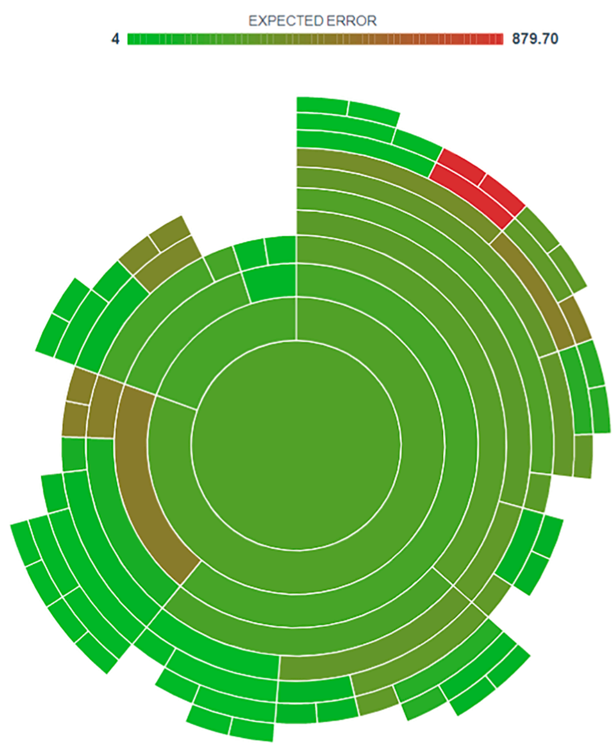
b) Training strategy: Perform Training



c) Model Selection



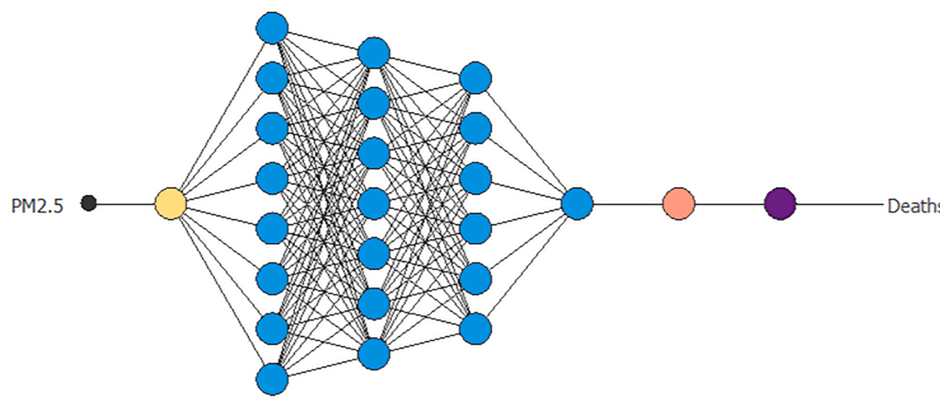
d) Testing Analysis (Lyon: circular flow with final error of 2.08)

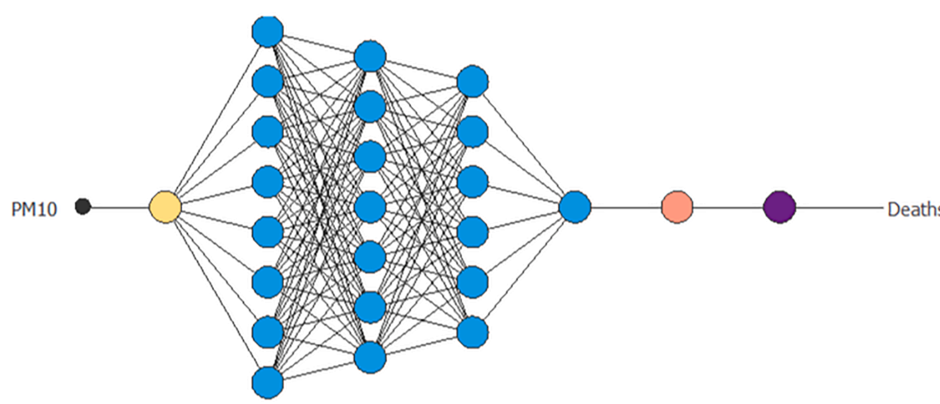


- Marseille

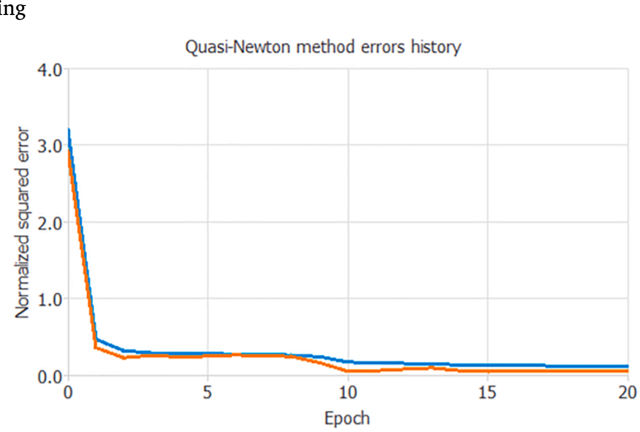
a) ANNs Perform inputs selection (PM_{10} and $PM_{2.5}$).

	Inputs number	Perceptrons number	Activation function
1	1	8	HyperbolicTangent
2	8	7	HyperbolicTangent
3	7	6	HyperbolicTangent
4	6	1	Linear

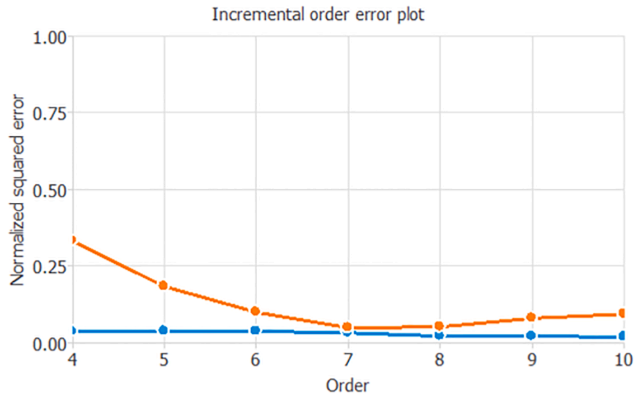




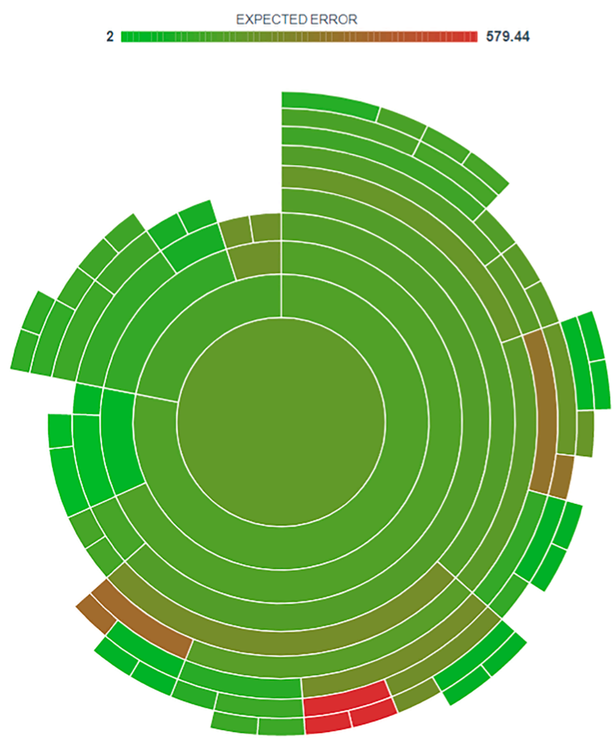
b) Training strategy: Perform Training



c) Model Selection



d) Testing Analysis (Marseille: circular flow with final error of 0.88)



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