



An urban air quality modeling system to support decision-making: design and implementation

H. Relvas¹ · A. I. Miranda¹

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Abstract

This paper describes the design and application of a modeling system capable of rapidly supporting decision-makers regarding urban air quality strategies, in particular, providing emission and concentration maps, as well as external costs (mortality and morbidity) due to air pollution, and total implementation costs of improvement measures. Results from a chemical transport model are used to train artificial neural networks and link emission of pollutant precursors and urban air quality. A ranking of different emission scenarios is done based on multi-criteria decision analysis (MCDA), which includes economic and social aspects. The Integrated Urban Air Pollution Assessment Model (IUAPAM) was applied to the Porto city (Portugal) and results show that it is possible to reduce the number of premature deaths per year attributable to particulate matter (PM₁₀), from 1300 to 1240 (5%), with an investment of 0.64 M €/year, based on fireplace replacements.

Keywords Decision-making · Air quality management · Artificial neural networks · Multi-criteria decision analysis · Integrated assessment modeling

Introduction

At a global scale and Europe, in particular, good air quality is still a challenge. The latest “Air quality in Europe” report, delivered by the European Environment Agency (EEA 2017), indicates that air quality policies have led to many improvements. However, substantial challenges remain and considerable impacts, on both human health and the environment, persist (Costa et al. 2014; Lelieveld et al. 2015; Newby et al. 2014).

European urban populations and ecosystems are still partially exposed to air pollution that surpasses European standards and, principally, the World Health Organization (WHO) Air Quality Guidelines. Estimates of the health impacts attributable to exposure to air pollution indicate that PM_{2.5} (particulate matter less than 2.5 μm in diameter) concentrations in 2014 were responsible for 339,000 premature deaths in the 28 European Union Member States (EEA 2017). Moreover, climate change is likely to increase air pollution-related

mortality, in all regions of the world (except Africa), particularly in India and East Asia (Dias et al. 2012; Silva et al. 2017).

Even if there are many possible interventions that can be made at the city scale, through measures, such as investment in public transport, low emission zones (LEZ), changes in heating and cooling systems, and street washing, it is difficult for policy-makers to quickly assess the consequences of policies and measures on local air quality. The efficacy of those policies and measures often depends on a combination of specific factors, such as meteorology, pollutants chemical reaction and dispersion, or topography, among others.

Integrated assessment models (IAM) are tools that can contribute to the evaluation of strategies for environmental pollution control and improvement. Ideally, such models cover the whole range of problem from pollutant emissions to their environmental and health effects (Karvosenoja et al. 2010; Vedrenne et al. 2014). IAM models typically answer questions of the “what if...” type (scenario analysis) by defining different scenarios for human activities. The models explore a variety of possible future developments, thus illustrating possible consequences of alternative strategies (Thunis et al. 2016), with some IAM including options for optimization (Carnevale et al. 2012a). Scenario analysis can be useful to test and compare a reduced number of scenarios, because air quality model simulations are time-consuming. The optimization approach requires a more detailed

✉ H. Relvas
helder.relvas@ua.pt

¹ CESAM, Department of Environment and Planning, University of Aveiro, 3810-193 Aveiro, Portugal

emissions inventory, in order to link activities to measures. This type of approach can be useful when a large list of measures is available (usually just technical measures) and the goal is to find the best set to achieve established targets. In this kind of approach, source–receptor relationships are used to reproduce the air quality model behavior (Camevale et al. 2012b) in order to increase the speed and allow performing thousands of optimization calculations. Both approaches have the same advantages and disadvantages and a possible way forward would be to develop a mixed system easily applied by decision-makers.

The main objectives of this paper are to (i) design an urban integrated assessment modeling system to support decision-making, (ii) test the designed system in the Porto Urban Area, and (iii) identify future research/work lines. The system is innovative by including social aspects, health effects, and implementation costs in the decision process (usually, only the last two are included). This system makes it easier to implement local measures by requiring less information compared to similar tools such as RIAT+ (Miranda et al. 2016). Moreover, it is focused on the urban scale where air pollution is more relevant and is able to quickly process and analyze different options (mainly local measures), by incorporating state-of-the-art techniques.

The paper is structured as follows: “[The IUAPAM approach overview](#)” section introduces the Integrated Urban Air Pollution Assessment Model (IUAPAM). “[Application results](#)” section tests the IUAPAM in the Porto Urban Area along with a description of the dataset and the main results. “[Multi-criteria analysis of scenarios](#)” section is dedicated to multi-criteria decision analysis of the results, while “[Conclusions](#)” section is devoted to the conclusions.

The IUAPAM approach overview

The Integrated Urban Air Pollution Assessment Model (IUAPAM) has been developed with the objective of supporting regional and local authorities in the design and assessment of air quality improvement plans or emission reduction strategies. The model is based on the relationships between emissions and concentration levels, and can be used to answer the following questions:

- How efficient is a given emission reduction strategy in terms of cost, air quality and health impacts?
- Is a given emission reduction strategy for the study area strong enough to achieve the air quality targets?
- How can air quality measures which are part of an emission reduction strategy be ranked?

These questions can be answered using IUAPAM by a consistent approach. The system provides estimates on the costs and air quality/human health benefits of alternative

emission control strategies. Figure 1 displays the core IUAPAM components as well as the main inputs and outputs.

First, meteorological, land use, and emissions data are used as inputs for a chemical transport model (CTM); the results are then used to train and validate artificial neural networks (ANN) and to establish source–receptor relationships. After that, the user can select one air quality objective (e.g., annual mean PM10 concentration) and improvement measures from a database. IUAPAM will then estimate the new concentrations and perform a health impact assessment. In the last stage, multi-criteria decision analysis (MCDA) is used to compute a final measure ranking, taking into account different criteria such as social acceptance, health benefit, or implementation costs.

The model was developed in Python programming language, and at the current stage, it does not have an interface. It allows for a rapid exploration of potential air quality improvements from emissions reduction and possible measures/scenarios.

IUAPAM is able to provide emission and concentration maps with high quality in addition to the possibility of exporting all the data in tabular text files. In a near future, a graphical user interface (GUI) for simplifying input file preparation and output results presentation will be available, aimed at minimizing the involvement of the user with the code.

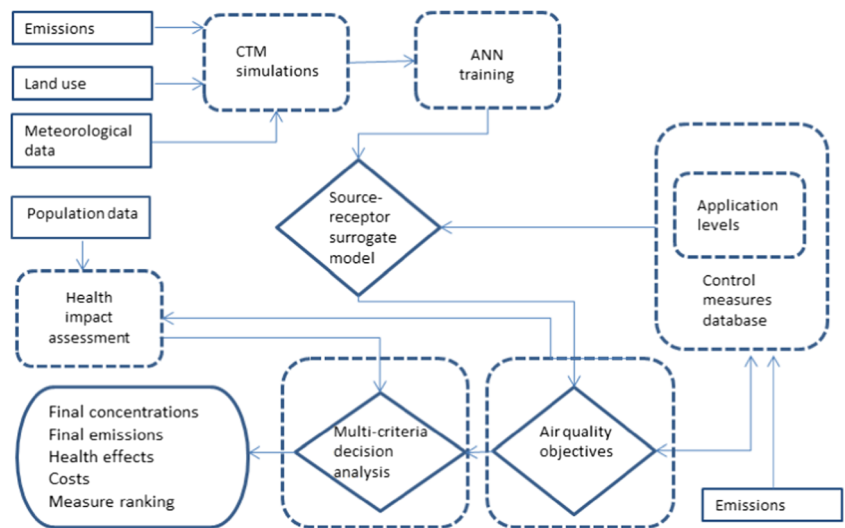
Emissions

IUAPAM is preconfigured to work with a predefined set of emissions input data. By default, an emissions inventory that covers the Portuguese main cities at high resolution ($1 \times 1 \text{ km}^2$) is included. The system is not limited to Portuguese domains and can accommodate any inventory, domain and spatial resolution; this allows for simple and straightforward testing of new air quality policies/measures on any given domain, local or not. If no regional/local inventory exists, the emissions data can be based on European inventories, such as EMEP (Vestreng et al. 2007) or TNO-MACC (Kuenen et al. 2014).

Chemical transport model

Successful air quality policies and management require accurate and detailed information on ambient air quality levels in order to assess its state and detect any problems that may be relevant to health impacts, such as an exceedance of legislated limit values. In IUAPAM, a chemical transport model (CTM), TAPM (Hurley et al. 2005), was used to simulate ten different emission scenarios for the Porto Urban Area (Portugal) with a 2-km by 2-km spatial resolution. The emissions data for 2009, provided by the Portuguese Environment Agency, was projected to 2020. More details about the model configuration and scenario creation may be found in Miranda et al. (2016). These simulations are available in the system by default. The

Fig. 1 The general scheme of IUAPAM model



user, by means of a different CTM and/or spatial resolution, can perform different simulations in order to provide IUAPAM with emission-concentration relationships for a specific case study. Detailed technical guidance on best modeling practices for assessment purposes can be found in the EEA technical report 2011/10 (EEA 2011).

The objectives

The Air Quality objective can be defined by the user as one of the following indexes:

- Annual mean PM10 concentration;
- Annual mean PM2.5 concentration;
- Annual mean NO₂ concentration.

The user can test the effect of different emission reductions for different SNAP (Selected Nomenclature for Air Pollution) macrosectors. The air quality index (AQI) can be described as follows:

$$AQI(E(\alpha)) = \beta(E_{x,y}^{z,k}(\alpha^{z,k})) \tag{1}$$

where

- $z \in Z =$ (particulate matter (PM), nitrogen oxides (NO_X), volatile organic compounds (VOC), ammonia (NH₃), sulfur oxides (SO_X)) identifies the precursors;
- $k \in K = (1, 2 \dots 11)$ is the macrosector (SNAP level 1);
- $E_{x,y}^{z,k}$ is the emission of the z precursor species for macrosector k , for the cell x,y ;
- $\alpha = \alpha^{z,k}$ is the decision variable set, namely the percentage of precursor z emission reduction in macrosector k ;
- β in this study represents ANN

If one scenario includes more than one measure related with the same macrosector k , the abatement cost is calculated as follows:

$$AC(X) = \sum_{m \in M} C_k X_{mk} \tag{2}$$

where

- AC are the abatement costs [euro] for macrosector k .
- $m \in M = (1, 2 \dots n)$ is the measure/technologies that can be applied in macrosector k to reduce pollutant z .
- C_k are the annualized unit costs [euro] of the application of measure/technology
- X_{mk} represents the application rate (between 0 and 1, respectively minimum and maximum value) of measure/technology m to macrosector k .

Therefore, the total costs [euro] are:

$$TC(X) = \sum_k AC \tag{3}$$

Artificial neural networks

In order to quickly compute different emission scenarios and reduce computational time, non-linear models based on artificial neural networks (ANN) (Carnevale et al. 2012b; Relvas et al. 2017) can be applied. This approach compared to the traditional linear source–receptor relationships (Seibert and Frank 2004; Vedrenne et al. 2014) captures the non-linearity in the relationships between emissions and concentrations, maintaining a low computational time.

By default, IUAPAM includes code to train ANN making use of a Python library called “Pyrenn,” which is capable of creating a feedforward or recurrent neural network. The

library allows saving the structure and the trained weights of a neural network to a .csv file. A pre-processor is used inside IUAPAM in order to provide ANN inputs. It considers inputs coming from four contiguous quadrants, thus considering prevalent wind directions (Carnevale et al. 2012b). This configuration has the advantage of being adjustable to different conditions by modifying the dimensions of the quadrants. However, other techniques can be used (Clappier et al. 2015).

Health impact assessment

Air pollution is a relevant cause for the intensification and development of respiratory diseases, especially in children and the elderly. Several diseases can be mentioned, such as asthma, chronic obstructive pulmonary disease (COPD), and lung cancer, as well as a substantial impact on cardiovascular disease (Anderson et al. 2013; Costa et al. 2014; Lim et al. 2012).

Based on the achieved air quality state for a specific abatement scenario, IUAPAM can estimate the human health impacts related with PM and NO₂ making it possible to perform cost-benefit analyses. Generically, the impacts can be computed as:

$$\Delta R = \sum_{z=1}^Z CRF * IR * P_z * C_z. \quad (4)$$

where

- ΔR is the response as a result of the number of the unfavorable implications overall health indicators ($i = 1, \dots, n$);
- CRF is the correlation coefficient between the pollutant concentration variation and the probability of experiencing a specific health indicator;
- IR is the baseline morbidity/mortality annual rate (%);
- P_z is the population exposed to pollution in cell z ;
- C_z indicates the average pollutant concentration, in cell z .

The evaluation of the health cost linked to health impacts can be performed by multiplying the ΔR value by its associated economic value.

Considered health outcomes were selected based on the availability of long-term CRF functions meta-analyzed from peer-reviewed literature. The methodology followed is recommended for European health impact assessments by the health risks of air pollution in Europe (HRAPIE) project (WHO 2013) of the World Health Organization. The relative risk (RR) data in Table 1 may be interpreted as follows: the RR of long-term mortality for a 10- $\mu\text{g}/\text{m}^3$ PM10 increment is 1.045 for people older than 30 years, consequently the number of premature losses increase by 4.5% for every 10 $\mu\text{g}/\text{m}^3$ PM10 increment.

Following the recommendation of the HRAPIE project, estimated impacts of the different pollutants are not added to avoid, in most practical circumstances, an overestimation of the true impact. The “impacts estimated for one pollutant only

will, on the other hand, underestimate the true impact of the pollution mixture, if other pollutants also affect that same health outcome” (WHO 2013). Therefore, depending of the air quality objective selected by the user (e.g., annual mean PM10 concentration) the IUAPAM will automatically select the related health functions.

The user can select mortality, morbidity or both, considering long-term effects. In the case of PM10 incidence and prevalence for chronic bronchitis, they should be selected together because they are applied to different population groups. According to WHO (2013), cost-benefit analyses show that mortality impacts dominate the analysis as a whole, and mortality data are complete and better standardized in EU countries.

Multi-criteria decision analysis

The IUAPAM combines the scenario approach, able to identify sound solutions when dealing with easily measurable or estimated indexes, like costs and pollutant concentrations, with a multi-criteria decision analysis (MCDA) with the opportunity to include social aspects and create an air quality measures/scenarios ranking. MCDA methods have been extensively applied to a range of environmental management challenges (Kiker et al. 2005).

MCDA methods can be generally classified into reference-level models, value measurement models, and outranking models (Thokala and Duenas 2012). Once we were interested in establishing a ranking of the different scenarios/measures, we opted for outranking models. Outranking methods are characterized by pairwise comparison of alternatives on each criterion, which, in turn, are then combined to create a partial and total ranking of the different alternatives (Thokala et al. 2016).

In this work, the PROMETHEE method (Kiker et al. 2005) is used, but there are other options like the ELECTRE method family (Figueira et al. 2013; Roy 1990), or GAIA (Brans and Mareschal 1994). Behzadian et al. (2010) delivers more details about the PROMETHEE method and performs a comprehensive review of applications.

The base of PROMETHEE is the pairwise comparison between alternatives along each known criterion. Alternatives are evaluated according to different criteria (defined by experts or decision-makers), which have to be maximized or minimized. In order to implement the method, two additional kinds of information are required (Behzadian et al. 2010):

- The weight-like in all other multi-criteria methods the decision-maker needs to be able to weigh the criteria appropriately.
- The preference function for each criterion, “the preference function translates the difference between the evaluations obtained by two alternatives into a preference degree ranging from zero to one.” Several examples of preference functions are suggested by Brans and Vincke (1985).

Table 1 Relative risk (RR) estimates, baseline data external costs used for the estimation of mortality, and morbidity due to air pollution (per 10 $\mu\text{g}/\text{m}^3$ increase)

Pollutant	Health outcome	Age group (year)	RR per 10 $\mu\text{g}/\text{m}^3$ (95% CI)	Baseline annual rate (%)	Cost (€)	Unit	Sources
PM10	Chronic bronchitis (incidence)	> 18	1.117 (1.040–1.189)	3.9	11,300 (a)	Year	(WHO 2013)
	Chronic bronchitis (prevalence)	6–18	1.080 (0.980–1.190)	18.6	11,300 (a)	Year	(WHO 2013)
	Total mortality	< 1	1.040 (1.020–1.070)	2.5	40,000 (b)	Case	(Desaigues et al. 2011; WHO 2013)
		> 30	1.045 (1.029–1.060)	1.0	40,000 (b)	Case	(Castro et al. 2017; Desaigues et al. 2011; WHO 2013)
PM2.5	Total mortality	> 30	1.062, (1.040–1.083)	1.0	40,000 (b)	Case	(Desaigues et al. 2011; WHO 2013)
NO ₂	Mortality, all (natural) causes, age 30+ years	> 30	1.055 (1.031–1.080)	1.0	40,000 (b)	Case	(Desaigues et al. 2011; WHO 2013)
	Prevalence of bronchitic symptoms in asthmatic children	5–14	1.021 (0.99–1.06)	21.1	11,300 (a)	Year	(WHO 2013)

(a) Based on average cost per day of hospitalization of 1982 €, and an average hospitalization time of 5.7 days/case

(b) Based on Desaigues et al. (2011) who recommends a monetary value of a life year (VOLY) of 40,000 € for cost–benefit in the European Union

- In this work, the Visual PROMETHEE software (<http://www.promethee-gaia.net/software.html>), which has been deliberately created to simplify the PROMETHEE process, was used. Different MCDA software tools can be found in literature (Mustajoki and Marttunen 2017).

Application results

IUAPAM was applied to the Northern Region of Portugal aimed at testing emission reduction scenarios over the Porto Urban Area. This area is densely populated and industrialized, and is repeatedly affected by high PM concentrations (Gama et al. 2018). In 2015, the Porto Urban Area had around 1,342,000 inhabitants and a mortality rate of 1050 deaths per 100,000 inhabitants (see Table 2).

Concerning the ANN training and validation, a dataset composed by ten yearly simulations carried out using the TAPM model, and previously published by Relvas et al. (2017) and Miranda et al. (2016), was used. The number of TAPM simulations have to be minimized due to computational requirements and time required to run an entire year. Nevertheless, the simulations must be able to represent, as closely as possible, the cause-effect relationship between PM10 precursor emissions (NO_x, SO₂, PM10, and VOC) and the average yearly PM10 concentration. The emissions data for 2009 (provided by the Portuguese Environment Agency) was projected to 2020 and used to create the different emission scenarios; the domain has been divided into 5625 cells, each with a size of $2 \times 2 \text{ km}^2$. Further details on emission scenario creation can be found in Relvas et al. (2017).

Reference vs. what-if scenarios

The transport sector (road traffic), together with residential combustion and industrial emissions, remains the main causes of air pollution in the Porto Urban Area. In order to test IUAPAM, four local emission reduction scenarios were generated:

- CLE—Current Legislation Emission level for 2020 (the reference year).
- S1—taking into account previously published studies (Borrego et al. 2010; Duque et al. 2016) that identified residential combustion as an important contributor to the total PM10 emissions, this scenario implies the replacement/reconversion of 50% of the conventional residential fireplaces by more efficient equipment able to reduce 70% of PM10 emissions, according to the GAINS database (Amann et al. 2011).
- S2—production processes associated with industrial sectors such as wood, metal-mechanical, or mineral products are the major sources of PM10 emissions in the Porto Urban Area (Relvas et al. 2017). This scenario assumes the application of clean technologies (high-efficiency dedusters such as cyclones and fabric filters) in addition to good practice in industrial processes-storage and handling, that allows a reduction of 5% in PM10 emissions from production processes (SNAP4).
- S3—we intend to test the effect of banning diesel cars from the Porto municipality in PM10 concentrations. Taking into account the current Portuguese share of gasoline and diesel passenger vehicles (respectively 46.2 and 52.3%), considering the restriction applied to diesel

Table 2 Key figures of the Porto Urban Area (source: National Statistical Institute of Portugal-INE)

Feature	Value
Number of municipalities	11
Area	1024 km ²
Population in 2015	1,341,432
Environmental public institution	Northern Portugal Regional Coordination and Development Commission (CCDR-N)
All-cause mortality rate in 2015	8800 deaths per 100,000 inhabitants
Life expectancy at birth in 2015	77.6 years for male, 83.3 for women

vehicles older than 10 years (57%), and a motorization rate of 457 vehicles per 1000 inhabitants, a reduction of 32,000 diesel vehicles inside municipality is expected. To estimate the resulting emission reduction, the COPERT4 emission model was used considering 1.4–2.0 cylinder diesel vehicles and EURO 4 standards (conservative estimate). An average of 20,000 km driven, by each vehicle each year, was assumed. The total emission reduction is around 32 t/year of PM10 (exhaust and non-exhaust). It is considered that the diesel vehicles are just taken out of circulation inside the municipality, and are not replaced by other polluting vehicles.

ANN training and validation

The default TAPM model simulations were used as a dataset for the identification of the ANN. First, a pre-processor was used inside IUAPAM to provide ANN inputs. The ANN inputs (i.e., the sum of precursor emissions over the quadrants), were then pre-processed by means of a normalization procedure ([0, 1]). A log-sigmoid transfer function was used in the hidden layer, and a linear function was used in the output layer. Figure 2 shows the validation results for the PM10 neural network model, by means of a scatter plot where TAPM results are compared with the ANN outputs.

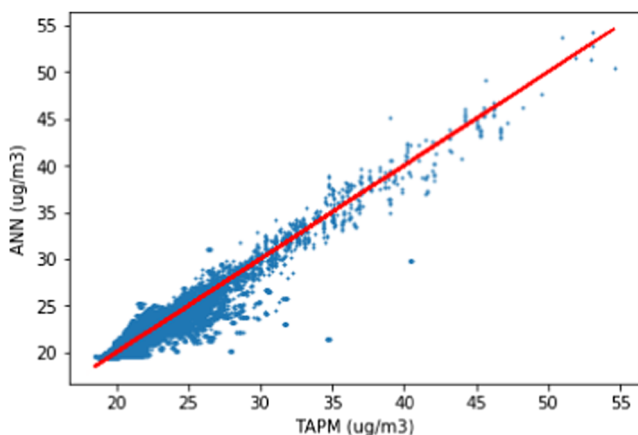


Fig. 2 ANN validation scatter plot between TAPM (*x*-axis) and ANN (*y*-axis) for yearly PM10 [$\mu\text{g}/\text{m}^3$]

The correlation value ($R^2 = 0.95$) and a low value of the normalized root mean squared error ($\text{RMSE} = 0.62$) highlight the good ANN performance. Nevertheless, the identified neural networks marginally overestimate PM10. The obtained result is quite similar to the ones achieved by Relvas et al. (2017), for the same set of ANN input data, using the Matlab Neural Network Toolbox as a tool.

Main results

After ANN training and validation, the four emissions reduction scenarios were tested. Figure 3 displays the PM10 base scenario concentrations (CLE 2020), and Fig. 4 shows the results obtained for the three other scenarios as well as their impact in relation to the CLE 2020 regarding the annual mean of PM10.

With the exception of Porto nearby area, where PM10 concentration values exceed the annual limit value ($40 \mu\text{g}\cdot\text{m}^{-3}$) the remaining study domain is characterized by low levels of PM10.

The results show that scenario 1 (fireplaces) is able to reduce PM10 levels up to $4 \mu\text{g}\cdot\text{m}^{-3}$ over the Porto Urban Area, while scenarios 2 and 3 only have minor local benefits (Porto municipality). The old diesel vehicles circulation restriction (scenario 2) allows for reductions of up to $0.4 \mu\text{g}\cdot\text{m}^{-3}$ on the annual PM10 mean, and the application of clean technologies in industry (scenario 3), $0.6 \mu\text{g}\cdot\text{m}^{-3}$.

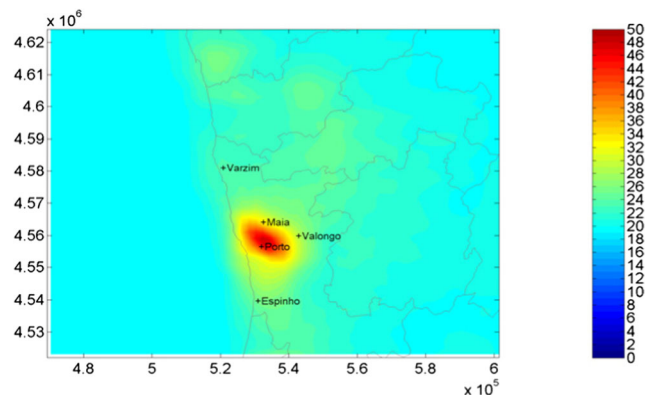
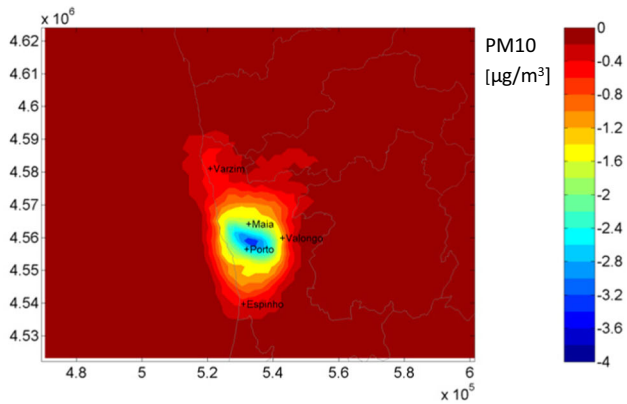
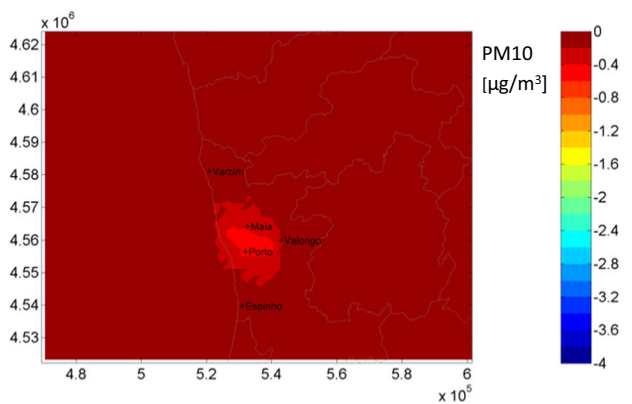


Fig. 3 Base case scenario CLE 2020. The coordinates are in UTM (meters)

S1



S2



S3

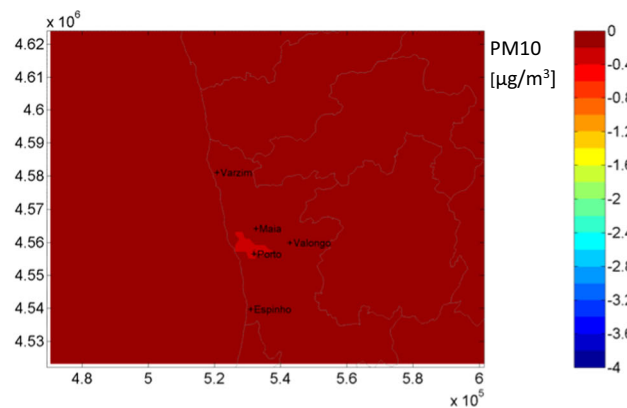


Fig. 4 Modeling results: final concentration maps of PM10 comparatively to the base case scenario CLE 2020. The coordinates are in UTM (meters)

The restriction of old diesel cars seems to have very low impacts on PM10 concentrations, this may be explained by the high efficiency of diesel particulate filters (or DPF) installed in the vehicles. The application of clean technologies in

industry (high-efficiency dedusters such as cyclones and fabric filters), in order to reduce 5% of industrial process emissions (in addition to the already applied technologies), has a low impact on PM10 concentrations. However, additional emissions reduction will be difficult to achieve because some of the industries already applied the best available techniques (BAT).

For all scenarios, despite the air quality improvement, PM10 concentration values are still higher than the annual limit value ($[PM10] > 40 \mu\text{g}\cdot\text{m}^{-3}$) over the Porto and Gaia municipalities and the nearby area. From the concentration maps, it is possible to conclude that the remaining domain is characterized by moderately low PM10 annual mean concentrations ($18\text{--}20 \mu\text{g}\cdot\text{m}^{-3}$), with the exception of Porto nearby area.

Figure 5 shows the IUAPAM estimate for total mortality (population < 1 and > 30 years old) due to exposure to PM10 for all the scenarios in analyzed, morbidity effects were not selected. Our results suggest that with the CLE2020 scenario, the premature mortality attributable to PM10 can reach 1300 deaths per year, just in the Porto Urban Area (11 municipalities).

Among the three tested scenarios, the Fireplace replacement/reconversion is the one able to achieve the highest reduction of the number of premature deaths (65 less premature deaths). Nevertheless, the industry and diesel scenarios should also be considered in air pollution control strategies, because they can reduce 12 and 4 premature deaths per year, respectively.

Notwithstanding the improvement in air quality and health, stronger air quality control measures will be necessary, particularly in the Porto municipality, in order to reduce the number of premature deaths.

Multi-criteria analysis of scenarios

Table 3 displays the list of tested air quality scenarios and related outputs: the external (or estimated health benefits)

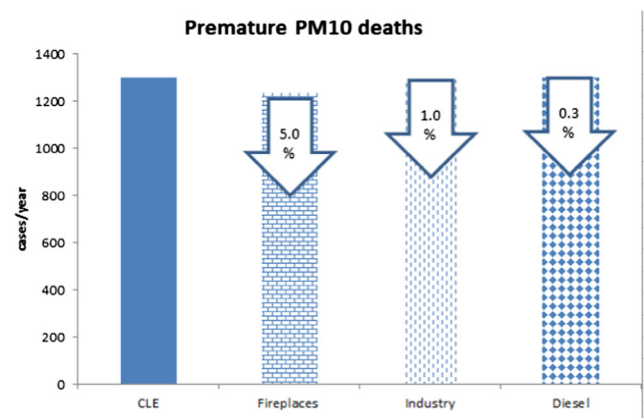


Fig. 5 IUAPAM estimate for total mortality (population < 1 and > 30 years old) due to exposure to PM10

Table 3 List of air quality scenarios and related outputs

Code	SNAP macrosector	Measure	Application rate (%)	Internal costs (M €/year)	Average PM10 concentration ($\mu\text{g}/\text{m}^3$)	Health (M €/year)
S1	2	Fireplace improved	100	0.64	26.50	2.59
S2	4	Industry	100	3.50	27.21	0.48
S3	7	Diesel	100	1.03	27.35	0.14

costs based on IUAPAM health functions, the internal costs (associated with measure implementation), and the final Porto Urban Area average PM10 concentration.

The S1 scenario requires the replacement of 14,122 units of open fireplaces by new and improved fireplaces, with an average estimated cost of 900 €/unit and a lifetime of 20 years.

The S2 scenario involves good practices in industrial processes-storage and handling, which is difficult to quantify in terms of costs, and dusts (e.g., cyclones and electrostatic precipitators), which price depends on the removal efficiency and industrial dimension. We considered a public fund of 3.5 M€/year available to industrial emission improvements.

The S3 scenario demands the installation of new signage estimated in 17.3 k€ km⁻² (25 years lifetime), and 24.6 k€ km⁻² year⁻¹ associated with surveillance actions. The costs are based on the Lisbon's low emission zone (LEZ) (CCDR-LVT 2006).

On average, the S1 scenario allows for a higher PM10 concentration reduction, with a difference of approximately 1 $\mu\text{g}\cdot\text{m}^{-3}$ compared to S3. The PROMETHEE method was then employed considering three criteria:

- C1, social acceptance;
- C2, health benefit;
- C3, cost of the measures.

The qualitative criteria (social acceptance) have scores that range from 0 to 10 and the direction of preference is ascending. This means that if the scenario is easily accepted by the population, it has the maximum score of 10. Social acceptance is quite important because even if an air quality improvement measure is able to achieve good results, it could be hard to implement, from a decision-maker perspective, if it is not accepted by the population. Quantitative criteria (internal costs and health benefits) do not need to be normalized (see Table 4). Both qualitative scores and weighting factors for the criteria were defined by academic experts based on questionnaires. It is assumed that both criteria cost and health benefit have a linear partial value function, but higher performance in the “health benefit” criterion is better, whereas lower performance in the “cost” criterion is better. Table 4 shows the obtained scores for each scenarios and the weight of the different criterion.

Table 5 presents the ranking of the different scenarios based on the different criteria and weight. It is based on the determination of two preference flows (Phi+ and Phi-). The positive flow expresses how much an alternative is dominating the others and the negative flow how much it is dominated. Phi net flow represents the difference between Phi+ and Phi-.

S1 is clearly the best choice, with the reduction of residential combustion emissions dominating the other proposed measures. S2 is the worst one, taking into account the three predefined criteria. The use of visual PROMETHEE software in conjunction with IUAPAM is particularly advantageous when the number of measures/scenarios is ample, or when the number of criteria to satisfy is large, in these cases, different types of graphs/diagrams can be produced, in order to facilitate the analysis and support the decision-making process.

Conclusions

Air quality policy-makers have to develop plans and strategies to reduce population exposure to air pollution. The IUAPAM is an IAM intended to comprehensively evaluate the effect of local and regional policies in urban air quality and human health, as well as support the decision-making process.

IUAPAM makes use of ANN (S/R non-linear models), going beyond the classical approach of using linear S/R models, or computational demanding CTM, which facilitates the test of several emission scenarios. After training and validating the ANN, IUAPAM is able to give, in less than 30 s, emission and concentration maps, the external costs (mortality

Table 4 Matrix containing the scores for each scenario, and the weight of the different criteria

Code	Social acceptance	Cost	Health benefit
S1	5.0	0.64	2.59
S2	9.0	3.50	0.48
S3	6.5	1.03	0.14
Weight of the criterion	0.1	0.3	0.6

Table 5 PROMETHEE ranking of the different scenarios and related Phi, Phi+, and Phi– scores

Rank	Scenario	Phi	Phi+	Phi–
1	S1	0.6466	0.7643	0.1177
2	S3	–0.1305	0.3177	0.4483
3	S2	–0.5160	0.1552	0.6712

and morbidity) due to air pollution and the total implementation costs. The ranking of the different emission scenarios can be done based on MCDA, including health, economic, and social aspects in the decision process.

The second stage of the work was focused on the application of IUAPAM in the Northern Region of Portugal to evaluate the impact of different emission scenarios on concentrations and population health due to PM10 exposure.

The results underline that to reduce particulate matter exposure in Northern Portugal, and specifically in the Porto Urban Area, the fireplace scenario (S1) is the most relevant, allowing for an average reduction up to $4 \mu\text{g}\cdot\text{m}^{-3}$ of annual PM10 concentrations, and a decrease of 65 premature deaths per year. The other two scenarios appear to be more limited in their reach.

The MCDA approach was applied in order to compute a final scenario ranking, aggregating social acceptance (evaluated by experts), as well as costs (external and internal). Based on the final ranking, it was clear that S1 is the best choice, with the industrial clean technologies (S2) being the worst. However, MCDA is heavily dependent on the selection of considered criteria and the experts' choice of criteria weights.

This work shows that IUAPAM is able to rapidly reproduce the effects of emission reduction scenarios, identifying the most suitable set of abatement measures, facilitating the decision-making process.

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