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A multi-objective optimization approach for Air Quality and Energy plans

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Abstract: This study addresses a multi-pollutant, multi-objective optimization problem to identify efficient air quality control strategies for the cities of the Po Valley, Northern Italy. The objective is to minimize PM2.5 and NO_2 concentrations while considering the feasibility of achieving the new European Directive, reducing health impacts. The evaluation is conducted for 2030, assessing air quality projections under current legislation and additional emission reduction measures (including end-of-pipe, energy, and fuel-switch). Results show that current legislation ensures compliance with NO_2 standards, but PM2.5 remains above the threshold in several cities due to secondary formation. Additional measures reduce PM2.5-related deaths by 29% and NO_2-related mortality drops virtually to zero. The co-benefits of additional air quality policies on greenhouse gas emissions reduction are estimated at 17% of the current legislation in 2030.

Keywords: Integrated Assessment Modelling; Multi-objective Optimization; Air Quality; Pollutant trade-offs; Greenhouse Gases

1. INTRODUCTION

Air pollution is a critical public health issue, with the World Health Organization (WHO) estimating that 99% of the global population breathes polluted air (WHO, 2019). Among air pollutants, fine particulate matter (PM2.5), particulate with a diameter under 2.5 µm, has the greatest health risk (Clark et al., 2024). Long-term exposure to PM2.5 is linked to severe health incomes, including stroke, cardiovascular disease, lung cancer, and respiratory infections (Sang et al., 2022; Sangkham et al., 2024).

The European Union (EU) has introduced stricter air quality standards to mitigate these impacts. The 2024 Directive (Directive 2024/2881/EU, 2024) sets the annual mean limit of 10 $\mu g/m^3$ for PM2.5 and 20 $\mu g/m^3$ for NO_2 (another harmful pollutant that affects cities) to be achieved by 2030. However, even compliance with these standards does not eliminate the health risk, as WHO guidelines recommend lower thresholds of 5 $\mu g/m^3$ for PM2.5 and 10 $\mu g/m^3$ for NO_2 (WHO, 2021).

Consequently, EU member states must implement effective air quality plans to meet regulatory targets and, where possible, achieve further reductions. Meeting these targets is particularly challenging in some regions due to geographical features and high population density. One of these areas is Northern Italy, specifically the Po Valley (Scotto et al., 2021; Squizzato et al., 2013). The elevated concentration levels affect the resident population, particularly in urban areas. A study analyzing 969 European cities found that five cities in the Po Valley have the highest associated health impacts: Brescia, Bergamo, and Vicenza for PM2.5; Turin and Milan for NO_2 (Khomenko et al., 2021).

Previous studies have shown that even substantial emission reductions in the Po Valley do not guarantee compliance with WHO or EU standards, highlighting the complexity of air quality management in this region (Colombo et al., 2024).

The valley's enclosed topography and stagnant airflows significantly limit pollutant dispersion, leading to the accumulation of both primary and secondary pollutants. Secondary PM2.5, formed through complex atmospheric reactions, can constitute up to 50% of total concentrations (Scotto et al., 2021), further complicating mitigation efforts.

Given the role of long-range transport and chemical transformations, controlling air quality in urban areas requires regional-scale strategies rather than isolated city-level interventions. For example, source apportionment studies have shown that PM2.5 concentrations in Milan, a city heavily influenced by traffic and residential emissions, are strongly affected by ammonia emissions, which are mainly emitted by agricultural activities in rural areas (Clappier et al., 2021). This highlights the need for integrated control approaches that account for multi-sectoral and multi-regional interactions.

Using an Integrated Assessment Model (IAM) (Turrini et al., 2018), this study evaluates 2030 air quality projections based on the current implemented strategy (Ministry of Economic Development et al., 2019) and assesses additional targeted measures to reduce urban pollution.

The analysis implements a multi-pollutant, multi-objective optimization, where the air quality index accounts for a multi-pollutant environment (PM2.5 and NO_2) and includes population-weighted concentration, ensuring that mitigation strategies prioritize areas with the highest health impact. The co-benefits of greenhouse gas (GHG) emission reductions are assessed.

Section 2 delineates the formalization of the decision problem, the models employed for its resolution, and the data collected for application to the case study. Section 3 presents the main results in terms of emission and concentration reduction, measure selection, and health impact.

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2. MATERIALS AND METHODS

The study proposes two future scenarios. The first considers the designed legislative measures up to 2030 (CLE2030). It is defined by projecting the application of national and regional plans. The second is the solution of a multi-objective problem. It includes the measures planned by the current multi-scale legislation and the additional efficient measures, solution of the multi-objective problem.

2.1 Multi-pollutant multi-objective optimization

The components of the objective function include an air quality index and an economic index.

The first component (AQI) corresponds to a multi-pollutant index that considers PM2.5 and NO_2 concentrations. To define a value that represents the entire domain, the average of the local concentrations weighted by the resident population of each location is taken. This value tends to be more representative of the pollution's health impact than the simple spatial average because urban areas, which are more densely populated, tend to be more polluted than rural areas. The second component of the objective function represents the costs of implementing emission reduction measures (IC).

The problem's decision variables (θ) are the degrees of implementation of each emission reduction measure, and the objective function can be written as:

$$\min_{\theta \in \Theta} \left[AQI\left(E(\theta)\right),\ IC(\theta) \right] \qquad (1)$$

where θ represents the set of emission-reduction measures and Θ is the feasible space, defined by the problem constraints that assure the mutual exclusion of measures and energy conservation as described in (Turrini et al., 2018).

The multi-pollutant air quality index implemented in this study uses a fairness approach that balances the maximum reduction of the two pollutants. The objective is to minimize an index that is a sum of the normalized differences between the value obtained from the combined optimization process and the single optimization of each pollutant.

The methodology consists of two main steps. First, the set of ideal points (z_j^I) is determined by each fixed cost level. These ideal values represent the minimum achievable concentration obtained by independently minimizing each pollutant index, namely the population-weighted average PM2.5 (z_{PM}) and NO_2 (z_{NO2}).

The ideal points serve as reference values to compute the deviation of each pollutant index from its respective ideal solution when performing the combined optimization. The absolute deviation is given by:

$$d_j = \left\| z_j^{com} - \left(z_j^I\right) \right\|_2 \qquad j = \{PM2.5, NO_2\} \qquad (2)$$

where z_j^{com} is the pollutant concentration value obtained from the combined optimization. To ensure comparability across pollutants, the deviation is normalized using the range between the worst-case scenario (i.e., the base-case scenario concentration z_j^{CLE}) and the ideal value:

$$\overline{d_j} = \frac{d_j}{\left\| z_j^{CLE} - \left(z_j^I\right) \right\|_2} \qquad j = \{PM2.5, NO_2\} \qquad (3)$$

where $\overline{d_j}$ represents the normalized distance of pollutant j from its ideal point.

Finally, the AQI is computed using a weighted function, ensuring that the pollutant with the highest deviation has a greater impact on the final index:

$$AQI = w_1 \cdot max\left(\overline{d_{PM}}, \overline{d_{NO2}}\right) + w_2 \cdot min\left(\overline{d_{PM}}, \overline{d_{NO2}}\right) \qquad (4)$$

where w_1 and w_2 are predefined weights, such that $w_1 > w_2$.

The control variables are the degree of adoption of end-of-pipe (γ_m), fuel consumption (ψ_f), and fuel switch (ϕ_s) measures' application rate. The former reduces the emissions of an individual activity without altering its energy use, the second directly reduces the energy consumption, and the third modifies the fuel used to one with lower emissions. In this study, the set of control variables comprises 845 variables, consisting of 611 end-of-pipe measures, 222 energy measures, and 12 switch measures.

Implemented measures directly affect the emissions released. The emission of each precursor (p) in a single portion of the domain (d) is computed as a sum of the emissions released by all the sources (k):

$$E^{d,p}(\theta) = \sum_k \left[A_k^d \cdot ef_k^p \cdot \left(1 - \left(\sum_{s \in S_k} \phi_s + \sum_{f \in F_k} \psi_f\right)\right) \cdot \left(1 - \sum_{m \in M_k} eff_m^p \cdot \gamma_m\right) \right] \qquad (5)$$

where A_k^d is the activity level of the emission source k in the location d (expressed in a.l.u., activity level unit), ef_k^p is the unabated emission factor of the pollutant p for the activity k (in t/a.l.u.), eff_m^p is the removal efficiency (%) of the end-of-pipe measure m on the precursor p, and F_k, S_k, and M_k represent the sets of fuel consumption, fuel switch, and end-of-pipe measures, applicable to the k-th activity.

The link between emissions and concentration, $AQI(E^{d,p})$, is estimated with a surrogate model (Carnevale et al. 2012, Ferrari & Guariso, 2023) that simplifies the complex relation that occurs in the atmosphere. The spatialized concentrations are then elaborated to compute the aggregated AQI.

The costs are computed as a function of the measure application rate by multiplying the degree of diffusion of each measure by its unit cost.

2.2 Model set-up

The decision model is implemented and solved using the MAQ (Multi-objective Air Quality) tool (Turrini et al., 2018, Arrighini et al., 2023; De Angelis et al., 2022; Zecchi et al., 2024). The tool is composed of four modules: emissions computation, source-receptor model, health impact assessment, and cost evaluation. Each module is made of different models and databases identified and populated for a specific decision problem. The interaction between the modules is represented in Figure 1. The evaluation starts from a base-case scenario as a reference scenario. The application of measures impact on emissions, which are computed as in equation (1).

The emissions, defined per cell and pollutant, are the input of a surrogate model, which estimates the yearly average concentration of PM2.5 and NO_2 per cell. The model implements Artificial Neural Networks (ANNs).

These modules implement the optimization process described in Section 2.1 and return the efficient set of measures, emission reductions, and the concentration levels per cell.

The latter are then elaborated by the health impact assessment module, which implements a dose-response function to compute the health impact in the form of attributable deaths.

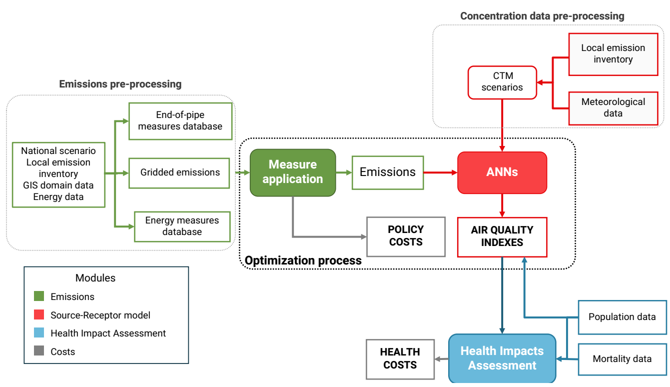

Figure 1. MAQ model framework.

The costs are computed in the optimization process as the total costs of the selected measures, but also as the savings obtained by health impacts.

2.3. Domain and data

The case study is the Po Valley, a vast area in Northern Italy, including the regions of Piedmont, Lombardy, Veneto, and Emilia-Romagna (see Figure 1). This area covers 71,000 km^2 and hosts almost 20 million inhabitants, corresponding to 30% of the national population. The domain is subdivided into 92*59 cells of 6*6 km^2 each.

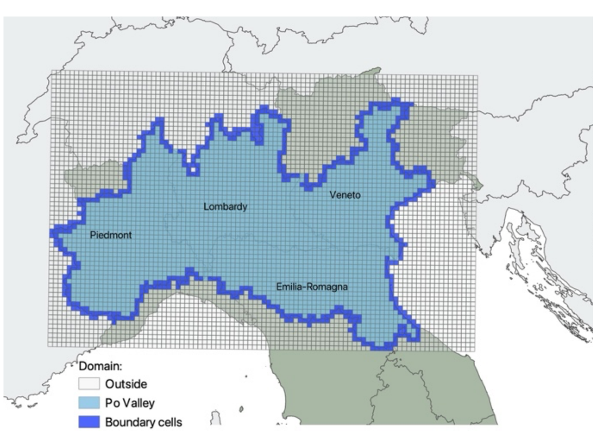

Figure 2. Studied domain, divided by policy application domain (light blue), boundary cell (blue), and outside domain.

The analysis is built on the 2030 scenario. The base case corresponds to the current legislation projection. The data required to define the 2030 scenario are:

- Local Emission inventory data: in this case, the INEMAR 2017 elaborated in the LIFE PREPAIR project (https://www.lifeprepair.eu)
- Measures database, which defines the available measures to each emissions source, their efficacy, and costs. The database is taken from the GAINS model (https://iiasa.ac.at/models-tools-data/gains), in particular, the Outlook scenario (the reference year 2030).
- National energy plan, PNIEC (Ministry of Economic Development et al., 2019), which points out the target trajectory at the national level for energy sectors.
- Emissions and concentration datasets for ANN training are collected from simulations obtained with CAMx (https://www.camx.com), a chemical and transport model, with different emission scenarios, starting from INEMAR 2017 and 2019 meteorology (Ferrari & Guariso, 2023). The ANNs' performance indexes are reported in Table A1
- Population and mortality data are collected by the National Institute of Statistics (ISTAT, https://esploradati.istat.it/databrowser/). Data are produced at the municipality level with reference year 2019. No future projections on population are implemented.
- Relative Risks correlated to PM2.5 and NO_2 exposure, taken from the literature (Joana Soares et al., 2024).

The 2030 scenario is obtained by the integration of the Outlook 2030 scenario with the PNIEC target (emissions can be found in Table A2). The local inventory provides data about the location of sources and their emissions intensity. The current data are projected following the technology application and fossil fuel use expected to 2030.

3. RESULTS

The multi-objective optimization problem is solved using an ε-constraints algorithm, where the costs are fixed and iteratively changed, while the AQI is minimized. The weight values chosen for the computation of AQI are the elements of a mathematical series with a ratio equal to 0.1 and a sum equal to 1.

The base case scenario in 2030 corresponds to a yearly average PM2.5 population-weighted concentration of 13.1 $\mu g/m^3$ and NO_2 equal to 12.46 $\mu g/m^3$. This is the starting point of optimization and represents the intersections of Pareto fronts in Figure 3 with the y-axis.

The costs of application of measures are estimated as an additional cost to those prevented by legislation. The maximum feasible reduction corresponds to a cost of 27 billion euros, reaching 9.1 $\mu g/m^3$ for PM2.5 and 4.3 $\mu g/m^3$ for NO_2.

The solutions to the decision problem show the different variability of the two pollutants, which is more visible for NO_2 (65% from starting concentrations), while it is limited for PM2.5 (only 32 %).

The Pareto curves show the highest curvature with costs below 200 M€/year, suggesting that incentivizing the application of additional measures above these costs would have a marginal impact on air quality. From the efficient set of scenarios selected, those with a cost of 100M€ and an average weighted value of 10.9 μg/m³ for PM2.5 and 6.1 μg/m³ for NO_2 (which corresponds to Scenario E in Figure 3).

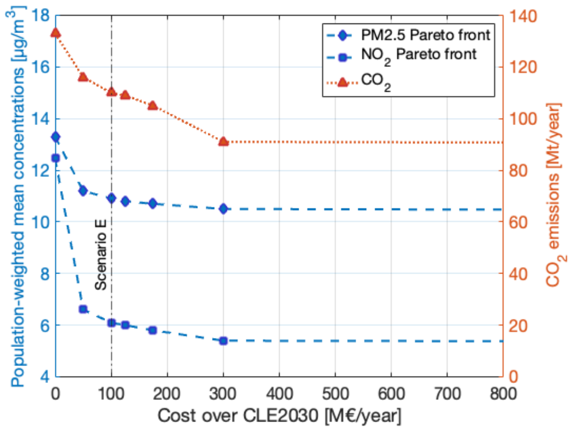

Figure 3. Solutions to the decision problem. Population-weighted annual average of PM2.5 and NO_2 in μg/m³ on primary vertical axes, CO_2 emissions in Mt/year on secondary vertical axis, and total costs over the 2030 base-case scenario (CLE2030) in M€/year.

Figure 4 and Figure 5 show how the concentrations (not weighted by population) are distributed in the domain for PM2.5 and NO_2, respectively.

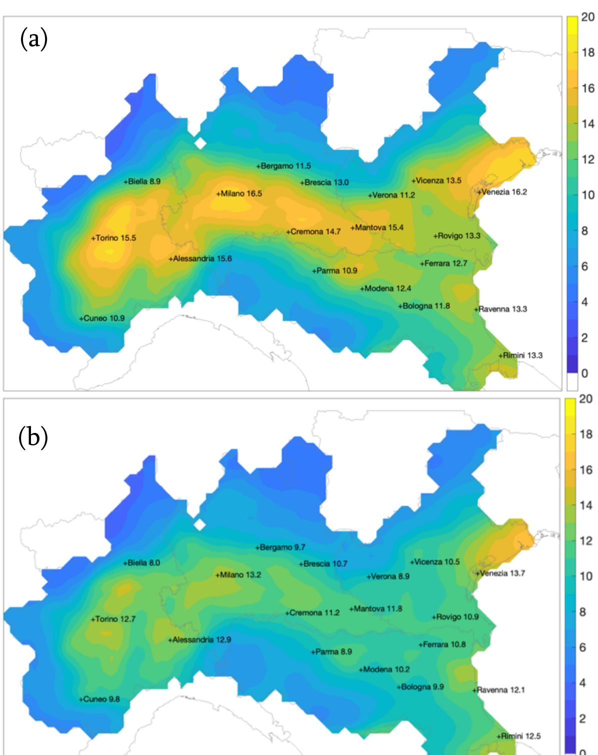

Figure 4. Yearly average PM2.5 in μg/m³ concentration over the domain in the CLE2030 (a) and efficient (b) scenarios.

Following the current legislation, in 2030 only 10 out of 36 cities in the Po Valley would be able to meet the EU directive for PM2.5. By contrast, only one city (Milan) would fail to reach the NO_2 target. Nevertheless, it appears that all cities for PM2.5 and 22 cities for NO_2 are above the WHO guidelines.

With the additional measures (Scenario E), all the cities reach the NO_2 UE standards and on the health side, only one city (Rimini) overpasses the WHO guideline. For PM2.5 the average value continues to stay above the EU target for a major part of the cities (18). Also, in this case, all the cities exceed the 5 μg/m³.

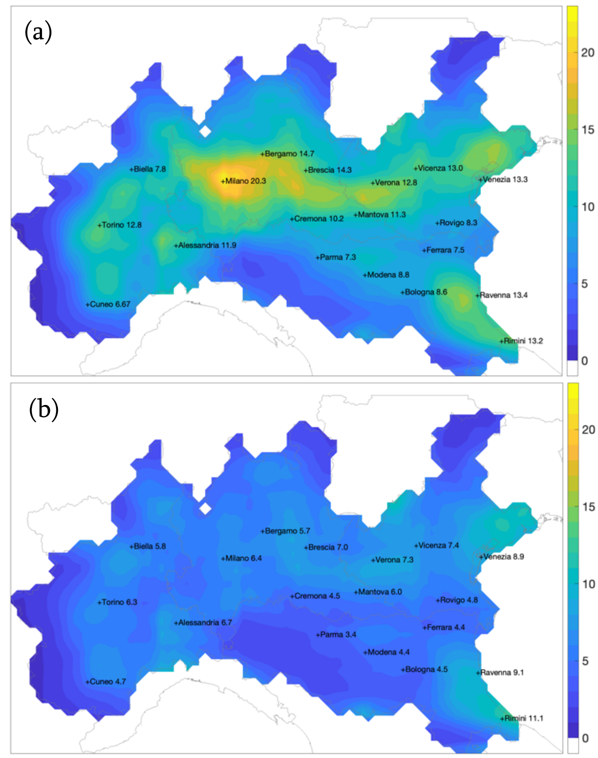

Figure 5. Yearly average NO_2 in μg/m³ concentration over the domain in the CLE2030 (a) and efficient (b) scenarios.

3.1 Efficient measures

This section summarizes the efficient measures selected by the solver. Table 1 shows how costs are allocated to the different macrosectors, referred to CORINAIR SNAP97 classification (Table A3), with a distinction between energy and end-of-pipe measures.

Table 1. Additional costs [M€/year] from CLE2030 allocated to each macrosector for Energy and End-of-Pipe (EoP) measures.

MS	Energy measures [M€/year]	EoP measures [M€/year]	Total [M€/year]
01	0.8	16.1	16.9
02	5.3	41.2	46.5
03	0.1	7.2	7.3
04	-	0.6	0.6
06	-	0.4	0.4
07	6.4	14.2	20.5
08	2.2	0.2	2.4
10	-	6.1	6.1
TOT	14.7	86.0	100.8

The selected strategy uses almost half of the budget for the application of measures in the residential sector (MS02). Additionally, 20% is allocated to the road transport (MS07) and 17% to the energy production (MS01) sector. The industrial combustion sector (MS03), agriculture (MS10), and off-road transport (MS08) are also relevant.

The corresponding emissions reductions are reported in Table 2. The selected measures mainly reduce NOx, thanks to transport sectors (MS07 and MS08) and energy production (MS01) strategies. Primary PM2.5 is reduced by interventions in the domestic heating sector, while ammonia is lowered through policies in the agricultural sector (MS10).

Table 2. Percentage emissions reduction contribution per macrosector in Scenario E (100 M€/year) by CLE2030, defined per precursor and CO_2.

MS	NOx	VOC	NH_3	PM2.5	SO_2	CO_2
01	4.4%	0.1%	-	0.3%	4.4%	1.0%
02	1.6%	0.5%	-	13.4%	-	-
03	3.6%	-	0.1%	5.3%	5.4%	-
04	0.3%	-	-	0.4%	1.2%	-
06	-	4.0%	-	-	-	-
07	25.1%	0.4%	0.2%	2.1%	0.5%	14.2%
08	4.4%	0.2%	-	0.9%	0.1%	2.3%
10	-	-	6.8%	0.1%	-	-
TOT	39.4%	5.2%	7.1%	22.6%	11.6%	17.5%

The implementation of energy measures also impacts the total release of CO_2 emissions, with a reduction of 17%, mainly from MS07. To achieve a more significant impact on CO_2, a scenario with higher investments (over 300 M€) is required, as represented in Figure 1 (nearly 32% reduction).
The measures with higher application chosen by the algorithm are reported in Table 3. The energy measures application is focused on the transport sector, in particular on urban fleet electrification. Measures on commercial vehicles consist of the optimization of goods delivery and the payment of a tax to reduce the use of these vehicles in the city center. On the end-of-pipe measures side, the sector application is wider and includes the combustion sectors (MS01 and MS03) and the non-combustion sectors, such as MS04 and MS10.

Table 3. Energy (underlined) and End-of-Pipe measures with a higher application rate (AR) in Scenario E. Each measure is applied to a specific Macrosector (MS)-Sector-Activity.

MS	Sector	Activity	Measure	AR
7	Buses-urban	Diesel	Switch to EV vehicles	90%
7	Cars-urban	Gasoline	Switch to EV vehicles	87%
8	Agriculture	Diesel	Particulate filters	63%
7	LDVs-urban	Diesel	Optimization of urban goods delivery	58%
7	HDVs-urban	Diesel	Toll payment on ordinary roads	50%
1	Power & district heat plants	Biomass fuels	Selective non-catalytic reduction	100%
3	Industrial furnaces	Biomass and waste fuels	High efficiency deduster	100%
10	Poultry	-	Feed modification	100%
4	Cement and lime	-	High efficiency deduster	58%

3.1 Health Impact

The health impact on resident populations is computed as the attributable deaths due to PM2.5 and NO_2 exposure. The relative risks (RR) are taken from the literature, and the final impact is computed with 95% confidence intervals (CI), using the uncertainty of RR and ANNs.
The results are expressed as attributable deaths over 100k inhabitants and reported in Figure 6.
The AD due to PM2.5 is higher than 100 deaths/100k inhabitants in 15 cities (50% of the total). The application of efficient measures leads to a reduction in health impact, with only one city (Venice) over the value of 100 deaths/100k inhabitants.
The impact on health due to NO_2 exposure is lower, caused by a lower Relative Risk and concentration levels in CLE2030 close to the WHO guidelines. For PM2.5, the total AD average reductions are 29% (CI: 9%-37%). While for NO_2, the application of measures results in virtually zero attributable deaths.

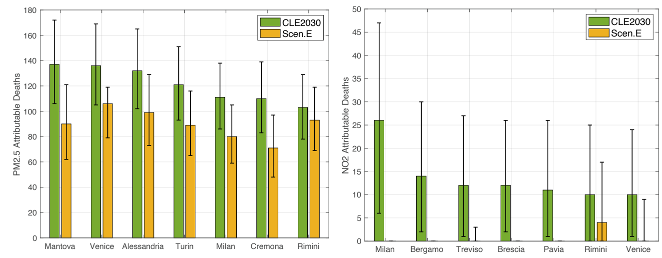

Figure 6. Attributable deaths due to PM2.5 and NO_2 over 100k inhabitants in the most polluted cities of the Po Valley in CLE2030 and Scenario E (Scen.E)

4. CONCLUSIONS

This study aims to define air quality control strategies for the cities of the Po Valley, minimizing pollutant concentrations while considering the feasibility of achieving the EU air quality directive by 2030. To address this challenge, a methodology is proposed to design air quality plans that minimize exposure to multiple pollutants (PM2.5 and NO_2) and evaluate CO_2 emission reductions. The multi-pollutant, multi-objective optimization problem is solved using an Integrated Assessment Model.
The results indicate that under the current legislation, the EU directive can be complied with for NO_2, but PM2.5 levels remain above the threshold in several cities.
The implementation of additional emission reduction measures leads to further improvements in air quality, but in some cities, the attainment of the PM2.5 standard remains unachievable. This discrepancy arises from the distinct behaviors of the two pollutants: while NO_2 concentrations are primarily driven by NOx and VOC emissions, PM2.5 has a more significant secondary component formed through complex chemical reactions involving numerous precursors, making its reduction more challenging despite stringent emission controls. Despite these limitations, the application of additional measures provides significant health benefits, with a 29% reduction in PM2.5 attributable deaths by CLE2030, and the NO_2 that reaches the WHO guidelines levels.

Appendix A

Table A1. Performance indexes of ANNs in the validation phase, compared with CAMx data simulations.

	Emilia Romagna	Lombardy	Piedmont	Veneto
PM2.5				
RMSE (μg/m^3)	0.39	0.5	0.46	0.46
R^2	0.99	0.99	0.99	0.99
σ (μg/m^3)	0.39	0.5	0.46	0.45
NO_2				
RMSE (μg/m^3)	0.73	0.66	0.5	0.65
R^2	0.99	0.99	0.99	0.99
σ (μg/m^3)	0.73	0.66	0.5	0.64

Table A2. Emissions in kt/year per precursor and macrosector (MS) in the CLE2030 scenario.

MS	NOx	VOC	NH_3	PPM10	PPM2.5	SO_2
01	12.09	2.26	0.12	0.27	0.24	3.27
02	22.20	17.58	1.01	15.95	15.10	1.49
03	28.40	10.79	0.78	3.39	2.60	10.37
04	5.02	31.60	0.18	1.22	0.59	7.62
05	0.00	8.49	0.00	0.00	0.00	0.00
06	0.39	163.02	0.04	1.83	1.61	0.02
07	54.96	31.49	1.17	13.52	4.00	0.56
08	10.82	2.33	0.01	0.44	0.41	0.58
09	0.89	0.63	1.22	0.83	0.73	0.18
10	1.44	149.20	215.31	2.34	0.52	0.12
11	1.16	182.74	0.30	3.26	2.73	0.24
TOT	137.37	600.14	220.14	43.06	28.53	24.46

Table A3. CORINAIR SNAP 97 macrosector classification.

MS	Macrosector
01	Combustion in energy and transformation industries
02	Non-industrial combustion plants
03	Combustion in manufacturing industry
04	Production processes
05	Extraction and distribution of fossil fuels and geothermal energy
06	Solvent and other product use
07	Road transport
08	Other mobile sources and machinery
09	Waste treatment and disposal
10	Agriculture
11	Biogenic

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