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# Scenario analysis of strategies to control air pollution

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ABSTRACT

Air quality in Europe has been improving over the last decades. Notwithstanding, urban areas are still facing exceedances of the Air Quality Directive's limit and target values. In this study, we analyzed the effect of two mitigation measures on urban air quality: i) improvement of the biomass residential combustion appliances, and ii) electrification of passenger's cars fleet. Five European cities (Lisbon and Porto - Portugal, Athens - Greece, Kuopio - Finland, and Treviso - Italy) were used as case studies to evaluate the impact of the measures on the fine particle fraction ($PM_{2.5}$) concentrations. To facilitate decision making and the quick test of new measures, the LIFE Index-Air tool was developed. In this tool, the air pollutant concentrations are predicted by Artificial Neural Networks trained using a set of air quality modelling simulations. The results indicate that the replacement of old biomass heating systems by new improved fireplaces can be more effective in Treviso. On the other hand, the replacement of gasoline and diesel passenger vehicles by electric ones seems to be more effective in reducing $PM_{2.5}$ concentrations over Lisbon, Porto, and Athens. In Kuopio, both mitigation measures have an identical effect.

## 1. Introduction

During the last decade, different air pollutants have been associated with a widespread range of health effects (Cohen et al., 2017; GBD, 2020; Landrigan et al., 2018; Manisalidis et al., 2020). Furthermore, there is evidence that air pollution has an impact on economic activities, such as tourism (Eusébio et al., 2020), and it could also be linked to depression and suicide (Braithwaite et al., 2019). Nowadays, air pollution issues attract the media and social attention pushing politicians to act. Despite the many improvements verified as a result of effectively implemented measures worldwide, diseases due to air pollution continue causing significant excess mortality and loss of life expectancy, especially through cardiovascular diseases (Lelieveld et al., 2020; Newby et al., 2015). In Europe, air quality is still poor in some areas, in particular concerning particulate matter (PM) and nitrogen oxides (NOx) in urban areas (EEA, 2020). PM with an equivalent diameter smaller than 2.5 μm ($PM_{2.5}$) are of particular concern because they are able to travel deeply

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**Fig. 1.** Map showing the locations of the urban case studies.

into the respiratory tract, reaching the lungs and even into the bloodstream (Shou et al., 2019). Still, a lot of challenges remain to be faced and the objective of providing good air quality to all European citizens is not fulfilled.

According to the last European Environment Agency report (EEA, 2020), air quality improvement can be achieved by acting on the following key areas: road transport (expansion of infrastructures for biking; better planning to give sustainable transport services; improvement of public transport), residential heating (transition to lower emission fuels; raise public awareness), and industry (transition to lower emission fuels; installation of emission control equipment in all facilities). Mitigation and adaptation measures at urban scale include, among others, the expansion of district heating or replacement to cleaner fuels, the introduction of low-emission zones (LEZ) (Gehrsitz, 2017), the promotion of public transportation and switch to cleaner buses (Olawepo and Chen, 2019), the promotion of the bicycle use, lower speed limits and taxes for traffic (EEA, 2020). It should be noted that measures applied at the local scale may have different results due to several variables, such as micrometeorology, chemical reaction of the pollutants emitted and atmospheric dispersion, topography, among others (Fabregat et al., 2021).

To help policy makers choose the best air quality improvement measures, scenarios assessment tools are needed. The use of Integrated Assessment Modelling (IAM), which combines air quality, health, social and economic aspects of the decision-making process, could strongly contribute to evaluate the efficiency and effectiveness of air quality improvement measures (Relvas and Miranda, 2018; Miranda et al., 2016).

European Member States have been adapting IAM to the national scale aiming to assess country-specific measures (De Angelis et al., 2021; Viaene et al., 2016). For the application at the urban scale, some IAM approaches have been elaborated, such as the USIAM (Mediavilla-Sahagún and ApSimon, 2006), the OTELLO (Comes et al., 2010) and the RIAT+ (Carnevale et al., 2012a; Miranda et al., 2016). Some of these IAM use non-linear relations based on trained Artificial Neural Networks (ANN) to connect emissions and air quality indixes (Carnevale et al., 2012b; Relvas et al., 2017). In recent years, there has been an increasing interest on the use of ANN for predicting and forecasting ambient air pollution (Cabaneros et al., 2019; Masood and Ahmad, 2021). ANN have been successfully implemented in many studies for the short and long-term forecasting of PM10, $PM_{2.5}$, NOx and $O_3$ (De Gennaro et al., 2013; Maleki et al., 2019; Mao et al., 2017; Park et al., 2018). Non-linear models based on ANN have been favored, since these studies are focused on the reduction of the concentration levels of pollutants (in particular PM) which are impacted by non-linear formation mechanisms and/or chemical processes taking place in the atmosphere (Miranda et al., 2016). In this scope and in the framework of the project LIFE Index-Air (https://www.lifeindexair.net/), a web-based tool was developed as an effort to address the existing gap between ambient air quality management and real-life exposure of urban populations and related health risks, to help stakeholders in the selection and assessment of air quality improvement measures to be applied in urban areas. The LIFE Index-Air tool includes data from emissions to health effects, providing, per reference case and for new emission scenarios: i) information on the spatial distribution of pollutant emissions, air quality concentrations and exceedances to EU standards; ii) exposure per population group; iii) and burden of disease.

The LIFE Index-Air brings progress beyond the state of the art by developing a web-based tool, that does not require the installation of any kind of software to be used (e.g. in the case of RIAT+), and by integrating into a single platform a set of modules that allow moving from emissions to health effects assessment. It will contribute to further investigate the growing evidence of the role of the environment/air pollution as a determinant of human health and to support decision-makers. The main limitation of the tool is that it

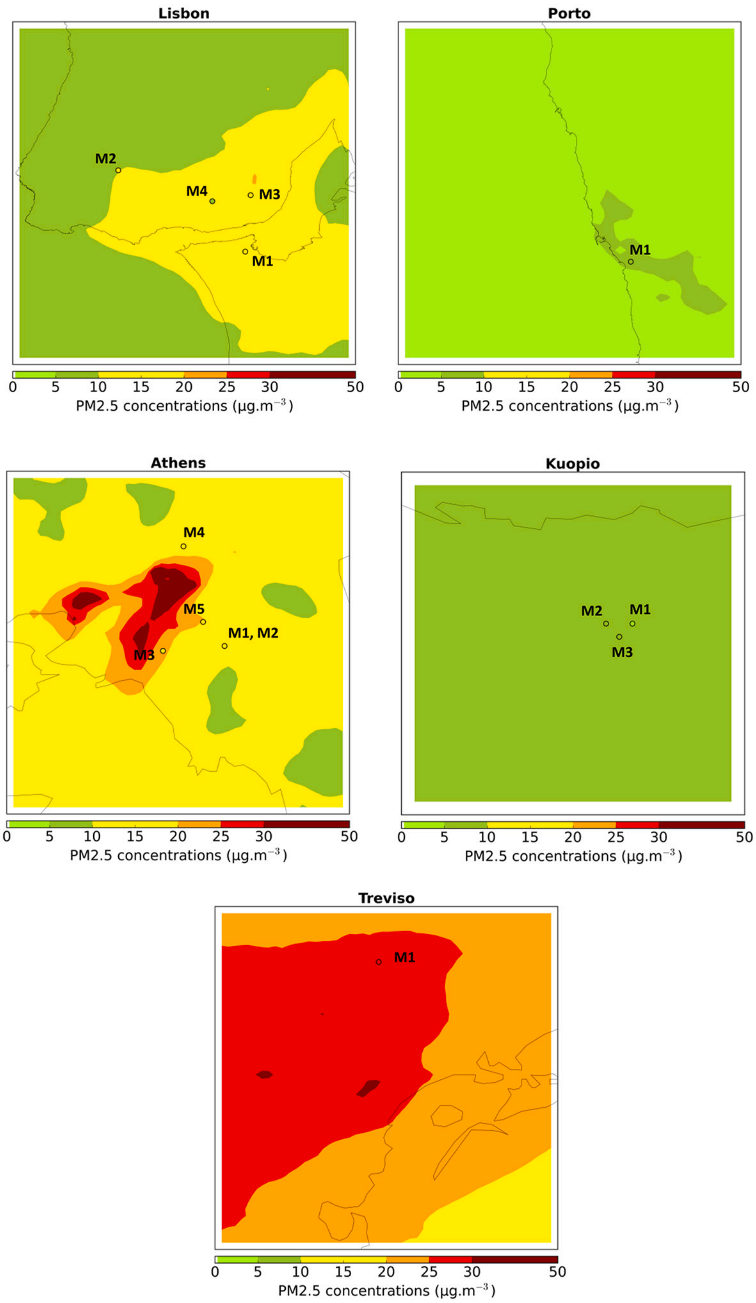


**Fig. 2.** Spatial distribution of annual averaged concentrations of $PM_{2.5}$ for Lisbon (Portugal), Porto (Portugal), Athens (Greece), Kuopio (Finland) and Treviso (Italy). The 2015 annual averaged values measured by the European air quality monitoring network are represented by small coloured circles. Lisbon, Porto and Athens domains cover 50 × 50 cells, Kuopio 25 × 25 cells and Treviso 20 × 20 cells, with 1 × 1 km$^2$ of resolution.

currently only allows the testing of mitigation measures linked to road traffic, residential combustion and maritime traffic. However, in the future, it is possible to expand the set of measures included.The main objectives of this paper are: (i) to present the core methodology used to develop the LIFE Index-Air tool, particularly the scenario building module, which allows the assessment of different air quality mitigation strategies; (ii) to test the developed methodology by applying two air quality mitigation measures over five urban areas (Lisbon and Porto – Portugal; Athens – Greece; Kuopio – Finland; Treviso - Italy). The paper is structured as follows: Section 2 describes the methodology used, including emissions estimation, the used chemical transport model and ANN approach. In Section 3, two mitigation measures are tested and the main results are presented, and finally, Section 4 is devoted to the conclusions.

## 2. Materials and methods

The Index-Air tool, developed in the framework of the LIFE Index-Air project, is based on an integrated exposure-dose-burden of disease assessment, both for the current state of air quality (Reference) and for different emission scenarios defined by the user (Scenario Building). The focus of this paper, the Scenario Building module of the LIFE Index-Air tool allows to quickly test the impact of emission changes (mitigation measure) in relation to a reference air quality scenario. To achieve this goal, the proposed solution is the use of ANN previously trained with a set of air quality modelling simulations, in order to assess the impact of emission reduction measures on air quality in the five European urban areas. This approach relies on the fact that Chemical Transport Models (CTM) are not recommended to be used because they are too time-consuming. . In the current paper, the developed ANN and scenario building methodology is described and applied to the five European urban areas of LIFE Index-Air project (Fig. 1): Lisbon and Porto (Portugal), Athens (Greece), Kuopio (Finland) and Treviso (Italy). These 5 cities represent different urban characteristics, covering different climates, cultures and topographies.

The selected air quality modelling system is composed by the Weather Research & Forecasting (WRF-ARW, version 3.7.1) (Skamarock et al., 2008) and the Comprehensive Air Quality Model with Extensions (CAMx, version 6.40) (ENVIRON, 2015). The WRF-ARW is a numerical weather prediction and atmospheric simulation model that provides meteorology to the CAMx model, which is an Eulerian chemical transport model suitable to be applied for different spatial scales, ranging from global to urban areas. The system was applied with a horizontal resolution of $1 \times 1$ km$^2$ and hourly temporal resolution, for the year 2015, to reproduce the meteorological patterns and the $PM_{2.5}PM_{2.5}$ levels in the different case studies. Lisbon, Porto and Athens domains cover 50 *50 cells, Kuopio 25 *25 cells and Treviso 20 *20 cells, with 1 *1 km$^2$ of resolution. Each domain comprises one or more municipalities. More details about the modelling setup can be found in (Ferreira et al., 2020; Korhonen et al., 2021).

ANN can be considered as computational models that are based on the structure and functions of biological neural networks and can reproduce the behavior of complex air quality modelling systems (Taherkhani et al., 2020). To generate these ANN, it was first necessary to select the model type, the input shape suitable for the domains under study and then, to identify a set of emission-concentration scenarios, to be simulated using WRF-CAMx. The input shape assumed that the air quality (yearly mean $PM_{2.5}$ concentration) values in a given cell also depend on the precursor emissions in distant cells. A second key factor to be considered is the dominant wind direction. Based on previous successful applications (Carnevale et al., 2012a; Miranda et al., 2016) a feed-forward neural network was selected. Once the ANN have been trained, it was used to provide results for different scenarios. Finally, the trained ANN were uploaded in the LIFE Index-Air tool allowing the quick estimation of air pollutant concentration values based on modified emissions of particulate matter and precursor gaseous pollutants, for each one of the 5 cities. More details about ANN training and validation can be found in section 3.2.

## 3. Application and results

Given the methodological approach described in section 2, this section presents the air quality results obtained for the base case scenario, the training and validation of the ANN, and the description and application of the mitigation measures/what-if scenarios.

### *3.1. Air quality assessment in the reference situation*

To evaluate the performance of the model, the $PM_{2.5}$ annual levels simulated by the WRF-CAMx modelling system for the 5 cities were compared with available measurements. The purpose was to guarantee the robustness of the data to be used to train and validate ANN, and to characterize the $PM_{2.5}$ air pollution patterns in the 5 cities.

Fig. 2 shows the annual averages of $PM_{2.5}$ concentration patterns as estimated by the WRF-CAMx modelling system, for 2015, and based on hourly results, and the annual averages of monitored data for air quality stations available within the simulation domains. The acquisition efficiency of at least 75% (small circles mentioned as M in Fig. 2). The measured data were obtained from the European air quality database – AirBase, which includes air quality monitoring data from all EU Member States. The exact GPS latitude and longitude coordinates of each station can be found in Table S1 (Supplementary material).

The modelling setup shows a good ability to simulate the spatial patterns of $PM_{2.5}$ over the European urban areas (the error was on average 2.4 μg.m$^{-3}$). This strengthens the robustness of the model setup and gives the confidence to use the obtained data to train and validate ANN. More detail about the WRF-CAMx accuracy for the annual average concentrations of $PM_{2.5}$ can be found in Fig. S1. The differences between the modelled and measured values can be justified by the uncertainties in the atmospheric emissions calculation (e.g. the non-inclusion of road dust resuspension) (Hosiokangas et al., 2004), especially in the case of Kuopio.The complex topography of the urban domain increases in Athens, it also increases the model uncertainties. . For Porto and Treviso, the performance of the model is quite similar. The performance obtained with WRF-CAMx is within the range obtained in previous studies (Coelho et al., 2021; Ferreira et al., 2020).

According to the obtained results Athens and Treviso did not comply with the European air quality standard (25 μg.m$^{-3}$) for the annual $PM_{2.5}$ levels over an area of 5% and 42% of the simulation domain, respectively, while the remaining cities (Lisbon, Porto and Kuopio) did not register any exceedances in 2015. The annual average of $PM_{2.5}$ concentration values over the whole domain was 24 μg.m$^{-3}$ for Treviso, 14 μg.m$^{-3}$ for Athens, 10 μg.m$^{-3}$ for Lisbon, 6 μg.m$^{-3}$ for Kuopio and 4 μg.m$^{-3}$ for Porto. Maxima annual concentrations were estimated for Athens (with a value of 40 μg.m$^{-3}$), followed by Treviso, Lisbon, Porto and Kuopio (where the lowest maximum value of 7 μg.m$^{-3}$ was obtained).

These results are associated with different $PM_{2.5}$ emission contributions in the urban areas under study. The European Monitoring

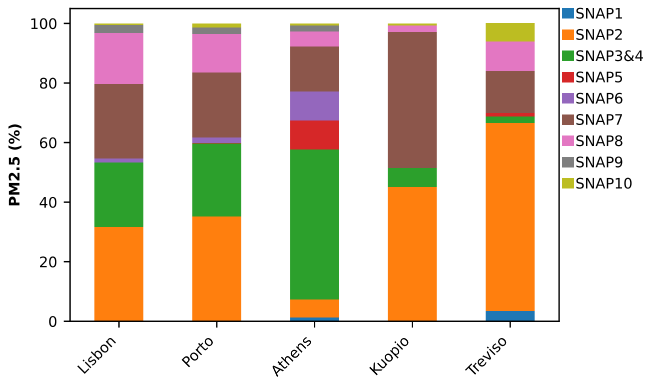


**Fig. 3.** Emissions share of $PM_{2.5}$ for Lisbon, Porto, Athens, Kuopio and Treviso urban areas for the following SNAP activities: SNAP1 – energy production, SNAP2 – commercial, services and residential combustion, SNAP3&4 – industrial combustion and production processes, SNAP5-extraction and distribution of fossil fuels, SNAP6 - solvents use, SNAP7 - road transport, SNAP8 – maritime transport, aviation, and off-road transport, SNAP9 - waste treatment and disposal, and SNAP10 – agriculture.

**Table 1.**
List of the emission reduction scenarios.

| Scenarios | $NO_X$ | VOC | PM10 | $PM_{2.5}$ | $SO_2$ |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | −28 | −21 | −29 | −23 | −33 |
| 2 | −56 | −41 | −58 | −46 | −65 |
| 3 | −56 | −21 | −29 | −23 | −33 |
| 4 | −28 | −41 | −29 | −23 | −33 |
| 5 | −28 | −21 | −58 | −46 | −33 |
| 6 | −28 | −21 | −29 | −23 | −65 |
| 7 | −56 | −41 | −29 | −23 | −33 |
| 8 | −56 | −21 | −58 | −46 | −65 |
| 9 | −56 | −21 | −29 | −23 | −65 |

and Evaluation Programme (EMEP) emission inventory (https://www.emep.int/) was used in the air quality modelling applications. The total $PM_{2.5}$ emissions values were: 5446, 3850, 9489, 139, and 2218 tons per year for Lisbon, Porto, Athens, Kuopio and Treviso, respectively. Fig. 3 shows the $PM_{2.5}$ emissions share for the 5 cities according to the Standard Nomenclature for Air Pollution (SNAP).

In Athens, the industrial sector is the main emission source (SNAP3&4; 50.4%) followed by road transport (SNAP 7; 15.1%) and solvents use (SNAP6; 9.82%). The highest anthropogenic emissions in Treviso come from residential (SNAP2; 63.2%), road transport (SNAP7, 14.1%) and non-road transport sectors (SNAP8; 9.88%). Despite Lisbon values complying with the European air quality standard for the annual $PM_{2.5}$ levels, they were higher than the World Health Organization guideline (10 $\mu g.m^{-3}$) over an area of 37% of the simulation domain, with residential (SNAP2; 31.5%) and road transport (SNAP7; 25.0%) as the main contributing activities. In the cities of Porto and Kuopio, that had the lowest $PM_{2.5}$ concentration values, the air pollution levels are mainly affected by residential (Porto = 35.1%; Kuopio = 45.1%), road transport (Porto = 21.7%; Kuopio = 45.7%) and industrial sectors (Porto = 24.5%; Kuopio = 6.4%).

It should be noted that the accuracy of the WRF model was also evaluated through the direct comparison of modelled results against measurements. The measured data were acquired at the National Oceanic and Atmospheric Administration (NOAA) database (Reynolds et al., 2010) from the National Centers for Environmental Information and at the national meteorological stations network (when available), on an hourly base. This analysis revealed that the most important meteorological variables for the air quality modelling (temperature and wind velocity) are well reproduced by the WRF model, which strengthens the robustness of the model setup and gives confidence in the obtained air quality modelling results. For the year under study, the modelled results show that in Lisbon, the annual mean temperature was around 17 °C (Hot-Summer Mediterranean climate according to the Köppen–Geiger climate classification system, with short, mild and rainy winters and warm to hot, dry summers), the annual wind speed was of 3.8 $m{\bullet}s^{-1}$ and blows (predominantly) from North. In Porto urban area, the annual mean temperature was 15 °C (Warm-Summer Mediterranean climate, with mild wet winters and warm dry summers); the wind blows from North/Northwest with an annual magnitude of 4 $m{\bullet}s^{-1}$. The annual mean temperature in Kuopio was around 4.3 °C (classified as Subarctic climate), with long and cold winters (with temperatures below zero from November until March), and short and relatively mild summers. The annual wind speed for this city was 4.4 $m{\bullet}s^{-1}$, blowing (predominantly) from the South. In Treviso, the annual mean temperature was 13.3 °C (Humid subtropical climate). The wind direction in Treviso varied throughout the year (without clear prevailing conditions), with an annual magnitude of 3.3 $m{\bullet}s^{-1}$. The annual mean temperature in Athens was 16.5 °C (Hot-Summer Mediterranean climate); the magnitude of wind speed experiences substantial seasonal variation for the year, blowing predominantly from the North.

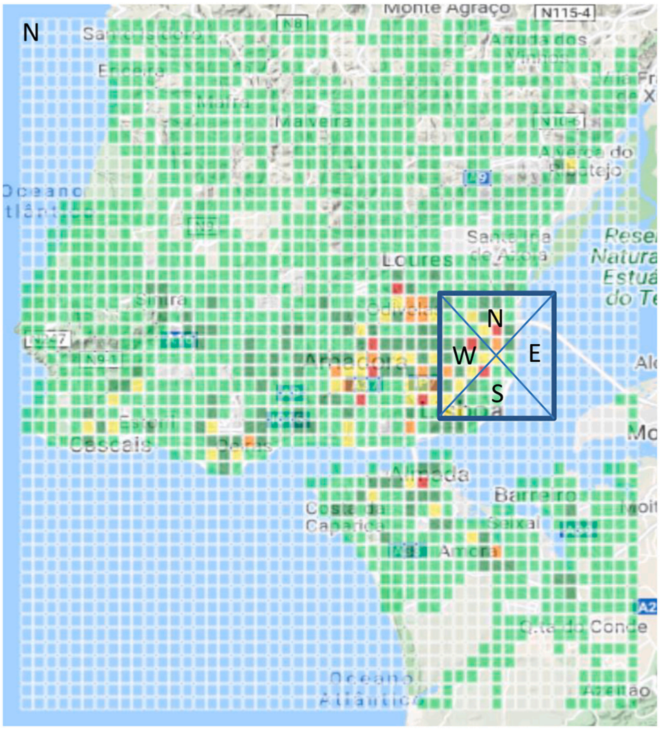


**Fig. 4.** Scheme representing, for Lisbon, the 4 areas on which the emissions are considered as input for the ANN, in terms of wind directions.

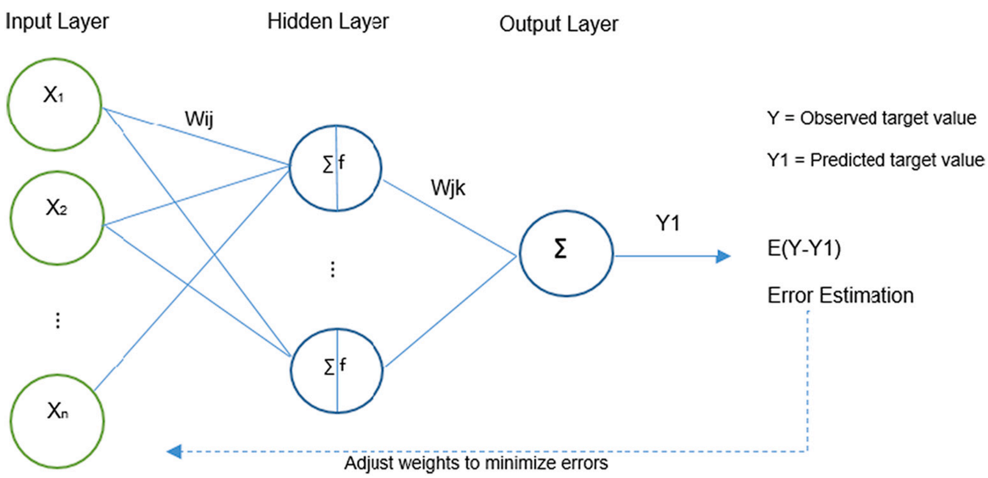


**Fig. 5.** Scheme of the typical feed-forward back-propagation ANN applied in this study.

### 3.2. ANN training and validation

The WRF-CAMx simulations results were used as datasets for ANN training and validation. The validation cells represent 25% of the total available cells and are extracted to guarantee a uniform coverage of the domain. More specifically, a set of 10 emission reduction scenarios, combining precursor emissions reductions, were carried out using the WRF-CAMx modelling system and were then used to train the ANN (see Table 1). The scenarios include two levels of emissions: low emission reductions and high emission reductions, considering the average Maximum Feasible Reduction provided by the GAINS database (https://gains.iiasa.ac.at/). That means that, given the technologies currently available, it is not possible to reduce for example more than 56% of the NOx emissions. The low emission reductions are obtained as half of high emission reductions levels. The scenarios were compulsorily limited in number due to the needed computational time. However previous works (Carnevale et al., 2014; Relvas et al., 2017) had demonstrated that it is possible to achieve reliable results with a narrow number of scenarios.

**Table 2**
ANN best parameters for the different case studies.

| ANN features | PM$_{2.5}$ value | | | | |
|---|---|---|---|---|---|
| | Lisbon | Porto | Athens | Kuopio | Treviso |
| Nodes in the input layer | | | 18 | | |
| Hidden layer function | | | hyperbolic tangent (tanh) | | |
| Hidden layer nodes | 40 | 60 | 30 | 18 | 40 |
| Output transfer function | | | linear | | |
| Training function | | | Levenberg–Marquardt algorithm | | |
| Cells of influence (nr) | 4 | 4 | 4 | 2 | 4 |
| Training set (% of cells) | | | 75 | | |
| Validation set (% of cells) | | | 25 | | |

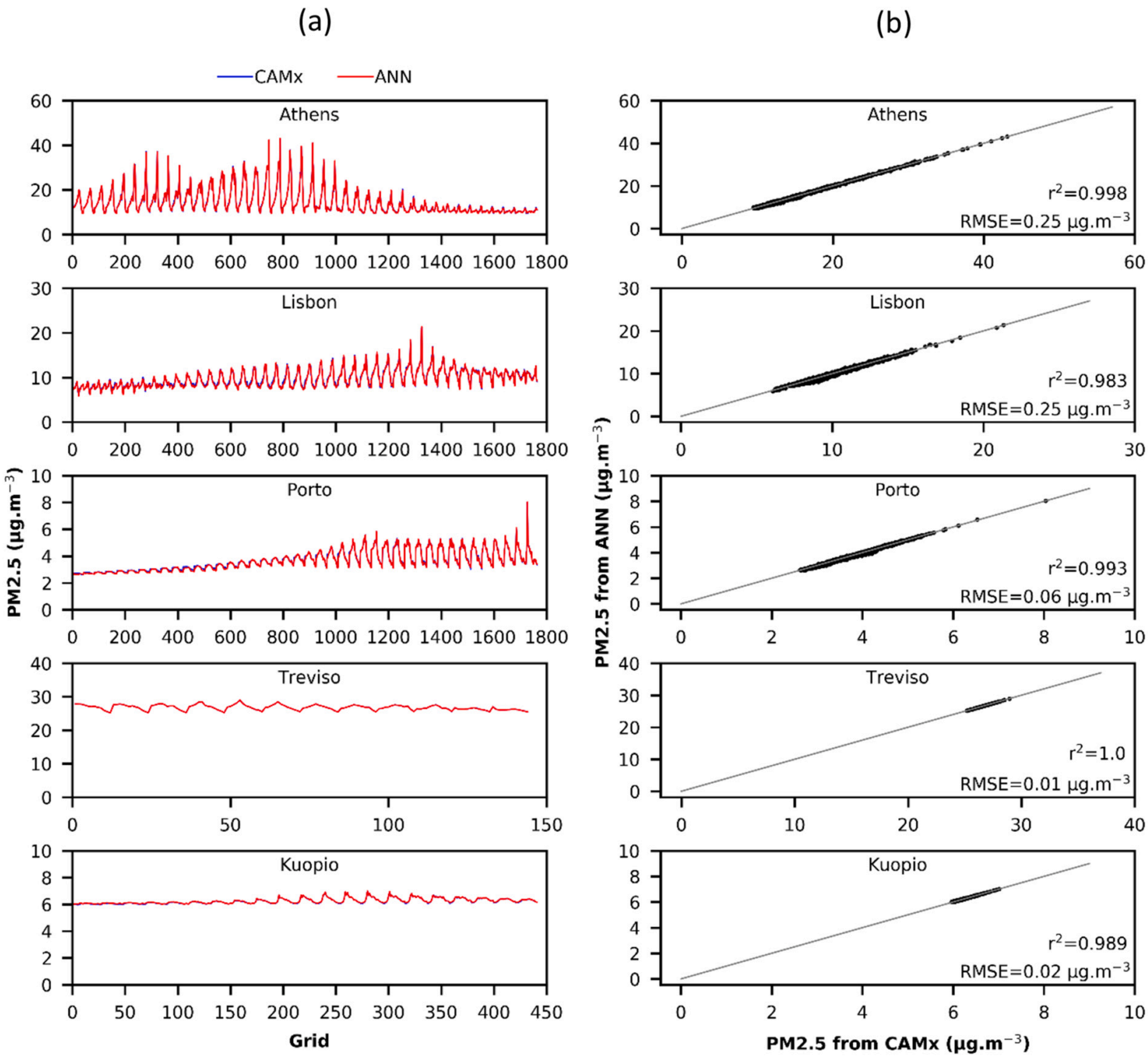


**Fig. 6.** PM$_{2.5}$ concentrations for each domain cell (a). Surrogate model validation scatter plot between WRF-CAMx (x-axis) and ANN (y-axis) for PM$_{2.5}$ yearly average concentration (b).

The training is a time-consuming task that implies selecting the model type, architecture, and an input shape adequate to the domain under study. The selected emission input considers the total precursor emissions over 4 areas corresponding to four quadrants, which are chosen taking into consideration the dominant winds. An influence distance of 4 km means considering emissions of 8 × 8

**Table 3**
Share of biomass-based heating appliances by type, for each city, for the reference case, and for the scenario considering the total replacement of conventional residential fireplaces by more efficient equipment.

| | Percentage of distribution (%) | | | | | New percentage of distribution (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lisbon | Porto | Athens | Kuopio | Treviso | Lisbon | Porto | Athens | Kuopio | Treviso |
| Open Fireplace | 33.4 | 33.4 | 3.2 | 7.8 | 13.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| More Efficient Fireplaces | 15.4 | 15.4 | 1.8 | 16.2 | 13.7 | 76.6 | 76.6 | 44.0 | 68.0 | 84.4 |
| Woodstove | 20.0 | 20.0 | 8.0 | 38.0 | 36.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Wood burning furnace | 11.0 | 11.0 | 5.3 | 11.8 | 0.0 | 11.0 | 11.0 | 5.3 | 11.8 | 0.0 |
| Salamander Stove | 7.8 | 7.8 | 31.0 | 6.0 | 20.8 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Boiler | 7.2 | 7.2 | 31.0 | 2.2 | 3.2 | 7.2 | 7.2 | 31.0 | 2.2 | 3.2 |
| Oven | 4.3 | 4.3 | 16.0 | 3.0 | 7.6 | 4.3 | 4.3 | 16.0 | 3.0 | 7.6 |
| Wood burning water heater | 0.6 | 0.6 | 1.5 | 3.2 | 4.7 | 0.6 | 0.6 | 1.5 | 3.2 | 4.7 |
| Furnace | 0.4 | 0.4 | 2.2 | 11.8 | 0.0 | 0.4 | 0.4 | 2.2 | 11.8 | 0.0 |
| Sum | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

$km^2$ around the a given cell, subdivided in 4 quadrants, to determine the $PM_{2.5}$ concentration of that cell. This pre-processing of the emissions is done inside the tool each time the emissions are changed by the user (mitigation measure selection) through a Python code pre-processor. Fig. 4 shows the selected areas for the Lisbon case study.

A feed-forward neural network (Fig. 5) was selected to reproduce the annual mean $PM_{2.5}$ concentrations resulting from the given emission scenarios.

In this study, the training of the ANN was performed using Levenberg–Marquardt backpropagation algorithm (Sapna et al., 2012; Yu and Wilamowski, 2018) over more than 400 epochs, after normalizing all the data between −1 and 1.

The ANN used consists of an input layer, one or more intermediate layers (hidden layers) and an output layer, in which a node in each layer is connected by a weight (*wij*) to all the nodes in the next layer. Each node in a hidden layer has a nonlinear activation function, usually a sigmoid function. The values of input attributes are fed to the network which will then be weighted, summed up and fed to the activation function in each hidden layer node. This procedure is followed to the output node, where the predicted output variable is estimated. Then this predicted value ($PM_{2.5}$ concentrations) is compared against the actual value and the resulting error is propagated backwards through the ANN to modify the weights to reduce the error by a small amount.

The following parameters were tested:

- the number of neurons in the hidden layer;
- the activation functions: linear, hyperbolic tangent sigmoid, logsigmoid;
- the spatial coverage of input values (radius of influence of emissions)

The validation cells represent 25% of the total available cells and are extracted to guarantee a uniform coverage of the domain. Table 2 resumes the best ANN parameters considered for each city.

Fig. 6 presents the validation results for the $PM_{2.5}$ neural network model based on a scatter plot that compares the WRF-CAMx output results with the ANN outputs.

Fig. 6 also includes the root-mean-square error (RMSE), which gives essential information about the skill in predicting the magnitude of a variable allowing to diagnose the variation in the errors in a set of predicted values, and the coefficient of determination ($r^2$), which indicates the strength of the relationship between variables. The high obtained $r^2$ values and the low RMSE highlight the good fit between both approaches (CTM and ANN). The best performance was obtained for Treviso because there is only a slight variation of the $PM_{2.5}$ concentrations among grid cells.

The good performance achieved with the ANN allowed its incorporation and use in the LIFE Index-Air tool, in order to obtain quick estimations of air pollutant concentration values for different emission scenarios, for each one of the 5 cities. The Scenario Building module is a key feature of the tool, since it allows the quantitative assessment of selected mitigation measures, in support of effective air quality management.

### *3.3. Mitigation measures and results*

The transport sector (SNAP7) together with the residential combustion (SNAP2) are the two main PM emission sources in all the case studies. The exception is Athens, for which the residential combustion is not so relevant (Fig. 3), and where the industrial zone located on the west side of the city is the largest source of $PM_{2.5}$. Thus, it was decided to test two different air quality improvement measures that are related to these two relevant emission sectors: the total replacement of conventional residential fireplaces by more efficient equipment; and the total replacement of petrol and diesel passenger vehicles by electric ones.

First, for the residential sector, statistical information regarding biomass-based heating appliances (open fireplace, more efficient fireplaces, woodstove, wood burning furnace, salamander stove, boiler, oven, wood burning water heater and furnace) was collected for the different case studies/countries as well as the amount of biomass burned annually (Table 3). The new scenario considers the total replacement of conventional residential fireplaces (Open fireplaces), Woodstoves, and Salamander stoves by more efficient equipment, namely More efficient fireplaces.

**Table 4**
Share of passenger cars fuel, for the reference case, and the scenario considering the total replacement of petrol and diesel passenger vehicles by electric ones.

| | Percentage of distribution (%) | | | | | New percentage of distribution (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lisbon | Porto | Athens | Kuopio | Treviso | Lisbon | Porto | Athens | Kuopio | Treviso |
| Petrol Passenger Cars (%) | 37.6 | 37.6 | 92.4 | 74.2 | 51.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Diesel Passenger Cars (%) | 62.1 | 62.1 | 7.2 | 25.7 | 48.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Electric Passenger Cars (%) | 0.3 | 0.3 | 0.4 | 0.1 | 0.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| Sum | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |

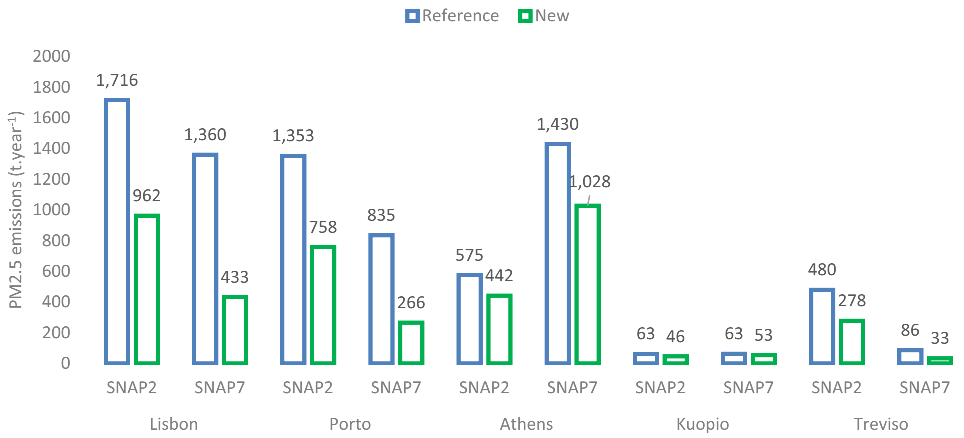


**Fig. 7.** Reference emissions and new emissions (t.year$^{-1}$) achieved by the application of the residential sector (SNAP2) and the transport sector (SNAP7) mitigation measures over Lisbon, Porto, Athens, Kuopio and Treviso.

Then, typical emission factors for the different types of residential heating equipment were used to estimate the emissions (bottom-up approach). Finally, the share of emission was applied to the EMEP emission inventory (https://www.emep.int/), allowing the recalculation of the emissions based on a change in the share of biomass-based heating appliances and/or on the change in the amount of biomass burned.

Regarding road traffic, statistical information about the fleet composition in each case study was collected, namely fleet age and type of fuel used Table 4). These data were used to recalculate the emissions using the Transport Emission Model for line sources (TREM transport emissions model (Tchepel et al., 2012) (bottom-up approach). Then, the share of emissions was applied to the EMEP emission inventory allowing the recalculation of the emissions based on a change in the distribution of the fleet. The new scenario considers the replacement of all petrol and diesel passenger vehicles by electric ones. The total number of vehicles considered in each city was: 1351444, 854,445, 2,991,572, 59,821 and 140,111 for Lisbon, Porto, Athens, Kuopio and Treviso, respectively.

Fig. 7 shows $PM_{2.5}$ emissions obtained for the different cities, for the reference case and for the considered scenarios (SNAP2 – residential sector; SNAP7 – transport sector).

The results in terms of emission reductions show that there are big differences among the urban case studies. For Porto, Kuopio and Treviso, a higher $PM_{2.5}$ reduction is achieved with the residential combustion measure, and for the other urban domains, the electrification of passenger's cars fleet seems to be more effective. These results are in line with the $PM_{2.5}$ emissions share (Fig. 3). The major emission reductions are estimated for Lisbon (927 t/year), followed by Porto (594 t/year) and Athens (402 t/year), being Kuopio the area where the reduction is smaller.

The changes in emissions were used as input to the ANN previously trained for each one of the urban case studies. Figs. 8 and 9 present the maps of the $PM_{2.5}$ concentration difference between the reference case and the residential heating and the vehicular traffic reduction scenarios, respectively, as provided by the Scenario Builder module of the LIFE Index-Air tool.

The obtained concentration reduction levels are quite different among cities and scenarios. Lisbon is where the effect of passenger's fleet electrification seems to have a higher impact (achieving in some cells more than 5 μg.m$^{-3}$ of reduction), followed by Athens (up to 3 μg.m$^{-3}$ of reduction). This was expected because in both capital cities, private passenger vehicles are used as the main means of transport. There is, however, a substantial difference between them; while in Lisbon the fleet is mainly diesel-based, in Athens the petrol fleet is dominant. This has an impact on the emission reduction achieved (Fig. 7) and in the $PM_{2.5}$ concentration reductions. Even though Porto displayed the second higher reduction in emissions (569 t/year), the effect in $PM_{2.5}$ concentrations is quite low, up to 1 μg.m$^{-3}$, which can be explained by the already very low reference $PM_{2.5}$ concentrations (up to 8 μg.m$^{-3}$) (see Fig. 2). The total $PM_{2.5}$ emissions (3850 t/year) in Porto are much lower than the emissions in Lisbon (5446 t/year) and in Athens (9489 t/year), the two case studies with a simulation domain size similar the Porto's domain. Size. The same can be mentioned for Kuopio, where the maximum $PM_{2.5}$ annual reduction is close to 1 μg.m$^{-3}$. The reduction in the Treviso urban domain is mainly achieved over the

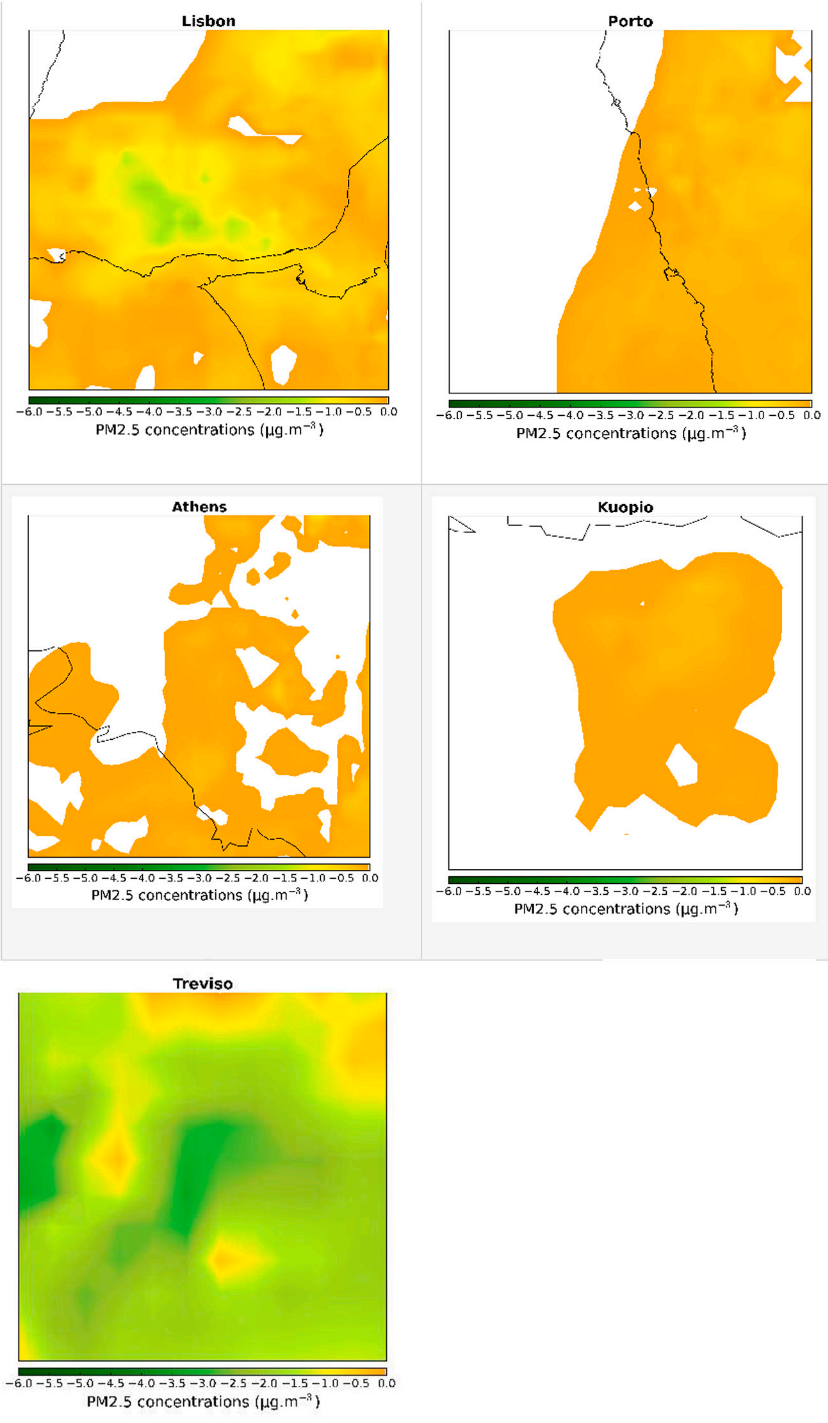


**Fig. 8.** $PM_{2.5}$ concentration differences between the reference case and the emission reduction scenario for residential heating, for the cities case studies.

municipality of Treviso, but the effect of fleet electrification seems extremely limited.

Treviso is where the effect of open fireplaces seems to have a higher impact (achieving in some cells more than 3 μg.m$^{-3}$ of reduction), followed by Lisbon (up to 2 μg.m$^{-3}$ of reduction). In Athens, the contribution of residential eating is already very small (see Fig. 3), and for that reason the investment in the replacement of fireplaces would not be highly effective. In the case of Porto and Kuopio, the effect on concentrations is also very low.

In Fig. 10, the concentration reductions (in μg.m$^{-3}$) are presented for the Lisbon, Porto, Athens, Kuopio and Treviso municipalities.

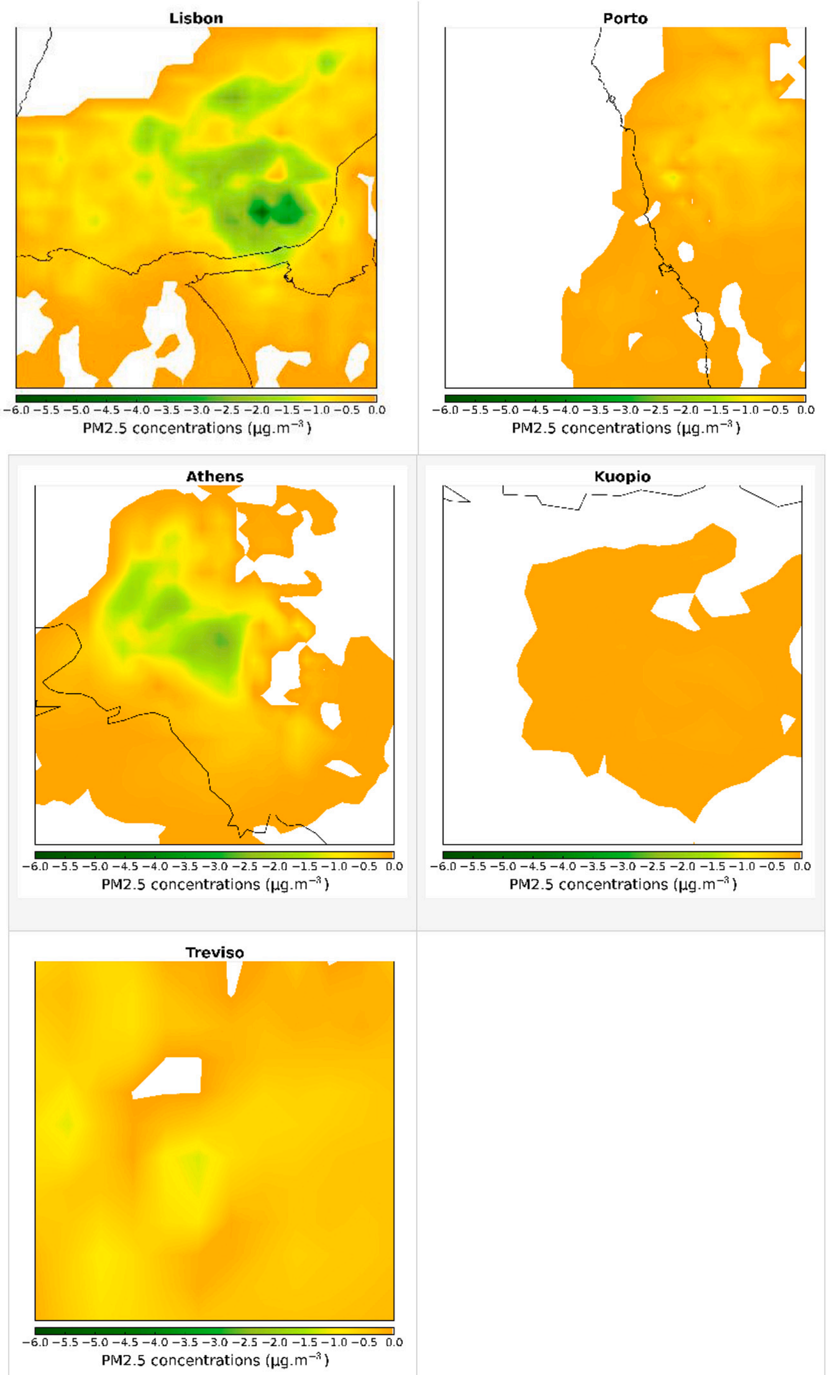


**Fig. 9.** $PM_{2.5}$ concentration differences between the reference case and the emission reduction scenario for vehicular traffic, for the cities case studies.

The assessment of the effect of the scenarios on the city centers, represented by the main municipality of each city (please note that the simulation domains can contain one or more municipalities), is especially relevant because these areas are particularly affected by air pollution due to urbanization and high population density.

Fig. 10 shows that there is high variability in the concentration reductions among the different municipalities. This is mainly explained by the emission source that is affected by the mitigation measure, meaning that, in some cells, the emission is null or practically null and in other cells, the emission is high. This variability, in addition to the meteorological influence, justifies the shown differences.

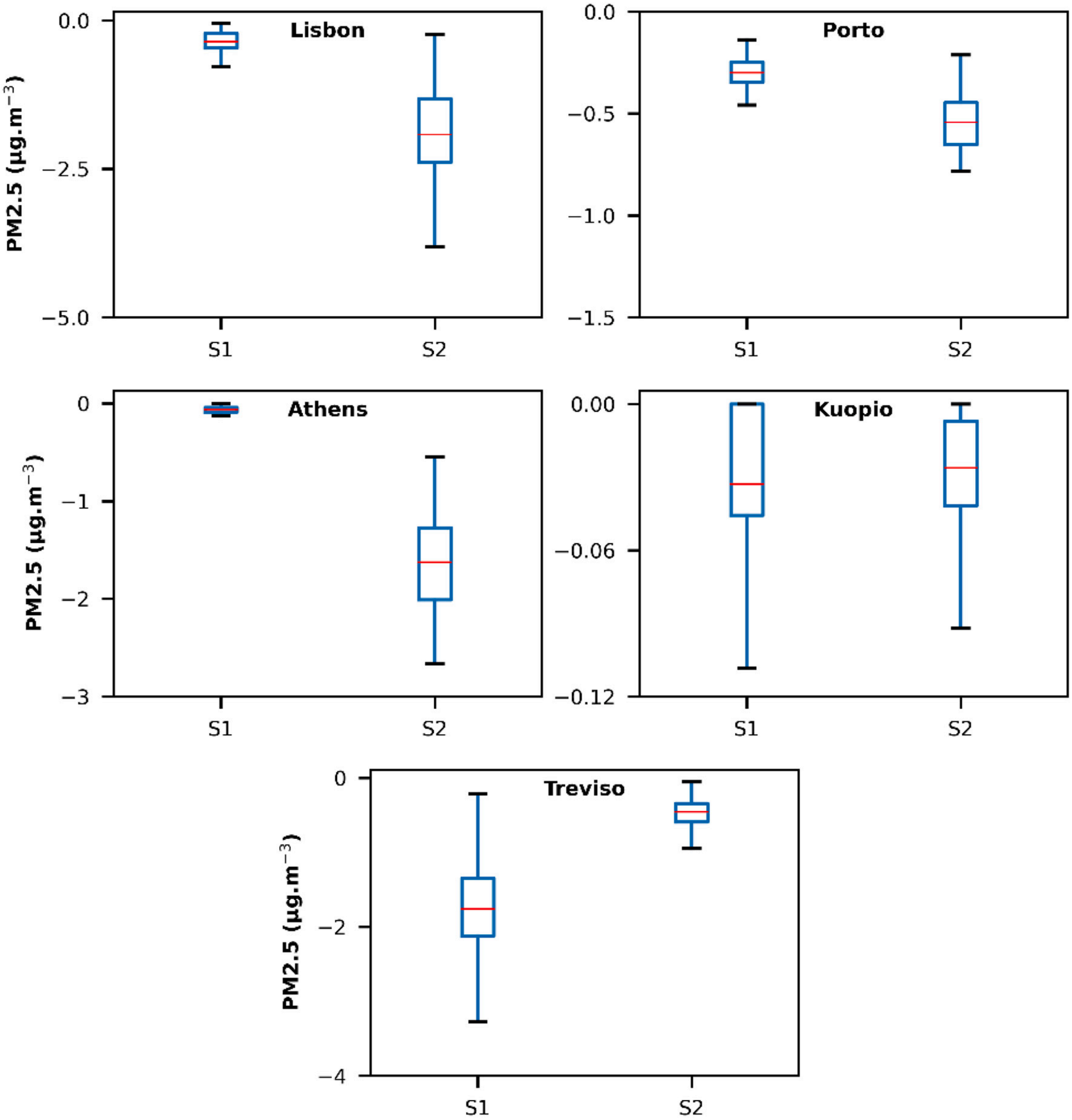


**Fig. 10.** Reduction of $PM_{2.5}$ concentrations over the main municipality (city centre) for each simulation domain, considering the two emission reduction scenarios. The red line represents mean, boxes the 25th and 75th quartiles while the whiskers show the maximum value of 95th percentile and minimum value of 5th percentile. Note that the scales are different. S1 concerns the residential heating scenario and S2 the vehicular traffic scenario. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

It is possible to see a higher impact of the vehicles traffic reduction scenario (S2) in Lisbon, Athens and Porto when the central municipality is assessed instead of the entire simulation domain, indicating that the city centre is mostly affected by road traffic on annual average. The results also point out that in the case of Lisbon and Athens municipalities the electrification of passenger fleet is very effective, with an average reduction of 1.5 µg.m$^{-3}$ but achieving reductions higher than 3 µg.m$^{-3}$ in the city centres. In the Porto municipality, the electrification of the passenger fleet seems to be less effective, with a reduction of only 0.5 µg.m$^{-3}$ on average. However, the reference $PM_{2.5}$ concentrations in Porto are already very low compared with Lisbon and Athens.

## 4. Conclusions

Air quality is an increasingly concerning issue and decision-makers need simple and fast tools to support decisions. This paper presents the methodology used to create the Scenario Building module of the LIFE Index-Air tool. First, the WRF-CAMx modelling system was applied to simulate the reference scenario over five cities / case studies (Lisbon and Porto – Portugal; Athens – Greece;

Kuopio – Finland; Treviso – Italy). The obtained validation results were in line with the results reported in previous studies with the same modelling system, confirming the ability to simulate the $PM_{2.5}$ concentrations. Air quality simulations indicate that, for the simulation year, Athens and Treviso did not comply with the European air quality standards (25 μg.m$^{-3}$) for the annual $PM_{2.5}$ levels over 5% and 42% of the simulation domain, respectively, while the remaining cities (Lisbon, Porto and Kuopio) did not show any exceedances. The annual average of $PM_{2.5}$ concentrations over the whole domain was 24, 14, 10, 6, and 4 μg.m$^{-3}$ for Treviso, Athens, Lisbon, Kuopio, and Porto, respectively. Then a set of emission reduction scenarios were created for each case study and used as input for a feed-forward ANN training and validation. Validation results demonstrated the ANN capacity to mimic the behavior of the WRF-CAMx modelling system over the case studies. To test the created scenario building module, two mitigation measures were applied: i) improvement of the biomass residential combustion appliances; and ii) electrification of passenger's cars fleet. The selection of these measures was made based on the $PM_{2.5}$ main emission sources. Results show that the replacement of old biomass heating systems by new improved fireplaces can be more effective in Treviso. On the other hand, the replacement of gasoline and diesel passenger vehicles by electric vehicles seems to be more effective in reducing the $PM_{2.5}$ concentrations over Lisbon, Porto, and Athens. In Kuopio, both mitigation measures have a low and equivalent effect. To further enhance the urban air quality, in addition to passenger vehicles electrification, the electrification of light-duty vehicles, heavy-duty vehicles and buses is strongly recommended.

The results show that this approach based on ANN, calibrated using a limited number of air quality modelling system simulations, can reproduce competently the concentration values. The main advantage of this approach is that it considers the specificities of each domain and requires less computational power and time than a CTM, allowing the application/development of tools and decision support systems. Future work will include the application of the LIFE Index-Air tool with its remaining modules (Exposure, Dosimetry and Burden of Disease) to estimate the health benefits related to these measures over the five case study cities. The LIFE Index-Air tool is not only particularly useful for decision-makers, but it can also be used in schools to raise responsibility and awareness on air quality.

## CRediT authorship contribution statement

**Hélder Relvas:** Methodology, Software, Visualization, Writing – original draft. **Diogo Lopes:** Software, Visualization. **Joana Ferreira:** Formal analysis, Writing – review & editing. **Afonso Silva:** Formal analysis. **Sandra Rafael:** Software. **Myriam Lopes:** Formal analysis. **Susana Marta Almeida:** Funding acquisition, Writing – review & editing. **Vânia Martins:** Writing – review & editing. **Evangelia Diapouli:** Writing – review & editing. **Antti Korhonen:** Writing – review & editing. **Mihalis Lazaridis:** Writing – review & editing. **Ana Isabel Miranda:** Supervision, Writing – review & editing.

## 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.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2022.101201.

## References

Braithwaite, I., Zhang, S., Kirkbride, J.B., Osborn, D.P.J., Hayes, J.F., 2019. Air pollution (particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: a systematic review and meta-analysis. Environ. Health Perspect. 127, 126002 https://doi.org/10.1289/EHP4595.

Cabaneros, S.M., Calautit, J.K., Hughes, B.R., 2019. A review of artificial neural network models for ambient air pollution prediction. Environ. Model. Softw. 119, 285–304. https://doi.org/10.1016/j.envsoft.2019.06.014.

Carnevale, C., Finzi, G., Guariso, G., Pisoni, E., Volta, M., 2012a. Surrogate models to compute optimal air quality planning policies at a regional scale. Environ. Model. Softw. 34, 44–50. https://doi.org/10.1016/j.envsoft.2011.04.007.

Carnevale, C., Finzi, G., Pisoni, E., Volta, M., Guariso, G., Gianfreda, R., Maffeis, G., Thunis, P., White, L., Triacchini, G., 2012b. An integrated assessment tool to define effective air quality policies at regional scale. Environ. Model. Softw. 38, 306–315. https://doi.org/10.1016/j.envsoft.2012.07.004.

Carnevale, C., Finzi, G., Pederzoli, A., Turrini, E., Volta, M., Guariso, G., Gianfreda, R., Maffeis, G., Pisoni, E., Thunis, P., Markl-Hummel, L., Blond, N., Clappier, A., Dujardin, V., Weber, C., Perron, G., 2014. Exploring trade-offs between air pollutants through an integrated assessment model. Sci. Total Environ. 481, 7–16. https://doi.org/10.1016/j.scitotenv.2014.02.016.

Coelho, S., Rafael, S., Lopes, D., Miranda, A.I., Ferreira, J., 2021. How changing climate may influence air pollution control strategies for 2030? Sci. Total Environ. 758 https://doi.org/10.1016/j.scitotenv.2020.143911.

Cohen, A.J., Brauer, M., Burnett, R., Anderson, H.R., Frostad, J., Estep, K., Balakrishnan, K., Brunekreef, B., Dandona, L., Dandona, R., Feigin, V., Freedman, G., Hubbell, B., Jobling, A., Kan, H., Knibbs, L., Liu, Y., Martin, R., Morawska, L., Pope, C.A., Shin, H., Straif, K., Shaddick, G., Thomas, M., van Dingenen, R., van

Donkelaar, A., Vos, T., Murray, C.J.L., Forouzanfar, M.H., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015. Lancet 389, 1907–1918. https://doi.org/10.1016/S0140-6736(17)30505-6.

Comes, T., Doll, C., Fröhling, M., Hiete, M., Ilsen, R., Krail, M., 2010. Challenges for national clean air policy. Ökologisches Wirtschaften - Fachzeitschrift 25. https://doi.org/10.14512/oew.v25i2.689.

De Angelis, E., Carnevale, C., Marcoberardino, G.D., Turrini, E., Volta, M., 2021. Low emission road transport scenarios: an integrated assessment of energy demand, air quality, GHG emissions, and costs. IEEE Trans. Autom. Sci. Eng. 1–11 https://doi.org/10.1109/TASE.2021.3073241.

De Gennaro, G., Trizio, L., Di Gilio, A., Pey, J., Pérez, N., Cusack, M., Alastuey, A., Querol, X., 2013. Neural network model for the prediction of PM 10 daily concentrations in two sites in the Western Mediterranean. Sci. Total Environ. 463–464, 875–883. https://doi.org/10.1016/j.scitotenv.2013.06.093.

EEA, 2020. Air Quality in Europe — 2020 Report. https://doi.org/10.2800/786656.

ENVIRON, 2015. CAMx. User's Guide. Comprehensive Air Quality Model with Extensions. Version 6.2.

Eusébio, C., Carneiro, M.J., Madaleno, M., Robaina, M., Rodrigues, V., Russo, M., Relvas, H., Gama, C., Lopes, M., Seixas, V., Borrego, C., Monteiro, A., 2020. The impact of air quality on tourism: a systematic literature review. J. Tour. Futur. https://doi.org/10.1108/JTF-06-2019-0049.

Fabregat, A., Vázquez, L., Vernet, A., 2021. Using machine learning to estimate the impact of ports and cruise ship traffic on urban air quality: the case of Barcelona. Environ. Model. Softw. 104995 https://doi.org/10.1016/j.envsoft.2021.104995.

Ferreira, J., Lopes, D., Rafael, S., Relvas, H., Almeida, S.M., Miranda, A.I., 2020. Modelling air quality levels of regulated metals: limitations and challenges. Environ. Sci. Pollut. Res. 27, 33916–33928. https://doi.org/10.1007/s11356-020-09645-9.

GBD, 2020. Global burden of 87 risk factors in 204 countries and territories, 1990-2019: a systematic analysis for the global burden of disease study 2019. Lancet (London, England) 396, 1223–1249. https://doi.org/10.1016/S0140-6736(20)30752-2.

Gehrsitz, M., 2017. The effect of low emission zones on air pollution and infant health. J. Environ. Econ. Manag. 83, 121–144. https://doi.org/10.1016/j.jeem.2017.02.003.

Hosiokangas, J., Vallius, M., Ruuskanen, J., Mirme, A., Pekkanen, J., 2004. Resuspended dust episodes as an urban air-quality problem in subarctic regions. Scand. J. Work Environ. Health 30, 28–35.

Korhonen, A., Relvas, H., Miranda, A.I., Ferreira, J., Lopes, D., Rafael, S., Almeida, S.M., Faria, T., Martins, V., Canha, N., Diapouli, E., Eleftheriadis, K., Chalvatzaki, E., Lazaridis, M., Lehtomäki, H., Rumrich, I., Hänninen, O., 2021. Analysis of spatial factors, time-activity and infiltration on outdoor generated $PM_{2.5}$ exposures of school children in five European cities. Sci. Total Environ. 785, 147111 https://doi.org/10.1016/j.scitotenv.2021.147111.

Landrigan, P.J., Fuller, R., Acosta, N.J.R., Adeyi, O., Arnold, R., Basu, N. Nil, Baldé, A.B., Bertollini, R., Bose-O'Reilly, S., Boufford, J.I., Breysse, P.N., Chiles, T., Mahidol, C., Coll-Seck, A.M., Cropper, M.L., Fobil, J., Fuster, V., Greenstone, M., Haines, A., Hanrahan, D., Hunter, D., Khare, M., Krupnick, A., Lanphear, B., Lohani, B., Martin, K., Mathiasen, K.V., McTeer, M.A., Murray, C.J.L., Ndahimananjara, J.D., Perera, F., Potočnik, J., Preker, A.S., Ramesh, J., Rockström, J., Salinas, C., Samson, L.D., Sandilya, K., Sly, P.D., Smith, K.R., Steiner, A., Stewart, R.B., Suk, W.A., van Schayck, O.C.P., Yadama, G.N., Yumkella, K., Zhong, M., 2018. The lancet commission on pollution and health. Lancet 391, 462–512. https://doi.org/10.1016/S0140-6736(17)32345-0.

Lelieveld, J., Pozzer, A., Pöschl, U., Fnais, M., Haines, A., Münzel, T., 2020. Loss of life expectancy from air pollution compared to other risk factors: a worldwide perspective. Cardiovasc. Res. 116, 1910–1917. https://doi.org/10.1093/cvr/cvaa025.

Maleki, H., Sorooshian, A., Goudarzi, G., Baboli, Z., Tahmasebi Birgani, Y., Rahmati, M., 2019. Air pollution prediction by using an artificial neural network model. Clean Techn. Environ. Policy 21, 1341–1352. https://doi.org/10.1007/s10098-019-01709-w.

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., Bezirtzoglou, E., 2020. Environmental and health impacts of air pollution: a review. Front. Public Health. https://doi.org/10.3389/fpubh.2020.00014.

Mao, X., Shen, T., Feng, X., 2017. Prediction of hourly ground-level $PM_{2.5}$ concentrations 3 days in advance using neural networks with satellite data in eastern China. Atmos. Pollut. Res. 8, 1005–1015. https://doi.org/10.1016/J.APR.2017.04.002.

Masood, A., Ahmad, K., 2021. A review on emerging artificial intelligence (AI) techniques for air pollution forecasting: fundamentals, application and performance. J. Clean. Prod. 322, 129072 https://doi.org/10.1016/j.jclepro.2021.129072.

Mediavilla-Sahagún, A., ApSimon, H.M., 2006. Urban scale integrated assessment for London: which emission reduction strategies are more effective in attaining prescribed PM10air quality standards by 2005? Environ. Model. Softw. 21, 501–513. https://doi.org/10.1016/j.envsoft.2004.06.010.

Miranda, A.I., Relvas, H., Viaene, P., Janssen, S., Brasseur, O., Carnevale, C., Declerck, P., Maffeis, G., Turrini, E., Volta, M., 2016. Applying integrated assessment methodologies to air quality plans: two European cases. Environ. Sci. Pol. 65, 29–38. https://doi.org/10.1016/j.envsci.2016.04.010.

Newby, D.E., Mannucci, P.M., Tell, G.S., Baccarelli, A.A., Brook, R.D., Donaldson, K., Forastiere, F., Franchini, M., Franco, O.H., Graham, I., Hoek, G., Hoffmann, B., Hoylaerts, M.F., Künzli, N., Mills, N., Pekkanen, J., Peters, A., Piepoli, M.F., Rajagopalan, S., Storey, R.F., 2015. Expert position paper on air pollution and cardiovascular disease. Eur. Heart J. 36, 83–93. https://doi.org/10.1093/eurheartj/ehu458.

Olawepo, J.O., Chen, L.W.A., 2019. Health benefits from upgrading public buses for cleaner air: a case study of Clark County, Nevada and the United States. Int. J. Environ. Res. Public Health 16. https://doi.org/10.3390/ijerph16050720.

Park, S., Kim, Minjeong, Kim, Minhae, Namgung, H.-G., Kim, K.-T., Cho, K.H., Kwon, S.-B., 2018. Predicting PM10 concentration in Seoul metropolitan subway stations using artificial neural network (ANN). J. Hazard. Mater. 341, 75–82. https://doi.org/10.1016/J.JHAZMAT.2017.07.050.

Relvas, H., Miranda, A.I., 2018. An urban air quality modeling system to support decision-making: design and implementation. Air Qual. Atmos. Health 11, 815–824. https://doi.org/10.1007/s11869-018-0587-z.

Relvas, H., Miranda, A.I., Carnevale, C., Maffeis, G., Turrini, E., Volta, M., 2017. Optimal air quality policies and health: a multi-objective nonlinear approach. Environ. Sci. Pollut. Res. 24 https://doi.org/10.1007/s11356-017-8895-7.

Reynolds, R.W., Gentemann, C.L., Corlett, G.K., 2010. Evaluation of AATSR and TMI satellite SST data. J. Clim. 23, 152–165. https://doi.org/10.1175/2009JCLI3252.1.

Sapna, S., Tamilarasi, A., Kumar, M.P., 2012. Backpropagation learning algorithm based on Levenberg Marquardt algorithm. Comp. Sci. Inf. Technol. 2, 393–398.

Shou, Y., Huang, Y., Zhu, X., Liu, C., Hu, Y., Wang, H., 2019. A review of the possible associations between ambient PM2. 5 exposures and the development of Alzheimer's disease. Ecotoxicol. Environ. Saf. 174, 344–352.

Skamarock, W.C., Klemp, J.B., Dudhi, J., Gill, D.O., Barker, D.M., Duda, M.G., Huang, X.-Y., Wang, W., Powers, J.G., 2008. A Description of the Advanced Research WRF Version 3, Technical Report. https://doi.org/10.5065/D6DZ069T.

Taherkhani, A., Belatreche, A., Li, Y., Cosma, G., Maguire, L.P., McGinnity, T.M., 2020. A review of learning in biologically plausible spiking neural networks. Neural Netw. 122, 253–272. https://doi.org/10.1016/j.neunet.2019.09.036.

Tchepel, O., Dias, D., Ferreira, J., Tavares, R., Isabel Miranda, A., Borrego, C., 2012. Emission modelling of hazardous air pollutants from road transport at urban scale. Transport 27, 299–306. https://doi.org/10.3846/16484142.2012.720277.

Viaene, P., Belis, C.A., Blond, N., Bouland, C., Juda-Rezler, K., Karvosenoja, N., Martilli, A., Miranda, A., Pisoni, E., Volta, M., 2016. Air quality integrated assessment modelling in the context of EU policy: a way forward. Environ. Sci. Pol. 65, 22–28. https://doi.org/10.1016/j.envsci.2016.05.024.

Yu, H., Wilamowski, B.M., 2018. Levenberg–marquardt training. In: Intelligent Systems. CRC Press, pp. 11–12.