Assessing the impact of PM$_{2.5}$ on respiratory disease using artificial neural networks

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Abstract

Understanding the impact on human health during peak episodes in air pollution is invaluable for policymakers. Particles less than PM$_{2.5}$ can penetrate the respiratory system, causing cardiopulmonary and other systemic diseases. Statistical regression models are usually used to assess air pollution impacts on human health. However, when there are databases missing, linear statistical regression may not process well and alternative data processing should be considered. Nonlinear Artificial Neural Networks (ANN) are not employed to research environmental health pollution even though another advantage in using ANN is that the output data can be expressed as the number of hospital admissions. This research applied ANN to assess the impact of air pollution on human health. Three well-known ANN were tested: Multilayer Perceptron (MLP), Extreme Learning Machines (ELM) and Echo State Networks (ESN), to assess the influence of PM$_{2.5}$, temperature, and relative humidity on hospital admissions due to respiratory diseases. Daily PM$_{2.5}$ levels were monitored, and hospital admissions for respiratory illness were obtained, from the Brazilian hospital information system for all ages during two sampling campaigns (2008–2011 and 2014–2015) in Curitiba, Brazil. During these periods, the daily number of hospital admissions ranged from 2 to 55, PM$_{2.5}$ concentrations varied from 0.98 to 54.2 $\mu$g m$^{-3}$, temperature ranged from 8 to 26 $^\circ$C, and relative humidity ranged from 45 to 100%. Of the ANN used in this study, MLP gave the best results showing a significant influence of PM$_{2.5}$, temperature and humidity on hospital attendance after one day of exposure. The Anova Friedman’s test showed statistical difference between the appliance of each ANN model ($p < 0.001$) for 1 lag day between PM$_{2.5}$ exposure and hospital admission. ANN could be a more sensitive method than statistical regression models for assessing the effects of air pollution on respiratory health, and especially useful when there is limited data available.

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1. Introduction

Increased particulate matter (PM) concentrations have correlated with rises in the prevalence of adverse health effects, mainly concerning respiratory and circulatory problems (Langrish et al., 2012; Sorensen et al., 2012; Wu et al., 2012). Such effects are
dependent on particles size, chemical composition, and atmospheric concentration (Davidson et al., 2005). Atmospheric particles with aerodynamic diameter less than 2.5 μm (PM$_{2.5}$) can be deposited in the pulmonary alveoli and can lead to respiratory problems. Moreover, PM$_{2.5}$ is able to access the bloodstream, deposited in the pulmonary alveoli and can lead to respiratory problems. Moreover, epidemiological studies concerning air pollution effects on human health are now focusing on exposures to pollutants at levels even below the existing air quality standards (Li et al., 2015; Nardocci et al., 2013).

The chemical composition of Particulate Matter (PM) depends on several factors such as source types, aging in the atmosphere (and its related transformations), and meteorological conditions that are responsible for transport of atmospheric particles. Several studies have previously investigated the health impact of PM and compared it to the chemical composition and sources of emissions (Hoek et al., 2002; Magari et al., 2002; Valavanidis et al., 2008; Wu et al., 2012). Statistical regressions models, such as Generalized Linear Models (GLM) (Lazzari, 2013; McCullagh and Nelder, 1989; Tadano et al., 2012; Vanos et al., 2014) or the Generalized Additive Models (GAM) (Bakonyi et al., 2004; Hastie and Tibshirani, 1990; Nardocci et al., 2013) are usually applied to evaluate health risks from the exposure to air pollution. Another possibility to address this issue is to face this problem as a nonlinear mapping task, which raises the possibility the employment of Artificial Neural Networks (ANN). This ANN is widely used in many different types of predictive models, including mapping air pollution. However, there are only a few published accounts of its application in assessing potential air pollution impacts on human health (Kassomenos et al., 2011; Sundaram et al., 2016; Tadano et al., 2016; Wang et al., 2008). The output data from the statistical regression models previously applied to predict air pollution health impacts comprise the well-known relative risk, an indirect measure of hospital admissions. On the other hand, ANN output is measured with the same metric as the response variable, which is the number of hospital admissions, a more convenient measure. In addition, due to lack of resources, many pollution databases in major cities around the world are incomplete in such situations, statistical regression models are often not useful to measure the influence of air pollution on human health, and ANN may provide an important alternate approach.

To determine the potential influence of PM$_{2.5}$ on respiratory health we, conducted two sampling campaigns in Curitiba, Brazil. We recorded daily levels of PM$_{2.5}$ in comparison with chronic and acute respiratory health. Source identification was performed using Absolute Principal Component Analysis (APCA). Then, we applied three well-known ANNs: Multilayer Perceptron (MLP), Extreme Learning Machines (ELM) and Echo State Networks (ESN), aiming to assess the effect of PM$_{2.5}$ on hospital admissions due to respiratory diseases.

Based on the above exposed scenario, the objective of this article is to use a new method to assess the influence of air pollution on human health based on ANN as a substitute to traditional statistical regressions models. This alternative approach allows more suitable outputs and is more robust when dealing with limited pollution data sets than standard methods.

2. Materials and methods

This section describes PM$_{2.5}$ sample location and methodology, as well as the determination of concentration, chemical composition, and source determination of pollutants. It is described the application of artificial neural networks models to address on hospital admissions due to respiratory diseases, and the case studies main characteristics.

2.1. Sampling site description

The study site was located at Curitiba, Paraná state, Brazil, at the National Institute of Meteorology (INMET) station (Fig. 1), coordinates 25° 26′ 93° latitude, 49° 13′ 85° longitude, and 924 m above sea level. Curitiba is situated 50 km off the coast and behind a mountain range up to 1800 m high between the city and the sea. The sampling site is a residential area close to the city Centre, near three of the most important city highways. These highways have a significant flow of traffic of both light and heavy-duty vehicles.

Curitiba has a subtropical highland climate with a historic average temperature of 16.8 °C, maximum average temperature 23.1 °C, and minimum average temperature 12.5 °C. Due to its altitude Curitiba is the coldest among Brazil’s state capitals. Rain is abundant throughout the year, with no dry season, and the historic average annual precipitation is 1483 mm. The lowest monthly average precipitation is in August with 73 mm (INMET, 2016). According to the preferential wind direction (East and Northeast) the study site has a low influence from industrial emissions, as the city’s main industrial area is located to the southwest.

2.2. PM$_{2.5}$ sampling

Daily PM$_{2.5}$ mass sampling was conducted from September 2008 to July 2011 (campaign 1), and from September 2014 to September 2015 (campaign 2) using an inertial low volume Harvard impacter sampler (de Miranda et al., 2012; Marple et al., 1987). The Harvard impactor was positioned at 2 m height and operated with a vacuum pump at 10 L min$^{-1}$ and a 37 mm polycarbonate filter. Additionally, field blank filters were kept to track and reduce errors due to filter handling and transport.

To determine PM$_{2.5}$ mass concentration, filters were weighed before and after sampling with a microbalance and an electrostatic charge eliminator. Black Carbon (BC) mass concentration was obtained using a transmissometer SootScan OT21 (Magge Scientific) at an 880 nm wavelength (infrared). Measurements of PM$_{2.5}$ elements were performed on a Minipal-4 (PANalytical, Almeio, The Netherlands) equipped with a Silicon Drift Detector (SDD), which is thermo-electrically cooled. The optimum tube voltage and current were determined based on reference standards (Micromatter, Seattle, WA, USA) and validated by the measurement of various thin layer standards for each element, and a reference material from NIST (2783 air particulate on filter media). The best spectra and calibration curves were obtained from He-atmosphere with 600 s of acquisition time under two conditions: a tube voltage of 30 kV, and a current of 0.3 mA with the limit of detection in brackets in ng·m$^{-3}$ for Br (0.99), Cr (0.39), Cu (0.32), Fe (0.69), Mn (0.35), Pb (0.81), Se (0.40), Ti (0.35), K (1.3) and Zn (0.5); a tube voltage of 9 kV and a current of 1.0 mA for Al (0.53), Si (2.3), S (1.4), Ca (0.39), Cl (1.9), and Mg (9.0).

2.3. Source apportionment

2.3.1. Enrichment factor analysis (EF)

We used EF analysis to differentiate anthropic sources from crustal ones as previously described (Godoi et al., 2006; Lee and Hieu, 2011). This was calculated based on the concentration of an individual element found in PM compared to its concentration pattern in nature (Equation (1)) (Hoornaert et al., 2004; Molnar et al., 1993). In this study, the chosen crustal reference element

$$EF_{\text{element}} = \frac{C_{\text{element}} / C_{\text{related}}} {C_{\text{crust}} / C_{\text{related}}}$$
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